Firm and Industry Characteristics, Long-term Returns and Survival of Initial Public Offerings [IPOs]: A Critical Re-Evaluation

Uzonwanne, Nnamdi John

Submitted in accordance with the requirements for the degree of Doctor of Philosophy

University of Leeds

Leeds University Business School

The Centre For Advanced Studies In Finance [CASIF]

December 2013

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In Memory of my Beloved Mother – May her soul rest in the bosom of the Lord till we meet to part no more.

ACKNOWLEDGEMENTS

I give thanks to the Almighty God for the mental and physical strength given to me to complete this work. Also, I would like to thank Profs Phil Holmes and Nick Wilson for their insightful suggestions, helpful comments and invaluable guidance throughout the work. I also give thanks to my parents for their prayers and unalloyed support throughout the duration of my study in England.

ABSTRACT

This study tracks IPOs from the time of their entry into the public domain up to at least six years post-listing. In the first part of this study, the post-listing performance of these firms relative to that of a set of control firms in event and calendar time is evaluated, using a fresh sample of 746 IPOs in the UK market over the period 1999-2006 and stepwise matching algorithms that select the matching firms from the general population on the basis of key firm risk factors that includes three new factors – pre-IPO performance, turnover growth and earnings yield – employing a refined matching technique and a battery of methods. Given that the majority of the studies in the literature find that IPOs are poor investments in the long-term, the findings in the first part suggest firstly, that investing in IPOs beyond the immediate after-market may not be a bad trading strategy since the relative after-market performance is dependent on the proportions in which the stocks are stacked in the investor's portfolio; secondly, value-weighted performance does not provide strong evidence against market efficiency when compared to an equally-weighted measure of abnormal performance [which tends to suggest that the former may provide a more useful benchmark in assessing the post-event risk-adjusted performance of IPO firms since it more accurately captures the investors' wealth effects] and; thirdly, the under-performance of new issues of common stock remains an anomaly that really challenges the efficient

market hypothesis only when performance is equally-weighted. In the course of analysing the performance of the firms in the first part, this work finds that the under-performance is more prevalent in some groups of IPOs than others. Hence, in the second part of the work, the economic importance and significance of key firm and industry risk factors prior to or at the IPO that may predict or explain this under-performance is tested. The author's findings reveal that industry risk factors of IPO surplus value, profitability, market-to-book and equity volatility in addition to firm risk factors of size, market-to-book, past performance, underwriter reputation and the 'hot' IPO market can help distinguish the best performing from the worst performing firms. More importantly, the industry effects here are economically large and are first documented in this study. In the third and final part of the work, the firms are tracked in event and calendar time, equally using only that information that is available prior to or at the IPO. The author's findings reveal that industry risk factors of IPO surplus value and profitability in addition to firm risk factors of size, past performance, initial market return volatility [IPO risk], underwriter prestige and the 'hot' IPO market can foreshadow an IPO's survival. More importantly, the industry effects here are also first documented in this study. More particularly, the evidence here on past performance and underwriter prestige is strong and overwhelming with the results suggesting that firms desirous of going public should first build a track record of profitable performance, while the latter lays credence to the fact that firms underwritten by prestigious underwriters are less likely to fail. The results also suggest that potential IPO investors, IPO firms and their investment bankers should consider industry risk factors prevailing at the time of the IPO to provide them with additional information on whether or not to invest in the IPO [in the case of the investor] or go ahead with the IPO, or alternatively, withdraw and re-launch at a more auspicious date [in the case of the issuing firm and its investment banker].

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CHAPTER 1 - INTRODUCTION

[1.1] Introduction

Initial Public Offerings [IPOs][1] have historically been found to be poor investments following their debut on worldwide stock exchanges, unless one can get in at the primary market stage and exit in the immediate secondary after-market. While average first-day and immediate after-market returns are large, buying and holding these IPOs after this initial period have generally been found to be unprofitable, much against the tenets of the market efficiency hypothesis. The decision to invest in an IPO is usually made on the basis of the offer document and any other supplementary information that may be available to the investor at the time of the IPO. These investors usually take a gamble that the financial projections in the prospectus would materialise in the long-run as they look forward to good returns on their investments. However, the value of these investments can either rise or fall and investors may not get back their initial capital outlay.

In general, it is known from the IPO literature that firstly, they are profitable investments in the short-term; secondly, they are poor investments in the long-term either in relation to a market benchmark or a set of comparable firms with fairly similar risk profiles matched on the basis of size, market-to-book and industry using event time

[1] An IPO is a stock market launch where the shares of a firm are sold to the public on a stock exchange for the first time.

methodologies and/or calendar time techniques that rebalance the IPO stocks in monthly portfolios and; thirdly, the decision to float [by firms and their investment bankers] or invest [by investors] in an IPO are usually made on the basis of firm specific and market conditions prevailing at the time of the IPO. However, it is not known firstly, if the documented under-performance of IPOs is a manifestation of the statistical inadequacies of previous matching methods or inadequate matching criteria; secondly, if it is really an anomaly that challenges the efficient market hypothesis; thirdly, if the scale and magnitude of the observed under-performance is sensitive to the matching process [i.e. whether changing the way the control firms are selected from the general population into the composite benchmark portfolio by either varying the statistical technique or the number of matching criteria has any effect on the observed under-performance] and; fourthly, beyond the firm and market risk factors prevailing at the time of the IPO that are usually outlined in the offer document, the potential impact of salient industry conditioning risk factors on the performance and survival of these new issues.

Following from the above, the three key issues that will be investigated in this study are as follows: firstly, the sensitivity of the under-performance finding, with respect to the choice of empirical method and matching criteria, using an improved technique that seeks to remove the ambiguity surrounding previous conventional approaches; secondly, the impact of a raft of industry conditioning risk factors ranging from an adjusted IPO valuation [i.e. IPO surplus value], profitability and leverage to market-to-book, concentration and equity volatility on the long-run performance of IPOs and; thirdly, the impact of this same battery of factors on the survival likelihood of these firms. Hence, the life cycle of IPOs is examined in three strands right from their transition from private to public life, as their performance and ultimate survival is tracked within a minimum 6-year cycle[2].

There appears to be harmony in prior research on the long-term performance of new issues of common stock that because it lacks a proper methodological framework, the scrutiny has been essentially unsophisticated. Lyon, et al [1999] further buttress the fact of the inappropriateness of the current approaches by positing that the use of the size and market-to-book factors alone as firm risk factors can lead to misspecified test statistics and spurious inferences in certain sampling situations. Therefore, before IPO performance is accepted as an example of market inefficiency, it will seem reasonable to further re-examine the robustness of these international findings, using a fresh sample of IPOs employing a unique multi-dimensional procedure that seeks to reduce

[2] Based on the average life cycle of new listings, this is the estimated time period it should take an IPO firm to establish a foothold in the market by remaining a going concern or fail and be delisted.

the perceived imperfection in previous procedures and approaches used in the literature. Against this backdrop, the goal of the first empirical study is to unearth these additional key risk factors using a unique multi-dimensional procedure and in the process establish the various dimensions upon which the analysis of the performance of new issues of common stock should be based.

Investment decisions and expectations on new stock issues are usually based on the prospectus [‘offer document’], which contains information on the firm and offering characteristics as well as financial projections about the future performance of the firm. Hence, any industry and other supplementary information not contained in the prospectus that could be germane to the performance of new issues would prove invaluable to these investors in their search for value, as it enables them to either avoid new issues that could potentially under-perform and/or fail in the post-IPO years or demand better discounts on their pricing at the IPO stage. This information could also be of immense value to the IPO firms and their investment bankers as they seek to time their offerings to coincide with favourable industry conditions. In addition, an understanding of the association between key firm and industry characteristics at the IPO date and the performance and survival of new issues of common stock in the post-IPO period should firstly, provide an indication of the performance and survival likelihood of these firms and secondly, allow issuing firms and their investment bankers to make better decisions about proceeding with or delaying the offering. Hence, the goal of the second and third empirical studies is to firstly, determine the class and profile of IPO firms that under-perform and/or fail and secondly, ascertain if a set of observable firm and industry characteristics prior to or at the IPO can foreshadow the performance and survival likelihood of the issuing firms in the long-term.

[1.2] Main Findings

In the first empirical study, the post-listing performance of the IPO firms is tracked relative to that of a set of control firms in event and calendar time. The findings reveal that, indeed, in line with the majority of extant research, IPOs are poor investments either in event time methodologies or calendar time techniques that rebalance the IPO stocks in monthly portfolios, using the equally-weighted technique. However, the evidence is mixed when a value-weighted performance measure is adopted. Under this scenario in event-time methodologies, the under-performance is also largely evident; however, when the risk-adjusted performance of the IPO stocks is tracked in calendar time, this work finds under-performance to be non-existent in some cases, and at best, weak in some others. This pattern of results is robust to the inclusion or exclusion of the late 1990s technology bubble. Overall, given that the majority of the studies in the literature find that IPOs are poor investments in the long-term, the findings from the first empirical study suggest firstly, that investing in IPOs beyond the immediate after-market may not be a bad trading strategy since the relative after-market performance is dependent on the proportions in which the stocks are stacked in the investor's portfolio; secondly, value-weighted performance does not provide strong evidence against market efficiency when compared to an equally-weighted measure of abnormal performance and; thirdly, under-performance of new issues of common stock remains an anomaly that really challenges the efficient market hypothesis only when performance is equally-weighted.

In the course of analysing the performance of these new issues in the first part, the observed under-performance is found to be more prevalent in some groups of IPOs than others. A wide variation in the performance of these firms by industry is also obnserved, which tends to suggest that the characteristics of these industries may be germane to the short and long-term performance of these firms. Against this backdrop, this work test for the economic importance and significance of key firm and industry risk factors prior to or at the IPO that may predict or explain this cross-sectional variation in the second empirical study. When doing this, the work controls for and confirms the results of previous studies on the impact of firm-specific risk factors. More specifically, size, market-to-book, past performance, underwriter reputation and the 'hot' IPO market are found to be important predictors of IPO performance in a cross-section. The work also finds that industry level risk factors relating to IPO surplus value, profitability, market-to-book and equity volatility can help distinguish the best performing from the worst performing firms. These results are robust to including controls for variables known to predict IPO long-term performance. However, apart from industry profitability and industry market-to-book to a limited extent, the other industry risk factors are not robust to the exclusion of the late 1990s technology bubble, which suggests that those years are driving some of the results.

In the third and final empirical study, the IPO firms are tracked for an extended period in event and calendar time. An analysis of the distribution of the post-IPO states of these firms by industry reveals a wide variation in the survival and failure rates which also tends to suggest that there may be some industry structure variables that impinge on the entry and ultimate survival of these firms in the market place. This work confirms that firm risk factors of size, past performance, initial market return volatility [IPO risk], underwriter reputation and the 'hot' IPO market are important predictors of the probability of IPO survival in cross-sectional regressions, using only that information that is available prior to or at the IPO. The author's findings also reveal that industry risk factors of IPO surplus value and profitability can be valuable determinants of an IPO's survival prospects. Following from the first empirical study, the findings in the second and third empirical studies suggest that investing in IPOs beyond the immediate after-market may not be a bad trading strategy and that investors can improve their long-run returns by strategically investing in carefully and well-selected IPOs, after due consideration of key and relevant firm, industry and other supplementary information at the IPO date.

[1.3] Contribution to the Literature

In the words of Lyon, et al [1999, pp. 198], 'the analysis of long-run abnormal returns is treacherous; as such, we recommend that the study of long-run abnormal returns be subjected to stringent 'out-of-sample' testing'. Fama [1998, pp. 283] also posits that 'apparent anomalies can be due to methodology [and] most long-term return anomalies tend to disappear with reasonable changes in technique'.

Lyon, et al [1999, pp. 198] also aver that 'researchers should conduct a detailed descriptive analysis to reveal other firm specific risk factors that could be used in selecting the control firms from the population to be used as benchmarks for the IPO firms'. In the light of the above, the first empirical study contributes to the literature in two ways; firstly, it adds further evidence on the sensitivity of the under-performance finding, with respect to the choice of empirical method, using a distance metric matching technique [the first of its kind in the UK market] that seeks to remove the ambiguity surrounding previous conventional approaches; secondly, it goes beyond the size, market-to-book and industry risk factors commonly used by most researchers in selecting the control firm from the general population used as a reference for measuring abnormal returns by introducing pre-IPO performance, turnover growth and earnings yield as additional key risk factors [the first of its kind in the literature, to the best of the author's knowledge] that could be employed in selecting the control firm.

The second empirical study contributes to the literature in three ways; firstly, to the best of the author's knowledge, the unique relationships between industry risk factors of IPO surplus value, market-to-book, profitability, equity volatility and IPO long-run performance are first documented in this study; secondly, it is the first to study the impact of industry-specific risk factors on the long-run performance of IPOs in the UK market and; thirdly, it helps provide potential IPO investors with additional useful information that they could use to build their investment opportunity sets at the offering stages of these firms.

The third empirical study contributes to the literature in four ways; firstly, to the best of the author's knowledge, the unique relationships between industry risk factors of IPO surplus value, profitability and IPO survival likelihood are first documented in this study; secondly, it is the first to study the impact of industry-specific risk factors on the survival of IPOs in the UK market; thirdly, it provides an initial estimate of the survival likelihood of new issues which helps managers of IPO firms, their investment bankers and potential IPO investors with additional useful information that they could use in their decision-making process at the IPO date and; fourthly, it helps us better understand the milieu of factors that prevent the capital market from growing in terms of the number of listed firms.

Finally, to my knowledge, this is the first work in the UK market that extensively analyses the long-term performance and survival of IPOs in one empirical study. It first studies the relative performance of these firms, employing an appropriately-matched firm technique, in a fixed time period using different windows [1 - 5 years] and thereafter tracks the survival of this same cohort, on a 'stand-alone' basis, in event time and duration models. Conclusively, despite using a multi-faceted and comprehensive approach that utilises salient firm and industry information prior to or at the IPO date to re-assess the performance and survival likelihood of IPO firms, future research is encouraged into identifying other salient firm and industry risk factors that could be used in selecting the control firms from the general population in re-assessing IPO long-run performance and also help in distinguishing between firms that are likely to perform and/or survive from those that are likely to under-perform and/or fail.

The rest of the thesis is organised as follows: Chapter 2 provides a background to the study by analysing the new issues market and the allure of the IPO procedure to firms in the market place amongst other competing alternatives. Chapter 3 re-evaluates the long-run performance of IPOs using a raft of methods and techniques, while Chapter 4 investigates the impact of salient firm and industry conditioning risk factors on the long-run performance of these firms. The impact of this range of factors on the survival likelihood of these firms using a battery of techniques is explored in Chapter 5, while Chapter 6 summarises and concludes the work.

CHAPTER 2 – THE NEW ISSUES MARKET

[2.1] Introduction

This chapter sets the background to the study as it examines the market for new issues. Section 2.2 presents the various methods of raising capital that are available to both public and private firms in the market place, while Section 2.3 discusses the appeal of the IPO procedure to private firms desirous of going public amid other competing alternatives. Section 2.4 examines the global and UK IPO trends both in terms of the number of deals and the amount of capital raised commencing in the 'dotcom' period [i.e. 1999-2001] through the period of the global financial crisis [i.e. 2008-2009] till the middle of this year [i.e. June 2013].

[2.2] Methods of Flotation

To comprehend the motivations for equity offerings, it is vital to differentiate those offerings that raise new capital and those that do not. Firms can float new shares ['primary shares'] via a variety of methods ['public offering', 'rights issue' or 'private placement'] which effectively increases the number of outstanding shares and the market capitalisation of the firms in the market place, in the case of listed firms. In some other cases, they can also offer shares held by existing shareholders ['secondary shares'] through an 'offer for sale', usually in conjunction with a primary share offer. It is important to emphasize that only primary share issuances raise new capital which can then be used to finance investments. In contrast, the proceeds from an ‘offer for sale’ do not go to the firm, but to the existing shareholders who sell them. There are basically four main ways of floating securities in the new issues market. At the extremes, a firm can either list its shares on the stock exchange by 'introduction' – where no new money is raised – or decide to undertake an ‘initial public offering’ [IPO] or a ‘rights issue’, where institutions and private individuals [in the case of an IPO] and existing shareholders [in the case of a rights issue] are invited to invest in the offering. A mid-way procedure is a ‘private placement’ in which the shares of the firm are offered for sale on a limited basis, primarily to a select group of institutional investors.

A firm, with at least 25 per cent of its shares already in public hands [the ‘free float’], can list by ‘introduction’ on the stock exchange without any need to raise new capital. An advantage of this process is that it is the least expensive route to the market since it involves no underwriting, advertising or marketing fees. The additional upside is that the firm has the opportunity of listing on the stock exchange ‘quietly’ and in the process avoids the adverse selection costs that are usually associated with an IPO. This ‘quiet’ listing paves the way for an efficient price discovery for its stock which can reduce the potential level of under-pricing and the ‘amount of money left on the table’, if and when it decides to conduct an IPO. However, the downside is that opportunities for boosting the firm's profile and visibility are very limited. A 'private placement' typically involves the offering of the shares of an unlisted firm to a limited and choice group of institutional investors. This method allows the firm firstly, to raise capital with lower costs and secondly, more discretion to choose its shareholders. However, the drawback of this process is that it results in a lower liquidity in the shares of the firm resulting from a narrower shareholder base.

In an 'IPO', a fixed number of securities of a previously unlisted firm are offered to both private and institutional investors at a specified price or price range through a prospectus. This procedure, usually underwritten by investment banks and the most expensive route to the market, is often used by larger firms or those looking to raise substantial amounts of capital. When an already listed firm does not want to dilute the controlling interest of the current shareholders, a 'rights issue' is undertaken where it raises new capital by issuing its shares to existing and qualifying shareholders whose names appear in the register of members at a designated date ['the pre-qualification date']. Despite being a relatively costly procedure, the IPO process remains the choice method of floating new securities for most firms in the market place given that it offers greater opportunities for raising cheaper capital and boosting the firm's visibility in the market place.

[2.3] The IPO Process

Following its debut on the stock exchange, the firm's life as a private firm comes to an end as it transits to public life, where its shares are owned, exchanged and traded publicly. IPOs are made by different firms for a number of reasons. Small firms may seek to list their shares on the stock exchange to provide them with a platform to raise cheaper capital required for further expansion. Some other firms that may already be of substantial size may wish to use the IPO to other ends. For example, they may see the advantages of an enlarged and diversified equity base and the increased levels of public consciousness that are part and parcel of undergoing an IPO.

Firms in the market place desirous of raising capital to prosecute large scale investments can do so either by issuing debt or equity. When prevailing interest rates are low and capital markets are bearish, firms tend to issue debt since it is cheaper and more conducive. On the other hand, when interest rates in the economy are high coupled with a buoyant capital market characterised by positive investor sentiments, firms are more disposed to raising equity capital than debt. This process tends to be very straight forward for already listed firms in the stock exchange as a fair price for its shares can be readily determined. Under this scenario, these firms can effortlessly raise additional capital via a seasoned equity offering [SEO], usually at a price close to the prevailing market value. Given that information on these firms are already available in the public domain and coupled with the fact that they have a visible track record of performance in the market place, investors are better placed to make informed decisions on whether to invest in the offering or not.

For a private firm, the going public process is a critical turning point in its life cycle and the most significant event in its history given that this process leads to significant changes in its life. The IPO market provides a real platform for a growing private firm to access relatively cheap capital. The decision by private firms to go public is more often than not motivated by the need to raise capital for organic growth and acquisitions, create liquidity for the shares of the firm, take advantage of high valuations and favourable market conditions, rebalance the capital structure by reducing or repaying lingering debt and create an exit route for private equity or venture capital in the firm. However, this debut equity capital raising exercise, which also brings the firms under increased disclosure and regulatory requirements, is a bit complicated given that the firms are not yet listed which makes it difficult to determine their fair values. Under this scenario, some of these firms could either decide to remain unlisted and conduct a 'private placement' or initially list the shares by 'introduction'. The latter option has the advantage of dousing the uncertainty and adverse selection costs that may surround the firm's stock on the eventual IPO day. On the flip side, buoyant economic conditions characterised by an improving economy, 'hot' markets, a huge demand for capital, low equity volatilities and positive investor sentiments may be too strong for some other private firms to resist and consequently, they are tempted to raise equity by issuing shares through an IPO.

[2.4] Global and UK IPO trends

Table 2.1 reports IPOs by the number of deals and amount of capital realised for the global and UK markets. From the table, this section finds that in the period around the technology bubble years [i.e. 1999-2000], the IPO market was tense as many firms rushed to the market to raise capital on the back of massive investor over-optimism in the market at the time. However, the 'bubble bust' in 2001, occassioned largely by the failure of information technology [IT] stocks which were at the forefront of the boom, reverberated through the market as investors' enthusiasm ebbed with its attendant negative impact on equity markets as many firms halted their plans to go public. As of a consequence, the number of IPOs globally fell from 1,883 in 2000 to 876 in 2001. This lull in the IPO market continued till 2004 when the markets appear to have picked up again. In that year, 1,520 firms made initial offerings globally, raising $131b in the process. This pattern is also observable in the UK IPO market as the number of IPOs

TABLE 2.1: IPOS BY VOLUME AND VALUE

The table reports IPOs by volume [number of IPOs] and value [total capital raised] for the period 1999 to 2012. Panels A *[Source: Dealogic, Thomson Financial, Ernst & Young]* and B *[Source: www.londonstockexchange.com]* report the figures for the global and UK markets respectively. The average deal value per year is the deal value divided by the number of deals in that year.

Panel A: Global Markets

Year	No of Deals	Deal Value [$'b]	Av. Deal Value [$'b]
1999	1,372	177	0.129
2000	1,883	210	0.112
2001	876	99	0.113
2002	847	70	0.083
2003	812	58	0.071
2004	1,520	131	0.086
2005	1,552	180	0.116
2006	1,796	267	0.149
2007	2,014	295	0.146
2008	769	96	0.125
2009	577	113	0.196
2010	1,393	285	0.205
2011	1,225	170	0.139
2012	837	129	0.154
TOTAL	**17,473**	**2,280**	**0.130**

Panel B: UK Market

Year	No of Deals	Deal Value [£'b]	Av. Deal Value [£'b]
1999	145	12	0.083
2000	326	18	0.055
2001	175	11	0.063
2002	99	5	0.051
2003	86	5	0.058
2004	295	7	0.024
2005	423	16	0.038
2006	367	29	0.079
2007	269	27	0.100
2008	73	7	0.096
2009	22	2	0.091
2010	95	9	0.095
2011	76	13	0.171
2012	67	8	0.119
TOTAL	**2,518**	**169**	**0.067**

FIGURE 2.1: GLOBAL IPOS BY VOLUME AND VALUE

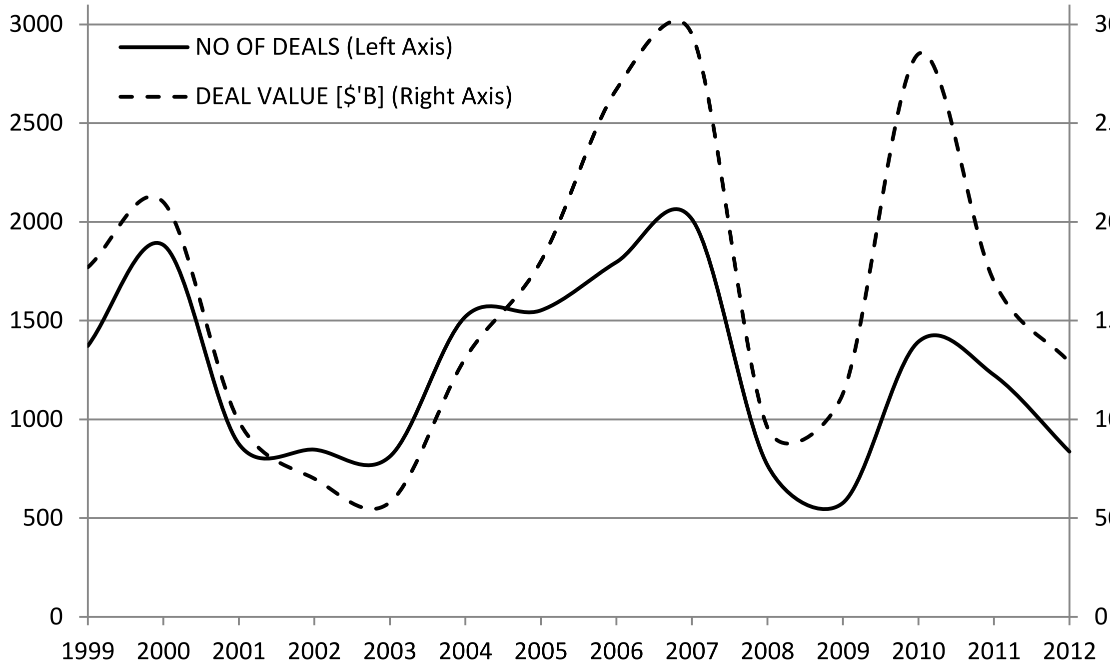
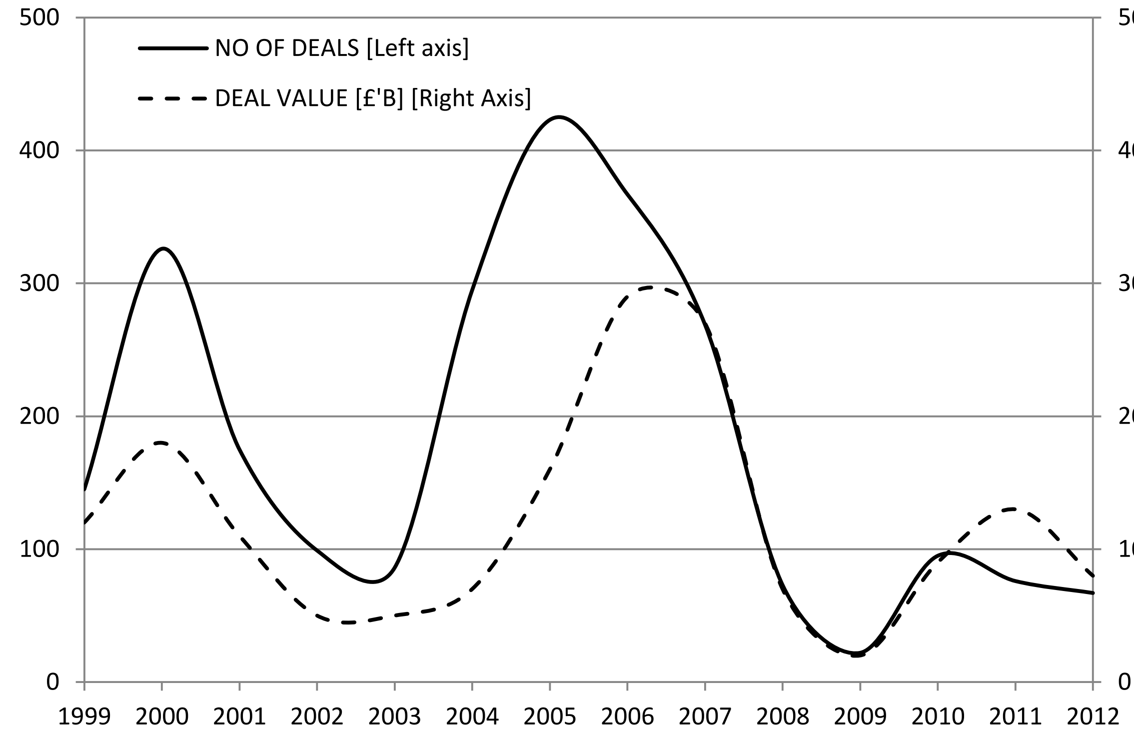


FIGURE 2.2: UK IPOS BY VOLUME AND VALUE



fell progressively from 326 in 2000 to 86 in 2003 [deal value also dropped from £18b to £5b] before rising to 295 in 2004. This intense activity in the market was maintained through to 2007 with the global deal volume and value rising further to 2,014 and $295b respectively [UK: 269 and £27b] in that year before dropping to 769 and $96b respectively in 2008 [UK: 73 and £7b]. This remarkable decline coincided with the global economic turmoil that commenced in the same year [i.e. 2008], rocking financial markets across the world with negative consequences for financial and equity markets. This period was also characterised by high equity volatilities and negative investor sentiments which made it difficult for firms to launch their offerings. It is also observed from the same table and the corresponding diagrams in Figures 2.1 and 2.2 that the IPO market appears to have picked up again from 2010 onwards on the back of improved economic conditions and stock market indices, reduced stock market volatilities and renewed investor enthusiasm. This market rebound has continued into the current year [2013] as 344 IPOs around the world [UK: 23] raised $68.4b [UK: £2.4b] in the first half of the year as firms took advantage of strong equity market rallies and soaring investor appetite.

Undoubtedly, patterns are observed in the IPO market that are somewhat tied to the state of the economy and investors' sentiments at any given point in time. This section finds an upswing in the number of IPOs in the 'technology bubble' period [i.e. 1999-2000] on the back of brimming investor optimism and a high demand for capital. The 'bubble bust' in 2001 permeated through world equity markets and rocked investors' confidence leading to a lull in the IPO market, over the period 2001 to 2003, as many firms either withdrew or cancelled their initial plans to go public. The market picked up again from 2004 as investors' confidence was restored, but this was shortlived as the global financial turmoil that started in 2008 took its toll on the market. It is also observed that the equity market has, once again, picked up from the rubbles of the financial crisis given the upward swing in the number and value of IPO deals from 2010 and upwards.

It is pertinent to point out that despite the surge in the number of firms going public every year as can be clearly seen from the Table, the rate of IPO failure is still relatively high[3]. Given that IPO firms are fundamentally different from public firms that already have a visible track record of performance in the market place, there is a potentially greater uncertainty and risk associated with their valuation and by extension, their performance and survival in the long-term. On the part of potential investors, financial performance, information presented in the offer document and the 'road show', the strength of the management team, industry specific conditions and the need for

[3] See Section 5.5.2.2, pp. 353-354.

another asset class in their investment basket are some of the factors they consider before deciding to invest in an IPO. A firm conducting an IPO may not have a long track record of visible performance in the market place and consequently, could be difficult to value. It is the uncertainty surrounding the valuation of IPOs occasioned by this lack of visible performance data that make investors somewhat cagey of new stock issues. If many of these issues under-perform [which is still a subject of debate in the finance literature today] and subsequently fail in the post-IPO years, then it would be worthwhile to examine key predisposing firm and industry risk factors prior to or at the IPO that could signal this to potential IPO investors.

Against this backdrop, the first part of this study attempts a re-evaluation of the long-run performance of IPOs relative to a set of fairly similar firms using a raft of methods and techniques, while the second part investigates the impact of salient firm and industry conditioning risk factors prior to or at the IPO on the after-market performance of these firms. The impact of this same battery of factors on the survivorship of these firms, using a range of techniques, is explored in the third and final part of the study.

CHAPTER 3 - LONG-RUN PERFORMANCE

[3.1] Introduction

The persistent long-run under-performance of IPOs has been a vexed issue in the literature which has equally represented a challenge to market efficiency. Even after the considerable amount of attention that has been paid to this phenomenon [Barber and Lyon, 1997a; Kothari and Warner, 1997; Lyon, et al, 1999; Loughran and Ritter, 2000; Ritter and Welch, 2002; Brav, et al, 2000; Fama, 1998; Jegadeesh and Karceski, 2004; Eckbo, et al, 2007; Petersen, 2005; Ahmad-Zaluki, et al, 2007; Boissin and Sentis, 2010; Thomadakis, et al, 2012], the debate is far from settled. The majority of extant literature reveals, in general, the existence of long-run under-performance of new issues of common stock, for periods upwards of three years from the event day. However, it is still an unsettled issue amongst financial economists on what the cause of this under-performance may be as it has been found to be very sensitive to the expected return model and methodology employed. As a result, the methodological research in this area becomes of great importance because it shows how very easy it is to assume under-performance when there may really be none.

An onslaught of attacks has been launched on these results by other researchers who argue that the choice of a performance measurement methodology directly determines both the magnitude of the measured abnormal performance and the size and power of the statistical tests. In that context, Lyon, et al [1999, pp. 198] affirm that the 'analysis of long-term abnormal returns is treacherous'. This work also argues that IPO under-performance may just be manifestations of the statistical inadequacies of traditional matching methods or inadequate matching criteria rather than an anomaly that challenges the efficient market hypothesis. The original IPO under-performance results are dramatic and generally imply that IPOs are poor investments. But recent findings [Freitas, et al, 2008; Xia and Wang, 2003; Kiymaz, 2000; Kutsuna, et al, 2009; Thomadakis, et al, 2012; Alli, et al, 2010] and the critical review of the anomalies literature by Fama [1998] suggest that this under-performance phenomenon merits further inquest.

There has been so much controversy in the literature on how IPO firms should be evaluated. From the event-time to the calendar-time methodologies and the various asset pricing models, the issue of the performance of IPOs in the long-run has not been fully laid to rest. Put differently, the jury is still out on this issue. In the context of the event-time methodologies, it may well be that the documented under-performance is due to imperfect matching procedures, while in calendar-time procedures, it may be the result of the approach not being able to fully explain the variation in the cross-section of stock returns. A common technique in prior research is the matching method which matches issuing firms to a set of comparable non-issuing firms on a dimension-by-dimension basis using some pre-defined callipers and a set of ex-ante firm characteristics. The purpose of this approach is to establish the existence of an abnormal price performance by comparing the ex-post stock returns of IPO firms with those of non-IPO firms having similar risk profiles. This work argues that the traditional matching methods may potentially not yield good matches because of a multi-dimensional matching problem which makes it difficult to match simultaneously on multiple dimensions. Hence, the key issue here is about the dimensions on which the analysis of the performance and indeed survival of new issues of common stock should be based. The goal is to develop a robust and well-rounded performance measurement approach that will help provide answers to this knotty question. More specifically, this work seeks to identify and introduce key risk factors that could be pivotal in determining and shaping the return profile of the average firm into the model for assessing the post-event risk-adjusted performance of new issues of common stock.

In characteristics-based approaches[4], this work seeks to match event firms with similar non-event firms on certain key return-determining risk factors using a systematic

[4] Under this approach, we have the buy-and-hold abnormal returns [BHAR] and cumulative abnormal returns [CAR] as barometers for measuring long horizon stock price performance.

approach to enable us determine if the documented under-performance finding is genuine. To accomplish this task, the work follows Jegadeesh [2000] by introducing a multi-dimensional procedure that constructs a deviation metric measure that assesses event firms to non-event firms on carefully selected return-determining characteristics and then chooses for each event firm a matching non-event firm that is closest to the event firm on this constructed measure. By so doing, the work would firstly, ensure that event and non-event firms have similar risk profiles in all possible respects and secondly, reduce, to some extent, the potential problem of 'bad modelling' that may have plagued previous studies on the long-horizon performance analysis of new listings[5]. The price performance of the sample and benchmark firms subsequent to the IPO event is then tracked in characteristics and factor based approaches[6].

In this multi-dimensional process, the work goes beyond the traditional factors of size, market-to-book and industry by introducing new firm risk factors [turnover growth, pre-IPO performance and earnings yield] not previously used in the literature, to the best of the author's knowledge, to select the control firms from the general population using stepwise matching algorithms that seek to ensure that the sample firms and benchmark

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[5] Fama [1970] posits that event studies are joint tests of market efficiency and a model of expected returns. Fama [1998] corroborates this point by asserting that all models of expected returns are incomplete descriptions of the systematic patterns in average stock returns.

[6] This is also known as the Jensen alpha or the calendar time portfolio approach.

firms have fairly similar risk profiles. Now, what informs the choice of variables to be employed in the matching models? It is generally agreed that firms that are in the same industry and with similar sizes, turnover and growth performances are assumed to have analogous economic and competitive factors and in most cases tend to have comparable operating, investing and financing opportunity sets [Perry and Williams, 1994]. Also, prior literature[7] that has studied the interface between firms in competitive industries shows that these firms consider the joint actions of their peers when making crucial financial decisions. Although, a myriad of factors may impinge on a firm's decision to diversify its ownership base by issuing some of its shares to the public, it is an accepted view that this decision has implications on its financial structure and overall market value.

To achieve the author's matching objectives and also guarantee a fair assessment of the relative ex-post performance of the issuing firms subsequent to the IPO date, the work ensures that the ex-ante characteristics of the sample and control firms at the IPO date are fairly similar in all possible respects. Against this backdrop, the work uses information available prior to or at the IPO date to select the matching firms from the general population. In this regard, industry and pre-IPO performance [to control for

[7] See Brander and Lewis [1986], Maksimovic [1988], Maksimovic and Zechner [1991], Williams [1995], Fries, et al [1997] and Mackay and Philips [2005].

possible differences in firm specific performance before the IPO date], market capitalization [to control for size effects and possible differences in investing opportunity sets], turnover growth [to control for possible differences in operating opportunity sets], market-to-book ratio [to control for possible misalignments in growth potentials] and earnings yield [to control for possible differences in firm specific performance and potential returns to investors] are used as probable dimensions for choosing the matching non-event firms from the population. This informs the motivation behind the first part of the study as it seeks to re-examine the validity, reliability and robustness of the documented under-performance using a fresh sample of 746 IPOs in the UK market over the period 1999 – 2006 and stepwise matching algorithms that select the matching firms from the general population on the basis of key firm risk factors that includes three new risk factors – pre-IPO performance, turnover growth and earnings yield – employing a refined matching technique and a battery of methods.

The findings reveal that, indeed, in line with the majority of extant research, IPOs are poor investments either in event time methodologies or calendar time techniques that rebalance the IPO stocks in monthly portfolios, using the equally-weighted technique. However, the evidence is mixed when a value-weighted performance measure is adopted. Under this scenario in event-time methodologies, the under-performance is also largely evident; however, when the risk-adjusted performance of the IPO stocks is tracked in calendar time, the under-performance is found to be non-existent in some cases, and at best, weak in others. This pattern of results is robust to the inclusion or exclusion of the late 1990s technology bubble. The results also show that the scale of the under-performance, which varies substantially and in some cases disappears altogether across the matching board, is sensitive to firstly, the choice of empirical method; secondly, the choice of matching firms in the benchmark portfolio; thirdly, the method of cumulating abnormal returns; fourthly, the weighting scheme employed; fifthly, the horizon over which it is measured and; sixthly, the inclusion or exclusion of the late 1990s technology bubble. This work also documents a novel finding. It is found that in almost all the cases, the observed under-performance is least, and in some cases evaporates, when the matching algorithm includes industry as an additional risk factor, which tends to suggest that a matching criteria that includes the industry of the firms is vital in the matching process as it ensures that issuing and non-issuing firms are fairly similar, thus making for better comparisons.

Overall, given that the majority of the studies in the literature find that IPOs are poor investments in the long-term, the findings suggest firstly, that investing in IPOs beyond the immediate after-market may not be a bad trading strategy since the relative after-market performance is dependent on the proportions in which the stocks are stacked in the investor's portfolio; secondly, value-weighted performance does not provide strong evidence against market efficiency when compared to an equally-weighted measure of abnormal performance [which tends to suggest that the former may provide a more useful benchmark in assessing the post-event risk-adjusted performance of IPO firms since it more accurately captures the investors' wealth effects] and; thirdly, under-performance of new issues of common stock remains an anomaly that really challenges the efficient market hypothesis only when performance is equally-weighted.

The first empirical study contributes to the literature in two ways; firstly, it adds further evidence on the sensitivity of the under-performance finding, with respect to the choice of empirical method, using a distance metric matching technique [the first of its kind in the UK market] that seeks to remove the ambiguity surrounding previous conventional approaches; secondly, it goes beyond the size, market-to-book and industry risk factors used by most researchers in selecting the control firm from the general population used as a reference for measuring abnormal returns by introducing pre-IPO performance, turnover growth and earnings yield as additional key risk factors [the first of its kind in the literature, to the best of the author's knowledge] that could be employed in selecting the control firm. Despite the additional risk factors used in this first empirical study to select the control firm, future research is encouraged into identifying other salient risk factors that could be used in selecting the control firms from the general population. Some of these factors could potentially include liquidity [Paster and Stambaugh, 2001; Amihud, 2002; Dey, 2005; Eckbo and Norli, 2005], leverage [Bhandari, 1988; Eckbo and Norli, 2005], access to credit markets [Perez-Quiros and Timmermann, 2000] and skewness [Singleton and Wingender, 1986; Tang and Shum, 2003], albeit, it has been argued that sensitivity to some of these risk factors are already captured by the size and value [i.e. book-to-market] factors and hence, already priced in, which then suggests that they may not be distinct sources of additional risk.

[3.2] Literature Review

[3.2.1] Approaches to abnormal performance measurement

There are two main approaches to assessing the post-event risk-adjusted performance of a sample of firms – the characteristics-based approaches in event time and the factor based approaches in calendar time. Under the event time approach, there are two main methods - the BHAR and CAR techniques. Mitchell and Stafford [2006, pp. 296] describe BHAR returns "as the average multi-year return from a strategy of investing in all firms that complete an event and selling at the end of a pre-specified period versus a comparable strategy using otherwise similar non-event firms". Essentially, this approach, which typically does not involve rebalancing, uses a matched firm technique to risk adjustment and is not immune from the joint test problem of market efficiency and a model of expected return since it is hinged on the validity of the assumption that event firms differ from the 'otherwise similar non-event firms' only in that they experience the event. A positive [negative] BHAR is generally interpreted as the specific IPO portfolio out-performing [under-performing] the designated benchmark. A related measure is the wealth relative which explores how the sample of IPOs performs relative to the matching benchmark. A wealth ratio greater than 1 is generally interpreted as the specific IPO portfolio out-performing the benchmark, whereas a wealth ratio of less than 1 indicates under-performance.

The CAR returns can be described as the summation of the average of the monthly portfolio returns over a pre-specified period from a strategy of investing in all firms that complete an event contrasted with a comparable strategy using otherwise similar non-event firms. This approach frequently involves rebalancing which may give rise to security microstructure issues. A positive [negative] CAR is generally interpreted as the specific IPO portfolio out-performing [under-performing] the designated benchmark. The allure of the BHAR approach over the CAR lies in the fact that it more accurately captures investors' real life investment experience. The factor based approach is an alternative to the event time approaches. This approach calculates calendar time portfolio returns for firms experiencing an event and determines if these returns are abnormal in a multi-factor asset pricing regression framework. The estimated intercept from the regression of the time series of portfolio excess returns relative to the return on a risk-free instrument [usually mimicked by treasury bills] against factor returns is the post-event abnormal performance of the sample of event firms [Kothari and Warner, 2007]. The asset pricing model could either be specified as the capital asset pricing model [CAPM] or the Fama and French 3-factor [FF3F] model or the FF3F model with Cahart's [1997] momentum factor [FF-Cahart-4F model].

Barber and Lyon [1997a] evaluate two general approaches for developing a benchmark for calculating abnormal returns - the market portfolio and the matched control firm techniques. The use of a market-index based model of expected return, which is usually mimicked by the market portfolio and involves frequent rebalancing, is less favoured due to the fact that firms that constitute the market index typically include new firms that begin trading after the event month, which in most cases under-perform. A more favoured approach is the control firm technique which matches issuing firms to a set of comparable non-issuing firms on a dimension-by-dimension basis using pre-defined callipers and a set of ex-ante firm characteristics. The purpose of this approach is to establish the existence of an abnormal price performance by comparing the ex-post stock returns of IPO firms with those of non-IPO firms having fairly similar risk profiles.

The choice of a weighting scheme is also a relevant issue in measuring abnormal performance. Fama [1998] argues that apparent anomalies in long-term post-event returns shrink and often disappear when event firms are value-weighted rather than equally-weighted because the former more accurately captures the total wealth effects of investors. Hence, value-weighted performance provides a more useful benchmark and may not provide strong evidence against market efficiency when compared to an equally-weighted measure of abnormal performance. It is worthy to note that if the intention is to study the impact of a stock market mispricing, an equally-weighted technique would be more appropriate. However, if the objective is to accurately measure the real life investment experience of investors and the ensuing wealth effects, the proper approach would be a value-weighted performance measure.

[3.2.2] Under-pricing and Short-run performance

An overwhelming body of research has developed to suggest evidence of significant under-pricing of new issues of ordinary equity in the days and weeks following the initial listing [Mcdonald and Fisher, 1972; Ibbotson, 1975; Ritter, 1984 and 1991; Barlow and Sparks, 1986; Smith, 1986; Tinic, 1988]. Following the works of Ibbotson

TABLE 3.1: INTERNATIONAL EVIDENCE ON SHORT-RUN PERFORMANCE SHOWING THE RETURNS AVAILABLE TO IPO SUBSCRIBERS IN THE IMMEDIATE AFTER-MARKET SUBSEQUENT TO THE IPO

Country	Study	Period	Sample size	Initial ret. [%]
MALAYSIA	DAWSON [1987]	1978-83	21	166.60
CHINA	XIA & WANG [2003]	1997-98	147	116.13
MALAYSIA	ISA [1993]	1980-91	132	80.30
BRAZIL	AGGARWAL, ET AL [1993]	1979-90	62	78.50
KOREA	DHATT, ET AL [1993]	1980-90	347	78.10
THAILAND	ALLEN, ET AL [1999]	1985-92	150	63.49
THAILAND	WETHYAVIVORN & KOO-SMITH [1991]	1988-89	32	58.10
JAPAN	JENKINSON [1990]	1986-88	48	54.70
POLAND	LYN & ZYCHOWICZ [2003]	1991-98	103	54.45
PORTUGAL	ALPHAO [1992]	1986-87	62	54.40
JAPAN	DAWSON & HIRAKI [1985]	1979-84	106	51.90

TABLE 3.1 - CONT'D				
Country	Study	Period	Sample size	Initial ret. [%]
GREECE	KAZANTZIS & THOMAS [1996]	1987-94	129	51.70
GREECE	KAZANTZIS & LEVIS [1994]	1987-91	79	48.50
UNITED STATES	RITTER [1987]	1977-82	364	47.80
TAIWAN	CHEN [1992]	1971-90	168	45.00
HUNGARY	JELIC & BRISTON [1999]	1990-98	25	44.00
NIGERIA	ADJASI, ET AL [2011]	1990-2006	80	43.10
TAIWAN	HUANG [1999]	1971-95	311	42.60
UK	MENYAH, ET AL [1995]	1981-91	75	41.36
SINGAPORE	DAWSON [1987]	1978-83	39	39.40
SWEDEN	RUDQVIST [1993]	1970-91	213	39.00
SWITZERLAND	KUNZ & AGGARWAL [1994]	1983-89	42	35.80
SRI LANKA	SAMARAKOON [2010]	1987-2008	105	33.50

Table 3.1 - CONT'D				
Country	Study	Period	Sample size	Initial ret. [%]
POLAND	AUSENEGG [2000a]	1991-98	159	33.10
MEXICO	AGGARWAL, ET AL [1993]	1987-90	37	33.00
ITALY	CHERUBINI & RATTI [1992]	1985-91	75	29.70
AUSTRALIA	FINN & HIGHAM [1988]	1966-78	93	29.20
NEW ZELAND	VOS & CHEUNG [1993]	1979-91	149	28.80
GERMANY	LJUNGQVIST [1999]	1978-99	407	27.70
SINGAPORE	KOH & WALTER [1989]	1973-87	66	27.00
TUNISIA	NACEUR [2000]	1992-97	12	24.50
ITALY	AROSIO, GUIDICI & PALEARI [2000]	1985-2000	164	23.94
SPAIN	FREIXAS & INURRIETA [1991]	1986-90	58	22.40
CANADA	KOOLI & SURET [2004]	1991-98	445	20.57
UNITED STATES	RITTER & WELCH [2002]	1980-2001	6,169	18.80

Table 3.1 - CONT'D				
Country	Study	Period	Sample size	Initial ret. [%]
HONG KONG	MCGUINNESS [1993]	1980-90	80	17.60
HONG KONG	CHEUNG & LIU [2007]	1996-2000	209	16.58
CHILE	AGGARWAL, ET AL [1993]	1982-90	19	16.30
BELGIUM	ROGIERS, ET AL [1993]	1984-99	69	15.70
THAILAND	CHORRUK & WORTHINGTON [2010]	1997-2008	142	15.42
UNITED STATES	IBBOTSON, ET AL [1994]	1960-92	10,626	15.30
HUNGARY	LYN & ZYCHOWICZ [2003]	1991-98	33	15.12
UNITED STATES	RITTER [1987]	1977-82	664	14.80
FINLAND	KELOHARJU [1993a]	1984-92	91	14.40
UK	LEVIS [1993]	1980-88	712	14.30
UK	LEVIS [1995]	1980-89	713	14.20
UK	LOUGHRAN, ET AL [1994]	1959-99	2,802	13.90

Table 3.1 - CONT'D				
Country	Study	Period	Sample size	Initial ret. [%]
HONG KONG	DAWSON [1987]	1978-83	21	13.80
BELGIUM	MANIGART & ROGIERS [1992]	1984-90	28	13.70
FRANCE	DERRIEN & WOMACK [2003]	1992-98	264	13.20
TURKEY	KIYMAZ [2000]	1990-96	163	13.10
SPAIN	OTERO & FERNANDEZ [2000]	1985-97	58	12.80
GERMANY	LJUNGQVIST [1993]	1974-92	119	12.40
JAPAN	KANEBO & PETTWAY [1994]	1989-93	37	12.00
AUSTRALIA	LEE, ET AL [1996]	1976-89	266	11.90
CANADA	JOG & RIDING [1987]	1971-83	100	11.00
UNITED STATES	REILLY [1977]	1972-75	486	10.90
SPAIN	RAHNEMA, ET AL [1993]	1985-90	85	10.80
UK	JENKINSON & MAYER [1988]	1983-86	143	10.70

Table 3.1 - CONT'D				
Country	Study	Period	Sample size	Initial ret. [%]
UNITED STATES	AGGARWAL & RIVOLI [1990]	1977-87	1,598	10.67
PORTUGAL	ALMEIDA & DUGUE [2000]	1992-98	21	10.50
GERMANY	LJUNGQVIST [1997]	1970-93	180	9.20
CANADA	JOG & SRIVASTAVA [1996]	1971-92	254	7.40
NETHERLANDS	BUIJS & EIJGENHUIJSEN [1993]	1982-91	72	7.40
SOUTH AFRICA	ALLI, ET AL [2010]	1995-2004	141	7.35
HONG KONG	VONG & TRIGUEIROS [2010]	1994-2005	480	6.90
AUSTRIA	AUSENEGG [2000b]	1964-96	67	6.50
NEW ZEALAND	CHI, ET AL [2010]	1991-2005	114	5.91
NETHERLANDS	WESSELS [1989]	1982-87	46	5.10
FRANCE	JACQUILLAT [1986]	1972-86	87	4.80
UK	JENKINSON & MAYER [1988]	1983-86	68	4.70

Table 3.1 - CONT'D				
Country	Study	Period	Sample size	Initial ret. [%]
FRANCE	HUSSON & JACQUILLAT [1990]	1983-86	131	4.00
DENMARK	JAKOBSEN & SORENSEN [2001]	1984-92	76	3.90
UK	MENYAH, ET AL [1995]	1981-92	75	3.50
BRAZIL	FREITAS, ET AL [2008]	2004-06	30	3.10
UK	JENKINSON & MAYER [1988]	1983-86	26	-2.20

Initial returns, measured from the first trading day or some day after trading opens, can either be unadjusted or market-adjusted.

[1975] and Ritter [1984], numerous researchers have revealed that in different countries and at different periods in time, the phenomenon of the under-pricing of IPOs is a generalized phenomenon. Table 3.1 compiles some of the works that have analysed the initial returns of going public and their results. The table, ranked by the level of initial returns, shows the early returns that are available to IPO subscribers in the immediate after-market. It is also a reflection of the significant level of under-pricing and the consequent 'amount of money left on the table' by the issuing firms at the close of the offering. The initial return ranges from -2.2% to 166.6%, with most showing returns of 10% or more. In fact, all but one of the returns, are positive.

The most recent of these findings can be found in the works of Freitas, et al [2008] in their study of 30 Brazilian new offerings; Adjasi, et al [2011] in their study of 80 Nigerian IPOs; Alli, et al [2010] in their study of 141 South African new equity issuances; Chorruk and Worthington [2010] in their price performance analysis of 142 new listings in the Thai capital market and Chi, et al [2010] in their study of 114 New Zealand new issues of common stock. Several theories have been proposed to explain the extensive international evidence of initial under-pricing and its variability across the different capital markets around the world and there is little consensus regarding those factors that could explain this puzzle. These include the 'winner's-curse-hypothesis' of

Rock [1986], the 'legal-liability-argument' proposed by Tinic [1988], the 'merchant-banker-and-issuer-inexperience' explanation of Kunz and Aggarwal [1994], the 'underwriter-issuer-information asymmetry' theory of Baron [1982], the 'cost-of-information-acquisition' model of Benveniste and Spindt [1989], the 'market-feedback-hypothesis' of Chemmanur [1993], Jegadeesh, et al [1993] and Spiess and Pettway [1997], the 'bandwagon theory' of Welch [1992] and the 'underwriter-price-support' model of Ruud [1993][8]. However, the dominant theoretical perspective applied to examinations of IPO under-pricing seems to be the signalling theory [Bhattachaya, 1979; Certo, et al, 2001; Ross, 1977]. The model suggests 'certain variables or indicators send signals to potential investors about the capabilities and future values of firms' [Deeds, et al, 1997; pp.33] and is consistent with the perspective that IPO issuers are more informed than investors [Anderson, et al, 1995; Keasey and Short, 1997; Lawless, et al, 1998; Marshall, 1998]. Under this model, firms deliberately under-price new issues to signal their quality to potential investors in the hope that the 'huge amount of money left on the table' would be recouped from subsequent seasoned

[8] Other explanations that have been advanced in the literature can be found in the works of Habib and Ljungqvist [2001], Loughran and Ritter [2002], Carter and Manaster [1990], Allen and Faulhaber [1989], Beatty and Ritter [1986], Booth and Chua [1996], Brennan and Franks [1997], Aggarwal and Rivoli [1990], Chen, et al [1999], Rajan and Servaes [1997], Bossaerts and Hillion [1999], Fulghieri and Spiegel [1991], Baron and Holmstrom [1980], Su and Fleisher [1999] and Mauer and Senbet [1992].

offerings that would be valued at a price closer to the ‘true values’ of the firms which would have been revealed to investors via their operating and market performances.

Inspection of Table 3.1 shows that the evidence of initial under-pricing is overwhelming, though more severe in the emerging Latin and Asian markets. This, however, may not be unconnected with the institutional and market bottlenecks in these countries characterized by thin markets and thin trading, high information asymmetry, heavy oversubscription and large initial price run-ups [Dawson, 1987].

[3.2.3] Long-run Performance

Unlike the overwhelming international evidence that has established the under-pricing of new issues of common stock, the performance of these stocks in the long-run remains controversial. No theory has been proposed that satisfactorily explains the long-run under-performance of IPO stocks that is observed for up to three years after their listing. Only very few theories provide useful frameworks for analysing this phenomenon. The closest have been the ‘behavioural’ theories. In his ‘divergence of opinion hypothesis’, Miller [1977] argues that this phenomenon may be due to heterogeneous expectations of optimistic and pessimistic investors, whose divergence of opinion narrows as more information becomes available which causes prices to drop.

Shiller's [1990] 'impresario hypothesis' suggests that the market is subject to fads[9], implying that firms could 'time' IPOs strategically in the sense that they may predict when over-optimism in the market is likely to occur and favourable offer prices can be obtained. As more information becomes available, investors adjust their initial over-valuation, which causes long-run returns to fall. Ibbotson and Jaffe [1975] and Ritter [1984] provide evidence of the existence of 'hot issue markets'. Ritter [1991] and Shiller [1990] have argued that during these hot periods, many poor quality IPOs are floated in the market, taking advantage of market over-optimism. All of the above mentioned theories are consistent with the 'over-reaction hypothesis' of De Bondt and Thaler [1985 and 1987]. Loughran and Ritter [1995] also go as far as to describe the short and long-term share price behaviour of the IPO firm as being a 'puzzle'.

Table 3.2 lists some of the works that have analysed the long-run returns of going public and their results. The findings so far are mixed with varying results for different regions in the world, albeit a preponderance of under-performance is evident. The table, ranked by the magnitude of long-run returns, shows the level of risk-adjusted returns, excluding the initial returns, available to IPO investors in the after-market up to a period of six years from the listing date. There is a wide variation in the level of the returns,

[9] Investors behave irrationally in the sense that they value newly listed firms beyond fair values, such that prices drop over time as information on the true values become available in the market. This position is corroborated by Aggarwal and Rivoli [1990].

TABLE 3.2: INTERNATIONAL EVIDENCE ON LONG-RUN PERFORMANCE SHOWING THE RISK-ADJUSTED RETURNS AVAILABLE TO IPO INVESTORS OVER DIFFERENT INVESTMENT HORIZONS

Country	Study	Period	Sample size	Window	Long-run ret. [%]
KOREA	KIM, ET AL [1995]	1985-89	169	3.00	91.59
AUSTRIA	AUSSENEGG [1997]	1984-96	51	5.00	74.00
TURKEY	KIYMAZ [1999]	1990-95	138	3.00	44.10
US	CUSATIS, ET AL [1993]	1965-88	146	3.00	33.60
CHINA	XIA & WANG [2003]	1997-98	147	3.00	25.19
MALAYSIA	JELIC, ET AL [2001]	1980-95	182	3.00	21.98
POLAND	AUSSENEGG [1997]	1991-96	57	3.00	20.10
MALAYSIA	DAWSON [1987]	1978-83	21	1.00	18.20
BRAZIL	FREITAS, ET AL [2008]	2004-06	30	1.00	12.80
TUNISIA	NACEUR [2000]	1992-97	12	1.00	11.04
THAILAND	ALLEN, ET AL [1999]	1985-92	150	3.00	10.02
US	SIMON [1989]	1934-40	20	5.00	6.20

Table 3.2 - CONT'D					
Country	Study	Period	Sample size	Window	Long-run ret. [%]
SWEDEN	LOUGHRAN, ET AL [1994]	1980-90	162	3.00	1.20
SOUTH AFRICA	ALLI, ET AL [2010]	1995-2004	141	3.00	1.08
JAPAN	KUTSUNA, ET AL [2009]	1997-2003	487	1.00	-0.05
HONG KONG	CHEUNG & LIU [2007]	1996-2000	209	1.00	-0.17
NIGERIA	ADJASI, ET AL [2011]	1990-2006	80	3.00	-0.6
ITALY	GIUDICI & PALEARI [1999]	1985-99	84	3.00	-2.60
SINGAPORE	DAWSON [1987]	1978-83	39	1.00	-2.70
TAIWAN	HUANG [1999]	1971-95	311	4.00	-3.90
GERMANY	WITTLEDER [1989]	1961-87	67	1.00	-4.00
HUNGARY	LYN & ZYCHOWICZ [2003]	1991-98	33	3.00	-4.92
GERMANY	EHRHARDT [1997]	1960-90	160	3.00	-5.20
SWITZERLAND	KUNZ & AGGARWAL [1994]	1983-89	34	3.00	-6.10
FRANCE	DERRIEN & WORMACK [2003]	1992-98	264	2.00	-6.30

Table 3.2 - CONT'D					
Country	Study	Period	Sample size	Window	Long-run ret. [%]
AUSTRALIA	FINN & HIGHAM [1988]	1966-78	93	1.00	-6.52
SWITZERLAND	DROBETZ, ET AL [2005]	1983-2000	120	1.17	-6.80
GERMANY	SCHLAG & WODRICH [2000]	1884-1914	163	5.00	-7.80
MALAYSIA	AHMAD-ZALUKI, ET AL [2007]	1990-2000	454	3.00	-8.16
SINGAPORE	HIN & MAHMOOD [1993]	1976-84	45	3.00	-9.20
HONG KONG	DAWSON [1987]	1978-83	21	1.00	-9.30
FRANCE	BOISSIN & SENTIS [2010]	1991-2005	270	5.00	-10.00
GERMANY	SCHMIDT, ET AL [1988]	1984-85	32	1.00	-10.20
US	REILLY [1977]	1972-75	486	1.00	-11.60
GERMANY	UHLIR [1989]	1977-86	70	1.25	-11.90
GERMANY	LJUNGVIST [1997]	1970-90	145	3.00	-12.10
GERMANY	BESSLER & THIES [2007]	1977-95	218	3.00	-12.70
US	AGGARWAL & RIVOLI [1990]	1977-87	1,598	0.68	-13.73

Table 3.2 - CONT'D					
Country	Study	Period	Sample size	Window	Long-run ret. [%]
PORTUGAL	ALMEIDA & DUQUE [2000]	1992-98	21	1.00	-13.80
CANADA	KOOLI & SURET [2004]	1991-98	445	5.00	-16.86
HONG KONG	MCGUINNESS [1993]	1980-90	72	2.00	-18.30
MEXICO	AGGARWAL, ET AL [1993]	1987-90	44	1.00	-19.60
US	RITTER & WELCH [2002]	1980-2001	6,169	3.00	-23.40
CHILE	AGGARWAL, ET AL [1993]	1982-90	36	3.00	-23.70
POLAND	LYN & ZYCHOWICZ [2003]	1991-98	103	3.00	-24.44
US	STIGLER [1964]	1949-55	46	5.00	-25.10
THAILAND	CHORRUK & WORTHINGTON [2010]	1997-2008	142	3.00	-25.39
FINLAND	KELOHARJU [1993b]	1984-89	79	3.00	-26.40
JAPAN	CAI & WEI [1997]	1971-92	180	3.00	-27.00
SPAIN	ALVAREZ & GONZALEZ [2005]	1987-97	37	3.00	-27.80
US	BRAV, ET AL [2000]	1975-92	4,622	5.00	-28.40

Table 3.2 - CONT'D					
Country	Study	Period	Sample size	Window	Long-run ret. [%]
US	RITTER [1991]	1975-84	1,526	3.00	-29.13
US	LOUGHRAN & RITTER [1995]	1970-90	4,753	5.00	-30.00
DENMARK	JAKOBSEN & SORENSEN [2001]	1984-92	83	5.00	-30.00
FRANCE	LELEUX & MUZYKA [1997]	1985-89	56	3.00	-30.30
GREECE	THOMADAKIS, ET AL [2012]	1994-2002	254	3.00	-31.43
CANADA	SHAW [1971]	1956-63	105	5.00	-32.30
GERMANY	JASKIEWICZ, ET AL [2005]	1990-2000	153	3.00	-32.80
US	LOUGHRAN [1993]	1965-87	3,656	6.00	-33.30
US	GOMPERS & LERNER [2003]	1937-72	3,661	5.00	-34.80
SPAIN	JASKIEWICZ, ET AL [2005]	1990-2000	43	3.00	-36.70
US	STIGLER [1964]	1923-28	70	5.00	-37.70
US	SIMON [1989]	1926-33	35	5.00	-39.00
NEW ZEALAND	CHI, ET AL [2010]	1991-2005	114	3.00	-42.40

Table 3.2 - CONT'D					
Country	Study	Period	Sample size	Window	Long-run ret. [%]
BRAZIL	AGGARWAL, ET AL [1993]	1980-90	62	3.00	-47.00
INDIA	MARISETTY & SUBRAHMANTAM [2010]	1990-2004	2,713	3.00	-50.10
AUSTRALIA	LEE, ET AL [1996]	1976-89	266	3.00	-51.26
SOUTH AFRICA	PAGE & REYNEKE [1997]	1980-91	118	4.00	-63.45

[i] Window is the number of years over which the long-run returns are measured.

[ii] Long-run returns are calculated over the investment horizon and thus are annualized. They also exclude the initial returns and are generally risk-adjusted. Some studies employ a battery of benchmarks and methodologies; in these cases, a representative result is depicted.

ranging from a high of 91.59% to a low of -63.45%, with most showing negative returns of -5% or more. In fact, about 80% of the studies report negative returns or IPO under-performance. The findings also generally reveal that the under-performance finding is sensitive to the benchmark model and/or methodology employed.

The results for the developed markets appear conclusive with most of the studies documenting long-run stock price under-performance. The earliest were undertaken in the United States [US] and several document the existence of under-performance. Stern and Bornstein [1985] show that 1,922 new issues floated during the 1975-85 period under-perform the market by 22%. In contrast, Ibbotson [1975], using an aggregated return across time and securities [RATS] [10] model conditioned on an equally-weighted average of the returns on the New York Stock Exchange, finds that the after-market performance of US stocks floated during the 1960s is positive in the first year and negative in the next three years before returning to positive in the fifth year. Ritter [1991] investigates 1,526 US IPOs floated during 1975-84 and finds a significant under-performance to the tune of 29.13% over a 3-year period, employing a set of firms matched on industry and size as the return benchmark. He also finds varying degrees of under-performances using the value-weighted averages of the

[10] This is a variation of the Jensen alpha or calendar time approach that allows for the variation of the systematic risk of an issuing firm, subsequent to the IPO event.

NASDAQ and NYSE stock exchanges as benchmarks. Other researchers in the US market have also documented this under-performance [11]. However, there are exceptions. Simon [1989], using the time-series of portfolio returns conditioned on the return on the NYSE in a CAPM model, documents an out-performance of 6.2% in his study of US IPOs over the period 1934-40. Cusatis, et al [1993] equally find a similar result in their investigation of the price and return performance of spin-offs[12] and their parent firms in the US over the period 1965-88. Measuring stock returns of spin-offs, their parent firms and parent-spin-off combinations for periods up to three years following the spin-offs using the BHAR metric and the return on a size and industry-matched firm as the benchmark, they find positive abnormal returns of 33.6%.

More recent studies in the US market are those of Brav, et al [2000], Ritter and Welch [2002] and Gompers and Lerner [2003]. In a comprehensive study of 4,622 IPOs and 4,526 seasoned equity offerings [SEOs][13] over the period 1975-1992 with the sole purpose of examining the robustness of IPO and SEO under-performances with respect to various model specifications, using a 5-year post-event window and the market return as the benchmark, Brav, et al [2000] document long-term abnormal

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[11] See Table 3.2.

[12] Spin-offs are similar to IPOs in that they represent newly-traded shares in the market place.

[13] These are firms that come to the market to raise more capital by issuing more equity subsequent to their IPOs.

returns ranging from -7.8% to -30.1% for SEOs and -8.8% to -44.2% for IPOs, implying that both IPOs and SEOs under-perform during the period. However, there is a striking revelation in their findings. Using an alternative model that matches IPO firm returns to size and book-to-market portfolios, which are themselves free of the issuing firms, the observed under-performance disappears. In fact, 5-year average excess returns of the IPO firms are actually positive ranging from 1.4% to 9.7%.

Ritter and Welch [2002] document under-performances ranging from -5.1% to -23.4% depending on the benchmark used for measuring abnormal return in their study of 6,169 IPOs over the period 1980-2001 employing a 3-year post-event window. They reach the same conclusions in calendar time analysis using multi-factor regression models. Gompers and Lerner [2003] find the same evidence when they undertook a large scale study of 3,661 IPOs over the period 1935 to 1972, using 3 and 5-year post-event windows and the value-weighted return on the market index and the return on a portfolio of firms with the same size and book-to-market ratio as benchmarks. They document abnormal performances ranging from -8.4% to -34.8% under a buy-and-hold trading strategy using a value-weighted performance measure. However, this under-performance disappears when they vary the trading strategy and/or the weighting of the stocks in the portfolio. Under a CAR strategy employing an equally-weighted performance measure, the abnormal performance turns from negative to positive ranging from 2% to 8.7%. Using the calendar time models, they find no significant abnormal performance as the CAPM and FF3F intercepts are not significantly different from zero. The first comprehensive study on the Canadian market was undertaken by Kooli and Suret [2004] who investigate the after-market performance of 445 IPOs over the period 1991-1998 for up to five years after listing. Using the control firm approach, they document varying levels of under-performances for the IPO sample depending on the return metric and weighting scheme employed. More specifically, they report higher under-performances of between 15.16% and 26.50% when using the BHAR technique as against between 11.02% and 20.65% when adopting the CAR metric.

Many other researchers have also reported long-run under-performances in several European markets. In a study of 37 Spanish IPOs over the period 1987 to 1997, Alvarez and Gonzalez [2005] analyse the long-run performance across 1, 3 and 5-year windows employing different return benchmarks spanning the index return on the Madrid Stock Exchange as well as size and book-to-market matched firms and portfolios. Their results, in general, reveal the existence of positive abnormal returns in the first year. However, in the other two horizons considered [i.e. 3 and 5 years], the abnormal return turns negative ranging between -18.59% and -32.16% for the 3-year window and between -1.98% and -37.05% for the 5-year window.

In a study of a sample of 218 German IPOs that came to the market over the period 1977 to 1995 using a 3-year post-event window, the BHAR metric and a variety of market benchmarks, Bessler and Thies [2007] find that abnormal returns are positive for the first 15 months, but then turn negative after 36 months rising to a significant -12.70%. Thomadakis, et al [2012] analyse the long-run performance of 254 Greek IPOs that were listed during the period 1994 to 2002, computing BHARs and CARs over a 3-year window, using the standard CAPM and multi-index models as benchmarks. Their results reveal a persistence of IPO out-performance that ranges between 8.09% and 13.49% up until the 24th month subsequent to the listing date. However, when the window period is extended by another 12 months, the measured abnormal performance enters negative territory in the range of -16.17% and -31.43%.

A study of Finnish IPOs by Keloharju [1993b] reports a -26.4% long-run market adjusted return for 79 issues going public between 1984 and 1989. Jakobsen and Sorensen [2001], in a study of 83 Danish IPOs over the period 1984-92, document 5-year BHAR under-performances of 30% and 13% using the market and control firm techniques as the benchmarks respectively. Lyn and Zychowicz [2003] study the price and return behaviour of a sample of 103 Polish and 33 Hungarian equity offerings over the period 1991-1998 and find significant under-performances in both markets. They document negative CARs of -24.44% and -4.92% for Poland and Hungary respectively using a 3-year post-event horizon and the market index return as the benchmark.

Similar results have also been found in the Australian markets. Lee, et al [1996] examine 266 Australian IPOs over the period 1976-89 and find long-term performance to be inconsistent with an efficient market expectation. Using a 3-year post-listing window and the market index as the return benchmark, they document negative abnormal returns of -51.26% for the IPO sample over the period. Chi, et al [2010] study the performance of a sample of 114 New Zealand IPOs and calculate 3-year CARs and BHARs using the New Zealand stock market index as the return benchmark. They document 3-year CARs ranging between -42.4% and -47.8% as well as 3-year BHARs in the region of -27.8% and -36%. In the same market, Mustow [1992] and Allen and Patrick [1994] document significant long-run under-performance and 36-month post-listing returns of -112.8% and -25.38% are reported respectively.

Long-run under-performance has also been found in the Latin American stock markets. Aggarwal, et al [1993] report respective -47% and -23.7% 3-year returns for 62 Brazilian IPO offerings in the period 1980-90 and 36 Chilean IPOs for 1982-90 as well as a 1-year return of -19.6% for 44 Mexican IPOs during 1987-90. However, Freitas, et al [2008] document positive 1-year abnormal returns of 12.8% for a sample of 30 Brazilian IPOs that were listed on the Brazilian Stock Exchange between the period 2004 and 2006, using the Sao Paulo stock market index as the benchmark.

These under-performances have also been replicated in the African markets, albeit the studies have been few and far between[14]. Page and Reyneke [1997] document an under-performance of 63.45% over a 4-year period for 118 South African IPOs that came to the market over the period 1980-1991, using a set of comparable firms [matched on size] and the Johannesburg Stock market index as benchmarks. Adjasi, et al [2011], in a study of 80 Nigerian IPO offerings over the period 1990-2006 using the index return on the Nigerian Stock Exchange as the benchmark, find an insignificant under-performance of 0.6% using a post-event window of three years. Naceur [2000] finds a positive abnormal performance of 11.04% when investigating the 1-year performance of 12 Tunisian IPOs that were listed in the Tunisian Stock Exchange over the period 1992-1997, using the market return as the benchmark. Alli, et al [2010] document 1, 2 and 3-year out-performances of 4.25%, 3.29% and 1.08% respectively

[14] Despite the increasing attention to the study of IPOs in emerging markets, there is relatively limited research on IPOs or SEOs of firms in the African continent. One major reason for the lack of studies on the African capital markets is the relatively small size and low liquidity of the equity markets in most African countries and the reliability of data on African capital market transactions [Alli, et al; 2010].

for a sample of 141 IPOs in the South African market over the period 1995-2004, employing the Johannesburg Stock Exchange market index as the benchmark for calculating abnormal returns.

However, it is worth noting that the evidence in Asia is not quite conclusive. Kim, et al [1995] find positive 3-year BHARs that ranges from 80.63% to 91.59% for 169 Korean IPOs over the period 1985 to 1989 using the market return and a set of comparable firms [matched on industry and size] as benchmarks, with most of the returns coming in the early weeks. Dawson [1987] reports negative long-run performances for IPOs in Hong Kong and Singapore, but positive for Malaysia [18.2%], employing the market index as the benchmark return for all the countries. Wu [1993] examines both the short and long-run performance of 70 Malaysian IPOs in the period between 1974 and 1989. Adjusted 1, 2 and 3-year period BHARs are positive. Sufar [1993] investigates the performance of a sample of 43 Malaysian new issues made over the 1980-86 period. The results show under-pricing in the first day of trading [140.5%] and a positive after-market performance 12 months following official listing [10.9%]. Mohamad, et al [1994] study the initial and long-term performance of 65 IPOs from the Kuala Lumpur stock exchange during 1975-90. Their findings show an initial under-pricing of 135% and significant positive CARs after 2 and 3 years. Cheung and Liu [2007] find an insignificant 1-year under-performance of 0.17% in a study of a sample of 209 Hong Kong IPOs over the period 1996-2000, using the return on the Hong Kong stock index as the benchmark.

Chorruk and Worthington [2010] examine the stock price performance of 142 IPOs on the Thailand Stock Exchange from 1997-2008 using various return metrics. They document positive average CARs from the first month up until the 23rd month. However, these returns turn negative from month 24 right up to the 36th month peaking at -468.81%. A similar pattern emerges for the other measures. The average BHAR is positive up until month 18 after which it drifts into negative territory, culminating in a BHAR of -25.39% after 3 years. The wealth relative measure stays above one up until month 18 after which it dips and even enters negative territory from month 31 till month 36. In general, their findings show that Thai IPOs initially out-perform market benchmarks in the early years and under-perform thereafter. In a study of the long-run performance of IPOs in China using a sample of 147 firms who made their offerings between July 1997 and December 1998, employing the market benchmark across a host of return metrics, Xia and Wang [2003] show that IPOs in China out-perform the market in the long-run with the out-performance a positive function of the length of the observed horizon. More specifically, they find CARs of 12.19%, 13.39% and 25.19%;

BHARs of 13.78%, 23.93% and 27.80% and wealth relatives of 1.13, 1.17 and 1.22 for the 1, 2 and 3-year windows respectively. The results indicate, contrary to the majority of existing literature, that IPOs out-perform the market in the long-run.

In an investigation of the 3-year share price behaviour of a sample of 454 Malaysian IPOs over the period 1990-2000 using a plethora of benchmarks, weighting schemes and return metrics, Ahmad-Zaluki, et al [2007] find significant out-performance using the market benchmark in conjunction with an equally-weighted performance measure. However, this out-performance disappears in procedures where matching firms are used as the benchmark and/or a value-weighted scheme is employed to calculate returns. They also find no out-performance in asset-pricing regressions, using the FF3F model. Their results are consistent with the view of Gompers and Lerner [2003] that the reported relative performance of an IPO sample depends on the method used to measure performance. Kutsuna, et al [2009] also find an insignificant 1-year abnormal stock performance of -0.05% in their analysis of a sample of 487 Japanese IPOs over the period 1997-2003. Marisetty and Subrahmanyam [2010] study the price performance of 2,713 IPOs in India over the period 1990-2004 and calculate 3-year CARs and BHARs using the market index as the return benchmark. They document

TABLE 3.3: EVIDENCE OF LONG-RUN PERFORMANCE IN THE UK MARKET

Country	Study	Period	Sample size	Window	Long-run ret. [%]
UK	MENYAH, ET AL [1995]	1981-91	75	1.10	6.45
UK	LEVIS [1993]	1980-88	712	3.00	-8.10
UK	GREGORY, ET AL [2010]	1975-2004	2,499	3.00	-12.60
UK	LEVIS [1995]	1980-88	713	4.00	-14.50
UK	LELEUX & MUZYKA [1997]	1987-91	220	3.00	-19.20
UK	GOERGEN, ET AL [2007]	1991-95	240	3.00	-19.49
UK	BROWN [1999]	1990-95	232	3.00	-20.10
UK	ESPENLAUB, ET AL [2000]	1985-92	588	5.00	-21.30

[i] Window is the number of years over which long-run returns are recorded.

[ii] Long-run returns are calculated over the investment horizon and thus are annualized, exclude the initial returns and are generally risk-adjusted. Some authors use a range of benchmarks; in these cases, a representative result is shown. Computation methodologies vary.

average CARs of -10.5%, -25%, -37.3% and BHARs of -36.6%, -44.8%, -50.1% for 1, 2 and 3-year windows respectively and conclude that the under-performance of new equity issuances relative to the market return in the India stock exchange seems to grow with the length of the post-event window, at least up to three years after listing.

The studies in the UK have been few and far between with the majority of the evidence supporting the general trend in the literature as shown in Table 3.3. Levis [1993] documents a 3-year stock under-performance for 712 IPOs over the period 1980-88, ranging from -8.13% to -22.96%, using the CAR metric and between -6.77% and -42.11%, using the BHAR. He also documents wealth relatives ranging from 0.787 to 0.958, signifying that the IPOs under-perform all the market benchmarks used in the study[15]. There are obvious doubts on these results as Levis made no explicit adjustments for risk, assuming that the risk profile of the IPO sample and that of the market are one and the same. Also, the several biases associated with using event-time methods of CAR and BHAR alongside the market index as the benchmark reference portfolio are well documented [Barber and Lyon, 1997a; Lyon, et al, 1999]. Levis also did not control for event-clustering and cross-correlation in IPO returns.

[15] The benchmarks used are the FTSE All-Share Index [FTA], the Hoare Govett Smaller Companies Index [HGSC] and a weighted All-Share Index [ALLSH]. The FTA is a value-weighted index comprising approximately 90% of UK stocks by value. The HGSC is also a value-weighted index comprising the lowest 80% of UK stocks by value, while the ALLSH is a specially constructed equally-weighted index of all UK stocks.

Levis undertook a follow-up study in 1995 where he studied 713 IPOs with subsequent offerings of stock and finds similar results, using the HGSC index as the return benchmark. Menyah, et al [1995] undertook a long-run performance study of 75 UK privatization IPOs [PIPOs][16] alongside another sample of private IPOs over the period 1981-91, using the BHAR metric and the FTSE All-Share as the market benchmark. Interestingly, they document 13-month out-performances of 32.89% and 6.45% for the PIPO and IPO samples respectively.

Espenlaub, et al [2000], study the long-run performance of 588 IPOs that were launched in the UK market over the period 1985-92. They tried to improve on the work of Levis by making adjustments for systematic risk and cross-sectional varying exposure to size effects. They also control for event-clustering and cross-correlation in IPO stock returns by using the calendar-time approach that was originally developed by Jaffe [1974] and Mandelkar [1974] and subsequently used by Loughran and Ritter [1995] and Brav and Gompers [1997]. They document a 5-year CAR ranging from -4.30% to -42.77% and a calendar time return ranging from -4.20% to -40.20%, using a variety of benchmarks spanning the CAPM, HGSC index and the FF3F models. Goergen, et al [2007] followed with their study of a sample of 240 IPOs that were listed on the London Stock Exchange [LSE] from 1991 to 1995. Given the issues surrounding

[16] These are state-owned firms where government sells a portion of its holdings to the public via an IPO.

the measurement of abnormal returns, they calculate long-run returns for a period of three years following the listing date using different methodologies and index returns on the FTSE All-Share [FTA], the HGSC indexes and size decile portfolios[17] as the return benchmarks. Overall, they document abnormal returns ranging from -13.17% to -21.98%.

The biggest sample to date on the UK market is that of Gregory, et al [2010] in their study of 2,499 IPOs that were launched into the market over the period 1975-2004. They document a general level of under-performance in event and calendar time using equally and value-weighted techniques, employing decile reference portfolios and a matched firm technique constructed on market capitalization only as the return benchmarks. More specifically, they report 3 and 5-year under-performances of 12.60% and 31.60% respectively in event time. In calendar time regressions using the equally-weighted technique, they also document under-performances of 0.7% and 0.6% per month over 36 and 60-month horizons respectively which evaporate in a value-weighted approach where each firm is weighted according to its market capitalization. Despite an attempt to improve on the previous works in the UK market, the study may

[17] These are specially constructed portfolios of non-issuing firms on the LSE to which sample IPO firms are allocated based on their market capitalization at the start of each sample year.

not have used appropriate benchmarks in calculating the risk-adjusted returns of the IPO firms as matching was only based on size.

It is important to note that virtually all of the prior studies that have studied the long-run performance of new issues of common stock using the control firm technique to select matching non-issuing firms used as a benchmark for evaluating the performance of the issuing sample firms have used the traditional matching method[18], with the majority of the evidence revealing IPO under-performance. Cheng [2003] and Li and Zhao [2006] employ propensity score methods[19] to re-evaluate the long-run performance of SEOs in the US. Using data on SEOs offered between 1970 and 1997, the former finds significant BHARs of between -6% and -14% over 3-5 years when matches are constructed on size, book-to-market and industry adopting the traditional method. However, using a propensity score approach, they find little evidence of significant abnormal returns. The latter study, using data on SEOs offered between 1986 and 1997, finds an average 3-year BHAR of -16% using conventional matching which drops to an insignificant -4% with propensity score matching.

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[18] This is the technique that matches non-event firms to event firms on a dimension-by-dimension basis using pre-defined callipers.

[19] This is the technique that reduces the problems of choosing a matching non-event firm to a single problem of matching on an estimated score - the propensity score. The event effect is then estimated as the difference in outcome between the event firm and the non-event firm with the same propensity score.

In summary, it can be seen immediately that unlike the undisputed overwhelming evidence of IPO under-pricing and short-term returns which cuts across the globe, the evidence on long-run performance is far from conclusive and is at best, mixed and controversial. It is very obvious from the preceding analysis that the issue of the under-performance or otherwise of IPO stocks is a function of a whole gamut of factors ranging from the market being examined, the sample period, the sample size, the length of the window over which the IPOs are being examined, the reference benchmark employed, the method of cumulating abnormal returns, the method of selecting the control firms and finally, the weighting schemes employed. This is clearly illustrated by the varied findings in the works of Cheng [2003] and Li and Zhao [2006] for the US market.

[3.2.4] Econometric and Methodological Issues

In the light of the mixed results from the previous studies, the evidence on long-run IPO under-performance, which if firmly established will be unassailable evidence against market efficiency, merits further investigation. In fact, Lyon, et al [1999], Ritter and Welch [2002], Loughran and Ritter [2000], Barber and Lyon [1997a], Brav, et al [2000] and Fama [1998] have all raised doubts on the documented long-run under-performance of IPOs.

The key issue here is about the dimensions on which the analysis of the performance of new issues of common stock should be based. In his study of major corporate events in the finance literature in general, Fama [1998] posits that most of the long-term return anomalies associated with these events become marginal or even disappear when exposed to different models of expected returns or when different statistical approaches are used to measure them. Furthermore, he attributes most of the anomalies to chance events with an overall expected abnormal return of zero implying that markets are still, by and large, efficient. More specifically, in the case of IPOs, he finds that previous studies may not have captured all possible risk factors in the determination of abnormal performance. Put differently, he questions the results of previous studies on IPO long-run under-performance by asserting that all possible risk factors associated with the average firm stock return may not have been accounted for in the models used in determining abnormal returns. He further asserts that neither the use of the firm characteristics [size and book-to-market factors only] based approach nor the FF3F model is free from bad model problems in the estimation of long-horizon abnormal stock returns and as such, the results of studies based on these approaches should be treated with caution. He concludes that all models of expected returns are incomplete descriptions of the systematic variation of expected returns across firms and as the measured horizon is extended, the inadequacies of the models are accentuated due to a compounding of pricing errors.

The several biases associated with using event-time methods and the market index as a reference portfolio for measuring abnormal returns are well documented by Barber and Lyon [1997a]. These biases include the new listing bias[20], the rebalancing bias[21] and the skewness bias[22]. They further claim that CARs are most affected by the new listing bias and a measurement bias[23], therefore long-run cumulative returns and the associated test statistics are generally positively biased. In contrast, BHARs are most affected by rebalancing and skewness biases and as a result, holding period returns and the associated test statistics are generally negatively biased. Barber and Lyon

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[20] This arises because sample firms generally have a long post-event history of returns, while firms that constitute the market index typically include new firms that begin trading after the event month [Barber and Lyon, 1997a]. The use of a market-index based model of expected return may bias upwards the BHARs and CARs of a random sample of stocks since the market index includes these new firms which tend to under-perform [Ritter, 1991].

[21] This arises because the compound returns on a market portfolio are typically calculated assuming rebalancing, while the returns of sample firms are compounded without rebalancing [Barber and Lyon, 1997a]. This frequent rebalancing amplifies any possible biases in the periodic returns arising, for example from bid-ask errors, non-synchronous trading or price discreteness which generates 'substantial spurious returns'. Hence, BHARs and CARs constructed with the aid of market indices will be biased downwards [Conrad and Kaul, 1993].

[22] This arises because long-run abnormal returns are positively skewed leading to negative skewness in the sampling distribution of the standard t-statistics which may cause an over-rejection of the null of zero abnormal return in favour of an alternative of negative abnormal performance.

[23] CARs tend to be poor predictors of an investor's wealth experience as measured by the BHAR method because BHAR involves compounding of returns, while CAR does not [Barber and Lyon, 1997a].

[1997a][24] and Fama [1998] favour BHAR over CAR because the former is more symbolic of an investor's long-run returns and typically does not involve rebalancing[25].

Barber and Lyon [1997a] further claim that the size and power of the test statistics associated with a measure of long-run abnormal returns could be severely undermined by the choice of the return metric and benchmark employed in evaluating abnormal returns. They posit that the use of CAR in conjunction with a market reference portfolio as the benchmark for calculating abnormal return yields misspecified test statistics in virtually all sampling situations. Hence, they advocate the use of BHAR [as the return metric] and the return of a well matched control firm [as the benchmark] in calculating abnormal returns. Fama [1998] and Mitchell and Stafford [2000] point out that BHAR may overstate long-run performance and suffers more skewness problems than CAR in statistical inferences. Mitchell and Stafford [2000] further aver that most event time studies assume independence in event firm stock returns leading to inadequate and spurious outcomes. They further argue that cross-sectional dependence and calendar clustering of stock returns can lead to spurious abnormal returns and misspecified test

[24] They evaluate three general approaches for developing a benchmark for calculating abnormal returns - the market portfolio, an appropriately matched control firm and the FF3F model – and posit that the market portfolio and the FF3F are most plagued with bad model problems.

[25] The BHAR approach also avoids biases that may arise from security microstructure issues when the portfolio is frequently rebalanced [Blume and Stambaugh, 1983; Roll, 1983; Ball, et al, 1995].

statistics in an event time analysis[26]. In order to redress this problem, they advocate the use of a calendar time portfolio approach that accounts for the dependence of event firm abnormal returns[27].

Mitchell and Stafford [2000] further argue that an alternative approach to using the calendar time approach[28] is to track the performance of an event portfolio relative to an explicit asset pricing model. However, Loughran and Ritter [2000] argue against using this approach because it might be biased towards finding results that supports market efficiency. Early studies of long-term abnormal returns used the Sharpe [1964] and Lintner [1965] CAPM model. Recently, some studies have used the FF3F and FF-Cahart-4F models. Even though these models are massive improvements on the CAPM, they are still not able to provide a full explanation for the variation in the cross-section of stock returns [Fama, 1998].

Lyon, et al [1999] add their voice to the debate by stating that the test statistics associated with long-run returns are only well-specified under two approaches – firstly,

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[26] They re-examine the reliability of long-term stock price performance estimates, using three large samples of major corporate events – mergers, SEOs and share repurchases. Using a calendar time portfolio approach, they find little or no evidence of long-term abnormal performance.

[27] Fama [1998], Lyon, et al [1999] and Brav, et al [2000] all show that the calendar time series returns yields well-specified test-statistics in almost all sampling situations.

[28] The main feature of the calendar time approach is to calculate calendar time portfolio returns for firms experiencing an event and determine whether they are abnormal in a multifactor regression framework. The estimated intercept from the regression is the post-event abnormal performance of the sample of event firms [Kothari and Warner, 2007].

the BHAR approach under event time using well-constructed reference portfolios as return benchmarks and secondly, the mean monthly abnormal return [MMAR] approach using calendar time portfolios. These methods alleviate the skewness, rebalancing and new listing biases also identified by Barber and Lyon [1997a]. However, they assert that these well specified test statistics only hold in random samples as there remains the seemingly intractable potential problem of 'bad asset modelling'. They further posit that all tests of long-run abnormal returns are implicitly a joint test of firstly, market efficiency and secondly, the validity of the asset pricing model used to estimate the abnormal returns. Following from this, they sound a note of caution that matching sample firms to control firms from the general population on the basis of size and book-to-market factors alone and/or controlling for same factors only in an explicit asset pricing model may not be sufficient to yield well-specified test statistics when samples are drawn from non-random samples, thus leading to incorrect inferences. To correct this, they recommend a detailed descriptive analysis of the population to reveal other firm specific risk factors or characteristics that could be used in selecting the matching firms to be used as benchmark for determining the long horizon abnormal returns of the sample firms.

Kothari and Warner [1997] affirm that long horizon results are potentially very sensitive to the assumed model for generating abnormal returns and that failure to use the correct model could lead to systematic biases and misspecifications. Their findings, in tandem with those of Fama and French [1993], also reveal that biases that arise from the method of cumulating abnormal returns, model specifications, survivorship and return variance which all tend to grow with the length of the observed window, more often than not lead to biased estimates of the test statistics resulting in incorrect inferences of abnormal performance. They also aver that non-random samples can have firm characteristics that are correlated with the determinants of firms' expected rates of return which can result in biased abnormal returns if the correct benchmark is not used. They conclude that only the application of non-parametric tests and bootstrap procedures are likely to reduce the misspecifications associated with tests for long-run abnormal returns.

In their study of the anomalies literature, Brav, et al [2000] explore the effect of various long-run horizon stock tests and their effect on the measured performance of IPO stocks. They find that IPO firm returns are similar to that of non-issuing firms matched on size and book-to-market factors. Their results also show that SEOs under-perform various characteristics-based benchmarks in event time methodologies, but not in time series factor based models. They also document a model misspecification problem in their study by showing that small changes to the factor specifications in the FF3F model improve the predictive power of the model. More specifically, they show in their results how a variation of models, trading rules and benchmarks influences the magnitude of the measured abnormal performances. In fact, using a benchmark that matches IPO firm returns on a portfolio composed of non-issuing firms that have been matched on size and book-to-market factors only, the measured abnormal performance swings from negative to positive over the measured horizon.

In their study of US IPOs over the period 1935-1972, Gompers and Lerner [2003] show that the magnitude of the measured performance of the sample firms depends upon the method of return measurement used in the analysis. They posit that the results of their study serve to underscore the questions about IPO performance with the weakness of the evidence for under-performance and by extension, against market efficiency raising doubts about whether a unique ‘IPO effect’ indeed exists. Ritter and Welch [2002] document different patterns of long horizon stock price performance of new issues of common stock in event time and assert that the measured performance is very sensitive to the choice of econometric methodology employed. In their study of US IPOs over the period 1980-2001, they find that the observed under-performance reduces when a matching-firm technique of calculating abnormal returns is used. They also document differing patterns in the measured performances in multifactor regressions in calendar time when the number of factors in the models are varied.

The choice of a weighting scheme is also a relevant issue in measuring abnormal performance [Brav and Gompers, 1997; Loughran and Ritter, 2000; Brav, et al, 2000]. Fama [1998] argues that apparent anomalies in long-term post-event returns shrink and often evaporate when event firms are value-weighted rather than equally-weighted, because the former more accurately captures the total wealth effects of investors. This becomes more illuminating when considered from the view-point of a large institutional investor who will not ordinarily hold an equally-weighted portfolio. Hence, value-weighted performance may provide a more useful benchmark and does not provide strong evidence against market efficiency when compared to an equally-weighted measure of abnormal performance.

Cheng [2003] and Li and Zhao [2006] employ propensity score methods to re-evaluate the long-run performance of firms conducting SEOs in the US. Using data on SEOs offered between 1970 and 1997, they both find significant BHARs when matches are constructed on size, book-to-market and industry using the dimension-by-dimension matching method. However, using a propensity score approach, they find little or no evidence of significant abnormal returns.

Following from the above, it does appear that an accurate model of expected return is at the heart of the current methodological debate in the literature and this has arisen because a model of expected return must be specified before abnormal returns can be delineated. Kothari and Warner [2007] aver that the bias as well as the precision of the measure of expected returns can vary across different methods, thus affecting the magnitude, direction and properties of the excess returns. They also contend that some of the critical issues that surround the analysis of long horizon stock price performance are risk adjustment, abnormal return modelling, the aggregation/measurement of abnormal returns and the statistical/economic significance of the abnormal return measure.

In long horizon tests, it is vital to make apt adjustments for risk to deduce an abnormal price performance for at least two reasons. Firstly, a very small error in adjusting for risk can make economic differences of great proportions when calculating abnormal returns over long periods. Secondly, it is still unclear, to date, which expected return model is appropriate, given that estimates of long horizon abnormal returns are very sensitive to the chosen return model. As pointed out by Fama [1998] and Brav, et al [2000], all the current approaches used for the estimation of abnormal returns are subject to problems as no method is able to minimize, let alone eliminate these problems. In fact, Lyon, et al [1999] recommend that the study of long-run abnormal returns be subjected to stringent ‘out-of-sample’ testing.

There seems to be a general consensus in the literature that the choice of a performance measurement methodology determines both the magnitude and direction of the measured abnormal performance as well as the size and power of the statistical tests. The current studies in the literature make a strong contribution to the literature on the analysis of long-term stock returns based on sound theoretical reasoning and empirical analysis. The studies do not find that one approach is always preferred to the other as they provide in each case the relative merits and demerits of each approach; however, there seems to be general unanimity on the existence of model misspecification problems, most especially with the time-series factor-based models. All the studies, most especially the methodology papers, generally agree that existing approaches in the literature are associated with well documented biases that make it difficult to reach definitive conclusions on the issue of the long horizon performance of new issues of common stock.

The methodology papers also agree on the two main approaches to long horizon security performance evaluation – the characteristics-based approaches in event time and the factor based approaches in calendar time. The former approach assumes that equity risk is captured by an observable set of firm-specific characteristics, while the latter assumes that the systematic patterns in average stock returns can be aptly captured by certain risk factors in an expected return model. The authors, however, caution that if these discernible characteristics are only inadequate proxies for risk, then the characteristics-based approach might misclassify firms' riskiness. They also point out that both approaches are likely to suffer from model misspecification problems.

Against this backdrop, the debate on the long horizon stock price performance of new issues of common stock is far from conclusive; however, there seems to be a general agreement amongst the studies that several potential firm characteristics and/or risk factors that shape the return profile of firms may be missing. In the context of the characteristics-based approaches in event-time, long horizon IPO stock price under-performance may be due to imperfect matching procedures, while in factor based approaches in calendar time, the phenomenon may likely be the result of these approaches not being able to fully explain the variation in the cross-section of stock returns. Also, there appears to be harmony in prior research on IPO long-term performance that because it lacks a proper methodological framework, the analysis has been less rigorous and essentially naive.

The inconclusive IPO under-performance evidence may just be a manifestation of the statistical inadequacies of traditional matching methods or inadequate matching criteria rather than an anomaly that challenges the efficient market hypothesis; hence, the finding may not be robust to changes in the matching procedure or criteria used in selecting the benchmark firms. Specifically, it could well be that by increasing the quality of the matching process using a multi-dimensional procedure that seeks to minimize the differences in ex-ante firm characteristics between the event and non-event firms at the IPO date, a solution could be found to the IPO under-performance puzzle.

It is also pertinent to note that though the singular objective of the matching algorithm of alternatively comparing new issues of common stock with a set of aptly matched firms[29] is to ensure that issuing and matching firms have fairly similar risk profiles, the results may indicate that the critical performance indices of new issues and matching firms may conform much better than for the size and market-to-book only matched firms. Therefore, this may mean that selecting the matching firms according to their size, market-to-book and other key firm risk factors related to stock returns may facilitate a better match between IPO and the control firms.

Lyon, et al [1999] further buttress the fact of the inappropriateness of the current approaches to the analysis of long-horizon stock analysis by positing that the use of the size and market-to-book factors alone as firm risk factors can lead to misspecified test statistics and spurious inferences in certain sampling situations. In fact, they are quoted

[29] An appropriate matching process would be one that goes beyond the traditional dimensions of size and market-to-book to considering other key return-determining factors that could be influential to experimental outcomes and in the process explain further the cross-sectional variation in firms' stock returns.

more clearly: “Though firm size and market-to-book ratio has received considerable attention from the recent research in financial economics, some would argue that other variables explain the cross-section of stock returns. To address this issue, we recommend that researchers compare sample firms to the general population on the basis of other characteristics. A thoughtful descriptive analysis should provide insights regarding the important dimensions on which researchers should develop a performance benchmark”. *[pp. 198]*. Barber and Lyon [1997b] also argue that “as future research in financial economics discovers additional variables that explain the cross-sectional variation in common stock returns, it will also be important to consider these additional variables when matching sample firms to control firms”. *[pp. 370-371].*

Against this backdrop, the principal motive of this study is to firstly, unearth these additional variables that could potentially explain further the cross-sectional variation in IPO stock returns; secondly, use them as additional risk factors to select the non-issuing control firms from the general population and finally, determine if the performance of the issuing sample firms are significantly different from those of the non-issuing control firms using a battery of methods and techniques that also checks for robustness.

[3.2.5] Matching Models

It is important to note that when examining long-run returns, the researcher must first of all, construct a control sample against which to measure abnormal returns. It is the vagueness surrounding the selection of this control sample [in the case of the characteristics-based approaches] and appropriate composite firm risk factors [in the case of the factor-based models] that generally provides the greatest source of criticism. The choice of a fitting expected return model is crucial to estimating the valuation effects of new equity issuances in the long-term as any study investigating the relative performance of securities must have a notion of what 'normal' or 'expected' returns are. To underscore this point more succinctly, let us express the t-period expected return on stock i as:

$$E\{r_i(t)|IPO\} = \varphi + E\{r_i(t)\} \ \ldots\ldots \ [3.1]$$

where φ is the element of the return attributable to the IPO [i.e. the 'IPO effect'], $E\{r_i(t)\}$ is the unconditional $t-period$ expected returns on stock i and $E\{r_i(t)|IPO\}$ is the observed $t-period$ returns on stock i conditioned on the IPO event.

Generally, event studies estimate the size of φ to determine the impact of the IPO event. Over a short horizon, $E\{r_i(t)\}$ is infinitesimal and the estimate of the return attributable to the IPO event, (φ), is usually not sensitive to the choice of the asset pricing model. However, over long periods, $E\{r_i(t)\}$ is generally greater than φ and as a result, makes it extremely intricate splitting perfectly the average ex-post returns into the two components in order to establish if a unique ‘IPO effect’ exists. Indeed, it has been shown that traditional asset pricing models such as the CAPM and the FF3F do not explain fully the cross-section of stock returns [Fama and French, 1993].

A valid scientific research enquiry into the analysis of firm returns would typically suggest that if expected returns are a function of a set of pivotal firm characteristics, then the researcher must match the sample returns to those on benchmarks comprising firms whose return-determining ex-ante characteristics are similar to that of the sample group. By so doing, the outcomes of any analysis of long horizon stock price analysis would be free of any form of bias, thus making it easier to reach definitive conclusions. This task is accomplished with a range of techniques available in the corporate finance literature spanning dimension-by-dimension, propensity score and distance score matching procedures.

Dimension-by-Dimension matching: This technique, also known as the traditional method of matching and the most used in empirical corporate finance, generally assesses the difference between two sets of firms – one experiencing the event $[E]$ and the other not experiencing the event $[NE]$ – based on a set of observable ex-ante attributes, X. Hence, the event effect for any firm i in the event group is the difference between its outcome and the outcome of a fairly similar firm j in the non-event group that matches it on all germane dimensions. If the post-selection outcomes for the event and non-event firms are denoted as Y_E and Y_{NE} respectively, then the event effect equals, $Y_{i,E} - Y_{j(i),NE}$, where $j(i)$ is such that $X_{i,k} = X_{j(i),k}$ for all k relevant dimensions [Kothari and Warner, 2007].

Matching on all possible dimensions and estimating the matched pair discrepancies in results using the traditional method poses great challenges. Firstly, characteristics are not always precisely matched as more often than not, the size and market-to-book factors are matched with callipers in the neighbourhood of 20-30%. When matches are imprecise, sizeable biases could amplify as one negotiates different characteristics or dimensions being matched. Secondly, when the number of dimensions to be matched increases and the matching callipers become thinner and finer [i.e. size and market-to-book factors matched within 5-10% rather than 20-30%], finding suitable matches become complex or even impossible [Li and Prabhala, 2007].

This probably explains why matching has been done on a limited range of variables to date, despite the assertions of Fama [1998] and Lyon, et al [1999] that researchers should conduct a comprehensive descriptive analysis to reveal other firm risk factors, other than the size and market-to-book, that can be used in explaining the cross-section of average stock returns[30]. This work avers that the previous studies may not have achieved sufficient breadth[31] and depth[32] in the matching process. Basically, better matching procedures should aim at achieving these twin objectives in the matching process.

Propensity Scores: To some extent, the propensity score technique[33] overcomes the challenges of dimension-to-dimension matching by reducing the problems to a single problem of matching on one criterion – the propensity score [Kothari and Warner, 2007]. The propensity score is the probability of the event, $pr(E|Z)$, usually estimated from the following probit model equation:

$$pr(E|Z) = pr(Z\gamma + \eta) > 0 \; \ldots\ldots \; [3.2]$$

where the event firms belong to group E, non-event firms belong to group NE, Z denotes a set of explanatory variables, γ is a vector of parameters and $1 - pr(E|Z)$ is

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30 Further, Fama [1998] argues that a matching technique based on size only can produce different abnormal returns from one that is based on size and market-to-book due to the fact that these factors do not capture all cross-firm variations in abnormal returns. Deductively, a matching technique based on size, market-to-book and other key return-determining firm risk factors should produce different abnormal returns when compared with a technique that is based on size and market-to-book only.

31 This basically entails matching event firms to non-event firms across a host of possible risk factors and key return-determining characteristics.

32 This involves choosing from a qualifying fixed set of non-event firms a matching non-event firm that is closest to the event firm as much as possible based on a criterion that seeks to minimise the differences of the characteristics of the event firm from the chosen non-event firm.

33 This technique has been used by Cheng [2003] and Li and Zhao [2006] in their study of the long-run performance of SEOs in the US market.

the probability of not undergoing the event. The post-selection outcomes for the event and non-event firms are given in the following equations below:

$$Y_E = X_E\beta_E + \epsilon_E \text{ ……. [3.3]}$$

$$Y_{NE} = X_{NE}\beta_{NE} + \epsilon_{NE} \text{ ……. [3.4]}$$

where, ϵ_c denotes error terms, X_c denotes explanatory variables, β_c denotes parameter vectors and $C \epsilon \{E, NE\}$. For the group of event firms, the effectiveness of the event is then judged by testing whether the difference in outcomes between the event and non-event groups is significantly different from zero using the following equation:

$$E\{(Y_E - Y_{NE})|C = E\} = 0 \text{ ……. [3.5]}$$

Hence, the event effect is the difference in outcome between the event and non-event groups with equal probability or identical propensity scores. The ease of the propensity score estimator and its uncomplicated rationalization makes it generally attractive; however, there are a few challenges in its implementation. Firstly, since the propensity scores are not known ex-ante, they must be estimated in the first instance, using parametric approaches, which may lead to imprecise estimates. Secondly, because the propensity score estimates are not exact, the corresponding event effects are also estimated with some error. Put differently, due to the fact that the event effects must be estimated, precise matching based on the exact event probability is virtually impossible. Thirdly, is the knotty issue of which variables are to be included in estimating the probability of undergoing the event [i.e. the propensity scores] and the event effects [Kothari and Warner, 2007][34].

Distance Scores: Similar in concept to the propensity score, distance scores equally surmounts the challenges of dimension-by-dimension matching by reducing the problems to a single problem of matching on a single criterion – the distance score. For each firm i in the event group, this approach calculates a distance score for each firm j in the non-event group based on a set of germane observable ex-ante characteristics or dimensions. The distance score for firm j, denoted as DS_j, in the non-event group is the sum of the absolute or squared differences between the characteristics of firm i in the event group and the characteristics of firm j standardized by the respective cross-sectional standard deviation of each of the characteristics k in the period when the characteristic is measured. More formally, the matching technique is set out as follows:

$$DS_j = \sum_{k=1}^{n} \frac{\{\theta_{i,E}(k) - \theta_{j,NE}(k)\}^2}{\rho_k} \quad \text{........ [3.6]}$$

where n is the number of dimensions that are matched, $\theta_{j,NE}(k)$ is the dimension value k of firm j in the non-event group, $\theta_{i,E}(k)$ is the dimension value k of firm i in the event group and ρ_k is the cross-sectional standard deviation of dimension k in the period when it is measured. Standardizing the absolute or squared deviations of a particular

[34] Heckman and Navarro-Lozano [2004] argue that using 'quality of fit' as a model selection in estimating propensity scores leads to great difficulties.

dimension with its cross-sectional standard deviation across all firms in the population ensures that dimensions with small cross-sectional variation are given more weight for the same magnitude of deviation when compared to those dimensions that are more diffused in the population [Jegadeesh, 2000]. For each given firm i in the event group, that firm in the pool of potential matches [i.e. non-event group] that minimises the sum of the standardized absolute or squared differences across all the possible dimensions is chosen as the benchmark [Butler and Wan, 2010]. More formally, the author's problem of choosing an appropriate matching firm from the non-event group for each firm in the event group reduces to optimizing the following expression:

$$Minimize\ \{DS_{j,NE} \mid i_E\} = \sum_{k=1}^{n} \frac{\{\theta_{i,E}(k) - \theta_{j,NE}(k)\}^2}{\rho_k} \text{ …….. [3.7]}$$

Due to the highlighted challenges with using the dimension-by-dimension and propensity score approaches, this study will adopt the distance score technique to select appropriate matching firms for the sample of IPO firms from the general population. The lure of this technique lies in the fact that it achieves significant depth and breadth in the matching process, just like in the propensity score approach, while avoiding the problems that tend to be associated with the latter. The simplicity of the distance score technique and its unfussy explanation also makes it generally attractive. The matching procedure closely follows that of Jegadeesh [2000] in his study of SEOs in the US. Spiess and Affleck-Graves [1995 and 1999], Butler and Wan [2010] and Gao, et al [2006] also adopt versions of this approach.

[3.2.6] Research Questions and Hypotheses

The methodological question is the most crucial of all the fundamental philosophical questions that underlie all enquiries into the performance of IPOs and the crux of the current debate in the IPO literature. How can the enquirer go about finding out whatever can be known about the performance of IPOs? The answer to this question is usually constrained by the answers to the ontological[35] and epistemological[36] questions; that is, not just any methodology is appropriate. A real objective and systematic approach that seeks to study the long-run performance of IPOs must be one that mandates control of all possible intervening factors or variables that can influence the performance of the average firm in the real world[37]. Hence, the methodological question cannot be reduced to a question of methods as the researcher must, prior to a

[35] What is the form and nature of the long-run performance of IPOs and therefore, what is there that can be known about it? Put differently, how 'really are things' in the world of IPO firms' performance? Only those questions that relate to the matter of the long-run performance of IPOs within a legitimate, unbiased, logical and 'water-tight' scientific enquiry can be admissible; all other questions, such as those bordering on values, moral significance, argumentation or interpretivism which fall outside of the realm of a valid logical enquiry, are ruled out.

[36] What is the nature of the relationship between the enquirer and what can be known about the long-run performance of IPOs? It is pertinent to note that the answer here is constrained by the answer to the ontological question in footnote 35. Here, the posture of the enquirer must be one of objectivity or value freedom in order to be able to study the long-run performance of IPOs.

[37] The aim in a valid enquiry into the long-run performance of IPOs is to determine if a 'unique' IPO effect indeed exists in the market place that makes issuing firms that are similar in all respects to a set of comparable non-issuing firms based on a set of ex-ante characteristics and differ only in that they experience the IPO event, perform significantly worse in the long-run than their non-issuing counterparts.

commencement of any study, have an impeccable pre-determined methodology to which methods must be fitted in order to arrive at unbiased outcomes. Do IPOs really underperform in the long-run? It seems achieving a better match between the IPOs and the control firms may eventually answer this question.

Following from the above, it may just be that the documented under-performance of new issues may be due to fundamental differences in firm characteristics between these new issues and mature non-issuing firms. It is also worthy to note that IPO firms may differ from their non-issuing counterparts with respect to a number of differing fundamental firm characteristics at the date of listing and provided that some of these characteristics are a function of stock returns, they might provide more illumination on the long-run price performance of the stock of IPO firms and why they also behave differently from those of seasoned non-issuing firms. In fact, there is a huge body of empirical literature that has established strong cross-sectional links between some of these firm characteristics and stock returns[38]. The results from the orthodox analysis of abnormal stock returns[39] should be interpreted with caution as this phenomenon may just be due to an imperfect match between the IPOs and the control firms. In the context of the traditional approaches in event time using the BHAR approach, IPO

[38] See Ritter [1991], Purnanandam and Swaminathan [2004], Teoh, et al [1998 (a and b)], Levis [1993], Loughran and Ritter [2001], Spiess and Affleck-Graves [1995], Jain and Kini [2000] and Bhabra and Pettway [2003].

[39] These are CAR, BHAR and FF3F.

under-performance may be the consequence of imperfect matching procedures, while in factor based approaches, the phenomenon may be the result of these approaches not being able to fully explain the variation in the cross-section of stock returns.

Do stocks of firms going public really under-perform those of more mature firms and, if so, over what horizon is the under-performance statistically significant? The definition of a “long horizon” in event studies is subjective and generally applies to event windows of over a year [Kothari and Warner, 2007]. Therefore, instead of merely relying on the typical length of three or five years that have been used in prior research [Brav and Gompers, 1997; Brav, et al; 2000; Kooli and Suret, 2004; Gompers and Lerner; 2003; Boisson and Sentis, 2010] this study will attempt an investigation of the long-horizon stock price performance over differing time horizons spanning 1-5 years.

A scientific approach of cautiously selecting the non-issuing control firms from the general population in the first stage and then controlling for all possible risk factors that could be associated with the average firm stock price performance in the second stage could help solve the protracted puzzle of the documented long-run under-performance of new issues of common stock. Against this backdrop, the first empirical study will undertake to provide an answer to the following knotty research question:

- Do IPOs really under-perform?

If the answer is in the affirmative, then the questions below would follow logically:

- Is the under-performance due to fundamental differences in firm characteristics between IPOs and the more seasoned non-issuing firms?
- Is the under-performance the result of an imperfect match between IPOs and the control firms?
- Is the under-performance a manifestation of statistical inadequacies of traditional matching methods or inadequate matching criteria?
- Is the scale of the observed under-performance sensitive to the matching process?
- Over what horizon is the under-performance statistically significant?
- Is the under-performance really an anomaly that challenges the efficient market hypothesis?

Following from the research questions above, the central hypothesis under investigation in the first empirical study is as follows:

Hypothesis – [H_0]: The documented under-performance of IPO firms is not genuine.

[3.3] DATA AND METHODOLOGY

[3.3.1] Data and Sample Selection

The following criteria are used in selecting the final sample [i] Only issues of common stock are retained with unit and exchange traded offerings excluded[40] [ii] All financial, real estate and utilities are excluded[41] [iii] All issues with offer price [offer proceeds] less than £0.1 [£0.5m] are excluded[42]. The LSE database provide all the offering characteristics for the final sample [date of issue, issuer, industry, offering price, number of shares on offer, gross proceeds, number of issued shares and market capitalization]. Finally, all firm characteristics are obtained from a unique database of all UK firms held at the University of Leeds[43]. The final sample of 746 IPOs is from a population of 1,724 IPOs [a fair representation of 43%] drawn from the LSE database

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[40] These offerings are not equity offerings of specific firms trading and operating in the market place; rather, they represent unit offerings of an investment basket across different asset classes by asset managers to potential investors. These offerings have also been excluded due to the difficulty in separating the value of the offerings [usually common stock with warrants].

[41] By excluding financial and real estate institutions, the study controls for 'extreme out-performance bias' since these IPOs usually come to the market at the maturity stage of these firms; this also applies to utilities which tend to be 'monopolists' in the market and are generally government privatised IPOs [Ritter, 1991; Menyah, et al, 1995; Espenlaub, et al, 2000].

[42] By excluding these relatively small IPOs, the study avoids firstly, any 'extreme under-performance bias' that may be associated with these class of offerings and secondly, the low-price stock effect [Loughran and Ritter, 1996].

[43] The author would like to thank Prof Nick Wilson, in conjunction with the Leeds University Business School, for providing this database which proved invaluable.

TABLE 3.4: SELECTION OF THE SAMPLE OF IPO FIRMS

The table shows how the filters were applied to arrive at the final sample of IPO firms listed on the LSE, going from January 1999 to December 2006.

Population		1,724
Exclude:		
Unit Offerings	82	
Financial Institutions	588	
Real Estate	68	
Utilities	15	
Issues with offer price [proceeds] < £0.1 [£0.5m]	155	
Issues with no price data on Datastream	70	
Total Exclusions		978
Final Sample		**746**

of IPOs and covers the period January 1999 to December 2006[44]. Table 3.4 illustrates how the filters were applied to arrive at the final sample of IPOs.

[3.3.2] Descriptive Statistics

Table 3.5 presents a distribution of the key offering characteristics for the IPO sample. Panel A presents the distribution of the sample by year, both in terms of the number of offers and the gross proceeds, while in Panels B and C, firms are categorized by gross

[44] The choice of period for the IPO sample is conditioned on the length of the event and evaluation windows. Firstly, given that the evaluation window for performance and survival for this fixed cohort of firms is five and six years with window end-points of 2011 and 2012 respectively for the last set of observed IPO firms [i.e. 2006 IPOs], the end-point for the event window must of necessity be 2006. Secondly, in order to permit as recent a dataset as possible that has previously not been investigated in the UK IPO market, the study has also decided to use 1999 as the start-off point for the event window.

proceeds and market capitalization respectively. In Panel D, firms are categorized by industry, while firms are categorized by industry and year in Panel E, where industry is determined by the standard industry classification [SIC] codes. The firms are categorized by underwriter market share in Panel F, where market share has been computed as the proportion of gross offer proceeds attributable to each underwriter in the period, while Panel G provides a summary of the key statistics.

Inspection of Panel A reveals that the sample shows clear evidence of clustering. For example, 545 of the 746 sample offers [73.06%] occurred in 2000 and the period going from 2004 to 2006. These years account for 61.53% [£16,619.16m of the £27,011.58m total] of the aggregate gross proceeds which seems to be consistent with the notion of 'hot' markets [Ritter, 1984][45]. A closer look at the IPO distribution shows that the number of IPOs moved sharply in 2000 to 150 [20.11% of total sample] from 48 IPOs [6.43% of total sample] in 1999. It subsequently fell in the three years following sliding progressively to 63 IPOs [8.44% of total sample], 50 IPOs [6.70% of total sample] and 40 IPOs [5.36% of total sample] in 2001, 2002 and 2003 respectively. There was an upswing in 2004 as the number of IPOs moved sharply to 138 [18.50% of total sample],

[45] Hot market periods are normally characterised by a large number of offerings, a high volume of gross offer proceeds and a high level of IPO under-pricing and immediate after-market returns. More often than not, start-ups, fledgling and poor quality firms also tend to take advantage of this booming market period to float their offers.

TABLE 3.5: DISTRIBUTION OF IPO FIRMS' OFFERING CHARACTERISTICS

The sample is 746 IPOs that went public between January 1999 and December 2006. In Panel A, firms are categorized by year with gross proceeds calculations based upon the amount sold at the offer and computed as the total number of shares offered multiplied by the offer prices. The average age/proceeds in each year is calculated as the total age/gross proceeds divided by the number of firms that went public in that year. In Panels B and C, firms are categorized by gross proceeds and market capitalization respectively. Market capitalization, which is based on the number of shares issued by each firm comprising the amount offered and the amount retained by the old shareholders, is calculated as the total shares on issue multiplied by the market prices on the first listing day for all the IPO firms in each category, while the average market capitalization is computed as the gross market capitalization in each category divided by the number of firms in that category. In Panel D, firms are categorized by industry with the gross proceeds in each industry representing the total shares offered by the firms in that industry multiplied by their respective offer prices. The average proceeds in each industry is computed as the total gross proceeds divided by the number of firms in that industry. In Panel E, firms are categorized by industry and year, where industry is determined by the standard industry classification [SIC] codes. Finally, in Panel F, firms are categorized by underwriter market share, where market share has been computed as the proportion of gross offer proceeds attributable to each underwriter in the period. Panel G provides a summary of the key statistics.

Panel A: By year

Year	No of IPOs	Average Age [Yrs.]	Gross proceeds [£'m]	Average proceeds [£'m]
1999	48	2.44	2,838.06	59.13
2000	150	2.58	6,685.24	44.57
2001	63	3.38	1,487.08	23.60
2002	50	4.99	3,932.43	78.65
2003	40	3.84	2,134.85	53.37
2004	138	3.11	2,679.68	19.42
2005	152	2.44	3,355.98	22.08
2006	105	2.74	3,898.26	37.13
TOTAL	**746**	**2.96**	**27,011.58**	**36.21**

Panel B: By gross proceeds

Bound [£'m]	No of IPOs	Gross proceeds [£'m]	Average proceeds [£'m]
≤ 10	463	1,621.85	3.50
< 10 BUT ≤ 20	107	1,407.36	13.15
< 20 BUT ≤ 50	89	2,744.02	30.83
< 50 BUT ≤ 100	37	2,516.79	68.02
> 100	50	18,721.56	374.43
TOTAL	746	27,011.58	36.21

Panel C: By market capitalization

Bound [£'m]	No of IPOs	Gross market cap [£'m]	Average market cap [£'m]
≤ 10	197	1,088.71	5.53
< 10 BUT ≤ 20	171	2,471.94	14.46
< 20 BUT ≤ 50	184	5,688.16	30.91
< 50 BUT ≤ 100	80	5,530.56	69.13
> 100	114	74,880.95	656.85
TOTAL	746	89,660.32	120.19

Panel D: By industry

Industry	No of IPOs	Gross proceeds [£'m]	Average proceeds [£'m]
Aerospace & Automobiles	6	185.00	30.83
IT & Computer Services	154	4,786.14	31.08
Health & Pharmaceuticals	79	1,313.67	16.63
Food Producers & Processors	14	63.12	4.51
Personal Care & Household Goods	18	193.19	10.73
Leisure, Hotel & Restaurants	64	2,778.95	43.42
Chemicals, Mining, Oil & Gas	130	3,401.06	26.16
Construction & Engineering	58	1,248.68	21.53
Wholesalers & Retailers	27	2,932.99	108.63
Media & Entertainment	79	3,830.85	48.49
Telecommunications	23	2,353.80	102.34
Transport	10	259.90	25.99
Support Services	84	3,664.23	43.62
TOTAL	**746**	**27,011.58**	**36.21**

Panel E: By industry & year

Industry	1999	2000	2001	2002	2003	2004	2005	2006
Aerospace & Automobiles	1	0	0	1	0	1	1	2
IT & Computer Services	15	61	9	5	4	26	25	9
Health & Pharmaceuticals	0	14	8	8	4	17	17	11
Food Producers & Processors	0	0	2	1	3	5	1	2
Personal Care & Household Goods	2	0	3	1	0	8	1	3
Leisure, Hotel & Restaurants	11	13	8	6	4	4	10	8
Chemicals, Mining, Oil & Gas	1	6	5	11	12	23	46	26
Construction & Engineering	3	3	6	5	2	11	15	13
Wholesalers & Retailers	4	7	2	3	1	3	3	4
Media & Entertainment	3	24	6	2	5	17	15	7
Telecommunications	2	4	2	0	0	3	6	6
Transport	0	4	1	1	3	0	0	1
Support Services	6	14	11	6	2	20	12	13
TOTAL	**48**	**150**	**63**	**50**	**40**	**138**	**152**	**105**

Panel F: By underwriter

Underwriter	No of IPOs	Market Share [£'m]	% of Market Share	Rank
Merrill Lynch Europe Plc	13	4,840.63	17.92	1
JP Morgan Cazenove Ltd	18	3,164.73	11.72	2
UBS Investment Bank Ltd	13	2,138.70	7.92	3
Goldman Sachs Equity	8	1,915.33	7.09	4
Lazard & Co. Ltd	3	1,884.90	6.98	5
Credit Suisse Securities	9	1,661.02	6.15	6
Linklaters	1	1,087.50	4.03	7
Citibank NA	2	974.47	3.61	8
Colins Stewart Europe Ltd	41	769.95	2.85	9
Deutsche Bank AG	4	753.08	2.79	10
Schroder Salomon Smith Barney	1	734.71	2.72	11
Others	633	7,086.56	26.22	12-109
TOTAL	**746**	**27,011.58**	**100.00**	

Using the technique of Megginson and Weiss [1991] and Beatty and Ritter [1986], the underwriter reputation variable for each underwriter has been derived based on the percentage of the market share, reflecting the total market gross offer proceeds for the sample over the study period. The total number of underwriters is 109 with rank 1 denoting the underwriter with the highest percentage of market share [tagged as the most prestigious underwriter] and rank 109 denoting the underwriter with the least percentage of market share [tagged the least prestigious underwriter].

Panel G: SUMMARY OF KEY STATISTICS FOR THE SAMPLE OF IPO FIRMS THAT WENT PUBLIC OVER THE PERIOD 1999 AND 2006

Total IPOs	746
Total Gross Proceeds [£'m]	27,011.58
Average Gross Proceeds [£'m]	36.21
Total Market Capitalization [£'m]	89,660.32
Average Market Capitalization [£'m]	120.19
No of Internet & IT Software IPOs	126
No of Internet & IT Software IPOs as % of Total IPOs	16.89
No of Internet & IT Software IPOs as % of 1999 & 2000 IPOs	32.32
2000 Internet & IT Software IPO Gross Proceeds as % of 2000 Gross Proceeds	35.24
Average Age [Yrs.] – All Internet & IT Software IPOs	2.75
Average Age [Yrs.] – 1999 & 2000 Internet & IT Software IPOs	1.77
Average Age [Yrs.] – All IPOs [Ex. Internet & IT Software IPOs]	3.01
Average Age [Yrs.] – All IPOs	2.96
No of Underwriters	109
Mkt. Share [%] of Most Prestigious Underwriters [11 of 109 total]	73.78
Mkt. Share [%] of Least Prestigious Underwriters [98 of 109 total]	26.22

rising further to 152 [20.38% of total sample] in 2005 before closing out at 105 IPOs [14.08% of total sample] in the final year [2006]. The period 1999-2001 is generally known as the ‘technology bubble’ or ‘dotcom’ years that actually started in 1997, a period that saw a great number of fledgling firms take advantage of the transitory opportunity created by the market heat at the time to float their IPOs. Hence, for this study, the period 1999 – 2001 will be treated as the ‘dotcom’ period.

The distribution of the sample by size, in terms of gross proceeds and market capitalization is presented in Panels B and C respectively. Both Panels show that tiny IPOs and small firms [gross proceeds and market capitalization < £10m] represent 463 and 197 of 746 total IPOs [62.06% and 26.41%] respectively, while large IPOs and big firms [gross proceeds and market capitalization > £100m] represent 50 and 114 of 746 total IPOs [6.70% and 15.28%] respectively. IPOs with gross proceeds and market capitalization between £10 and £100 million represent 31.24% and 58.31% of the sample respectively. The dispersion in the size of the IPOs and the sample firms and their subsequent performance will have a definite impact on the size and direction of the results via the weighting schemes employed. The distribution of the sample by industry both in terms of the number of offers and the gross proceeds is presented in Panel D. It reveals that the sample covers different industries. Information Technology [IT] and Computer Services; Leisure, Hotels and Restaurants; Chemicals, Mining, Oil and Gas; Media and Entertainment and Support Services represent 511 out of 746 total IPOs [68.50%]. About 68.35% [£18,461.23m of the £27,011.58m total] of the aggregate gross proceeds in the sample were raised by these industries.

In Panel E, which presents the distribution of the IPOs by industry and year, the number of Internet and Information technology [IT] Software IPOs [included in the IT and Computer Services industry] in 1999 and 2000 combined is 64 out of 198 sub-total IPOs [32.32%] with gross proceeds in 2000 alone of £2,356.09m out of £6,685.24m total in 2000 [35.24%]. Glowing growth projections and readily accessible capital led many fledgling Internet and IT software firms to the IPO market in this period. This boom in the IPO market was a global phenomenon at the time and was more pronounced in the United States. During these years, a record number of firms went from start-ups to IPOs in less than two years. The vibrant IPO market coupled with the desire of many private equity investors in some of the start-up firms to realize their investments and make swift returns led to a situation where many of these firms went public with unproven business plans [Westenberg and Gallagher, 2001].

Against this backdrop, it means that the performance of the 1999 - 2001 sub-group of IPO firms would have a considerable impact on the long horizon stock price performance of the IPO sample because firstly, at 34.99% [261 out of total 746], they represent a sizeable proportion of the overall sample. In addition, because an ebullient and ‘hot’ IPO market such as we had in 1999 - 2001, generally raises the prices at which a fixed cohort of firms can sell their securities, an opportunity is created for weak and marginal firms to float their own offers. Following from this, this study would not be surprised to find under-performance of these new issues over the study period even before any empirical analysis gets underway. Panel F presents the distribution of the sample by underwriter both in terms of the number of offers and an attributed share of market gross proceeds for the study period. It reveals that only 11 underwriters out of a total of 109 in the period [about 10%] accounted for about 74% of total market gross proceeds [£19,925.02m out of £27,011.58m total].

A summary of the key statistics for the IPO sample is presented in Panel G. Of particular note from this panel is the statistics relating to the internet and IT software IPOs, which was at the forefront of the market bubble in the ‘dotcom’ period. The number of these IPOs as a percentage of total IPOs stands at 16.89% [126 out of the 746 total] with the average age standing at 2.75 years. In fact, at the height of the boom [1999 and 2000], the average age of the internet and IT software IPOs launched in the market in those years is a mere 1.77 years. It is also observed that if this group of IPOs are excluded, the average age of the overall sample increases from 2.96 years to 3.01 years.

A brief descriptive analysis of the data of the sample firms regarding the offering characteristics is presented in Table 3.6. An inspection of that table shows that the mean values for the age at IPO date, market equity, gross offer proceeds, offer price, shares on issue and shares on offer are respectively 2.96 years, £120.19m, £36.21m, £0.96, 91.40m and 0.28m. A closer look at the table also shows that the distribution of all the offering variables is positively skewed and this is confirmed by the kurtosis values which are all greater than the threshold level of three. There also seems to be a wide dispersion in the offering characteristics, given by the range values. Of particular interest from the table is the distribution of the age and offer price at the IPO date. The oldest firm from the sample is Mouchel Ltd in the Support Services sector at nearly 95 years, while the youngest is IFTE Ltd also in the Support Service industry at less than a month old. The highest offer price is made by Autonomy Corp [IT and Computer Services industry] at £32.76, while the lowest offer price of £0.1 is posted by Designer Vision in the Aerospace and Automobile Industry.

Table 3.7 presents a descriptive analysis of the key characteristics of the IPO firms. An inspection of that table shows that the mean/[median] values for total assets, market equity, market value, turnover, profit before tax, profit margin, earnings per share, market leverage, market-to-book and turnover growth are £76.29m/[£8.20m],

TABLE 3.6: DESCRIPTIVE STATISTICS OF THE OFFERING CHARACTERISTICS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006. Offer price, total shares on offer, gross proceeds, shares on issue, market value of equity and age are all calculated at the IPO date. Total shares offered represent the amount of shares on issue sold at the IPO, while gross proceeds is based upon the amount sold at the offer multiplied by the offer prices. Market value of equity is based on the number of shares on issue for each firm comprising the amount offered and the amount retained by the old shareholders and is calculated as the total shares on issue multiplied by the market prices on the first listing day for all the IPO firms. The Age for each IPO firm is calculated as the difference between the year of incorporation [instead of the founding year] and the year of going public.

Statistic	Age [yrs.]	Mkt. Equity [£'m]	Gross proceeds [£'m]	Offer Price [£]	Shares on Issue ['m]	Shares on Offer ['m]
Mean	2.96	120.19	36.21	0.96	91.40	0.28
Median	0.86	19.94	5.50	0.72	43.36	0.13
St. Dev	5.84	491.28	120.86	1.48	157.06	0.50
Skewness	6.90	10.16	7.27	13.12	5.63	5.11
Kurtosis	82.79	124.65	63.31	265.44	45.96	33.27
Range	94.72	7,724.00	1,544.50	32.66	2,037	4.86
Minimum	0.03	1.00	0.50	0.1	3.00	0.01
Maximum	94.75	7,725.00	1,545.00	32.76	2,040	4.87

It was difficult obtaining the founding dates for all the sample firms as the obtained amount was way below a critical mass level. Hence, this work uses the dates of incorporation, which was readily available for all the sample firms, as a proxy.

TABLE 3.7: DESCRIPTIVE STATISTICS OF KEY FIRM CHARACTERISTICS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006. Market equity [ME] is calculated as the total shares on issue multiplied by the market prices on the first listing day for all the IPO firms. Market value [MV] is computed as the sum of the market value of equity and the book value of debt [sum of short-term and long-term debt] in the year of the IPO. Market Leverage [ML] is defined as the ratio of the book value of debt to the market value of each of the firms. The pre-IPO performance is measured by the operating profit margin [PM]/{earnings per share [EPS]}, where operating profit margin/{earnings per share [EPS]} is defined as the profit before tax [PBT] divided by turnover/[total shares on issue] in the preceding year to each IPO date for all the sample firms. Turnover growth [TOG] is defined as the change in turnover between the year of going public and the preceding year for all the sample firms. All figures represent characteristics in the preceding year to the date of each IPO, except for total assets [TA], market leverage [ML], market equity [ME], market value [MV] and market-to-book [MTB] which are in the year of the IPO. Figures on total assets, market value, turnover [TO] and profit before tax [PBT] are all in £'m, while profit margin, market leverage, market-to-book and turnover growth are in ratios. EPS is in pence [p].

Statistic	TA [£'m]	ME [£'m]	MV [£'m]	TO [£'m]	PBT [£'m]	PM	EPS [p]	ML	MTB	TOG
Mean	76.29	120.19	166.03	53.77	1.23	(9.33)	(1.44)	0.08	9.77	4.36
Median	8.20	19.94	20.92	1.10	(0.18)	(0.07)	(0.30)	0.01	3.31	0.48
St. Dev	382.96	491.28	554.09	238.28	31.23	45.76	11.12	0.14	47.21	24.88
Skewness	10.51	10.16	8.58	14.15	17.07	(6.77)	(2.63)	2.27	6.23	13.42
Kurtosis	127.84	124.65	89.42	257.11	331.96	59.38	28.36	5.37	63.86	213.20
Range	5,799.57	7,724.76	7,829.76	5,028	765.70	756.79	191.96	0.82	882.23	454.43
Minimum	0.0004	0.24	0.24	0.002	(117.70)	(537)	(108.20)	0.00	(321.37)	(1.00)
Maximum	5,799.57	7,725	7,830	5,028	648	219.79	83.76	0.82	560.86	455.43

TABLE 3.8: DISTRIBUTION OF KEY FIRM CHARACTERISTICS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006. In Panels A - D, firms are categorized by total assets, market value, turnover and pre-IPO pre-tax profits respectively. The averages are computed as the gross values divided by the number of firms in each category. All figures are in the year of the IPO except the pre-tax profits which is in the preceding year.

Panel A: By Total Assets

Bound [£'m]	No of Firms	Total Assets [£'m]	Av. Tot. Assets [£'m]
≤ 10	396	1,544.93	3.90
< 10 BUT ≤ 20	127	1,782.99	14.04
< 20 BUT ≤ 50	111	3,571.19	32.17
< 50 BUT ≤ 100	43	2,941.71	68.41
> 100	69	47,071.77	682.20
TOTAL	**746**	**56,912.59**	**76.29**

Panel B: By Market Value

Bound [£'m]	No of Firms	Total Mkt. Val. [£'m]	Av. Mkt. Val. [£'m]
≤ 10	197	948.91	4.82
< 10 BUT ≤ 20	134	1,911.76	14.27
< 20 BUT ≤ 50	187	5,842.65	31.24
< 50 BUT ≤ 100	90	6,408.15	71.20
> 100	138	108,749.97	788.04
TOTAL	**746**	**123,861.44**	**166.03**

Panel C: By Turnover

Bound [£'m]	No of Firms	Total Turnover [£'m]	Av. Turnover [£'m]
≤ 10	498	999.42	2.01
< 10 BUT ≤ 20	84	1,190.44	14.17
< 20 BUT ≤ 30	33	834.55	25.29
< 30 BUT ≤ 50	37	1,364.96	36.89
> 50	94	35,720.17	380.00
TOTAL	**746**	**40,109.54**	**53.77**

Panel D: By Pre-IPO Pre-tax Profits [PBT]

Bound [£'m]	No of Firms	Total PBT [£'m]	Av. PBT [£'m]
< 0	445	-1,425.59	-3.20
> 0	301	2,343.45	7.79
TOTAL	**746**	**917.86**	**1.23**

£120.19m/[£19.94m], £166.03m/[£20.92m], £53.77m/[£1.10m], £1.23m/[-£0.18m], -933%/[-7%], -1.44p/[-0.30p], 0.08/[0.01], 9.77/[3.31] and 436%/[48%] respectively. A closer look at the table also shows that the distribution of all the firm characteristics is positively skewed [except for the profit margin and earnings per share] and this is confirmed by the kurtosis values which are all greater than the threshold of three. There also seems to be a wide dispersion in the firm characteristics, given by the range values.

Table 3.8 presents a distribution of some of the key firm characteristics of the IPO firms. An interesting feature from the table is the pre-tax operating performance [PBT] of the IPO firms prior to their IPO dates shown in Panel D. The mean value for the PBT [£1.23m] belies the fact of the preponderance of loss-making firms amongst the sample firms as revealed by the median [-£0.18m]. In fact, a cross-sectional analysis shows that 445 firms out of the 746 total [59.65%] were already making losses prior to their respective IPO dates as reflected in the PBT, profit margin and EPS. The largest operating loss of £117.70m was posted by Debenhams Plc. in the Wholesalers and Retailers sector, while South African Breweries Plc., in the Leisure, Hotels and Restaurant Industry, posted the highest profit of £648m. The disparity in the size of the firms as reflected in their total assets and market values is also apparent from the distribution of these characteristics in Panels A and B respectively. Small firms [with total assets and market value less than £50m] represent 634 and 518 of 746 total IPOs [84.99% and 69.44%] respectively. This seems to concur with the size distribution of the firms according to their market capitalization from Panel C in Table 3.5, where small firms [firms with market capitalization less than £50m] constitute 73.99% of the sample [552 firms out of a total of 746]. These disparities are also noticeable across the turnover board shown in Panel C with small firms [turnover less than £30m] representing 82.44% of the sample [615 out of a total of 746].

Following from the above, if the weak pre-IPO operating performance noticeable in most of the sample firms continues unabated into the post-IPO period, the efficient market expectation is that investors' valuation of these firms may fall resulting in the market prices of the shares of these firms plunging as well to reflect this performance in equilibrium. If this is the case, it may lead us to suspect, for the second time, possible under-performance of this cohort of firms in the post-event window.

[3.3.3] Applied Empirical Design

The start-off point begins with the transformation of the stock prices into returns [$\mathrm{R_{it}}$], using the natural logarithms of the monthly prices at t [P_t] and t-1 [P_{t-1}] thus:

$$R_{it} = Ln[P_{it}] - Ln[P_{it-1}] \text{ …….. [3.8]}$$

Following from previous research, the initial returns have been excluded from the calculation of the long-term performance. Hence, instead of the issue price, the second month-end closing price following the listing day is used as the set off point for calculating long-term performance[46]. Also in line with the majority of previous research, the performance of the sample firms is studied over a 5-year period[47].

The BHAR return metric is used as the baseline barometer for measuring abnormal performance in event time in this study since this has been shown in the literature to be more representative of the long-run returns an investor can earn and typically does not involve rebalancing [Barber and Lyon, 1997a; Fama, 1998; Conrad and Kaul, 1993][48]. However, there is a need to benchmark the returns of the IPO firms to enable the author to calculate adjusted returns. In this regard, the benchmark is the return on control firms that have been carefully selected from the general population based on a host of matching criteria. Hence, the $H - month$ adjusted returns for each IPO stock is calculated as the difference between the holding-period return of a buy-and-hold

[46] Page and Reyneke [1997] stress the importance of examining IPOs from the standpoint of investors who are forced to purchase shares in the after-market since they are not able to obtain a full allotment of shares at the issue price due to over-subscription. Excluding this period after the IPO listing also ensures that the impact of any initial under-pricing and underwriter price support is reduced to the barest minimum.

[47] It gives a period long enough to study issues relevant to asset pricing theory, more so in the light of Graham's [1959, pp.37] contention that 'the interval required for a substantial under-/[over]-evaluation to correct itself averages 1.5 to 2.5 years'.

[48] However, Fama [1998] and Mitchell and Stafford [2000] point out that BHAR may overstate long-run returns and suffers more skewness problems than CAR in statistical inferences.

investment in the sample firms[49] and that of the chosen benchmark control firm with an appropriate expected return. The mean BHAR is then computed as the average of the abnormal returns for all IPOs in the sample using equally and value-weighted techniques[50]. But, first there is a need to formalize the BHAR approach.

The $H - month$ BHAR for the $i\text{-}th$ firm $[i = 1, \dots n]$ going public in month t $[t = 1, \dots T]$ is defined as:

$$BHAR_{it} = R_{it}^{ipo} - R_{it}^{match} = \prod_{\tau=t}^{t+H-1}\left[1 + R_{it,\tau}^{ipo}\right] - \prod_{\tau=t}^{t+H-1}\left[1 + R_{it,\tau}^{match}\right] \text{ …….. [3.9]}$$

where $R_{it}^{k} = \prod_{\tau=t}^{t+H-1}\left[1 + R_{it,\tau}^{k}\right]$ refers to the H-month BHAR of the $i\text{-}th$ IPO firm $[k = IPO]$ and its matching firm $[k = Match]$ and $\left[R_{it,\tau}^{k}\right]$ denotes the firms' month τ return. The BHAR for each firm going public in month t is derived from:

$$BHAR_{it} = \begin{cases} N_t^{-1} \sum_{i=1}^{N_t} BHAR_{it}, & if\ N_t > 0 \\ 0, & otherwise \end{cases}$$

The average BHAR for all $N = \sum_{t=1}^{T} N_t$ IPO firms in the sample is then obtained as:

$$\overline{BHAR} = \sum_{t=1}^{T} w_i BHAR_{it} = w^{\star} A^{\star} \text{ .... [3.10]}$$

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[49] If any of the IPO firms delists within any of the post-event windows, the author simply rebalances the portfolio by spreading the investible amount on the remaining securities in the portfolio. If the study continues to track firms that delist within any of the evaluation windows to the end of the designated window, it will only strengthen the point that IPOs under-perform in the long-run.

[50] The weight $[w_i]$ is calculated using two methods: $w_i = {}^{1}/_{n}$ for equally-weighted and $w_i = {}^{mv_i}/_{\sum mv_i}$ for value-weighted; n is the number of IPOs in the sample and mv_i is the market value of equity of the sample firms.

where the frequency weights are loaded in vector $w^{\star} = [w_{1\ldots\ldots}w_n]$ and the BHARs for each of the sample firms are stored in vector $A^{\star} = [BHAR_{1\ldots\ldots}\ BHAR_n]$.

The abnormal returns are then tested for being different from zero by performing the conventional t-test:

$$\acute{t} = \frac{\overline{BHAR}}{\acute{\sigma}[\overline{BHAR}]} \sim N[0,1] \text{ …….. [3.11]}$$

$$\acute{\sigma}[\overline{BHAR}] = \sqrt{\frac{1}{N}\frac{1}{N-1}\sum_{t=1}^{T}\sum_{i=1}^{N_t}[BHAR_{it} - \overline{BHAR}]^2} \text{ ………….. [3.12]}$$

In order to add some depth to the results, the CAR metric is also used to calculate abnormal returns. Using CAR, the benchmark-adjusted returns of each IPO at time, t is calculated as:

$$AR_{it} = R_{it}^{ipo} - R_{it}^{match} \text{ ………….. [3.13]}$$

where AR_{it} is the abnormal return of each IPO, R_{it}^{ipo} the raw return of each IPO and R_{it}^{match} the return on the benchmark all at month t.

The relative performance of the IPOs or the benchmark-adjusted returns for T months is the average cumulative abnormal return $[\overline{CAR}]$ from month 1 to month T, which is the summation of the average of the benchmark-adjusted returns, using equally and value-weighted techniques[51]:

[51] See footnote 50.

$$\overline{CAR} = \sum_{t=1}^{T} w_i CAR_{it} \text{ ………….. [3.14]}$$

Barber and Lyon [1997a] document that the long-horizon BHAR [CAR] returns are positively [negatively] skewed leading to negatively [positively] biased t-statistics. In line with their recommendation, skewness-adjusted t-statistics, originally developed by Johnson [1978], are adopted in place of the conventional t-tests for both the CAR and BHAR:

$$t = \sqrt{n}\ \left[S + \frac{1}{3}\gamma S^2 + \frac{1}{6n}\gamma\right] \text{…….. [3.15]}$$

$$S = \frac{\overline{AR}}{\sigma[AR]}\ ,\ \gamma = \frac{\sum_{i=1}^{n}[AR_i - \overline{AR}]^3}{\eta\sigma[AR_i]^3} \text{ …….. [3.16]}$$

where, γ is an estimate of the coefficient of skewness, $\overline{AR}$ is the mean CAR [BHAR] of the sample, $\sigma[AR]$ is the cross-sectional sample standard deviation, $\sqrt{n} * S$ is an approximate measure of the conventional t-statistic and n is the sample size.

Following Ritter [1991] and Loughran and Ritter [1995], long-run performance is also measured using wealth relatives $[WR_{i-m}]$, which is similar in concept to the BHAR method:

$$WR_{ipo-match,T} = \frac{\prod_{t=1}^{T}(1+R_{it}^{ipo})}{\prod_{t=1}^{T}(1+R_{it}^{match})} \text{ ………….. [3.17]}$$

The wealth relative explores how the sample of IPOs performs relative to the matching benchmark. A wealth ratio greater than 1 is generally interpreted as the specific IPO portfolio out-performing the benchmark, whereas a wealth ratio of less than 1 indicates under-performance.

Brav and Gompers [1997] and Lyon, et al [1999] argue that cross-sectional dependence and calendar clustering of stock returns can lead to spurious abnormal returns and misspecified test statistics in an event time analysis. In order to address this problem, the MMAR approach is used to also test for long-run performance. For each calendar month, the abnormal return is calculated for each sample firm using the control firms from the various matching algorithms as the benchmark according to equation [3.13]. Afterwards, a mean abnormal return $[MAR_t]$ across firms $[n_t]$ in the portfolio is calculated using equally and value-weighted techniques[52]:

$$MAR_t = \sum_{t=1}^{n_t} w_{it} AR_{it} \quad \text{.............. [3.18]}$$

A grand MMAR is then calculated as:

$$MMAR_t = \frac{1}{T} \sum_{i=1}^{T} MAR_t \quad \text{.............. [3.19]}$$

where T is the total number of calendar months. To test the null hypothesis of zero MMAR, a t-statistic is calculated, using the time-series standard deviation of the MAR $[\sigma(MAR_{(t)})]$[53]:

[52] See footnote 50. In the MMAR approach, the weights $[w_{it}]$ change from month to month depending on the number of firms in the portfolio and their market value of equity.

[53] Fama [1998], Lyon, et al [1999] and Brav, et al [2000] all show that calendar time-series returns yield well-specified test statistics in almost all sampling situations; hence, conventional t-statistics apply.

$$t(MMAR) = \frac{MMAR}{\sigma(MAR_{(t)})} * \sqrt{T} \text{ .... [3.20]}$$

Mitchell and Stafford [2000] argue that an alternative approach to using the calendar time methodology is to track the performance of an event portfolio relative to an explicit $k - factor$ asset pricing regression model with y_{jt} as the dependent variable as follows:

$$y_{jt} = \propto_{j0} + \beta_{j1}x_{1t} + \dots\dots \beta_{jk}x_{kt} + \varepsilon_{jt} \text{ ..... [3.21]}$$

where y_{jt} = mean monthly excess return of all firms in portfolio j

$\propto_{j0}$ = estimate of the relative performance of portfolio j

In most applications, equation [3.21] is specified as the CAPM or the FF3F model or the FF-Cahart-4F model as shown in equation [3.22] below.

$$R_{pt} = \propto_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + m_p MOM_t + \varepsilon_{pt} \text{ ..... [3.22]}$$

Typically, these asset pricing models are used to analyse the investment performance of a portfolio of firms in calendar time. These models calculate calendar time portfolio returns for firms experiencing an event and determine if these returns are abnormal in a multi-factor regression framework. The estimated intercept from the regression of the time series of portfolio excess returns relative to the return on a risk-free instrument [usually mimicked by treasury bills] against factor returns is the post-event abnormal performance of the portfolio of firms and provides a test of the null hypothesis that the MMAR on the calendar time portfolio is zero. The parameters, β_p, s_p, h_p and m_p stand for the loadings of the portfolio on the market, size, book-to-market and momentum factors respectively. However, the use of the calendar time portfolio approach is by no means limited to an analysis of the performance of a single portfolio of firms [Hoechle, et al, 2011]. It can be extended to a comparison of the investment performance of two separate portfolios of firms [$p_1 \; and \; p_2$], where the dependent variable is given by $\Delta y_t = p_{1t} - p_{2t}$. In this case, equation [3.21] can be re-written as follows:

$$\Delta y_j = \propto_{\Delta 0} + \beta_{\Delta 1} x_{1t} + \ldots\ldots \beta_{\Delta k} x_{kt} + \varepsilon_{\Delta t} \quad \ldots.. [3.23]$$

If portfolio 1 out-performs [under-performs] portfolio 2, then the coefficient estimate for $\propto_{\Delta 0}$ should be positive [negative] and significantly different from zero. Basically, this approach, which addresses risk measurement issues, is a zero investment portfolio that consists of long positions in sample stocks and short positions in their matched firm counterparts that have been selected based on a battery of unique firm and industry characteristics. These portfolios are then further adjusted for risk using calendar time factor models. Any remaining residual return is then deemed to be abnormal in that particular asset-pricing framework.

It is pertinent to note that the previous finding of IPO under-performance in calendar time could be due to omitted unique firm and industry risk factors associated with stock price performance that are embedded in the 'error' term in the factor models which consequently shows up in the alphas [intercepts]. The non-issuing control firms have been painstakingly matched to the IPO sample on the basis of a raft of firm and industry-specific risk factors, spanning size, market-to-book, profitability [i.e. pre-IPO performance], turnover growth, earnings yield and industry. Hence, to the extent that stocks with these unique characteristics are not fully captured by the factor based models, this variant of the calendar time portfolio approach, which appeals to the matched firm method of risk control that has been used by Jegadeesh [2000], Ikenberry and Ramnath [2002], Eberhart, et al [2002] and Loughran and Ritter [1995], should correct for any possible bias in the estimated intercept.

The factor-based models usually assume that the systematic pattern in average stock returns can be captured by the classical market, size and book-to-market factors. However, these factors may only be inadequate proxies for risk which may lead to a misclassification of firms' riskiness and then result in model misspecification and incorrect inferences. Beyond these classical factors, this author avers that there may be other unique firm/industry–specific or idiosyncratic risk factors that could be germane to the average firm stock price performance in the market place. The author posits that if the under-performance of IPO firms is merely a manifestation of lurking effects related to differences in beta, size, book-to-market, momentum and these other idiosyncratic factors, then the intercepts in the regressions from the factor models that include these factors should be economically and statistically indistinguishable from zero. Hence, the goal in this factor-based approach here is to attempt an isolation of the price performance that may be associated with these systematic and any possible idiosyncratic factors from that associated with the IPO event itself, to enable the author to firstly, delineate any unique 'IPO effect' in the market place [if any], and secondly, reach definitive conclusions on the under-performance or otherwise of IPO stocks.

The second part of the first empirical study seeks to examine the sensitivity of the alphas from the factor-based models to various benchmark portfolios constructed on various possible dimensions. A battery of firm and industry specific risk factors that could impinge on the average firm stock price performance are first controlled for by conducting firm-specific matching using the distance metric technique [also used in event-time] in conjunction with stepwise matching algorithms that seek to identify non-issuing control firms that are closest to the IPO firms on various key return-determining risk factors. The CAPM and FF-Cahart-4F models are then adopted as baseline factor models that capture the classical stock market factors to further control for any other variation in average stock returns that may be related to these factors. Essentially, in this variant of the calendar time portfolio approach, risk control is a two-staged approach. In the first stage, the cross-sectional average of the monthly return difference between a portfolio of sample firms and its corresponding benchmark portfolio matched on the stepwise algorithms is computed. In the second stage, the time-series of these return differences is then regressed on the risk factors in the CAPM and FF-Cahart-4F models to obtain fair estimates of the alphas.

More specifically, the price performance for each sample and benchmark firm is estimated over 60 months following the IPO event. In each calendar month over the entire sample period, portfolios of all the sample IPO firms and their corresponding non-issuing control firms matched on the stepwise algorithms are constructed. Since the number of IPO firms is not homogeneously distributed over the sample period on account of the fact that some firms are added and some exit each month, the sample and benchmark portfolios are rebalanced each month and an equal or value-weighted abnormal return, representing the difference between the sample portfolio and corresponding benchmark portfolio returns is calculated. For each calendar month, the IPO portfolio return $[R_{pt}^{ipo}]$ less the matching portfolio benchmark return $[R_{pt}^{match}]$ denoted by $[R_{pt}^{ipo} - R_{pt}^{match}]$ is calculated using equally and value-weighted approaches[54]. The time-series of this monthly difference in return between the IPO and the benchmark portfolio is then regressed on the market factor, measured by the excess returns of a value-weighted FTSE All-Share Index $[R_{mt}]$ over the monthly returns on 3-month Treasury bills $[R_{ft}]$, denoted by $[R_m R_f]$, using the CAPM model.

[54] See footnote 52.

The size $[SMB_t]$, book-to-market $[HML_t]$ and momentum $[MOM_t]$ factors[55] are then added to the CAPM model to form the FF-Cahart-4F model and a separate time-series regression is run. More formally, the performance of the IPO and benchmark portfolios relative to the CAPM and FF-Cahart-4F models is tracked using the following asset pricing regressions:

$CAPM$:

$(R_{ipo} - R_{ft}) = \propto_p + \beta_p(R_{mt} - R_{ft}) + \varepsilon_{pt}$ ….. [3.24]

$(R_{match} - R_{ft}) = \propto_b + \beta_b(R_{mt} - R_{ft}) + \varepsilon_{bt}$ ….. [3.25]

$FF - Cahart - 4F$:

$(R_{ipo} - R_{ft}) = \propto_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + m_p MOM_t + \varepsilon_{pt}$……… [3.26]

$(R_{match} - R_{ft}) = \propto_b + \beta_b(R_{mt} - R_{ft}) + s_b SMB_t + h_b HML_t + m_b MOM_t + \varepsilon_{bt}$…... [3.27]

Subtracting equation [3.25] from [3.24] on the one hand and [3.27] from [3.26] on the other hand yields the following final equations which are estimated for the IPO and benchmark portfolios across all the matching algorithms:

$CAPM$:

$(R_{ipo} - R_{match}) = \propto_{\Delta,p} + \beta_{\Delta,p}(R_{mt} - R_{ft}) + \varepsilon_{\Delta,pt}$ ….. [3.28]

---

[55] The size factor is a zero-investment size portfolio that measures the return difference between small and big firms; the book-to-market factor is a zero-investment value portfolio that measures the return difference between high book-to-market firms and low book-to-market firms, while the momentum factor is a zero-investment momentum portfolio that measures the return difference between high and low prior momentum stocks [Mitchell and Stafford, 2000; Kothari and Warner, 2007]. The author would like to thank Gregory, et al [2013] for providing these factors for the UK market.

$FF - Cahart - 4F$:

$$(R_{ipo} - R_{match}) = \propto_{\Delta,p} + \beta_{\Delta,p}(R_{mt} - R_{ft}) + s_{\Delta,p}SMB_t + h_{\Delta,p}HML_t + m_{\Delta,p}MOM_t + \varepsilon_{\Delta,pt} \text{ . [3.29]}$$

It is vital to note that for the CAPM model, estimating equation [3.28] is analogous to estimating equation [3.24] for the IPO portfolio and equation [3.25] for the different benchmark portfolios and then comparing the alphas from the IPO and different benchmark portfolios to see if the differences are significantly different from zero. The same also applies to equations [3.26], [3.27] and [3.29] for the FF-Cahart-4F model[56].

The estimate of the intercept term [$\alpha_{\Delta,p}$] from equations [3.28] and [3.29] provides a test of the null hypothesis that the difference in the MMAR between the IPO and benchmark calendar time portfolios is zero[57]. If the IPO portfolio out-performs [under-performs] the matching benchmark, then the coefficient estimate for [$\alpha_{\Delta,p}$] from the CAPM and FF-Cahart-4F models should be positive [negative] and significantly different from zero. The parameters, $\beta_{\Delta,p}$, $s_{\Delta,p}$, $h_{\Delta,p}$ and $m_{\Delta,p}$ stand for the differences in loadings between the IPO and benchmark portfolios on the market, size, book-to-market and momentum factors respectively. The use of several methodologies in evaluating long-run abnormal performance is to firstly, give the greatest possible level

[56] This technique was employed by Jegadeesh [2000].

[57] Since [$\alpha_{\Delta,p}$] is the average monthly difference in mean abnormal return between the IPO and benchmark portfolios, it can be used to calculate annualized post-event abnormal performance.

of depth and robustness to the results and secondly, reduce model bias which becomes more likely when one technique is favoured over the others.

[3.3.4] Matching Design and Variable Selection

A key part of the empirical design is the cautious construction of the control firms. However, before this, the group of potential qualifying matching firms or pool of potential matches must, first of all, be defined. This group must firstly, exclude firms whose IPOs occurred within the last seven years to each IPO date[58]. This process also guarantees the exclusion of the sample firms which are the subject of the test[59]. Table 3.9 illustrates how the filters were applied to arrive at the final control groups for the sample of IPO firms on a yearly basis. Firstly, the feasible set of non-issuing firms is drawn from all the firms listed on the LSE in each of the IPO years by excluding all financial, real estate and utilities and all new issues, as in the IPO sample. Secondly, in each IPO year, a final set ['the qualifying set' or 'pool of potential matches'] is drawn from the feasible set by excluding firms whose IPOs occurred within the last seven

[58] Following earlier studies [e.g. Ritter, 1991; Loughran and Ritter, 1995; Eckbo and Norli, 2005], the work compares the characteristics and returns of IPO firms with those of mature non-issuing control firms in order to be able to delineate the specificities of the effect of the 'IPO event' on the return profile of the sample firms. The definition of a mature firm is that firm whose IPO must have occurred at least seven years prior to each IPO date. Secondly, based on the average life cycle of new listings, it gives a period long enough for a newly-listed IPO firm to establish a foothold in the market-place either by remaining a going concern or fail and be delisted. As a result, the author expects firms that are still surviving after the 7th year of their listing anniversary to be firms that have passed this litmus test.

[59] Loughran and Ritter [2000, pp.364] point out that 'a test is biased towards high explanatory power and no abnormal returns if it uses a benchmark that is contaminated with many of the firms that are the subject of the test'.

TABLE 3.9: THE QUALIFYING SET OF NON-ISSUING CONTROL FIRMS

The table shows how the filters were applied to arrive at firstly, the feasible set of non-issuing firms and secondly, the qualifying set for each sub-group of the sample firms on a yearly basis, going from January 1999 to December 2006. The feasible set of non-issuing firms is drawn from firms listed on the LSE in each of the IPO years by excluding all financial, real estate and utilities and all new issues. The qualifying set or pool of potential matches is drawn from the feasible set by excluding firms whose IPOs occurred within the last seven years to each sample firm IPO date.

IPO Year	All Listed Firms	Feasible Set	Qualifying Set
1999	2,895	1,419	638
2000	2,778	1,302	691
2001	2,927	1,451	782
2002	2,880	1,404	921
2003	2,814	1,338	1,114
2004	2,681	1,260	1,046
2005	2,844	1,393	1,212
2006	3,088	1,575	1,433

years to each sample firm IPO date. For example, for the 1999 IPO firms, the feasible set of non-issuing firms would be firms listed on the LSE as at January 1999 excluding all financial, real estate and utilities. The qualifying set is then drawn from this feasible set by excluding firms whose IPOs occurred after December 1992 [i.e. firms with IPOs occurring from 1993 onwards].

The stepwise matching algorithms relies on six firm/industry dimensions or characteristics that are deemed by this study to be pivotal risk factors in the return of the average firm: [i] Market capitalization [to control for size effects and attendant differences in investing opportunity sets] [ii] Market-to-book ratio [to control for possible misalignments in growth potentials] [iii] Pre-IPO performance measured by operating profit before tax divided by the turnover in the year preceding the IPO date [to control for possible differences in firm specific performance before the IPOs] [iv] Turnover growth [to control for possible differences in operating opportunity sets] [v] Earnings yield [to control for possible differences in firm specific performance and potential returns to investors] [vi] Industry [to control for possible differences in financing, investing and operating opportunity sets facing the firms]. In the light of the assertion of Lyon, et al [1999], a rigorous descriptive analysis that provides the author with insights on some of the important dimensions on which the study could develop a performance benchmark is conducted. The rationale for the choice of risk factors for the stepwise matching algorithms is next provided:

Size: This is the most commonly used risk factor in the literature for selecting the control firm from the population for very obvious reasons. The size of a firm goes a long way in determining its competitiveness, performance and ultimate survival in the market place. Larger firms are able to survive the rigours of the market place, while small firms are normally the first to buckle under high wages and increasing investing opportunity costs [Lucas, 1978]. Also, in most cases, variable costs usually represent a greater [smaller] fraction of the total cost of small [large] firms with its attendant adverse consequences on the ability of small firms to stay competitive when prices fall in the market [Mata and Portugal, 1994]. Moreover, Banz [1981] and Basu [1983] both show that the stocks of firms with low market capitalizations tend to have higher average long-run returns than those of large market capitalization stocks. Following from the above, market capitalization is used to control for the size effects and possible differences in the investing opportunity set.

Market-to-Book: This is another commonly used risk factor in the literature. The market-to-book factor is a reflection of investors' expectations of the future value or growth potential of a firm based on the opportunities that abound in the firm's industry. This is also a proxy for the riskiness of a firm and, more often than not, the peer market-to-book average is used to determine the relative attractiveness of the firm. High market-to-book stocks [also known as 'growth stocks'] are usually firms whose prices trade higher than their current profits may warrant because, more often than not, they receive intense media and investor attention. Usually, investors buy such stocks [which tend to be riskier] based on their potential for future earnings. Savvy value investors hunt low market-to-book stocks [also known as 'value stocks'] because of their conviction that the stocks [which tend to be less risky] are trading below their intrinsic values. They also believe that the market occasionally overreacts to both good and bad news which results in price swings that do not match up with the company's long-term fundamentals [Bauman, et al; 1998]. Firms that issue equity tend to have higher-than-average market-to-book ratios because of the higher–than-average growth opportunities available to them in the market place. Rosenberg, et al [1985], Fama and French [1992], Chan, et al [1991] and Lakonishok, et al [1994] all show that 'value stocks' out-perform 'growth stocks' in the long-run. Hence, market-to-book factor is used as a risk factor to control for possible misalignments in growth potentials by investors in the market place.

Pre-IPO Performance: In efficient markets, it is expected that the positive [negative] operational performance of a firm will impound into its trading price in the market place as 'good [bad] news'. This operational performance is a reflection of the activities of the firm in its investing and operating space, which in turn is a function of its business environment. This is a key return-determining firm risk factor and a technique that matches benchmark firms with the issuing firms on this characteristic in the year prior to the IPO goes a long way in ensuring that benchmark and issuing firms are on the same footing. Hence, the profit margin, defined as the operating pre-tax profit divided by the turnover in the year preceding the IPO date, is used as a measure of operational performance to control for possible differences in firm specific performance before the IPOs.

Turnover Growth: Turnover growth is firstly, a measure of the extent to which a firm has exploited the business and growth opportunities reflected in its investing opportunity set in its industry on a yearly basis and secondly, a measure of the attractiveness of the firm to value investors. As a result, investors are increasingly focussing not only on bottom-line profits that firms generate, but also on their top-line revenues [Jegadeesh, 2002]. High year-on-year turnover or top-line growth, barring increasing operational costs, should trickle down to higher bottom-line profits and rising stock values in the market place. Hence, the turnover growth, defined as the change in turnover between the year of going public and the preceding year, is used to control for possible differences in the investing opportunity sets of the issuing and benchmark firms at the IPO date.

Earnings Yield: This is similar in concept to the market-to-book factor and the inverse of the conventional price-earnings ratio. Stocks trading at higher than 'peer average' price earnings ratio or lower than 'peer average' earnings yield are generally seen to be riskier and investors buying into such stocks take a gamble that the expectation of future earnings built into the current market price would be realised. Conversely, stocks trading at lower than 'peer average' price earnings ratio or higher than 'peer average' earnings yield are generally seen to be less risky and investors buying into such stocks usually purchase with a large 'margin of safety'. Firms that issue equity tend to have low earnings yield ratios in the same way that they have high market-to-book ratios. Basu [1977 and 1983] and Jaffe, et al [1989] all show that stocks with higher-than-average earnings yield ratios significantly out-perform stocks with lower-than-average earnings yield ratios. Similar to the intuition behind the use of the market-to-book factor, the earnings yield is used as an additional risk factor in selecting the matching firms from the population.

Industry: This is another risk factor commonly used in the literature. Firms that are in the same industry and with similar sizes, turnover and growth performances are assumed to have comparable economic and competitive factors and in most cases tend to have analogous operating, investing and financing opportunity sets [Perry and Williams, 1994]. It is an accepted view that the conditions of a firm's industry impacts on its financial structure and competitiveness amongst its peers. There is also empirical evidence that has demonstrated the connection between industry structure, financial structure and product markets [Chevalier, 1995; Philips, 1995; MacKay and Philips, 2005]. Brander and Lewis [1986], Maksimovic [1988], Maksimovic and Zechner [1991], Williams [1995] and Fries, et al [1997] show that firms reckon with the joint actions of their peers when making crucial financial decisions. Although, a myriad of factors may impinge on a firm's decision to diversify its ownership base by issuing some of its shares to the public, it is an accepted view that this decision has implications on its financial structure and overall market value. Hence, industry is used as an additional risk factor in selecting the matching firms from the population.

The problems associated with the traditional matching methods are well documented. On account of the fact that the first empirical study wants to achieve the greatest possible level of depth and breadth in the matching process in order to arrive at the best possible match for each of the IPO firms, a deviation metric approach that seeks to select a matching firm based on the least square deviations [LSD] between the characteristics of the IPO firms and those of the qualifying set of mature non-issuing firms is employed. The author's goal is to arrive at the best point estimate of the matching firm for each IPO firm across all possible dimensions and matching algorithms. The author believes that a method that seeks to minimize the differences between the characteristics of the control group of non-issuing firms and that of the sample firms and then chooses a benchmark firm on this basis provides the best point estimate, with all callipers and probable matching errors reduced to almost nil.

Firstly, for each sample IPO and matching algorithm, the discrepancies between the sample firm risk factors and the risk factors for each of the firms in the qualifying set is determined at each IPO date. These discrepancies are squared and then standardized with the cross-sectional standard deviation of that risk factor for all firms in the qualifying set for that year to arrive at a squared deviation metric [SDM]. Thereafter, for each IPO firm and matching algorithm, all firms are ranked in accordance with the SDM and that matching firm that has the lowest SDM is then chosen as the benchmark.

More formally, the matching technique is set out as follows:

$$SDM_j = \sum_{k=1}^{n} \frac{\{\theta_{i,ipo}(k) - \theta_{j,Q}(k)\}^2}{\rho_k} \text{ …….. [3.30]}$$

where n is the number of risk factors that are matched, $\theta_{j,Q}(k)$ is the risk factor k of firm j in the qualifying matching set Q, $\theta_{ipo}(k)$ is the risk factor k of IPO firm i and ρ_k is the cross-sectional standard deviation of risk factor k in the period when the risk factor is measured. Standardizing the squared deviations of a particular risk factor with its cross-sectional standard deviation across all the qualifying non-issuing firms on each IPO date ensures that risk factors with small cross-sectional variation are given more weight for the same magnitude of deviation relative to those risk factors that are more diffused in the population. For each IPO firm, that non-issuing firm that is closest to the issuing firm on the SDM is chosen as the benchmark and then, a ranking list is kept[60].

More formally, the problem of choosing an appropriate matching firm for each IPO firm $[F_{ipo}]$ reduces to optimizing the following function:

$$Minimize \left\{SDM_j \middle| F_{ipo}\right\} = \sum_{k=1}^{n} \frac{\{\theta_{i,ipo}(k) - \theta_{j,Q}(k)\}^2}{\rho_k} \text{ …….. [3.31]}$$

Hence, for each of the sample firms, the firm in the pool of potential matches that minimizes the sum of the standardized squared differences in size [Match 1], size and

[60] For each IPO, a ranking of matching firms according to the SDM is kept to provide a backstop to possible issues [i.e. incomplete price data history and/or delisting of original matching firms] that may arise in the tracking process.

market-to-book [Match 2], size, market-to-book and pre-IPO performance [Match 3], size, market-to-book, pre-IPO performance and turnover growth [Match 4], size, market-to-book, pre-IPO performance, turnover growth and earnings yield [Match 5] and size, market-to-book, pre-IPO performance, turnover growth, earnings yield and industry [Match 6] is chosen as the best match.

Expressing and expanding equation [3.31] in terms of the chosen risk factors yields the following distance metric objective equations for the six stepwise matching algorithms:

$$Minimize \left\{SDM_j \middle| F_{ipo}\right\} = \frac{\{\theta_{i,ipo}(size)-\theta_{j,Q}(size)\}^2}{\rho_{size}} \text{ …….. [3.32]}$$

$$Minimize \left\{SDM_j \middle| F_{ipo}\right\} = \frac{\{\theta_{i,ipo}(size)-\theta_{j,Q}(size)\}^2}{\rho_{size}} + \frac{\{\theta_{i,ipo}(mtb)-\theta_{j,Q}(mtb)\}^2}{\rho_{mtb}} \text{ …….. [3.33]}$$

$$Minimize \left\{SDM_j \middle| F_{ipo}\right\} = \frac{\{\theta_{i,ipo}(size)-\theta_{j,Q}(size)\}^2}{\rho_{size}} + \frac{\{\theta_{i,ipo}(mtb)-\theta_{j,Q}(mtb)\}^2}{\rho_{mtb}} + \frac{\{\theta_{i,ipo}(pipo)-\theta_{j,Q}(pipo)\}^2}{\rho_{pipo}} \text{…. [3.34]}$$

$$Minimize \left\{SDM_j \middle| F_{ipo}\right\} = \frac{\{\theta_{i,ipo}(size)-\theta_{j,Q}(size)\}^2}{\rho_{size}} + \frac{\{\theta_{i,ipo}(mtb)-\theta_{j,Q}(mtb)\}^2}{\rho_{mtb}} + \frac{\{\theta_{i,ipo}(pipo)-\theta_{j,Q}(pipo)\}^2}{\rho_{pipo}} + \frac{\{\theta_{i,ipo}(tg)-\theta_{j,Q}(tg)\}^2}{\rho_{tg}} \text{…. [3.35]}$$

$$Minimize \left\{SDM_j \middle| F_{ipo}\right\} = \frac{\{\theta_{i,ipo}(size)-\theta_{j,Q}(size)\}^2}{\rho_{size}} + \frac{\{\theta_{i,ipo}(mtb)-\theta_{j,Q}(mtb)\}^2}{\rho_{mtb}} + \frac{\{\theta_{i,ipo}(pipo)-\theta_{j,Q}(pipo)\}^2}{\rho_{pipo}} + \frac{\{\theta_{i,ipo}(tg)-\theta_{j,Q}(tg)\}^2}{\rho_{tg}} + \frac{\{\theta_{i,ipo}(ey)-\theta_{j,Q}(ey)\}^2}{\rho_{ey}} \text{ …. [3.36]}$$

$$Minimize \left\{SDM_j \middle| F_{ipo}\right\} =$$

$$\frac{\{\theta_{i,ipo}(size)-\theta_{j,Q}(size)\}^2}{\rho_{size}} + \frac{\{\theta_{i,ipo}(mtb)-\theta_{j,Q}(mtb)\}^2}{\rho_{mtb}} + \frac{\{\theta_{i,ipo}(pipo)-\theta_{j,Q}(pipo)\}^2}{\rho_{pipo}} + \frac{\{\theta_{i,ipo}(tg)-\theta_{j,Q}(tg)\}^2}{\rho_{tg}} +$$

$$\frac{\{\theta_{i,ipo}(ey)-\theta_{j,Q}(ey)\}^2}{\rho_{ey}} \quad \text{.... [3.37]}$$

$$subject\ to: Ind_j = Ind_{ipo}$$

where $size, mtb, pipo, tg, ey$ represent the risk factors for size, market-to-book, pre-IPO performance, turnover growth and earnings yield respectively. The industries of the IPO and benchmark firms are denoted by Ind_{ipo} and Ind_j respectively. Equations [3.32] to [3.37] represent the objective functions for matching algorithms 1 – 6 respectively.

The matching firm must have complete price data history; otherwise, the next closest firm on the ranking will be adopted as the matching firm. The matching firm's return is then adopted as the benchmark return for the IPO firm and this is maintained till the end of the 5-year test period[61] or until it is delisted, whichever occurs first. If a matching firm delists before the end of the tracking period, a second [and, if necessary, a third or fourth] matching firm will be chosen and the data from this replacement firm will be appended from the date of delisting of the previous matching firm till the end of the tracking period. The replacement firms are identified on the original IPO date and are based on the same selection procedures as the original matching firms. For example,

[61] This approach has been adopted as the alternative of rebalancing the control firm every year accentuates the new listing and rebalancing biases [normally present in a market-index based model of expected return] and creates another bias called the 'momentum bias' [Rau and Vermaelen, 1998].

for the first matching algorithm [where k = 1, the size factor], the potential replacement firms are simply the firms second, third and fourth on the ranking list closest in market capitalization to the IPO firm. For all the algorithms, the fisrt part of this work will see how the adjusted BHAR for the IPO sample firms compares. The expectation is that the difference in the BHAR between the IPO and control firms along any horizon should diminish as the number of dimensions or marching criteria is increased. Now, if this indeed is the case, the expectation is that in the limits [i.e. as the number of dimensions is further increased], the difference in the BHAR between the IPO firms and the control firms should gravitate to zero.

Mathematically:

Denote the long-run returns of holding the stock of the IPO and benchmark firms as:

$$\prod_{t=1}^{t}(1 + r_{ipo,t}) - 1$$

$$\prod_{t=1}^{t}(1 + r_{bt}) - 1$$

Denote the number of matching criteria as k, where k goes from 1………n.

As the number of matching criteria $k \uparrow$: $\lim_{k\uparrow} \left|\prod_{t=1}^{t}(1+r_{ipo,t}) - \prod_{t=1}^{t}(1+r_{bt})\right| \rightarrow 0$

The matching algorithms are conducted in stepwise fashion starting with the size factor [Match 1] and then adding the market-to-book [Match 2], pre-IPO performance [Match 3], turnover growth [Match 4], earnings yield [Match 5] and industry factors [Match 6] in that order. The author starts off with the size and market-to-book factors since these have been shown to be the common risk factors in average stock returns [Fama and French, 1993]. Moreover, the use of these factors is already well documented in the literature. The author then proceeds to add the profitability factor [i.e. pre-IPO performance] since this factor has been shown to be closely related to the common factors [Fama and French, 1993]. Turnover growth and earnings yield, also related to the profitability factor, are further added in that order as the study seeks to ascertain the plausible impact of these factors on stock performance. Finally, the industry factor is introduced as the study aims to achieve the finest possible level of matching by restricting the circumference of the potential matching firms to the industry of the IPO. Hence in this final process, matching firms from the industry of the IPO that are closest to the IPO firms on the basis of the previous five factors [i.e. size, market-to-book, pre-IPO performance, turnover growth and earnings yield] are selected. However, no particular ordering is expected to have any significant impact on the results as changes in the results are expected to come from the fact that the number of matching criteria is progressively increasing as the matching corridors [i.e. M1 to M6] are traversed.

TABLE 3.10: STEPWISE MATCHING CORRIDOR DYNAMICS

The sample is 746 IPOs that went public between January 1999 and December 2006. Panel A shows the dynamics in the control firm composition along the various stepwise matching corridors with each of the matching algorithms [M1 – M6] serving as the base match in each case. The figures represent the number of firms that drop out along each corridor. Panel B shows the changing firm composition along the corridors with the figures representing the number of firms that are retained in each corridor. The stepwise matching algorithms are based on firm characteristics spanning size [Match 1], size and market-to-book ratio [Match 2], size, market-to-book ratio and pre-IPO performance [Match 3], size, market-to-book ratio, pre-IPO performance and turnover growth [Match 4], size, market-to-book ratio, pre-IPO performance, turnover growth and earnings yield [Match 5] and finally size, market-to-book ratio, pre-IPO performance, turnover growth, earnings yield and industry [Match 6].

Panel A – Firm Drop-outs

Matching Corridor	No of Firms	%
M2 VS M1	670	90
M3 VS M2	219	29
M4 VS M3	282	38
M5 VS M4	392	53
M6 VS M5	706	95

Panel B – Firm Retentions

Matching Corridor	M1	M2	M3	M4	M5	M6
M1	746	76	62	25	23	7
M2	76	746	527	449	365	12
M3	62	527	746	464	382	21
M4	25	449	464	746	354	28
M5	23	365	382	354	746	40
M6	7	12	21	28	40	746

How do the matching firms change as the matching corridors are navigated? Panel A in Table 3.10 shows the dynamics in the control firm composition along the various stepwise matching corridors with each of the matching algorithms [M1 – M6] serving as the base match in each case. It is observed, for example, that going from M1 to M2 [i.e. M2 VS M1], only about 10% of the matching firms [76 of the 746 total] are retained with

670 new firms [about 90% of the 746 total] entering the fray. Similarly, if going from from M5 to M6 [i.e. M6 VS M5], only about 5% of the firms [40 of the 746 total] are retained, while 706 firms [about 95% of the 746 total] drop out.

A fuller and clearer picture of the dynamics in the firm composition is presented in Panel B, which shows the number of firms that are retained in each corridor [i.e. those that don't drop-out]. For example, if the constituent firms in M3 are juxtaposed with those in M1 [i.e. M3 VS M1], only about 8% of the matching firms [62 of the 746 total] are retained, while 684 new firms [about 92% of the 746 total] enter the fray. In the same light, comparing the constituent firms in M6 relative to those in M1 [i.e. M6 VS M1], only about 1% of the firms [7 of the 746 total] are retained, while 739 firms [about 99% of the 746 total] drop out. After the iterations, it is observed that the highest firm retentions occur in the M3 VS M2 corridor [527 of the 746 total], while the least firm retentions occur in the M6 VS M1 corridor [7 of the 746 total]. By extension, the least firm drop-outs [219 of the 746 total] as well as the highest firm drop-outs [739 of the 746 total] also occur along these respective corridors. Clearly, massive changes occur in the constituent stocks of the benchmark portfolios as the matching corridors are traversed, suggesting that the long-run abnormal returns may also change. More formally, the long-run IPO abnormal return at time, t is calculated as:

$$AR_t = R_t^{ipo} - R_t^{match_k} \quad \text{…………..} [3.38]$$

where AR_t is the long-run abnormal IPO return, R_t^{ipo} the raw return of the IPO portfolio and $R_t^{match_k}$ the return on the benchmark portfolio selected according to matching algorithm k, where k goes from 1 to 6.

It is also known that the benchmark portfolio return is given as:

$$R_t^{match_k} = \sum_{t=1}^{T} w_{ib} R_{it,b} = w_b^* R_b^* \quad \text{…………..} [3.39]$$

where, w_b^* and R_b^* are vectors comprising the individual weights and returns of the matching firms respectively in the benchmark portfolio.

Now, these vectors must surely be dependent on the composition of the firms in the benchmark portfolio given as:

$$w_b^* R_b^* = F[Match_k] \text{…………..} [3.40]$$

Following from the above, it must surely be the case that:

$$AR_t = R_t^{ipo} - w_b^* R_b^* \quad \text{…………..} [3.41]$$

where $\quad w_b^* R_b^* = F[Match_k]$

Clearly from equation [3.41], the magnitude and direction of the long-run abnormal IPO return $[AR_t]$ must be a function of the long-run returns of the matching firms which in turn, is dependent on the composition of the firms in the benchmark portfolio.

[3.4] EMPIRICAL ANALYSIS

[3.4.1] Buy-and-Hold Abnormal Return [BHAR]

Table 3.11 reports long-run abnormal returns for the sample of 746 IPOs that went public over the period January 1999 to December 2006. Equally and value-weighted BHARs are compared with the control firms selected according to the six matching algorithms as earlier defined. Panel A reports the equally-weighted returns, while Panel B reports value-weighted returns. The BHAR returns are generated by compounding monthly returns starting in the 2nd month after listing following equity issue till the 13th, 25th, 37th, 49th and 61st months for 1-year, 2-year, 3-year, 4-year and 5-year long-run returns. Abnormal return [AR] is the simple difference between the IPO raw average return [Raw] and the corresponding matching return [Bench].

Clearly, from Panel A, IPOs under-perform across the horizon and matching board. Two other striking features are observed from the results; firstly, the dismal performance of the IPO and control firms across the board [the performance of the IPO firms are worse][62] and secondly, the direct association between the performance of the firms and the length of the evaluation window[63]. An investor who purchases the IPO

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[62] This may not be unconnected with the choice of period of study which straddles the 'dotcom' years [1999 -2001]. The bust of the 'technology bubble' at the time had wide-spread ripple effects in the UK and indeed global markets with attendant adverse consequences on stock price performance and investors' sentiments.

[63] The dismal performance of the firms tends to grow as the investment horizon is increased.

TABLE 3.11: POST- IPO LONG-RUN EVENT-TIME BHAR RETURNS VERSUS CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS OVER THE PERIOD JANUARY 1999 TO DECEMBER 2006

The table reports long-run buy-and-hold abnormal returns for the sample of 746 IPOs that went public over the period January 1999 and December 2006. Equally and value-weighted BHARs are compared with control firms matched on various algorithms based on size only [Match 1], size and market-to-book ratio [Match 2], size, market-to-book ratio and pre-IPO performance [Match 3], size, market-to-book ratio, pre-IPO performance and turnover growth [Match 4], size, market-to-book ratio, pre-IPO performance, turnover growth and earnings yield [Match 5] and finally size, market-to-book ratio, pre-IPO performance, turnover growth, earnings yield and industry [Match 6]. Panel A reports equally-weighted returns, while Panel B reports value-weighted returns. BHAR returns are generated by compounding monthly returns starting in the 2nd month after listing following equity issue till the 13th, 25th, 37th, 49th and 61st months for 1-year, 2-year, 3-year, 4-year and 5-year long-run returns. Abnormal return [AR] is the simple difference between the IPO raw average return [Raw] and the corresponding matching return [Bench]. The BHAR return figures are in %. The figures in parentheses are the skewness-adjusted t-statistics. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

PANEL A - EQUALLY-WEIGHTED RETURNS

	Within the first year			Within the first 2 years			Within the first 3 years			Within the first 4 years			Within the first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	-23.85	-0.20	-23.65	-42.23	-3.64	-38.59	-51.82	-22.88	-28.94	-53.40	-31.30	-22.10	-58.49	-39.63	-18.86
			*(-5.33***)*			*(-7.82***)*			*(-6.16***)*			*(-4.55***)*			*(-3.12***)*
Match 2	-23.85	-5.58	-18.27	-42.23	-7.30	-34.93	-51.82	-19.10	-32.72	-53.40	-26.21	-27.19	-58.49	-26.27	-32.22
			*(-6.25***)*			*(-9.24***)*			*(-7.75***)*			*(-5.07***)*			*(-5.45***)*
Match 3	-23.85	-4.49	-19.36	-42.23	-7.56	-34.67	-51.82	-21.82	-30.00	-53.40	-29.59	-23.81	-58.49	-27.68	-30.81
			*(-6.43***)*			*(-9.30***)*			*(-7.24***)*			*(-4.51***)*			*(-5.07***)*
Match 4	-23.85	-5.43	-18.42	-42.23	-10.23	-32.00	-51.82	-21.84	-29.98	-53.40	-34.41	-18.99	-58.49	-36.92	-21.57
			*(-6.68***)*			*(-8.54***)*			*(-7.48***)*			*(-4.05***)*			*(-4.20***)*
Match 5	-23.85	-2.26	-21.59	-42.23	-3.91	-38.32	-51.82	-19.14	-32.68	-53.40	-25.91	-27.49	-58.49	-23.75	-34.74
			*(-7.19***)*			*(-10.06***)*			*(-8.44***)*			*(-5.63***)*			*(-7.06***)*
Match 6	-23.85	-8.02	-15.83	-42.23	-10.42	-31.81	-51.82	-22.40	-29.42	-53.40	-36.95	-16.45	-58.49	-41.22	-17.27
			*(-6.09***)*			*(-8.15***)*			*(-7.19***)*			*(-3.41***)*			*(-3.23***)*

PANEL B - VALUE-WEIGHTED RETURNS															
	Within the first year			Within first 2 years			Within first 3 years			Within first 4 years			Within first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	-12.04	-6.86	-5.18	-13.79	-13.90	0.11	-32.88	-14.37	-18.51	-37.40	-8.48	-28.92	-35.93	-16.87	-19.06
			(-0.60)			*(0.05)*			*(-1.44)*			*(-1.79*)*			*(-0.98)*
Match 2	-12.04	-3.27	-8.77	-13.79	14.03	-27.82	-32.88	8.42	-41.30	-37.40	-0.79	-36.61	-35.93	13.58	-49.51
			(-1.26)			*(-1.38)*			*(-2.51**)*			*(-1.76*)*			*(-2.37**)*
Match 3	-12.04	-3.22	-8.82	-13.79	13.08	-26.87	-32.88	6.99	-39.87	-37.40	-2.76	-34.64	-35.93	11.17	-47.10
			(-1.27)			*(-1.33)*			*(-2.43**)*			*(-1.66*)*			*(-2.25**)*
Match 4	-12.04	-3.37	-8.67	-13.79	13.68	-27.47	-32.88	8.70	-41.58	-37.40	-1.80	-35.60	-35.93	12.00	-47.93
			(-1.27)			*(-1.37)*			*(-2.54**)*			*(-1.72*)*			*(-2.31**)*
Match 5	-12.04	-4.37	-7.67	-13.79	11.05	-24.84	-32.88	5.39	-38.27	-37.40	-2.66	-34.74	-35.93	9.84	-45.77
			(-1.11)			*(1.24)*			*(-2.38**)*			*(-1.72*)*			*(-2.27**)*
Match 6	-12.04	-19.95	7.91	-13.79	0.11	-13.90	-32.88	4.76	-37.64	-37.40	-3.67	-33.73	-35.93	3.29	-39.22
			(0.67)			*(-0.57)*			*(-2.33**)*			*(-1.65*)*			*(-1.97**)*

stocks in the second month of trading[64] on an equally-weighted basis and holds them for a period of 12, 24, 36, 48 and 60 months suffers raw losses of 23.85%, 42.23%, 51.82%, 53.40% and 58.49% respectively. However, if this same investor had instead invested in a comparable set of firms, he would have suffered maximum losses of 8.02% [Match 6], 10.42% [Match 6], 22.88% [Match 1], 36.95% [Match 6] and 41.22% [Match 6] along the various horizons [12, 24, 36, 48 and 60 months] respectively.

It is also observed from the table that the abnormal returns are all significant across the matching and horizon board which initially tends to indicate that the matching process may not matter. However, a closer look also shows that the magnitude of the abnormal returns appears to be sensitive to the matching algorithm employed. Put differently, albeit the observed under-performances are strong and overwhelming, the extent appears to be sensitive to the matching dynamics as a wide variation in the scale of the abnormal returns is evident across the matching and horizon board. For example, within the 12-months horizon, the abnormal returns range from -15.83% [t-stats: -6.09] to -23.65% [t-stats: -5.33] as the matching corridors are traversed [Match 1 to Match 6]. Similarly, over the 36 – month horizon, the abnormal returns range from -28.94% [t-stats: -6.16] to -32.72% [t-stats: -7.75]. Over the four-year horizon, the under-

[64] Since the study excludes the initial returns from the long-run results, it is assumed that the investor enters the market in the second month of trading following listing.

performance in no particular order or pattern, ranges from 16.45% [t-stats: -3.41] to 27.49% [t-stats: -5.63]. On a related note, it is also found that, in general, the abnormal returns are the least [most] over the tracking windows when the M6 [M5] matching algorithm is used to select the benchmark firms from the population[65]. However, a different picture emerges if this same investor decides to hold the stocks in proportion to their market values [value-weighting][66]. It is observed from Panel B that an investor who purchases the IPO stocks in the second month of trading on a value-weighted basis and holds them for a period of 12, 24, 36, 48 and 60 months suffers raw losses of 12.04%, 13.79%, 32.88%, 37.40% and 35.93% respectively. However, if this same investor had instead invested in a comparable set of firms, he would have suffered maximum losses of 19.95% [Match 6] and 8.48% [Match 1] over 12 and 48 months respectively. However, on this same investment over the other horizons [24, 36 and 60 months], he reaps maximum positive raw returns of 14.03% [Match 2], 8.70% [Match 4] and 13.58% [Match 2] respectively. Under this weighting technique, the abnormal returns are not as strong and pervading across the matching and horizon board, like in the equally-weighted approach. In fact, in some cases, the evidence is weak and in

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[65] However, there is an exception in the first two horizons as the M1 algorithm produces the most under-performance finding.

[66] The under-performance using the technique of value-weighting reduces and in some cases, is non-existent which is in line with the argument of Fama [1998] that long-term post-event returns shrink and often disappear when event firms are value-weighted rather than equally-weighted because the former more accurately captures the total wealth effects of investors.

some others, non-existent. Also, just like in the equally-weighted approach, the scale of the abnormal returns appears to be sensitive to the matching dynamics as a wide variation across the matching and horizon board is noticed. For example, over the 60-month tracking window, the IPO portfolio under-performs a set of comparable firms by 19.06% [t-stats: -0.98] – Match 1, 49.51% [t-stats: -2.37] – Match 2, 47.10% [t-stats: -2.25] – Match 3, 47.93% [t-stats: -2.31] – Match 4, 45.77% [t-stats: -2.27] – Match 5 and 39.22% [t-stats: -1.97] – Match 6.

Comparing both set of results [i.e. equally and value-weighted], the under-performance is found to be more over the first two windows when returns are equally-weighted which reverses from the 36th month upwards when returns are value-weighted. Value-weighting the returns and changing the composition of firms in the benchmark portfolio is also found to produce no significant under-performance finding over the one and two-year horizons. Put differently, the scale and significance of the under-performance finding under the value-weighted approach appears to be sensitive to the matching process as some of the abnormal returns are now no longer significant across the board. For example, over the one-year horizon, the abnormal returns are not significant, ranging from -8.82% [t-stats: -1.27] to 7.91% [t-stats: 0.67]. Also, no significant under-performance is observed over the two-year window as the abnormal returns range from -27.82% [t-stats: -1.38] to 0.11% [t-stats: 0.05].

In general, the under-performance finding is found to be strong and overwhelming under the BHAR approach, using the equally-weighted approach with the results providing strong evidence against market efficiency. However, the results are mixed when a value-weighted performance measure is employed. Under this scenario, the under-performance finding is not as strong; in fact, in some cases, the evidence is weak and in some others, non-existent. The results generally show that the scale of the under-performance, which varies substantially and in some cases disappears altogether across the matching board, is sensitive to firstly, the choice of matching firms in the benchmark portfolio; secondly, the weighting scheme employed and; thirdly, the horizon over which it is measured.

The general under-performance finding, which is consistent with those of Ritter [1991], Ritter and Welch [2002], Gompers and Lerner [2003], Kooli and Suret [2004], Alvarez and Gonzalez [2005], Jakobsen and Sorensen [2001], Bessler and Thies [2007], Page and Reyneke [1997] and Chorruk and Worthington [2010] and contrasts with those obtained by Cusatis, et al [1993], Brav, et al [2000], Kooli, et al [2003], Kim, et al [1995] and Wu [1993], also shows that, in some cases [especially value-weighted performance], the observed under-performance is weak and in some others, disappears altogether when the matching algorithm includes industry as an additional risk factor, which tends to suggest that a matching criteria that includes the industry of the firms is vital in the matching process as it ensures that issuing and non-issuing firms are fairly similar, thus making for better comparisons.

To ensure robustness and also enable us reach more definitive conclusions, the long-run analysis is also performed using other methodologies in event and calendar time in the sections that follow.

[3.4.2] Robustness Checks

[3.4.2.1] Cumulative Abnormal Return [CAR]

Panels A and B of Table 3.12 provide a summary of equally and value-weighted CARs over similar horizons and matching board as another measure of performance in event time. From Panel A, IPO under-performance is found to be more severe across the board in the post-IPO period compared to the equally-weighted BHAR returns. However, just like in the equally-weighted BHAR returns, all the abnormal returns remain negative and highly significant as the matching corridors are negotiated. The scale of the under-performance finding appears to be sensitive to the matching dynamics, just like in the equally-weighted BHAR approach. For example, the abnormal returns are observed to be the least [most] when the M6 [M1] matching algorithm is employed to benchmark the firms. When the returns are value-weighted as shown in Panel B, the under-performances continue to be largely strong, albeit, the evidence

TABLE 3.12: POST- IPO LONG-RUN EVENT-TIME CAR RETURNS VERSUS CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS OVER THE PERIOD JANUARY 1999 TO DECEMBER 2006

The table reports long-run cumulative abnormal returns for the sample of 746 IPOs that went public over the period January 1999 and December 2006. Equally and value-weighted CARs are compared with control firms matched on the six stepwise algorithms as defined in Table 3.11. Panel A reports equally-weighted returns, while Panel B reports value-weighted returns. CAR returns are generated by summing monthly returns starting in the 2nd month after listing following equity issue till the 13th, 25th, 37th, 49th and 61st months for 1-year, 2-year, 3-year, 4-year and 5-year long-run returns. Abnormal return [AR] is the simple difference between the IPO raw average return [Raw] and the corresponding matching return [Bench].The CAR return figures are in %. The figures in parentheses are the skewness-adjusted t-statistics. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

PANEL A - EQUALLY-WEIGHTED RETURNS

	Within the first year			Within first 2 years			Within first 3 years			Within first 4 years			Within first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	-35.87	-1.06	-34.81	-85.24	-8.38	-76.86	-105.67	-11.64	-94.03	-106.05	-23.33	-82.72	-109.92	-26.86	-83.06
			*(-9.15***)*			*(-13.43***)*			*(-13.73***)*			*(-10.33***)*			*(-8.99***)*
Match 2	-35.87	-7.67	-28.20	-85.24	-12.92	-72.32	-105.67	-21.75	-83.92	-106.05	-30.77	-75.28	-109.92	-25.21	-84.71
			*(-7.99***)*			*(-13.77***)*			*(-12.50***)*			*(-9.16***)*			*(-9.01***)*
Match 3	-35.87	-6.03	-29.84	-85.24	-11.47	-73.77	-105.67	-23.07	-82.60	-106.05	-34.18	-71.87	-109.92	-31.92	-78.00
			*(-8.20***)*			*(-14.06***)*			*(-12.30***)*			*(-8.81***)*			*(-8.45***)*
Match 4	-35.87	-6.96	-28.91	-85.24	-13.29	-71.95	-105.67	-21.66	-84.01	-106.05	-34.45	-71.60	-109.92	-34.41	-75.51
			*(-8.24***)*			*(-14.13***)*			*(-13.13***)*			*(-9.19***)*			*(-8.53***)*
Match 5	-35.87	-4.90	-30.97	-85.24	-11.14	-74.10	-105.67	-26.87	-78.80	-106.05	-31.17	-74.88	-109.92	-27.07	-82.85
			*(-8.64***)*			*(-14.10***)*			*(-12.50***)*			*(-9.77***)*			*(-9.64***)*
Match 6	-35.87	-9.88	-25.99	-85.24	-19.18	-66.06	-105.67	-29.39	-76.28	-106.05	-39.66	-66.39	-109.92	-44.68	-65.24
			*(-8.01***)*			*(-13.52***)*			*(-11.98***)*			*(-8.87***)*			*(-7.80***)*

PANEL B - VALUE-WEIGHTED CAR RETURNS

	Within the first year			Within first 2 years			Within first 3 years			Within first 4 years			Within first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	-22.56	-5.60	-16.96	-63.66	-21.07	-42.59	-80.22	-15.63	-64.59	-80.32	-6.76	-73.56	-72.75	-14.75	-58.00
			(-1.69)*			*(-2.48**)*			*(-3.68***)*			*(-3.46***)*			*(-2.25**)*
Match 2	-22.56	-3.06	-19.50	-63.66	8.77	-72.43	-80.22	6.34	-86.56	-80.32	2.79	-83.11	-72.75	17.51	-90.26
			*(-2.09**)*			*(-3.59***)*			*(-4.42***)*			*(-3.47***)*			*(-3.91***)*
Match 3	-22.56	-2.73	-19.83	-63.66	8.46	-72.12	-80.22	4.83	-85.05	-80.32	0.54	-80.86	-72.75	14.13	-86.88
			*(-2.14**)*			*(-3.58***)*			*(-4.34***)*			*(-3.36***)*			*(-3.75***)*
Match 4	-22.56	-2.90	-19.66	-63.66	9.18	-72.84	-80.22	8.27	-88.49	-80.32	2.68	-83.00	-72.75	15.81	-88.56
			*(-2.13**)*			*(-3.63***)*			*(-4.48***)*			*(-3.51***)*			*(-3.87***)*
Match 5	-22.56	-3.39	-19.17	-63.66	6.71	-70.37	-80.22	2.13	-82.35	-80.32	0.60	-80.92	-72.75	11.85	-84.60
			*(-2.08**)*			*(-3.49***)*			*(-4.18***)*			*(-3.42***)*			*(-3.69***)*
Match 6	-22.56	-22.33	-0.23	-63.66	-26.96	-36.70	-80.22	-33.58	-46.64	-80.32	-36.97	-43.35	-72.75	-37.79	-34.96
			(-0.03)			*(-1.82*)*			*(-1.98**)*			*(-1.78*)*			*(-1.52)*

using the M6 algorithm is not as strong and in one case, weak. Three other striking features are also obseved from the results, just like in the BHAR results; firstly, the dismal performance of the IPO and control firms across the board [the performance of the IPO firms are worse]; secondly, the linear relationship between the performance of the firms and the length of the tracking window and; thirdly, the under-performances obtained from the CAR analysis are larger than those obtained from the BHAR analysis[67].

In general, while the IPOs tend to under-perform across the horizon and matching board using this performance measure, the results, which are broadly in line with those obtained by Ritter [1991], Jakobsen and Sorensen [2001], Ahmad-Zaluki, et al [2007], Chorruk and Worthington [2010] and Espenlaub, et al [2000] and contrast with those obtained by Wu [1993], Kim, et al [1995], Gompers and Lerner [2003] and Kooli, et al [2003], show that the scale of the under-performance, which varies substantially across the matching board, is sensitive to firstly, the choice of matching firms in the benchmark portfolio; secondly, the weighting scheme employed and; thirdly, the horizon over which it is measured. It is also found, in some cases [especially in the

[67] This is not unconnected with the fact that BHAR involves compounding of returns, while the CAR does not [Barber and Lyon, 1997a]. Hence, in a period of rising prices in the stock market, the CAR and BHAR results will be positive with the BHAR results larger absolutely, while in a period of declining share prices as we had for a large part of the study period, the CAR and BHAR results will be negative with the CAR results larger absolutely.

value-weighted approach] that the observed under-performance is weak, and in some other cases, non-existent when the matching algorithm includes industry as an additional risk factor.

[3.4.2.2] Wealth Relatives [WR]

Table 3.13 provides a summary of the wealth relative results under the various benchmarks over the various horizons, which is consistent with the BHAR result pattern. Wealth relatives measure investors' wealth gain or loss from an investment in a basket of IPO stocks relative to a similar investment in a set of matching non-issuing firms. Clearly from the table, the same pattern of results is more or less observed if this same investor decides to hold the stocks either in equal weights or in proportion to their market values [value-weighting], albeit, by and large, the wealth losses appear to be lower under value-weighting, just like in the other approaches, especially at the windows up to three years. A wide variation in the scale of the under-performance finding is also evident across the matching and horizon board. However, the results, which are broadly in line with those obtained by Ritter [1991], Levis [1993] and Chorruk and Worthington [2010] for the US, UK and Thai markets respectively and at variance with the findings of Menyah, et al [1995], show that the extent of the under-performance finding is again sensitive firstly, to the choice of matching firms in the

TABLE 3.13: POST- IPO LONG-RUN WEALTH RELATIVES RELATIVE TO CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS OVER THE PERIOD JANUARY 1999 TO DECEMBER 2006

The table reports long-run wealth relatives for the sample of 746 IPOs that went public over the period January 1999 and December 2006. Equally- and value-weighted wealth relatives are computed relative to the benchmark portfolios matched on the six stepwise algorithms as defined in Table 3.11. The periodic wealth relatives [WR1 – WR5] are calculated as the ratio of one plus the mean IPO holding period return [not in %] divided by one plus the mean benchmark holding period return [not in %] over the different horizons, while the corresponding wealth losses are calculated as [1 – wealth relative].

	Equally-Weighted					Value-Weighted				
	WR1	WR2	WR3	WR4	WR5	WR1	WR2	WR3	WR4	WR5
Match 1	0.7630	0.5995	0.6248	0.6783	0.6876	0.9444	1.0013	0.7838	0.6840	0.7707
Match 2	0.8065	0.6232	0.5955	0.6316	0.5630	0.9093	0.7560	0.6191	0.6310	0.5640
Match 3	0.7973	0.6249	0.6162	0.6618	0.5740	0.9088	0.7624	0.6273	0.6437	0.5763
Match 4	0.8052	0.6435	0.6164	0.7105	0.6581	0.9103	0.7583	0.6175	0.6374	0.5720
Match 5	0.7791	0.6012	0.5958	0.6290	0.5444	0.9198	0.7763	0.6369	0.6431	0.5833
Match 6	0.8279	0.6448	0.6209	0.7391	0.7062	1.0988	0.8612	0.6407	0.6498	0.6203

benchmark portfolio; secondly, the weighting scheme employed and thirdly, the horizon over which it is measured. The results also show that the observed under-performance is least [especially under the equally-weighted approach] when the matching algorithm includes industry as an additional risk factor.

[3.4.2.3] Mean Monthly Calendar Abnormal Returns [MMAR]

Using this variant of the calendar time approach, a similar picture emerges. The first three columns in Table 3.14 reports equally-weighted returns, while the last three presents value-weighted performance. In general, firstly, the dismal performance of the IPO and control firms is noted across the board [the performance of the IPO firms are worse], just like in the event time approaches, and secondly, the MMAR results approximate the CAR results in magnitude[68]. The evidence on IPO under-performance when performance is calculated as the return of a portfolio composed in each month by the stocks of those firms that have carried out an initial offering appears mixed. It can be observed from the table that when the portfolio firms are formed equally-weighted, the MMAR ranges from -1.31% [t-stats: -3.35] to -1.66% [t-stats: -4.04] across the matching board, corresponding to an under-performance range of 78.6% [-1.31% x 60

[68] This may not be unconnected with the fact that in a downturn as we had in the years following the bust of the technology bubble [1999-2001], it is not unlikely that common shocks may permeate and pervade the market. If these shocks are negative, then a drag on general market price performance is expected because the calendar approach captures important cross-correlations and dependencies in stock returns, missed out by the event time approach. When abnormal returns are measured in a downturn using the event time approach, the CAR metric returns a worse performance relative to the BHAR metric.

TABLE 3.14: 5-YEAR POST-IPO MEAN MONTHLY CALENDAR TIME ABNORMAL RETURNS [MMAR] VERSUS CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS OVER THE PERIOD 1999 TO 2006

The table reports MMARs for the sample of 746 IPOs that went public over the period January 1999 and December 2006. Equally-and value-weighted MMARs are compared with alternative benchmarks using the technique of control firms. The control firms are matched on the six stepwise algorithms as defined in Table 3.11. Monthly portfolio returns are calculated starting in the 2nd month after listing following equity issue. The simple difference between the IPO return in a given month and the designated benchmark is the abnormal return. MMAR is the simple sum of the monthly abnormal returns across firms in the portfolio each month. The grand MMAR is the sum of the time-series MMARs divided by the number of calendar months. The abnormal return [AR] is the simple difference between the grand mean monthly IPO raw average return [Raw] and the corresponding benchmark return [Bench]. The first 3 columns reports equally-weighted returns, while the last 3 report value-weighted returns. All the return figures are in %. The figures in parentheses are the t-statistics. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

	Equally-Weighted			Value-Weighted		
	Raw	Bench	AR	Raw	Bench	AR
M1	-1.86	-0.40	-1.46	-1.03	-0.33	-0.70
			*(-3.17***)*			*(-0.94)*
M2	-1.86	-0.29	-1.57	-1.03	0.16	-1.19
			*(-3.70***)*			*(-1.67*)*
M3	-1.86	-0.24	-1.62	-1.03	0.08	-1.11
			*(-3.73***)*			*(-1.27)*
M4	-1.86	-0.20	-1.66	-1.03	0.16	-1.19
			*(-4.04***)*			*(-1.67*)*
M5	-1.86	-0.29	-1.57	-1.03	0.04	-1.07
			*(-3.92***)*			*(-1.24)*
M6	-1.86	-0.55	-1.31	-1.03	-1.19	0.16
			*(-3.35***)*			*(0.15)*

months] and 99.6% [-1.66% x 60 months] for five years after the issue. Hence, when returns are equally-weighted, under-performance appears to be strong and persistent across the matching board. However, mixed findings are observed when a value-weighted performance measure is employed. Under this scenario, the MMAR ranges from -1.19% [t-stats: -1.67] to 0.16% [t-stats: 0.15] across the matching board, corresponding to a range of 71.4% [-1.19% x 60 months] and 9.6% [0.16% x 60 months] for five years after the issue. More importantly, a significant level of under-performance is ony found when the M2 and M4 matching algorithms are employed, and then only at the 10% level. The pattern observed in the event-time measures is clearly present in this approach as the scale and significance of the under-performance finding appears to be sensitive to the matching dynamics. It is observed that under the equally-weighted approach that, though, the abnormal returns are all significant across the matching board, they are least when the M6 algorithm is employed to benchmark the IPO firms. A similar pattern is observed when the returns are value-weighted with the M6 algorithm, once again, producing the least under-performance finding. In fact, no significant under-performance is found in four of the algorithms [i.e. M1, M3, M5 and M6] with the M6 algorithm even producing an insignificant out-performance finding.

Thus, with this version of the calendar time approach, there is a persistence of IPO under-performance across the matching board, albeit the evidence when the returns are value-weighted appears to be much weaker; however, it is also observed that the scale of the under-performance, just like in the event time approaches, appears to be dependent on the matching algorithm used in benchmarking the returns. The findings also reveal, in line with the event-time methodologies, that IPOs are poor investments using the equally-weighted technique. However, the evidence is much weaker when a value-weighted performance measure is adopted. Under this scenario, the under-performance is non-existent in some cases, and at best, weak in others.

[3.4.2.4] CAPM and FF-Cahart-4F Model

When the difference in performance between the IPO and benchmark portfolios relative to the CAPM and FF-Cahart-4F models is tracked equally in calendar time, a similar pattern is observable. The first two columns in Table 3.15 present the intercepts from the CAPM regressions, while the last two columns present those from the FF-Cahart-4F regressions. The evidence on IPO under-performance using these factor models appears mixed, just like in the MMAR and indeed the event-time approaches. Again, two salient features are noticeable from the results, just like in the event time and MMAR results; firstly, the dismal performance of the IPO firms across all benchmarks and secondly, the reduction in the level of the under-performance when returns are value-weighted.

The intercepts, which measure the differences in the MMAR between the IPO and benchmark portfolios, from the CAPM regressions across all benchmarks for the five years following the IPOs, are all negative and significantly different from zero on an equally-weighted basis. However, when the returns are value-weighted, the under-performance finding completely disappears, which may be an indication of the lower

TABLE 3.15: 5-YEAR POST-IPO INTERCEPTS FROM THE CAPM & FAMA-FRENCH-CAHART 4-FACTOR REGRESSIONS ON THE IPO & CONTROL FIRM PORTFOLIO MATCHED ON VARIOUS ALGORITHMS OVER THE PERIOD JANUARY 1999 TO DECEMBER 2006

This table reports the intercepts and t-values [in parentheses] of equally-weighted and value-weighted ordinary least squares [OLS] regressions. In all regressions, the discrepancy between the IPO firms' portfolio monthly return [IPO] and the monthly return of the designated control portfolio benchmark is the dependent variable, where the control firms have been selected based on the six stepwise matching algorithms as defined in Table 3.11. The sample comprises 746 firms going public between 1999 and 2006 and their matching mature control firms [firm age since IPO is at least 7 years]. The explanatory variables are the monthly excess return of the value-weighted FTSE All-Share index over 3-month Treasury Bills rate [RMRF], the return of a zero-investment size portfolio [SMB], the return of a zero-investment book-to-market portfolio [HML] and the return of a zero-investment momentum portfolio [MOM]. The first two columns present the results for the CAPM regressions, while the last two columns present FF-Cahart-4F regressions. The t-stats have been calculated using Davidson & Mackinnon [1993] robust standard errors. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
M1	-0.0146 *[-3.01***]*	-0.0106 *[-1.37]*	-0.0161 *[-4.01***]*	-0.0117 *[-1.86*]*
M2	-0.0150 *[-3.39***]*	-0.0119 *[-1.33]*	-0.0159 *[-4.31***]*	-0.0148 *[-2.07**]*
M3	-0.0157 *[-3.40***]*	-0.0110 *[-1.21]*	-0.0167 *[-4.20***]*	-0.0138 *[-1.86*]*
M4	-0.0159 *[-3.67***]*	-0.0120 *[-1.41]*	-0.0175 *[-4.78***]*	-0.0149 *[-2.15**]*
M5	-0.0155 *[-3.66***]*	-0.0101 *[-1.12]*	-0.0166 *[-4.38***]*	-0.0134 *[-1.82*]*
M6	-0.0127 *[-3.08***]*	0.0011 *[0.09]*	-0.0150 *[-3.83***]*	-0.0055 *[-0.47]*

[higher] long-run performance made by smaller [larger] IPO firms over the period. This is also in line with the assertions of Brav and Gompers [1997] who aver that if IPO under-performance is a small firm effect, value-weighting will reduce the measured under-performance. When the difference in performance between the IPO and

benchmark portfolios relative to the FF-Cahart-4F model is tracked, a slightly different picture emerges. The third column presents the FF-Cahart-4F time series regression results for the five years following the IPOs on an equally-weighted basis for the entire period. The intercepts across all benchmarks are all negative and highly significant at the 1% level. More importantly, IPO under-performance persists as the firms are mixed and matched in the composite benchmark portfolio, albeit they are lower when industry is included as an additional matching criterion. When the IPOs are value-weighted, the intercepts are still negative and largely significant across the matching board, unlike in the CAPM approach. However, it is also noted that the scale of the under-performance is not as strong, in some cases weak and in one case, non-existent[69].

It is also observed, just like in the MMAR and the event-time approaches, that the scale and significance of the under-performance finding under the CAPM and FF-Cahart-4F calendar approaches appears to be sensitive to the choice of matching firms in the benchmark portfolio. Under the equally-weighted technique, even though the abnormal returns are all significant across the matching board, the least under-performance finding is produced when the M6 algorithm is employed [CAPM: –1.27%, t-stats: -3.08; FF-Cahart-4F: –1.50%, t-stats: -3.83]. In the same vein, IPO under-performance is

[69] The intercept in Match 6, the matching corridor that includes the industry of the firms as an additional matching criterion, is not significantly different from zero.

most when the M4 algorithm is used to select the benchmark firms [CAPM: –1.59%, t-stats: -3.67; FF-Cahart-4F: –1.75%, t-stats: -4.78]. A similar pattern is evident when the returns are value-weighted as the M6 algorithm, once again, produces the least under-performance finding. In fact, the abnormal returns in this zone are insignificant [CAPM: 0.11%, t-stats: 0.09; FF-Cahart-4F: –0.55%, t-stats: -0.47], with the CAPM approach even producing an infinitesimal, albeit insignificant IPO out-performance finding.

In general, this first empirical finds firstly, that the under-performance persists in calendar time with all the intercepts [save for the CAPM value-weighted] still significant and in negative territory; secondly, when compared with the CAPM results, the magnitude of the under-performance is higher under the FF-Cahart-4F model; thirdly, just like in the other approaches, the magnitude of the under-performance reduces and in some cases disappears when the event firms are value-weighted rather than equally-weighted and; fourthly, the scale and magnitude of the observed under-performance appears to be sensitive to the matching process. The results, which are consistent with Ritter and Welch [2002], Loughran and Ritter [1995], Thomadakis, et al [2012], Espenlaub, et al [2000], Ahmad-Zaluki, et al [2007], also show that, in some cases [especially value-weighted performance], the observed under-performance is weak and in some others, disappears altogether when the matching algorithm includes industry as an additional risk factor, which tends to suggest that a matching criteria that includes the industry of the firms is vital in the matching process as it ensures that issuing and non-issuing firms are fairly similar, thus making for better comparisons.

[3.4.2.5] Exclusion of the late 1990s technology bubble

As a further robustness check, the ‘dotcom’ years [1999 – 2001] are excluded from the sample period the analysis with IPOs that went public over the period 2002 and 2006 is performed. The results are not too different from the previous results obtained for the full sample period. Tables 3.16 – 3.20 present the results for the period excluding the ‘dotcom’ years for the BHAR, CAR, WR, MMAR and the factor models [i.e. CAPM and FF-Cahart-4F] approaches respectively. In general, it is observed that excluding the ‘dotcom’ period produces a less marked under-performance finding across all the event time measures [i.e. BHAR, CAR and WR] using the equally and value-weighted approaches, which may not be unconnected with the dismal performance of the firms that had their IPOs over the technology bubble years [1999-2001]. In fact, under the value-weighted approach, the IPO firms out-perform their matching benchmarks over the 1-year investment horizon. However, the results are mixed in calendar time when the’dotcom’ period is excluded. Under an equally-weighted approach, the under-

TABLE 3.16: POST- IPO LONG-RUN EVENT-TIME BHAR RETURNS VERSUS CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS FOR THE SUB-PERIOD EXCLUDING THE 'DOTCOM YEARS' [2002 – 2006]

The table reports long-run buy-and-hold abnormal returns for the sample of 485 IPOs for the sub-period excluding the technology bubble ['dotcom'] years, going from January 2002 to December 2006. Equally and value-weighted BHARs are compared with control firms matched on the six stepwise algorithms as defined in Table 3.11. Panel A reports equally-weighted returns, while Panel B reports value-weighted returns. BHAR returns are generated by summing monthly returns starting in the 2nd month after listing till the 13th, 25th, 37th, 49th and 61st months for 1-year, 2-year, 3-year, 4-year and 5-year long-run returns. Abnormal return [AR] is the simple difference between the IPO raw average return [Raw] and the corresponding matching return [Bench]. The CAR return figures are in %. The figures in parentheses are the skewness-adjusted t-statistics. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

PANEL A - EQUALLY-WEIGHTED RETURNS

	Within the first year			Within first 2 years			Within first 3 years			Within first 4 years			Within first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	-11.62	9.93	-21.55	-27.61	4.77	-32.38	-42.08	-25.50	-16.58	-47.54	-45.61	-1.93	-56.47	-57.45	0.98
			*(-3.54***)*			*(-4.79***)*			*(-0.89)*			*(-0.05)*			*(0.12)*
Match 2	-11.62	5.08	-16.70	-27.61	3.65	-31.26	-42.08	-14.54	-27.54	-47.54	-29.24	-18.30	-56.47	-30.15	-26.32
			*(-4.28***)*			*(-6.10***)*			*(-4.86***)*			*(-2.57**)*			*(-3.44***)*
Match 3	-11.62	6.18	-17.80	-27.61	4.78	-32.39	-42.08	-17.48	-24.60	-47.54	-31.30	-16.24	-56.47	-30.47	-26.00
			*(-4.39***)*			*(-6.44***)*			*(-4.44***)*			*(-2.26**)*			*(-3.18***)*
Match 4	-11.62	3.49	-15.11	-27.61	1.38	-28.99	-42.08	-15.26	-26.82	-47.54	-35.39	-12.15	-56.47	-41.14	-15.33
			*(-4.13***)*			*(-5.80***)*			*(-4.75***)*			*(-2.00**)*			*(-2.50**)*
Match 5	-11.62	8.18	-19.80	-27.61	9.72	-37.33	-42.08	-13.55	-28.53	-47.54	-29.06	-18.48	-56.47	-31.75	-24.72
			*(-5.05***)*			*(-9.01***)*			*(-5.33***)*			*(-2.96***)*			*(-4.24***)*
Match 6	-11.62	5.32	-16.94	-27.61	13.31	-40.92	-42.08	-3.69	-38.38	-47.54	-29.44	-18.10	-56.47	-38.67	-17.80
			*(-5.38***)*			*(-8.02***)*			*(-7.35***)*			*(-3.05***)*			*(-2.77***)*

PANEL B - VALUE-WEIGHTED RETURNS

	Within the first year			Within first 2 years			Within first 3 years			Within first 4 years			Within first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	10.65	3.53	7.12	21.77	-5.00	26.77	-7.97	-9.63	1.66	-13.20	-8.84	-4.36	-12.14	-29.38	17.24
			(1.30)			*(2.38**)*			*(0.11)*			*(-0.25)*			*(0.82)*
Match 2	10.65	0.78	9.87	21.77	24.07	-2.30	-7.97	17.05	-25.02	-13.20	5.50	-18.70	-12.14	19.59	-31.73
			(1.17)			*(-0.12)*			*(-1.10)*			*(-0.67)*			*(-1.66*)*
Match 3	10.65	0.84	9.81	21.77	23.30	-1.53	-7.97	16.01	-23.98	-13.20	4.21	-17.41	-12.14	18.49	-30.63
			(1.17)			*(-0.09)*			*(-1.06)*			*(-0.63)*			*(-1.67*)*
Match 4	10.65	0.88	9.77	21.77	23.92	-2.15	-7.97	18.83	-26.80	-13.20	6.29	-19.49	-12.14	20.46	-32.60
			(1.17)			*(-0.11)*			*(-1.19)*			*(-0.70)*			*(-1.68*)*
Match 5	10.65	1.12	9.53	21.77	23.63	-1.86	-7.97	18.17	-26.14	-13.20	7.72	-20.92	-12.14	21.26	-33.40
			(1.14)			*(-0.10)*			*(-1.17)*			*(-0.76)*			*(-1.69*)*
Match 6	10.65	13.38	-2.73	21.77	57.18	-35.41	-7.97	69.17	-77.14	-13.20	55.41	-68.61	-12.14	78.46	-90.60
			(-0.29)			*(-2.74***)*			*(-1.83*)*			*(-3.44***)*			*(-3.92***)*

TABLE 3.17: POST- IPO LONG-RUN EVENT-TIME CAR RETURNS VERSUS CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS FOR THE SUB-PERIOD EXCLUDING THE 'DOTCOM YEARS' [2002 – 2006]

The table reports long-run cumulative abnormal returns for a sample of 485 IPOs for the sub-period excluding the technology bubble ['dotcom'] years, going from January 2002 to December 2006. Equally and value-weighted CARs are compared with control firms matched on the six stepwise algorithms as defined in Table 3.11. Panel A reports equally-weighted returns, while Panel B reports value-weighted returns. CAR returns are generated by summing monthly returns starting in the 2nd month after listing following equity issue till the 13th, 25th, 37th, 49th and 61st months for 1-year, 2-year, 3-year, 4-year and 5-year long-run returns. Abnormal return [AR] is the simple difference between the IPO raw average return [Raw] and the corresponding matching return [Bench]. The CAR return figures are in %. The figures in parentheses are the skewness-adjusted t-statistics. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

PANEL A - EQUALLY-WEIGHTED RETURNS

	Within the first year			Within first 2 years			Within first 3 years			Within first 4 years			Within first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	-15.72	9.98	-25.70	-53.74	2.30	-56.04	-90.75	-10.67	-80.08	-103.67	-35.14	-68.53	-107.45	-38.76	-68.69
			*(-5.58***)*			*(-8.17***)*			*(-9.75***)*			*(-7.01***)*			*(-6.00***)*
Match 2	-15.72	4.54	-20.26	-53.74	1.36	-55.10	-90.75	-15.97	-74.78	-103.67	-34.12	-69.55	-107.45	-30.69	-76.76
			*(-5.04***)*			*(-9.03***)*			*(-9.22***)*			*(-6.86***)*			*(-6.63***)*
Match 3	-15.72	5.34	-21.06	-53.74	3.38	-57.12	-90.75	-18.96	-71.79	-103.67	-38.54	-65.13	-107.45	-38.96	-68.49
			*(-4.96***)*			*(-9.44***)*			*(-8.89***)*			*(-6.47***)*			*(-5.93***)*
Match 4	-15.72	3.71	-19.43	-53.74	1.06	-54.80	-90.75	-14.03	-76.72	-103.67	-35.63	-68.04	-107.45	-36.59	-70.86
			*(-4.85***)*			*(-9.30***)*			*(-9.97***)*			*(-7.01***)*			*(-6.36***)*
Match 5	-15.72	6.13	-21.85	-53.74	6.67	-60.41	-90.75	-20.35	-70.40	-103.67	-33.57	-70.10	-107.45	-30.18	-77.27
			*(-5.40***)*			*(-10.40***)*			*(-9.41***)*			*(-7.36***)*			*(-7.21***)*
Match 6	-15.72	3.64	-19.36	-53.74	7.49	-61.23	-90.75	-5.72	-85.03	-103.67	-25.15	-78.52	-107.45	-30.79	-76.66
			*(-5.69***)*			*(-11.08***)*			*(-11.85***)*			*(-8.97***)*			*(-7.70***)*

PANEL B - VALUE-WEIGHTED RETURNS

	Within the first year			Within first 2 years			Within first 3 years			Within first 4 years			Within first 5 years		
	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR	Raw	Bench	AR
Match 1	9.13	4.36	4.77	1.18	-13.14	14.32	-21.28	-12.66	-8.62	-28.49	-3.71	-24.78	-20.61	-21.89	1.28
			(0.85)			*(1.36)*			*(-0.68)*			*(-1.11)*			*(0.11)*
Match 2	9.13	1.82	7.31	1.18	20.23	-19.05	-21.28	15.58	-36.86	-28.49	11.24	-39.73	-20.61	24.21	-44.82
			(0.94)			*(-0.77)*			*(-1.72*)*			*(-1.70*)*			*(-1.77*)*
Match 3	9.13	1.92	7.21	1.18	19.65	-18.47	-21.28	13.70	-34.98	-28.49	8.42	-36.91	-20.61	21.49	-42.10
			(0.93)			*(-0.75)*			*(-1.70*)*			*(-1.69*)*			*(-1.67*)*
Match 4	9.13	2.15	6.98	1.18	20.71	-19.53	-21.28	19.21	-40.49	-28.49	13.03	-41.52	-20.61	25.01	-45.62
			(0.91)			*(-0.80)*			*(-1.90*)*			*(-1.71*)*			*(-1.85*)*
Match 5	9.13	2.55	6.58	1.18	20.74	-19.56	-21.28	16.21	-37.49	-28.49	13.25	-41.74	-20.61	24.78	-45.39
			(0.85)			*(-0.79)*			*(-1.77*)*			*(-1.71*)*			*(-1.80*)*
Match 6	9.13	12.90	-3.77	1.18	39.45	-38.27	-21.28	41.06	-62.34	-28.49	29.91	-58.40	-20.61	41.32	-61.93
			(-0.40)			*(-1.79*)*			*(-2.03**)*			*(-1.87*)*			*(-2.14**)*

TABLE 3.18: POST- IPO LONG-RUN WEALTH RELATIVES VERSUS CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS FOR THE SUB-PERIOD EXCLUDING THE 'DOTCOM' YEARS [2002 – 2006]

The table reports long-run wealth relatives for the sample of 485 IPOs for the sub-period excluding the technology bubble ['dotcom'] years, going from January 2002 to December 2006. Equally-and value-weighted wealth relatives are computed relative to the benchmark portfolios matched on the six stepwise algorithms as defined in Table 3.11. The periodic wealth relatives [WR1 – WR5] are calculated as the ratio of one plus the mean IPO holding period return [not in %] divided by one plus the mean benchmark holding period return [not in %] over the different horizons. The corresponding wealth losses are calculated as [1 – wealth relative].

	Equally-Weighted					Value-Weighted				
	WR1	WR2	WR3	WR4	WR5	WR1	WR2	WR3	WR4	WR5
Match 1	0.8039	0.6909	0.7775	0.9646	1.0231	1.0688	1.2818	1.0184	0.9522	1.2441
Match 2	0.8411	0.6983	0.6778	0.7414	0.6232	1.0980	0.9814	0.7863	0.8227	0.7347
Match 3	0.8323	0.6908	0.7019	0.7636	0.6260	1.0973	0.9876	0.7933	0.8329	0.7415
Match 4	0.8540	0.7140	0.6836	0.8120	0.7396	1.0968	0.9826	0.7745	0.8167	0.7294
Match 5	0.8169	0.6597	0.6700	0.7396	0.6378	1.0942	0.9849	0.7788	0.8058	0.7245
Match 6	0.8391	0.6388	0.6015	0.7435	0.7097	0.9759	0.7747	0.5440	0.5585	0.4923

TABLE 3.19: 5-YEAR POST-IPO MEAN MONTHLY CALENDAR TIME ABNORMAL RETURNS [MMAR] VERSUS CONTROL FIRM BENCHMARKS MATCHED ON VARIOUS ALGORITHMS OVER THE PERIOD EXCLUDING THE 'DOTCOM' YEARS [2002 – 2006]

The table reports MMARs for a sample of 485 IPOs for the sub-period excluding the technology bubble ['dotcom'] years. Equally and value-weighted MMARs are compared with alternative benchmarks using the technique of control firms. The control firms are matched on the six stepwise algorithms as defined in Table 3.11. Monthly portfolio returns are calculated starting in the 2nd month after listing following equity issue. The simple difference between the IPO return in a given month and the designated benchmark is the abnormal return. MMAR is the simple sum of the monthly abnormal returns across firms in the portfolio each month. The grand MMAR is the sum of the time-series mean monthly abnormal returns divided by the number of calendar months. The abnormal return [AR] is the simple difference between the grand mean monthly IPO raw average return [Raw] and the corresponding benchmark return [Bench]. The first 3 columns report equally-weighted returns, while the last 3 columns present value-weighted returns. All the return figures are in %. The figures in parentheses are the t-statistics. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

	Equally-Weighted			Value-Weighted		
	Raw	Bench	AR	Raw	Bench	AR
M1	-2.14	-0.23	-1.91	-0.42	-0.19	-0.23
			*(-4.26***)*			*(-0.40)*
M2	-2.14	-0.09	-2.05	-0.42	0.53	-0.95
			*(-4.66***)*			*(-1.25)*
M3	-2.14	-0.15	-1.99	-0.42	0.50	-0.92
			*(-4.47***)*			*(-1.22)*
M4	-2.14	-0.19	-1.95	-0.42	0.56	-0.98
			*(-4.09***)*			*(-1.30)*
M5	-2.14	-0.47	-1.67	-0.42	0.45	-0.87
			*(-4.89***)*			*(-1.23)*
M6	-2.14	-0.53	-1.61	-0.42	0.81	-1.23
			*(-5.26***)*			*(-1.60)*

TABLE 3.20: 5-YEAR POST-IPO INTERCEPTS FROM THE CAPM & FAMA-FRENCH-CAHART 4-FACTOR REGRESSIONS ON THE IPO & CONTROL FIRM PORTFOLIO MATCHED ON VARIOUS ALGORITHMS FOR THE PERIOD EXCLUDING THE DOTCOM YEARS [2002 – 2006]

This table reports the intercepts and t-values [in parentheses] of equally-weighted and value-weighted ordinary least squares [OLS] regressions. In all regressions, the discrepancy between the IPO firms' portfolio monthly return [IPO] and the monthly return of the designated control portfolio benchmark is the dependent variable, where the control firms have been selected based on the six stepwise matching algorithms as defined in Table 3.11. The sample comprises 485 firms going public over the sub-period 2002 to 2006 [excluding the 'dotcom' period] and their matching mature control firms [firm age since IPO is at least 7 years]. The explanatory variables are the monthly excess return of the value-weighted FTSE All-Share index over 3-month Treasury Bills rate [RMRF], the return of a zero-investment size portfolio [SMB], the return of a zero-investment book-to-market portfolio [HML] and the return of a zero-investment momentum portfolio [MOM]. The first two columns present the results for the CAPM regressions, while the last two columns present FF-Cahart-4F regressions. The t-stats have been calculated using Davidson & Mackinnon [1993] robust standard errors. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
M1	-0.0195 *[-4.01***]*	-0.0069 *[-1.14]*	-0.0214 *[-4.29***]*	-0.0059 *[-0.94]*
M2	-0.0203 *[-4.25***]*	-0.0102 *[-1.27]*	-0.0208 *[-4.23***]*	-0.0100 *[-1.23]*
M3	-0.0199 *[-4.08***]*	-0.0100 *[-1.25]*	-0.0196 *[-3.87***]*	-0.0096 *[-1.18]*
M4	-0.0192 *[-3.68***]*	-0.0106 *[-1.32]*	-0.0194 *[-3.60***]*	-0.0105 *[-1.30]*
M5	-0.0165 *[-4.58***]*	-0.0087 *[-1.18]*	-0.0171 *[-4.55***]*	-0.0086 *[-1.19]*
M6	-0.0159 *[-5.00***]*	-0.0160 *[-1.93*]*	-0.0176 *[-5.55***]*	-0.0141 *[-1.67*]*

performance is generally more severe, while the reverse is the case when a value-weighted performance measure is adopted.

Clearly, from all the tables, the study finds that the under-performance results are robust to the inclusion or exclusion of the 'dotcom' period as it continues to be strong, pervading, overwhelming and highly significant across all the methodologies under an equally-weighted performance measure. However, the panels and columns of Tables 3.16 – 3.20 that report the value-weighted performance results present interesting findings. An exacerbation of the 'no under-performance finding' is found across the methodologies. For example, from Panel B of Table 3.16, the under-performance is found to be largely non-existent, save for the last horizon and the sixth matching algorithm [M6]. The under-performance is also largely non-existent from the CAR results in Panel B of Table 3.17 and the evidence is at best, weak. Under the WR approach, the results presented in Panel B of Table 3.18 shows a relatively weak finding. Excluding the M6 algorithm under the factor model approaches that include industry as an additional matching risk factor, the evidence on the 'no under-performance finding' presented in Tables 3.19 - 3.20 under the calendar time techniques [i.e. MMAR, CAPM and FF-Cahart-4F] is stronger as the MMAR and factor model alphas are shown not to be significantly different from zero.

Table 3.21 summarises the results of the under-performance finding over the matching and horizon board from the various methodologies used to test the null hypothesis that the difference in the return between the IPO and benchmark portfolios is zero, under the equally and value-weighted approaches. Clearly for the full period, the under-performance finding is strong and overwhelming across the various methodologies, using the equally-weighted approach with the results providing strong evidence against

TABLE 3.21: SUMMARY OF THE SIGNIFICANCE OF THE UNDER-PERFORMANCE FINDING FROM THE VARIOUS METHODOLOGIES USED TO TEST THE NULL HYPOTHESIS

FULL PERIOD [1999 – 2006]		
	EQUALLY-WEIGHTED	VALUE-WEIGHTED
EVENT-TIME APPROACH:		
BHAR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	NON-EXISTENT IN THE 1^{ST} 2 HORIZONS, ALBEIT PRESENT IN THE LAST 3 AT 5 AND 10% LEVELS
CAR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	MILDLY STRONG ALL THROUGH THE MATCHING AND HORIZON BOARD, MAJORLY AT 1%, ALBEIT WEAK AT M6
WR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	MILDLY STRONG ALL THROUGH THE MATCHING AND HORIZON BOARD
CALENDAR-TIME APPROACH:		
MMAR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	NON-EXISTENT; AT BEST, WEAK IN A COUPLE OF CASES
CAPM	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	NON-EXISTENT IN ALL CASES. INSIGNIFICANT OUT-PERFORMANCE EVEN OBSERVED UNDER M6
FF-CAHART-4F	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	MILDLY STRONG [NOT MORE THAN 5%], ALBEIT NON-EXISTENT UNDER M6
PERIOD EXCLUDING THE DOTCOM YEARS [2002 – 2006]		
EVENT-TIME APPROACH:		
BHAR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	LARGELY NON-EXISTENT, EXCEPT IN THE LAST HORIZON AND M6
CAR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	LARGELY NON-EXISTENT; AT BEST WEAK
WR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	LARGELY EXISTENT BUT WEAK
CALENDAR-TIME APPROACH:		
MMAR	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	NON-EXISTENT
CAPM	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	NON-EXISTENT; ALBEIT, WEAK EVIDENCE UNDER M6
FF-CAHART-4F	VERY STRONG ACROSS THE BOARD [ALL AT 1% LEVEL]	NON-EXISTENT; ALBEIT, WEAK EVIDENCE UNDER M6

market efficiency. However, the results are mixed when a value-weighted performance measure is employed. Under this scenario, the under-performance finding under the event-time methodologies continues to be largely strong, albeit not as pervading as in the equally-weighted approach. Under the calendar techniques, the under-performance is persistent under the FF-Cahart-4F model, albeit not as strong as in the equally-weighted approach; however, the evidence evaporates and is at best, weak under the MMAR and CAPM approaches. The same pattern is largely evident when the period that excludes the 'dotcom' years is considered.

In general, the findings show firstly, that the scale and magnitude of the observed under-performance is sensitive to the matching process; secondly, that under-performance is compelling, overwhelming and genuine only when returns are equally-weighted and; thirdly, the evidence on the under-performance finding is not as strong when returns are value-weighted; in fact in some cases, the evidence is weak and in some others, non-existent. The disappearance of the under-performance finding under the value-weighted technique may be an indication of firstly, the preponderance of small firms in the sample and secondly, the lower [higher] long-run performance made by the smaller [larger] firms over the period[70]. This is in line firstly, with the assertions of

[70] Indeed, Panel C of Table 3.5 reveals that the number of small firms [market capitalization < £50m] and big firms [market capitalization > £50m] is 552 and 194 respectively. The sum of the weights of the small

Brav and Gompers [1997] who avers that if IPO under-performance is a small firm effect, value-weighting will reduce the measured under-performance and secondly, with the argument of Fama [1998] that long-term post-event returns shrink and often disappear when event firms are value-weighted rather than equally-weighted because the former more accurately captures the total wealth effects of investors.

The intent of this study at the onset was to determine firstly, if a 'unique' IPO effect indeed exists that makes issuing firms that are similar in all respects to a set of comparable non-issuing firms based on a set of observable ex-ante characteristics and differ only in that they experience the 'IPO event', perform significantly worse in the long-run than their non-issuing counterparts; secondly, if the documented under-performance of IPOs is a consequence of imperfect matching procedures or inadequate matching criteria; thirdly, if the under-performance is due to fundamental differences in firm characteristics between the issuing IPO firms and the non-issuing benchmark firms prior to or at the IPO date[71]; fourthly, if the scale and magnitude of the observed under-performance is sensitive to the matching process and; fifthly, if the under-performance is a real anomaly that challenges the efficient market hypothesis. In

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firms in the portfolio in terms of equal-weighting and value-weighting are 74% and 9% in that order, while the corresponding figures for the big firms are 26% and 91% respectively.

[71] This is more so in the light of the assertion of Lyon, et al [1999] that researchers should look at other key firm risk factors that explains the cross-section of stock returns that could be used in selecting the control firms from the general population.

order to arrive at an appropriate performance benchmark, pre-IPO operating performance, turnover growth and earnings yield were identified as additional key risk factors beyond the size, market-to-book and industry factors that could be used in selecting the control firms from the population in order to appropriately match its risk profile to that of the IPOs.

Under the equally-weighted approach, the results show that after adjusting for market, size, book-to-market, pre-IPO performance, turnover growth, earnings yield and industry effects, the evidence for under-performance and by extension, against market efficiency is strong. The converse holds under a value-weighted performance approach as the under-performance finding and the evidence against market efficiency is not as strong, may not even exist, and in some cases, weak. The value-weighted results also reject any unique 'IPO effect' in the market place. Nevertheless, on the evidence of the equally-weighted results obtained, which is strong, consistent and overwhelming across the horizon and matching board, the author makes bold to say that IPO under-performance is neither due to imperfect matching procedures or inadequate matching criteria nor differences in fundamental characteristics between the issuing IPO firms and their non-issuing counterparts prior to or at the IPO date. The equally-weighted results, rather, establish the existence of a unique 'IPO effect' in the market place that makes IPOs significantly under-perform their comparable non-issuing counterparts.

The author also avers that this 'IPO effect' is not a function of the process of selecting the control firms or the actual choice of the benchmark firms from the general population. Clearly, from the results of the various methodologies under an equally-weighted performance, IPO under-performance persists despite using a more refined process to mix and match the control firms in the benchmark portfolios using key return-determining firm risk factors; however, the scale and magnitude of the observed under-performance also appears to be sensitive to the matching process.

[3.5] SUMMARY AND CONCLUSIONS

[3.5.1] Summary

The study re-examines the validity, reliability and robustness of the documented long-run under-performance of new issues of common stock using a fresh sample of 746 IPOs in the UK market over the period 1999 – 2006 adopting a distance metric matching approach that firstly, selects matching firms across several relevant dimensions and secondly, avoids the problems of the traditional matching methods used in the majority of earlier studies.

The IPO performance results across five different horizons are compared with the results of a set of matching firms selected according to the six stepwise matching algorithms as earlier defined. More importantly, the use of stepwise matching algorithms that select the matching firms from the general population on the basis of key firm risk factors that includes three new risk factors – pre-IPO performance, turnover growth and earnings yield – employing a distance metric matching technique is first documented in this study. The findings reveal that, indeed, in line with the majority of extant research, IPOs are poor investments either in event time methodologies or calendar time techniques that rebalance the IPO stocks in monthly portfolios, using the equally-weighted technique. However, the evidence is mixed when a value-weighted performance measure is adopted. Under this scenario in event-time methodologies, the under-performance is also largely evident; however, when the risk-adjusted performance of the IPO stocks is tracked in calendar time, the under-performance is found to be non-existent in some cases, and at best, weak in some others. This pattern of results is robust to the inclusion or exclusion of the late 1990s technology bubble.

The results also show that the scale of the under-performance, which varies substantially and in some cases disappears altogether across the matching board, is sensitive to firstly, the choice of empirical method; secondly, the choice of matching firms in the benchmark portfolio; thirdly, the method of cumulating abnormal returns; fourthly, the weighting scheme employed; fifthly, the horizon over which it is measured and; sixthly, the inclusion or exclusion of the late 1990s technology bubble. This first part of the work also documents a novel finding. It is found that in almost all the cases, the observed under-performance is least, and in some cases evaporates, when the matching algorithm includes industry as an additional risk factor, which tends to suggest that a matching criterion that includes the industry of the firms is vital in the matching process as it ensures that issuing and non-issuing firms are fairly similar, thus making for better comparisons. In general, the findings show firstly, that the scale and magnitude of the observed under-performance is sensitive to the matching process; secondly, that under-performance is compelling, overwhelming and genuine only when returns are equally-weighted and; thirdly, the evidence on the under-performance finding is not as strong when returns are value-weighted; in fact in some cases, the evidence is weak and in some others, disappears altogether.

Overall, given that the majority of the studies in the literature find that IPOs are poor investments in the long-term, the findings suggest firstly, that investing in IPOs beyond the immediate after-market may not be a bad trading strategy since the relative after-market performance is dependent on the proportions in which the stocks are stacked in the investor’s portfolio; secondly, value-weighted performance does not provide strong evidence against market efficiency when compared to an equally-weighted measure of abnormal performance [which tends to suggest that the former may provide a more useful benchmark in assessing the post-event risk-adjusted performance of IPO firms since it more accurately captures the investors' wealth effects] and; thirdly, under-performance of new issues of common stock remains an anomaly that really challenges the efficient market hypothesis only when performance is equally-weighted.

[3.5.2] Conclusions

The majority of the earlier studies document under-performance of new issues of common stock using the traditional method of matching to select the control firms from the general population, despite its drawbacks. This study's use of a more refined technique in choosing the benchmark firms provides mixed findings. Under an equally-weighted measure of performance, the results also generally suggest that investors who are crowded out of the initial offers in the primary market and hoping to find some succour in the immediate secondary market might be disappointed as a long-term investment in this set of IPOs from the second month of trading following the listing of these stocks relative to a similar investment in a set of comparable firms selected according to the six matching algorithms consistently produces an inferior performance across the horizon and matching board. The equally-weighted results also generally imply that for the study period, the market was not efficient given the prevalence of these negative abnormal returns in the long-run which also directly implies that investing in IPOs beyond the immediate after-market may not be a good trading strategy. However, under a value-weighted performance approach, which has been touted as the appropriate technique for measuring the wealth effects of the typical investor in the market place, the IPO under-performance evidence is not as strong and consistent, which suggests that the markets were, by and large, efficient.

Despite the fact that the greatest possible level of breadth, depth and robustness has been given to these results, the author warns that the results of this first empirical study only hold for the sample size and period used here as this may change if a different and/or larger sample were to be employed. Although this fisrt part of the work has used pre-IPO performance, turnover growth and earnings yield as additional risk factors in selecting the control firms from the general population, it is still not able to explain fully the cross-section of stock returns. Hence, future researchers are recommended to compare the sample firms to the general population on the basis of other characteristics.

CHAPTER 4 – FIRM AND INDUSTRY CHARACTERISTICS AND IPO PERFORMANCE

[4.1] Introduction

The outcome of the first strand of this study naturally leads the author to a second strand that examines the cross-sectional dynamics in the firm and industry characteristics of this fixed cohort of newly-listed firms in a bid to identify the range of variables that shape the long-term performance of these firms. Following from the first empirical study where the market performance of the issuing firms relative to a set of fairly similar non-issuing firms was tracked, the work now ascertains, in this second empirical study, which set of firms within the general group of the IPO firms really under-perform. It could well be that the under-performance is concentrated within a particular group of the issuing firms which invariably becomes a drag on the general performance of the IPOs. In fact, the results from the first empirical study seem to suggest that size could be a key risk factor, amongst others, in the post-IPO long-run performance of issuing firms given that value-weighted performance did not produce a strong and consistent under-performance finding.

The ‘window of opportunity’ hypothesis argues that when stock market indices and investor sentiments are high, firms tend to take advantage of these transitory opportunities occasioned by these favourable market conditions to float their offerings.

Extending this argument to include industry conditions, private firms desirous of going public are expected to also take advantage of favourable [adverse] industry conditions to float [delay] their offerings. For example, if firms in an industry believe the industry is over-valued which is reflected in high market-to-book multiples, they could time their offerings to obtain favourable offer prices and in the process, maximise the amount of capital they eventually raise. There could also be first-mover advantages from being the first firm to go public in an industry or competitive advantages from following a bandwagon of firms going public. Firms issuing IPOs in mature industries, dominated by established firms and where growth opportunities are limited, may find it difficult to perform in the market place. On the flip side, IPO firms that are domiciled in high growth industries may be able to use the additional capital raised from the IPO to take advantage of profitable niche opportunities in the market place.

The impact of several firm and offering characteristics on the subsequent performance of new issues is well documented; however, only a few others have studied the impact of industry conditioning risk factors on IPO after-market performance. By and large, the amount of published research on this area is still limited. It is also pertinent to point out that none, to the best of the author’s knowledge, has investigated the impact of industry structure variables on the post-listing performance of IPO firms albeit, some researchers have studied the relationship between industry structure and the performance of firms [Porter, 1980; Dess, et al, 1990]. This provides the springboard for the second empirical work as it seeks to ascertain the value and economic importance of salient industry conditioning risk factors prior to or at the issue date on IPO long-run performance. Realistically, a firm's long-run performance is not only a function of the firm, industry and market conditions around its IPO date but also on the industry and market conditions subsequent to the issue. However, the author's goal in this second part of the study is to determine if one can predict the long-run performance of new issues by using only that information that would be available to the issuer, its investment banker or the IPO investor prior to or at the IPO date[72].

Hence, the aim of the second empirical study is to firstly, determine the class and profile of IPO firms that under-perform and secondly, ascertain if a set of observable firm and industry characteristics prior to or at the IPO can foreshadow the performance of the issuing firms in the long-term. This information could prove invaluable to potential IPO investors in their search for value as it enables them to avoid new issues that could potentially under-perform in the post-IPO years. It could also be of immense value to IPO firms and their investment bankers as they aim to time their offerings to coincide with favourable industry conditions. The dearth in the amount of studies analysing the impact of industry characteristics on the after-market performance of new

[72] This excludes IPO risk, which is measured 30 days post-listing.

issues naturally leads the author to ask: which industry conditions are germane to IPO post-listing performance? In this regard, this second study evaluates the impact of six industry structure variables – an industry-adjusted IPO firm valuation [IPO surplus value], concentration, market-to-book value, profitability, leverage and equity volatility. The industry market-to-book value attempts to capture industry growth prospects, while industry profitability and concentration give an indication of the attractiveness of the industry. The industry leverage and equity volatility provide a proxy for the riskiness of the industry, while IPO surplus value tracks the valuation of the IPO firm relative to industry peers.

During major IPO waves occasioned by profound investor sentiments and a massive demand for capital, there is a tendency for valuations and attendant growth and investor expectations to vary widely between industries. More often than not, these expectations feed through into the stock prices of the constituent firms in these industries resulting in excessively high stock prices and as of a consequence, unfounded market capitalizations for these firms relative to industry peers with the same accounting data in the IPO year. This section of the srudy controls for this anomaly by computing a surplus value measure that tracks the valuation of the IPO firms relative to industry peers in the IPO year to enable us determine those trading at a ‘premium’ or a ‘discount’.

The industry leverage and equity volatility risk factors provide a proxy for the riskiness of the industry. An assessment of the level of threat posed by the IPO firm to industry rivals can be captured by the existing industry leverage. If this leverage is presently high which invariably puts the industry at great risk, then the IPO firm can steal a march on its rivals and enhance its competitiveness by raising equity capital which helps to rebalance its own capital structure. An evaluation of the riskiness of the industry can also be provided by its equity volatility. This volatility should naturally impinge on the constituent firms in the industry as their risk profiles are expected to reflect this. However, an assessment of the impact of this risk on the long-run performance of new issues of common stock is best addressed empirically.

The extant profitability of an IPO firm's industry can provide a measure of the relative attractiveness of that industry. It is pertinent to note that an IPO firm without a track record of visible performance in the market place is very difficult to assess. Hence, some investors become cagey of the firm and as of a consequence, may decide to wait to assess the firm's first set of publicly available accounting data before investing in the stock of the firm in the secondary market. However, other investors may decide to go ahead and invest in the offering based on the IPO firm's industry profit conditions which may help to reduce the adverse selection costs that may surround the firm's long-term prospects.

Using the same sample of 746 IPOs in the UK market over the period 1999 – 2006 as in the first empirical study, this part of the study tests for the economic importance of selected firm and industry-specific risk factors prior to or at the issue date to IPO firms, their investment bankers and potential IPO investors. When doing this, the work controls for and confirms the results of previous studies on the impact of firm-specific risk factors. Size, market-to-book, past performance, underwriter reputation and the 'hot' IPO market are found to be important predictors of IPO performance in a cross-section. The study also documents that industry risk factors relating to an adjusted IPO valuation [i.e. IPO surplus value], profitability, leverage, market-to-book, concentration and equity volatility can potentially be valuable in predicting or explaining the cross-sectional differences in IPO long-term performance. However, after controlling for other factors that are germane to IPO long-run performance in a cross-section, the findings reveal that only IPO surplus value, industry profitability, industry market-to-book value and industry equity volatility can be significant predictors of an IPO's long-term performance.

More specifically, significant negative relationships between industry conditioning risk factors of profitability, equity volatility and IPO long-run performance on the one hand and significant positive relationships between industry structure variables of IPO surplus value, market-to-book value and IPO long-term performance on the other hand are observed. These results are robust to including controls for other variables known to predict IPO long-term performance. However, apart from firm size, past performance, underwriter reputation, industry profitability and industry market-to-book to a limited extent, they are not robust to the exclusion of the late 1990s technology bubble, which suggests that those years are driving some of the results. In general, the results suggest that IPOs issued in low market-to-book and profitable industries with high equity volatilities and that also tend to trade at a discount relative to industry peers [i.e. trading below their industry-adjusted valuations] perform worse than other IPOs in the counterpart industries. Overall the findings suggest that not all IPOs are bad investments as potential IPO investors can substantially improve their long-run returns if these IPOs are painstakingly selected by considering prospectus and other salient industry information available prior to or at the IPO date. The results also suggest that IPO firms and their investment bankers should consider industry conditioning risk factors prevailing at the time of the IPO to provide them with additional information on whether to go ahead with the IPO, or alternatively, withdraw and re-launch at a more auspicious date.

The second empirical study contributes to the literature in three ways; firstly, the unique relationships between industry risk factors of IPO surplus value, market-to-book, profitability, equity volatility and IPO long-run performance are first documented in this study; secondly, it is the first to study the impact of industry-specific risk factors on the long-run performance of IPOs in the UK market and; thirdly, since the study investigates the long-run performance of newly-listed firms using a set of observable firm and industry characteristics prior to or at the IPO date, it helps provide the stakeholders [i.e. IPO firms, their investment bankers and potential IPO investors] with additional useful information that they could use in their decision making process. Despite assessing the relation between long-run performance and the firm and industry risk factors used in this study, future research is encouraged into identifying the impact of other salient firm and industry risk factors on the long-run performance of new issues of common stock.

The rest of the chapter is organised as follows: Section 4.2 reviews the literature on firm and industry characteristics and IPO long-term performance, while Section 4.3 describes the data and methodology used in assessing cross-sectional IPO performance. The empirical analysis and ensuing findings are reported in Section 4.4, while Section 4.5 summarises and concludes the study.

[4.2] Literature Review

[4.2.1] Firm Characteristics and IPO Performance

Most studies in the literature have analysed the relationship between certain firm characteristics and the long-run performance of new issues of common stock. In his path-breaking work, Ritter [1991] finds that under-performance is preponderant among relatively small, younger growth firms whose stocks are offered in periods of high stock activity ['hot markets'][73]. Loughran and Ritter [1995] report that IPOs that occur in years of low issuing activity ['cold markets'] show no significant under-performance, while those that occur in high volume periods ['hot markets'] severely under-perform, which is consistent with the findings of Helwege and Liang [2004] and Thomadakis, et al [2012]. In the same vein, Kooli and Suret's [2003 and 2004] results for the Canadian market are in line with the 'window of opportunity' hypothesis[74] suggested by Ritter [1991] and Loughran and Ritter [1995] as an explanation for the after-market performance of new issues of common stock.

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[73] Boisson and Sentis [2010] report a significant positive relationship between the 'hot market' variable and the 1-year performance of IPOs which becomes insignificant when the horizon is extended to 3 and 5 years.

[74] The hypothesis suggests that firms take advantage of investors' optimism during 'hot' market periods to float many poor quality IPOs.

Ritter [1991] also contends that IPOs that tend to have more initial returns[75] experience more under-performance in the long-run which is consistent with the 'fad' hypothesis of Aggarwal and Rivoli [1990] and the 'overreaction' hypothesis of De Bondt and Thaler [1985 and 1987][76] and in line with the findings of Levis [1993], Loughran and Ritter [2001], Spiess and Affleck-Graves [1995], Bhabra and Pettway [2003], Loughran, et al [1994], Jelic, et al [2001], Paudyal, et al [1998], Krigman, et al [1999], Goergen, et al [2007], Gao, et al [2006] and Chi, et al [2010]. However, these contrast with the findings of Ahmad-Zaluki, et al [2007] who document a positive relationship between initial returns and the after-market performance of new common stock issues for the Malaysian market. The difference in results could be a reflection of the differences in the sample composition, benchmark employed and time period, given that the studies of Paudyal, et al [1998] and Jelic, et al [2001] in the same market produce a negative relationship.

In the same vein, Ritter [1991] shows that there is a tendency for IPOs which have the greatest under-pricing, generally attributed to information asymmetry and investors'

[75] Ritter finds that younger firms tend to have more initial returns and the worse long-run performance, which is in line with the findings of Clark [2002] who documents a positive relationship between the firm age at the IPO and the after-market performance.

[76] Both hypotheses suggest that investors behave irrationally by valuing newly listed firms beyond fair values due to information asymmetry and over-optimism in the market place. As information on the true values of the firms become available to the market, prices drop over time. Hence, the hypotheses predict that the more extreme the initial price movement, the greater will be the subsequent price adjustment.

misevaluations in the marketplace, to have the worst long-run performance which is in line with the findings of Shaw [1971], Kooli and Suret [2004], Ibbotson and Jaffe [1975], Loughran [1993], Chi, et al [2010], Rajan and Servaes [1997], Carter, et al [1998] and Loughran and Ritter [1995], but contrasts with Kooli and Suret [2003][77]. He also avers that this phenomenon is stronger for young, small growth firms with high market-to-book ratios. Using a sample of 2,696 US IPOs issued during 1980 – 1995, Guo, et al [2006] examine the impact of another pervasive source of information asymmetry and valuation uncertainty – the pre-IPO intensity of the issuer's Research and Development [R-and-D] activities – on the long-run performance of these firms. They document a positive relationship between the R-and-D intensity and IPO long-term performance, as they find that the high R-and-D group out-perform their low or no R-and-D counterparts in the long-run.

The presence of expert informational intermediaries have also been shown to have a positive impact on the long-term performance of new issues due to the certification services they provide before, during and after the offering. These intermediaries include the underwriter and the venture capitalist. It has been shown that IPO firms underwritten by more prestigious underwriters show less severe under-performance in

[77] Kooli and Suret [2003] find that under-pricing is positively related to the long-run performance of Canadian IPOs, corroborating the signalling model of Deeds, et al [1997].

the long-run [Carter, et al, 1988; Michaely and Shaw, 1994; Logue, et al, 2002; Paudyal, et al, 1998; Ljungqvist and Wilhem, 2002; Chemmanur and Paeglis, 2005; Doukas and Gonenc, 2005; Gao, et al, 2006; Chan, et al, 2008; Johnson and Westberg, 2009; Chang, et al 2010]. Thomadakis, et al [2012] find a negative association between underwriter reputation and long-run performance, with the result implying that reputable underwriters tend to engender high post-listing market prices in the immediate after-market which eventually leads to severe negative returns in the long-term. Corwin and Schultz [2005], however, argue that the presence of a large underwriting syndicate is likely to narrow the gap between the offer price and the true value of the firm and in the process, reduce the consequent levels of under-pricing and long-run under-performance. The positive relationship between venture capital backing and IPO after-market performance is also well documented [Brav and Gompers, 1997; Jain and Kini, 2000; Megginson and Weiss, 1991; Chan, et al, 2008; Barry, et al, 1990; Boisson and Sentis, 2010; Hamao, et al; 2000; Tykvova and Walz, 2004; Rindermann, 2003; Espenlaub, et al, 1999; Levis, 2011]. Brav and Gompers [1997] examine the long-run performance of venture and non-venture capital backed firms and find that the under-performance is more severe for the latter. However, this contrasts with Boisson and Sentis [2010] who document a negative relationship between venture capital affiliation and the long-run performance of new stock issues. Specifically, they find that the market responds inauspiciously to the presence of venture capital at the time of the IPO[78].

Houge, et al [2001] and Schultz [1993] aver that IPOs with greater levels of risk and uncertainty, which are generally small, young and unseasoned firms with little or no track record, perform worse in the long-run. More specifically, the former study examines the nexus between investor uncertainty, divergence of opinion and the performance of IPOs. They employ three opening day variables to proxy for the uncertainty and divergence of opinion about the IPO stock – the percentage opening bid-ask spread, the time of first trade and the flipping ratio[79]. They find that IPO firms with wide opening spreads, late opening trades and high flipping ratios perform worse than their counterparts when the share price performance is tracked over a 3-year period. On a related note, Pukthuanthong-Le and Varaiya [2007] examine the impact of block sales[80] on the long-run performance of IPOs and find that IPOs with high block

[78] Hamao, et al [2000] suggest that conflict of interests could explain the high initial performance and long-run under-performance of venture capital backed IPOs. This is due to the tendency of the investment bankers, who are parent companies of the venture capitalists in most cases, to overstate the value of the IPO to investors at the offering stage. When investors recognise this, the share values are subsequently adjusted downwards, causing long-run returns to fall.

[79] The quoted 'bid-ask' spread reflects market makers' and dealers' order processing, adverse selection and inventory holding costs. The time of first trade is the time when the lead underwriter begins trading on the IPO stock after the market opens. The flipping ratio is the volume of sell-signed, large-block volume initial share allocations that are sold to retail investors, other institutional investors, market makers and underwriters on the opening day relative to the total trading volume [Houge, et al, 2001].

[80] Unlike Houge, et al [2001] who only use the immediate sale of initial IPO allocations by institutional traders on the opening day to determine the block sales and the corresponding flipping ratio,

sales perform better than those with low block sales from 20 days after the IPO to the lockup[81] expiration date. However, the picture changes when the firms are tracked from the lockup expiration date till the 3rd year after issue, as the high block sales IPOs under-perform their counterparts, with the results robust to cross-sectional regressions that control for other factors that influence IPO long-term returns. They also find that over-valued IPOs [i.e. 'hot market' IPOs] exhibit higher block sales than under-valued IPOs [i.e. 'cold market' IPOs] after controlling for underwriter reputation, opening trade return and IPO size. Using a sample of 4,057 US IPOs from 1980 to 2000, Gao, at al [2006] use the IPO firm's early market return volatility[82] to gauge the 'divergence of opinion' and uncertainty that may surround new issues of common stock. They find a significant and robust association between the early market return volatility and IPO long-term returns. They also use dispersion of analyst forecasts[83] to proxy for the divergence of opinion and find that the coefficient estimate is negative, which suggests that a greater dispersion in analyst forecasts leads to poorer IPO long-term returns.

Pukthuanthong-Le and Varaiya [2007] calculate the block sales ratio as the volume of sell-signed trading volume executed in blocks of over 3,500 shares in the first two trading days, comprising institutional, market maker, interdealer and short-seller trades expressed as a percentage of the total trading volume.

[81] The lockup period, usually between 3 – 6 months, is an attempt to control the supply of shares of the IPO stock in the immediate after-market. During this period, insiders and existing shareholders are prohibited from selling shares without the written permission of the lead underwriter [Yong, 2007].

[82] This is computed as the standard deviation of the IPO daily return for the first 25 days of trading after listing.

[83] This is computed as the standard deviation of annual earnings forecasts for the forthcoming fiscal year-end scaled by the stock price at the time the forecasts are made.

The above findings are consistent with Miller's [1977] 'divergence of opinion' hypothesis which suggests that the long-run under-performance of IPOs may be due to heterogeneous expectations of optimistic and pessimistic investors, whose divergence of opinion narrows as more information becomes available which makes investors adjust their initial over-valuation, leading to a fall in long-run returns.

Teoh, et al [1998a] suggest that the long-run performance is worse for IPOs that may want to 'window-dress' through 'creative accounting'. They argue that this is largely due to the fact that the IPO firm wants to 'look good' when it conducts its IPO; afterwards, the market recognizes the firm's true value and the value of the new share is downwardly adjusted[84]. More specifically, they examine the effects of discretionary accounting accruals to study the impact of 'subtle earnings management' by firms prior to going public[85]. They find that IPOs with the highest accruals in the IPO year experience poorer stock price performance in the following three years than those that had little or no accruals, which is consistent with the findings of Chan, et al [2008]. They also find that issuing firms with the most aggressive earnings management or

[84] This position is equally supported by Loughran and Ritter [1995] who find that firms going public at the moment of relative over-valuation [i.e. high market-to-book values] show more under-performance in the long-run.

[85] The earnings management hypothesis suggests that issuing firms exhibit unusually high operating performance relative to the industry average in the pre-IPO year which is intended to lead investors to be overly optimistic on the firms' prospects. Hence, the firms' reported earnings are more than the actual operating cashflows with the difference representing accounting accruals.

‘creative accounting’ exhibit the worst 3-year after-market performance compared to those with little or no earnings management. In a similar study, Teoh, et al [1998b] report that issuing firms have high earnings and positive accruals in the IPO year that is followed by low earnings and negative accruals in the immediate post-IPO years. They also find that these abnormal accruals in the IPO year explain to a great extent the cross-sectional variation in the post-issue operating and market performance of these firms. DuCharme, et al [2004] also document unusually high abnormal accounting accruals around new equity issuances which are more pronounced for issuing firms whose offers attract lawsuits afterwards. They aver that these accruals tend to reverse almost immediately after the offers with a consequent decline in the after-market stock price performance. Jelic, et al [2001] study the association between the long-run performance of Malaysian IPOs and management earnings forecasts with the evidence indicating a negative relationship in the first 12 months following the listing date of the IPOs.

Controlling for a raft of ex-ante variables that are known to investors at the time of the offering [industry, shares offered, underwriters, venture-capital backed, amongst others] or occurring within five years after the listing date [specifically, financial analysts’ recommendations], Boisson and Sentis [2010] study the link between this range of variables and post-IPO performance. They find that investors pay attention to analyst coverage when the IPOs have a huge underwriting syndicate, are venture capital backed and lowly under-priced. Specifically, they find that IPO firms with high analyst coverage perform better than those with little or no coverage, which is in agreement with the findings of Bradley, et al [2008] and Kooli and Suret [2003]. Michaely and Womack [1999] study the impact of affiliated analyst recommendations on IPO performance using a sample of US IPOs. They report that IPOs with affiliated analyst recommendations perform worse than those with unaffiliated analysts, which is consistent with the findings of Houston, et al [2006][86]. However, Rajan and Servaes [1997] document an inverse relationship between analyst over-optimism and long-term performance as they find that IPO firms with the highest projected growth perform substantially worse than those with the lowest growth projections. They adduce this to the decline in analysts' growth projections several months after the IPO when they eventually realise that their initial projections are flawed, over-estimated and cannot be attained. Investors, who rely on these initial projections to make their investment decisions, purchase these shares at inflated prices, which is downwardly adjusted in the long-term.

[86] This may not be unconnected with the fact that affiliated analysts tend to be positively biased in their recommendations of the subject IPO firms who may be trading poorly in the after-market. Rational investors would, expectedly, discount these recommendations relative to those of unaffiliated analysts.

Bessler and Thies [2010] analyse the abnormal return behaviour of a sample of German IPOs over the period 1977 to 1995 to better understand the cross-sectional pattern in the long-term returns. They find that differences in the initial returns, market value and security type do not really explain the pattern of returns in the sample. Intriguingly, they find that the single criterion that strongly explains the cross-sectional variation is whether each of the firms had an opportunity to raise additional funds in the capital market via an SEO after the IPO. Bhabra and Pettway [2003] also show that firms that have the opportunity of re-issuing equity subsequent to their IPOs exhibit a superior after-market stock price performance compared to those firms that continue to trade and did not re-issue equity.

The positive relationship between the size of the firm and IPO market performance is also well documented [Chi, et al, 2010; Bhabra and Pettway, 2003; Keloharju, 1993b]. Ritter [1991] also finds that US IPOs exhibit severe long-run under-performance with small firms having the worse after-market performance, which is consistent with the findings of Page and Reyneke [1997] and Goergen, et al [2007] in their studies of the long-run performance of South African and UK IPOs respectively. Also, Brav and Gompers [1997] and Brav, et al [2000] show that smaller firms have a worse post-listing stock price performance relative to large firms in their studies of the abnormal return behaviour of a sample of US IPOs. However, Ahmad-Zaluki, et al [2007], in a study of Malaysian IPOs, find that smaller firms [both in terms of gross proceeds and market value] perform better than large firms in the long-run, with the findings in tandem with those obtained by Jelic, et al [2001] in the same market, Durukan [2002] for the Turkish market and Xia and Wang [2003] for the Chinese market. The difference in results for the Malaysian and Turkish studies from the majority of the literature could be due to the small size of the samples and the peculiarities of the markets[87]. The variation in results for the Chinese study is attributed to the preference of investors in the Chinese market for capital gains rather than dividends, which leads to a situation where the stocks of small firms become attractive to market makers and investors alike since they require a relatively small amount of capital and also tend to be easier to manipulate.

Purnanandam and Swaminathan [2004] assert that IPOs that are priced higher than their market comparables [i.e. high market-to-book or price-earnings multiples] generally show higher first day returns, but the worse long-term performance, which is in line with the results obtained by Chang, et al [2010] who document lower post-IPO stock returns for firms with high price-earning [P/E] or low book-to-market [B/M] ratios. In the same vein, Corhay, et al [2002] and Xia and Wang [2003] find that the long-run

[87] The sample sizes for the Ahmad-Zaluki, et al [2007], Jelic, et al [2001] and Durukan [2002] studies are 454, 182 and 173 firms respectively.

under-performance of ‘value’ [i.e. low market-to-book or high book-to-market ratios] IPOs is less severe relative to ‘growth’ [i.e. low book-to-market or high market-to-book ratios] IPOs[88]. The results show that investors may be overly optimistic about the future of the IPO firms and in the process, over-project their future earnings. This leads them to pay excessively for the shares of these firms at the time of issuance; however, with the passage of time, their expectations are not met and as of a consequence, the share prices are subsequently adjusted downwards, causing long-run returns to fall.

Mikkelson, et al [1997] document a positive relationship between the change in pre and post-flotation IPO operating performance and long-run share price performance, which suggests that when post-listing operating performance fails to uphold pre-listing profitability levels, investors revise their expectations of the firm and the share price is downwardly adjusted in the long-term. The result, which is in tandem with those obtained by Goergen, et al [2007], indicates that firms go public at the peak of their performance. In the same vein, Bhabra and Pettway [2003] find a negative relationship between profitability and long-run performance, which appears to be inconsistent with the expectation that firms with a track record of good performance should perform better in the long-term. They adduce this variation in result to the downward revision of

[88] See Section 3.3.4, pp. 125-126.

expectations of future earnings for these firms due to their inability to sustain pre-listing performance levels.

Leland and Pyle [1977] argue that in line with agency theory[89], firms with a higher percentage of insiders selling their shares at the IPO should have a worse long-run performance. Jelic, et al [2001] find a weak association between both variables, while Paudyal, et al [1998] find no relationship. The findings of Goergen, et al [2007], Jain and Kini [1994], Durukan [2002] and Thomadakis, et al [2012] are in tandem with the predictions of the agency theory. In a study of the impact of managerial decisions and pre-IPO performance on the long-run performance of IPOs, Goergen, et al [2007] find a positive relationship between the multi-nationality [diversity in terms of products and subsidiaries] of a firm and its long-run performance. It has been argued that PIPOs exhibit better long-term performance compared to private firms, because they are more highly scrutinized at the time of listing [Perotti and Guney, 1993; Perotti, 1995; Megginson, et al, 2000]. There is a large body of evidence that has shown that firms under private ownership perform significantly worse than their state-owned counterparts [Durukan, 2002; Hingorani, et al, 1997; Megginson and Netter, 2001; Jones, et al, 1999; Keloharju, et al, 2008; Thomadakis, et al, 2012].

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[89] Jensen and Meckling [1976] argue that the incentives of an owner/manager change when their ownership is diluted by the issuance of shares to another party. In the same vein, Mikkelson and Partch [1985] show that a decrease in ownership concentration reduces the market value of listed firms.

Hsu [2010] investigates the relationship between board characteristics[90] and financial performance for US IPOs and finds that board independence [board quality] is negatively [positively] related to financial performance. Chang, et al [2010] document a negative relationship between board size and post-IPO stock returns, with the results suggesting firstly, that there is an optimal board size and secondly, that a very large board tends to reduce the efficacy of corporate monitoring [Yermack, 1996; Eisenberg, et al, 1998]. Baker and Gompers [2003] and Campbell and Frye [2006] also show that the presence of venture capital directors in the board is positively linked with financial performance. Kim and Kim [2007] find that demutualized firms[91] perform better than other stock insurance firms with the evidence suggesting that the two major market imperfections advanced in the literature for the under-performance of new issues of common stock – high information asymmetry and high agency costs - may just be valid.

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[90] Board characteristics include independence [i.e. percentage of outsider directors in the board], quality [i.e. board expertise and educational background] and the proportion of venture capital directors. Financial performance is measured by Tobin's Q computed as the total market value of the firm [sum of market value of equity, book value of preferred stock and book value of debt] divided by the book value of the firm's assets.

[91] Demutualization is a process whereby firms convert from a mutual company [where policyholders are the owners] to a stock company [where outside investors are the owners]. In a full demutualization, the policyholders give up their ownership rights in exchange for either shares in the new stock company, cash or policy credits. In a mutual holding demutualization, a stock holding company, under the aegis of a mutual holding company, is created to directly own a newly created stock insurance firm [Viswanathan and Cummins, 2003].

[4.2.2] Industry Characteristics and IPO Performance

It is important to point out that very little has been done to consider whether the characteristics of an issuing firm's industry are also germane to the post-listing performance of new stock issues, which is startling given the extant literature's widespread handling of other corporate finance issues. Simutin [2009] studies the relationship between the price choices of firms going public and the post-issue stock price performance and finds that the raw and risk-adjusted returns of IPOs is a rising function of the ratio of the issue price to the average industry price. More specifically, he finds that IPO firms with relatively high prices out-perform those with relatively low prices by 32% over a 3-year tracking period. In fact, they find that firms in the highest relative price group do not under-perform their matches in the same period.

Dong and Michel [2011] examine whether the growth prospects of an IPO's industry can help investors select good quality IPOs. Using analysts' ex-ante long-term earnings growth forecasts for the IPO firm's industry as a proxy for the IPO's growth potential and a sample of 7,608 US IPOs entering the market over the period 1982-2007, they examine whether an industry's growth prospects impacts on the issuing firm's long-run stock performance[92]. Given the documented association between industry conditions,

[92] Industry growth is measured by the value-weighted average of the mean analyst long-term earnings growth forecasts in the IPO firm's industry in the month prior to the offer.

stock returns and information flow [Barberis, et al, 2005; Hou, 2007; Cen, et al, 2010] coupled with the fact that an IPO firm's industry provides rational comparables for its characteristics [Edelen and Kadlec, 2005; Wang, et al, 2010], Dong and Michel [2011] show that the most prominent feature of an issuing firm prior to the offering is its industry. They document a strong positive relationship between the industry growth prospects and IPO long-term performance in the period before the 'dotcom' period [pre-1999] which reverses in the 'dotcom' period [1999-2000] and the period thereafter. Put differently, IPOs in high growth industries out-perform their counterparts in the three years following the IPOs, up to the period before the 'dotcom' bubble. However, in the 'dotcom' period and thereafter, these same IPOs under-perform their counterparts with the evidence suggesting that, excluding investors' overreaction to growth prospects in the 'dotcom' period, IPO investors tend to under-react to industry growth prospects, leading to superior performance both in the short and long-term.

Jain and Kini [2006], using a sample of 6,922 US IPOs listed over the period 1980-1997, examine the industry conditions that influence the clustering of IPOs and the impact of the clustering on the post-listing performance of these firms[93]. They find that IPO clustering is more rampant in fragmented and high growth industries characterized

[93] IPO cluster industries are identified as those industries where at least 20 IPO issues occurred and also where at least one-third of issuing firms went public during any 2-year adjacent period.

by favourable investor sentiments, high levels of investment in R-and-D and robust investment opportunities. They document significant positive relations between industry risk factors such as profit conditions, market-to-book and industry returns and IPO clustering. They also find an inverse relation between the post-listing operating performance and whether the IPO firm goes public in its industry cluster period[94].

Akhigbe, et al [2003] examine whether the entrance of IPO firms in the market place has any implications for rival industry firms using a sample of 2,493 US IPOs that were listed between 1989 and 2000. They aver that the average valuation effects for rival firms are insignificant, which may suggest that IPOs are purely firm-specific events with no industry ramifications. On the contrary, they document significant offsetting positive information and negative competitive effects, with the former coming from IPOs in regulated industries and industries with the first IPOs, while the latter results from relatively large IPOs in less concentrated, less risky and better performing industries[95].

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[94] They argue that the relatively poor post-IPO long-run performance in the cluster periods is due to the over-investment in the industry that arises as a result of too many firms in that industry chasing the same investment opportunities.

[95] Kohers [1999] argues that the constraints imposed by regulation are expected to reduce the diversity amongst firms in an industry which should result in stronger information effects for rival firms from firm-level events. Akhigbe, et al [1997] show how the first IPO relative to subsequent IPOs in an industry, after a period of prolonged dormancy, should result in greater valuation effects for rival firms. On the flip side, it is expected that rivals in more competitive industries will experience severe competitive effects following the additional capital raised by the IPO firm [Lang and Stulz, 1992]. It is also expected that large IPOs in less concentrated and less-risky industries will signal 'bad news' for industry rivals. Finally, rival firms in a high-performing industry could lose out because IPO firms could time their entry into the industry and reduce the excess rents.

In a related study using a sample of 2,483 US IPOs that were listed between 1990 and 2000 and computing 3-year BHARs, Akhigbe, et al [2006] examine whether an IPO provides an indication as to the direction and magnitude of industry returns in the long-term. They find that the industry experiences a worse after-market performance in the three years following the IPOs, which they adduce to competitive and/or timing effects[96]. They also show that the poor industry share price performance following the IPOs is accentuated when the industry is highly regulated, over-valued, has high operating and financial leverage, less concentrated [i.e. more competitive] and when there is a large industry run-up prior to the IPO filing[97]. In the same vein, Hsu, et al [2010] study the stock price, operating performance and the likelihood of survival of rival firms after a large IPO in their industry. Their results show that the successful completion of an IPO in an industry is 'bad news' for industry rivals as they experience negative stock price reactions after the IPO. They also find that the withdrawal of an IPO earlier announced

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[96] Akhigbe, et al [2003] aver that the IPO firm can serve as a threat to industry rivals by either pulling their market share or reducing their margins ['competitive effects']. Also, firms could strategically time their initial offerings to coincide with the peak performance of the industry ['timing effects] [Kim and Ritter, 1999; Loughran and Ritter, 2002; Lowry and Schwert, 2004; Pagano, et al, 1998; Jain and Kini, 1994].

[97] Industry concentration indicates the extent of significant barriers to entry that may confront new firms and is measured by the Herfindahl Index [HHI], computed as the squared sum of the proportions of industry sales by the rival firms. Financial [Operating] leverage is measured as the ratio of long-term debt [fixed assets] to total assets, while the industry valuation is measured as the ratio of the prevailing price-earnings multiple to its average multiple in the previous 3 years. A signal that industry valuations have peaked may be more damaging for those firms that have experienced significant price run-ups prior to the IPO, where run-up is measured as the median cumulative return in the industry portfolio for 100 days ending 20 days prior to the IPO.

has the opposite effect as the incumbent firms in the industry exhibit positive stock price reactions around the date of this announcement.

Several other studies have also investigated the impact of industry conditions on the volume of IPOs [Pagano, et al, 1998; Lowry, 2003]. IPO intensity has been found to be associated with increases in aggregate demand for capital, diminution in the level of information asymmetry and a bullish market fuelled by fierce investor optimism. Extant research has also linked the IPO versus takeover decision[98] to industry characteristics, market timing, demand for capital and firm-specific risk factors [Mitchell and Mulherin, 1996; Pagano, et al, 1998; Maksimovic and Pichler, 2001; Rajan and Servaes, 2003]. On a related note, Benveniste, et al [2003] show that a firm's decision to complete or withdraw an IPO as well as the terms of the offering is a function of the filing experiences of their industry peers [i.e. indirect feedback].

Clearly, the majority of prior studies on the long-run performance of new issues of common stock have mainly focussed on the impact of firm and offering characteristics on this stage of the life of these firms. The most researched variables in the literature have been size, underwriter reputation, IPO risk, pre-IPO performance, IPO market condition, age, venture capital, corporate governance, initial returns/under-pricing,

[98] Access to equity markets can also be accomplished through a takeover by a listed company [Brau, et al, 2003].

market-to-book ratio and earnings management. In general, these variables have been found to be significantly related to the after-market performance of new issues. However, apart from the works of Simutin [2009], Dong and Michel [2011] and Jain and Kini [2006], none has studied the relationship between industry structure variables and IPO long-run performance.

Given that this aspect of the IPO literature has been greatly under-examined in the literature and having also tracked the performance of these new issues relative to a similar set of firms with fairly similar risk profiles in the first empirical study, the second part of this work now seeks to ascertain whether potential IPO investors can use ex-ante industry information available prior to or at the offering date to foreshadow the performance of the firms in the long-run to enable them make more informed decisions on whether or not to invest in the offering. Since the focus of this second empirical study is on industry, a limited range of the variables that have been shown to be germane to the after-market performance of new listings is pre-selected as control variables in the empirical design. In this regard, size related variables of offer price, offer proceeds, market capitalization, total assets and market value as well as performance related variables of profit margin, return on assets and earnings yield are considered. The IPO market condition, firm leverage, firm age, market-to-book ratio, underwriter prestige, initial returns and IPO firm risk are also included. These are the variables which the majority of the previous studies have shown to be the most important in the assessment of the long-run performance of IPOs. Venture capital backing is not included because the author believes that the underwriter prestige variable provides an adequate proxy and effectively captures the role and impact of expert informational intermediaries on the long-run performance of IPOs. Earnings management, analyst recommendations and corporate governance characteristics are also excluded, as they are outside the scope of this work. The discussion of all the choice variables, which also include the selected industry conditioning risk factors, will be conducted in Section 4.3.2.

[4.2.3] Research Questions and Hypotheses

The literature on the impact of industry conditions at the time of the IPO on the post-issue performance of new issues of common stock is still shallow. Clearly from the previous section, the studies have been few and far between. Simutin [2009], Dong and Michel [2011] and Jain and Kini [2006] respectively study the ratio of the issue price to the average industry price, the growth prospects of the industry and industry clustering of IPOs on the long-run performance of new issues of common stock.

Access to capital markets depends on the state of the economy as well as market and industry conditions at the time the firm is ready to conduct the initial offering. On the one hand, if these conditions are not conducive around the time that the firm intends to go public, it may be very challenging to complete a successful offering. On the other hand, if the economic and industry conditions are right, the firm could effortlessly conduct a fruitful IPO that affords it the opportunity to raise sufficient funds to meet its growth and expansion needs that ultimately puts it a step ahead of its industry rivals. Against this backdrop, the success of an IPO and by extension, the subsequent after-market performance and survival of the firm very much depends on market timing in terms of whether it launches the IPO in strong market and industry conditions. It is important to note that the aim of the issuing firm and its investment banker is to locate an auspicious market and industry window to launch the IPO before the window is shut. If the window closes before the IPO takes place which is quite possible given that the IPO process typically takes between six to nine months to complete, then the issuing firm and its underwriter would have no other option but to withdraw the offering and re-launch at a more propitious date. The consequences of proceeding with the offering under these conditions could be damaging not only to the subsequent after-market performance and survival of the firm in the market place but also to the reputation of the investment banker given that they do not want to be associated with failed offerings. Hence, industry conditions prevailing at the time of the IPO could be germane to the post-listing performance and survival of new issues of common stock.

Against this backdrop, the goal of this second empirical study is to identify other salient industry conditioning risk factors prior to or at the IPO that can explain and/or predict the long-run performance of IPOs, using the works of Simutin [2009], Dong and Michel [2011] and Jain and Kini [2006] as a springboard. In this regard, this second study firstly, asks whether an industry-adjusted valuation of an IPO can foreshadow its long-run performance. Purnanandam and Swaminathan [2004], Chang, et al [2010], Corhay, et al [2002] and Xia and Wang [2003] all show that IPO valuation at the listing date could presage its long-term performance. The valuation of new listings is intriguing on at least two grounds. Firstly, Zheng [2007] avers that valuing IPOs based on accounting data is spurious[99] and secondly, Hawawini, et al [2003] posit that valuation levels and growth expectations may vary significantly between different industries, which are exacerbated during major IPO clusters. The author overcomes these challenges by using a similar technique used by Berger and Ofek [1995] to compute an industry-adjusted valuation of the IPO firms to enable us to determine those trading at a 'premium' or 'discount'.

Secondly, this second study investigates whether an IPO firm's industry concentration has any sort of impact on the long-run performance of these new issues. It is generally

[99] Zheng [2007] argues that investors' expectations, in general, is that IPO firms will increase their key performance indices after the IPO event and since these expectations are impounded in the stock prices of these firms at the time of the offer, it invariably follows that their market capitalization should, on average, be higher than that of their industry rivals with the same accounting data in the pre-IPO year.

accepted that the extent of an industry's concentration is likely to be influential in determining the demand for capital, investors' optimism and the extent of industry IPO activity[100]. Furthermore, it is also germane to the choice between IPO versus takeover as a means of raising equity capital [Brau, et al, 2003; Audretsch, 1995; Sharma and Kesner, 1996]. In less concentrated industries, it is unlikely that a dominant player has emerged which provides a good avenue for new entrants into the industry to deploy their equity capital more productively. Conversely, in highly concentrated industries which tend to be less competitive, there are fewer opportunities to deploy equity capital to maximum effect. Concentrated industries also tend to be characterised by less price and market-share wars, which provides a good platform for IPO firms, which are typically smaller, high growth firms, to spot lucrative niches overlooked by the dominant players. Furthermore, firms in the industry are more capable of warding off new entrants due to the high barriers to entry [Akhigbe, et al, 2006]. Conversely, firms issuing their IPOs in fragmented and less concentrated industries are more likely to use a greater portion of the IPO proceeds in forceful price and promotional wars, rather than value-maximising activities.

[100] The industrial economics literature has also emphasized the import of industry concentration as a measure of the extent of opportunity for complicity by firms in the industry [Hambrick and Lei, 1985].

Thirdly, this second empirical study inquires whether the relative valuation of an industry [i.e. market-to-book ratio] can help investors construct their investment opportunity sets as to which IPOs to select. It is well documented that firms could time their IPOs either after aggressive accounting accruals that creates a divergence between the reported earnings in the IPO year and the cashflows [Teoh, et al, 1998(a and b)] or when its own earnings and indeed valuation has peaked [Ritter, 1991; Jain and Kini, 1994]. In the same vein, poor quality firms could also time their IPOs when the valuations of comparable firms within the industry are at their peak, which makes equity issuance very attractive [Kim and Ritter, 1999; Loughran and Ritter, 2002; Lowry and Schwert, 2004; Pagano, et al, 1998; Rajan and Servaes, 2003]. During periods of strong investor sentiments towards an industry in response to sporadic increases in investment opportunities and an ensuing enormous demand for capital, many private firms and their investment bankers are tempted to choose comparables with high market-to-book multiples in their initial valuation of the IPOs when they want to go public [Jain and Kini, 2006; Kim and Ritter, 1999]. There are two opposing explanations for the relation between industry market-to-book ratio and the likelihood of going public [Pagano, et al, 1998]. The first explanation is in tandem with the views of Kim and Ritter [1999], Loughran and Ritter [2002], Lowry and Schwert [2004] and Rajan and Servaes [2003] that suggests that firms are motivated to go public to take advantage of their over-valuation in the market place by investors, which is consistent with the 'window of opportunity' hypothesis[101]. In the long-term, investors recognise the firm's true value and the share price and ensuing long-term returns plummet. Under the second explanation, a high industry market-to-book ratio may suggest that investors have high expectations of the future value of the firms based on the growth opportunities that abound in the industry which cause them to value the stocks highly. If these firms are to take advantage of these opportunities, they may then have to go public to raise the required amount of capital to finance the huge investment outlay. The expectation by investors is that these prices would be futher sustained to higher levels leading to positive stock returns in the long-term.

Fourthly, this second study examines whether an IPO firm's industry profit conditions can foreshadow its long-run performance. A firm can launch its IPO without any track record of sustained profitability, which consequently increases the adverse selection costs for investors as they have little or no information on the future prospects of these firms. Savvy investors can use an IPO firm's industry profit conditions to value firms going public and in the process reduce the information asymmetry and uncertainty

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[101] A 'window of opportunity' is defined as a period when issuers can raise equity capital on relatively favourable terms. However, there is a debate in the equity pricing literature as to what could be the reason for this. Bayless and Chaplinsky [1996] and Choe, et al [1993] argue that the window is due to time-varying asymmetric information, while Loughran and Ritter [1995] adduce this to investor over-optimism in the market place which leads to misevaluations of stock prices.

surrounding the firm's long-term prospects and by extension, the adverse selection costs they [i.e. the investors] may face at the IPO date. It is expected that investors' perceptions of the future prospects of these firms will be positively/[negatively] influenced by robust/[weak] industry profit conditions. Hence, investors' misevaluations and the level of under-pricing in the market-place should reduce as they pay higher for the offerings of these firms.

Fifthly, this second part of the work next asks whether investors can use the leverage of an IPO firm's industry to gauge the performance of the new issue in the long-term. Akhigbe, at al [2006] affirm that following the raising of additional capital which reduces the IPO firm's leverage ratio and in some cases actual debt burden when the IPO proceeds are used for debt repayment, the new firm could pose an increasing threat to rivals, which is accentuated in industries that are already less concentrated and highly leveraged.

Finally, the impact of the equity volatility of an IPO firm's industry on the future performance of new stock issues is investigated. If the volatility of an IPO firm's industry is a proxy for the riskiness of the industry, it is expected that this will increase the risk profile of each of the constituent firms in that industry. If this risk is priced sufficiently, then IPO firms from industries with high volatilities should earn higher returns in the long-term. On the other hand, higher risk could also imply a higher likelihood of poor performance in the long-term.

Following from the above, the second empirical study will provide answers to the following tricky questions:

- What are the industry characteristics of IPOs that under-perform?
- Can one foreshadow the performance of IPOs based on a battery of industry risk factors related to an adjusted firm valuation, market-to-book ratio, leverage, concentration, profitability and equity volatility at the IPO date?

Following from the research questions above, the central hypothesis under investigation in this second empirical study is presented below:

Hypothesis – [H_0]: Industry structure risk factors related to an adjusted IPO valuation [i.e.IPO surplus value], market-to-book ratio, profitability, leverage, concentration and equity volatility cannot foreshadow the long-run performance of IPOs.

[4.3] Methodology

[4.3.1] Applied Empirical Design

Sample segmentations and analysis of mean returns are first undertaken to give an insight as to the possible association and impact of these variables on long-run performance, before proceeding to conducting more detailed cross-sectional tests. Hence, in the first stage of the empirical analysis here, the sample is split into terciles to check for any general patterns. In the second stage, a regression based generalization of Jegadeesh and Karceski's [2004] robust version of the BHAR approach is introduced to establish the explanatory powers of these variables.

The BHAR approach is now generalised by forming an ordinary least squares [OLS] regression equation that regresses the BHAR $[BHAR_i]$, calculated from the first empirical study, on a set of $\mathcal{M}$ explanatory variables $[\mathcal{X}_{m,i}]$ as follows:

$$BHAR_i = \alpha + \sum_{m=1}^{M} \beta_m x_{m,i} + \mathcal{E}_i \quad \ldots\ldots\ldots \text{[4.1]}$$

In order to investigate the determinants of IPO long-run performance, several variants of equation [4.1] are estimated, using the IPO firm's 5-year BHAR with respect to an appropriately matched non-issuing firm as the dependent variable. Hence, in all regressions, the value-weighted BHAR calculated according to the fifth matching algorithm [M5] is used as the dependent variable[102]. The firm level independent variables are IPO market heat ['hot' and 'cold' dummy variables to be used as proxies], firm leverage [market leverage ratio to be used as measure] and earnings yield. The other variables are offer price, offer proceeds, market capitalization, total assets, market value, age, pre-IPO profit margin, pre-IPO return on assets, market-to-book ratio, underwriter prestige, initial returns and IPO firm risk. The industry level independent variables to be employed are those related to an adjusted IPO firm valuation [i.e. IPO surplus value], leverage, concentration, equity volatility, profitability and market-to-book ratio. These risk factors are each considered in the first instance, in isolation to determine their individual explanatory powers and in the second instance, in conjunction with other variables in a multivariate framework. Section 4.3.2 that follows this section provides the definitions and measurements of all the variables under consideration in this part of the study.

In the first of the univariate regressions, each firm's BHAR is regressed on its underwriter reputation variable. For the age variable, each firm's BHAR is regressed on its age variable in the second regression specification. In the third and fourth

[102] Using the M5 matching algorithm, IPO long-run returns have been benchmarked with the returns of control firms matched on size, market-to-book, pre-IPO performance, turnover growth and earnings yield. The study adopts the value-weighted 5-year M5-matched BHAR as the choice dependent variable as this is more representative of firstly, the risk-adjusted long-run performance of the IPO firm given that matching firms have been selected on the greatest possible range of factors and secondly, the long-run returns of the typical average investor in the market place.

regression specifications, the BHARs are regressed on the hot and cold dummy variables, with the variables taking the value of 1 for firms going public in hot and cold markets and 0 otherwise. In a fifth specification, the IPO firms' market leverage ratio is introduced as the explanatory variable in the regression.

In five following specifications, the size measures [offer price, offer proceeds, total assets, market capitalization and market value] are introduced as the explanatory variables in separate regressions as the study seeks to ascertain the impact of firm size on long-run performance. In three other specifications, the firms' pre-IPO performance measures [earnings yield, return on assets and profit margin] are considered as the explanatory variables in separate regressions as the study seeks to determine the impact of pre-IPO operating performance on long-run market performance. In three final firm specifications, the IPO firm's market-to-book ratio, initial return and risk [as measured by the volatility of the 30-day post-listing return] are presented as the explanatory variables. Finally, the study controls for all the firm level variables simultaneously in a multivariate framework by estimating a seventeenth regression specification.

The industry level variables earlier described in separate regressions are next introduced in order to determine the impact of an IPO firm's industry structure on its long-run performance. As such, in an eighteenth regression specification, the BHARs are regressed on the firms' industry-adjusted valuation measures [i.e IPO surplus value]. In a nineteenth specification, the firm's industry leverage is considered as the independent variable. What is the impact of an IPO firm's industry profitability on its long-run performance? This poser would be answered in a twentieth specification that introduces the industry profitability as the independent variable in the regression. In a twenty-first specification, the study seeks to determine the impact of an IPO firm's industry market-to-book ratio on its long-run performance. To accomplish this, the BHARs are regressed on the respective IPO firms' industry market-to-book ratios.

An IPO firm's industry concentration impact on its long-run performance will next be considered in a twenty-second specification that introduces the industry concentration proxy, the size-weighted Herfindahl index [HHI], as the independent variable in the regression. The relation between an IPO firm's industry equity volatility and its long-run performance will be examined in a twenty-third regression specification. The study controls for all the industry level variables simultaneously in a multivariate framework by estimating another regression specification. Finally, all the firm and industry level variables are controlled for simultaneously in a twenty-fifth and final regression framework.

[4.3.2] Variable Selection, Measurement and Expectations

Table 4.1 provides a summary of the definitions and measurements of all the variables that are under consideration in this second empirical study. The proxies for these variables, their measurements and envisaged relationship with IPO after-market performance [shown in brackets] are provided below:

IPO Market Heat {Hot (-); Cold (+)}: The hot and cold variables serve as proxies for IPO market heat, where hot_i and $cold_i$ are dummy variables set to 1 for firms going public in hot and cold markets respectively and 0 otherwise. The age at the IPO date, instead of the number of offerings and offer proceeds, serves as the study's most direct measure of market heat. The respective signs of the coefficients of these dummies would enable us to infer if the issue period has an impact on IPO long-run performance. IPOs issued in hot [cold] periods are expected to perform relatively worse [better] in the long-run [Ritter, 1991; Gompers and Lerner, 2003; Ritter and Welch, 2002] due to the overtly positive [modest] market sentiments at these times which tend to over-value [under-value] these firms unrealistically. Hence, the expected sign for the hot [cold] IPO dummy should be negative [positive].

Age (+): The age variable is calculated as $'Log\ (1 + age_{i,})'$, where age is calculated as the difference between the year of going public and the year of incorporation. Young firms tend to have very little trading history and are also less likely to be strong enough to withstand the vicissitudes of the industry and indeed the market place. Also, they tend to be uncertain about their future prospects and are also less likely to have the requisite managerial expertise to withstand the vagaries of the market place. For older firms, the age at the IPO date could also potentially reduce the uncertainty and adverse selection costs that may face investors due to the availability of several years of operating performance data. Hence, the long-run returns of younger firms is expected to be worse than that of their older counterparts [Ritter, 1991] and the sign of the coefficient estimate for the age variable to be positive.

Size (+): The offer price $[Price_{i,}]$, offer proceeds $[OP_{i,}]$, market capitalization $[ME_{i,}]$, market value $[MV_{i,}]$ and total assets $[TA_{i,}]$ serve as proxies for the size of the firm. The offer price is the price at which the IPO shares are sold to the public. For each firm, offer proceeds is computed as the total number of shares offered multiplied by the offer price. Market capitalization is based on the number of shares issued by each firm that comprises the amount offered and the amount retained by the old shareholders and is calculated as the total shares on issue multiplied by the market prices on the first listing day for all the IPO firms. Market value is computed as the sum of the market value of equity and the book value of debt [sum of short-term and long-term debt] in the year of the IPO. Large firms [with higher total assets, market capitalization and market value] which tend to have relatively higher offer prices and gross offer proceeds and also tend to be less risky are expected to perform better than smaller firms in the long-run [Ritter, 1991; Drobetz, et al, 2005]. If the coefficient estimates are positive and significant as expected, it would then indicate that large firms with relatively large IPOs perform better in the long-run.

Leverage (+): The market leverage ratio serves as a proxy for the firm's leverage where $[lev_{i,}]$ refers to the firm's market leverage by the end of year t. To compute debt, debt is identified as the sum of the book value of short-term debt and long-term debt. A firm's equity is identified as its market capitalization in year t. The leverage ratio is then the firm's debt divided by debt plus equity[103]. It has been argued that the presence of debt in the IPO firm's balance sheet prior to going public could potentially reduce the level of information asymmetry and ex-ante uncertainty of the firm as well as potential moral hazard costs to investors due to the supervision provided by debt holders. However, it is also a known fact that these benefits could be offset by increased financial distress costs that may arise from having too much debt. Eckbo and Norli [2005] also argue that a relatively low leverage ratio might be a vital factor in the under-performance of new stock issues as leverage has a *'turbo charging'* effect on the factor

[103] Welch [2004] explains why leverage based on the market value of equity, not book value of equity, is more relevant.

loadings in a multi-factor model. Against this backdrop, a positive relation between leverage and IPO long-run performance is predicted[104].

Pre-IPO Performance (+): Return on assets $[ROA_i]$, profit margin $[PM_i]$ and earnings yield $[EY_i]$ are used as proxies for the pre-IPO performance of the firms all as at year t-1 [earnings yield is computed in the year of the IPO]. For a given firm, earnings yield is the profit before tax scaled by the number of outstanding shares divided by the market price of the share of the firm in year t. The return on assets is computed as the profit before tax divided by the total assets, while profit margin is defined as the operating profit before tax divided by the total sales, all in year t-1. Investors' expectations of future superior earnings and cashflows are usually based on the operating performance and growth projections of these firms contained in the offer document prior to going public[105]. Highly profitable firms are generally seen to be less risky and should be less under-priced given that the ex-ante uncertainty level is reduced at the IPO date. Hence, IPOs with a stronger record of profitability at the time of the IPO are expected to exhibit superior performance in the long-term and as such, the coefficient estimates of the performance variables are expected to be positive.

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[104] It is important to note that the leverage of the IPO firm automatically reduces after the offering given that the firm now has a larger capital base. The leverage level can be further reduced if part of the IPO proceeds is used to rebalance the capital structure by repaying some or all of its debts.

[105] By and large, the value of any security in the market place is determined by investors' expectations of future earnings based on current operating performance.

Market-to-book ratio (-): The firm's market-to-book ratio, $[MTB_i]$ is calculated as the market capitalization divided by the book value of equity as at year t. Specifically, this study examines if the expectations of future earnings performance built into the prices of these firms at the time of their going public, reflected in their market-to-book values, has any impact on the after-market performance of these firms. If the coefficient estimate is positive [negative] and significant, it would then imply that IPOs with high market-to-book ratios perform better [worse] in the long-run than those with lower or modest market-to-book ratios. In line with the majority of the findings of previous studies that document an inverse relationship between market-to-book ratio and IPO long-run performance, the coefficient estimate of the market-to-book variable is expected to be negative.

Underwriter Reputation (+): The market share attributable to each underwriter in the sample period serves as the study's direct measure of the reputation of each of the 109 underwriters for this study. Using the technique of Megginson and Weiss [1991] and Beatty and Ritter [1986], an underwriter reputation variable $[UW_{i,}]$ is constructed for each of the sample IPOs based on the market shares of the underwriters that took them public. Market shares are computed as the proportion of total market gross offer proceeds attributable to each underwriter in the period. Prestigious investment banks cautiously hand-pick clients that tend to be less risky since they are very much concerned about losing their prized reputational capital garnered over the years [Johnson and Miller, 1988; Carter and Manaster, 1990; Carter, et al, 1998]. Hence, a positive relationship between underwriter reputation and IPO performance is expected, in line with the majority of previous studies. In the sample, rank 1 is assigned to the underwriter with the highest percentage of market share [tagged as the most prestigious underwriter], rank 2 to the next, and so on until rank 109, tagged as the least prestigious underwriter [see Panel F of Table 3.5, pp. 98]. Hence, the higher the numerical rank, the lower the prestige of the underwriter. Following from this, the coefficient estimate of the underwriter reputation variable is expected to be negative, which indicates a positive relationship to long-run performance.

Initial Returns (-): The firm's initial returns, $[IR_i]$ is the level of returns available in the immediate after-market to investors who subscribe to the offer at the IPO date. Initial return is computed as the sum of the daily returns from the 1st day of listing to the 30th day for each of the IPOs. If the coefficient estimate is negative [positive] and significant, it would signify that IPOs with high initial returns in the immediate after-market, 30 days post-listing, perform worse [better] in the long-run than those with lower or modest initial returns. If investors' valuations or expectations of the performance of IPO firms in the early after-market are not met in the long-run, then firms that have the most initial returns are expected to have the worst long-run performance. Hence, in line with De

Bondt and Thaler's [1985] overreaction hypothesis[106], a negative relationship between initial returns and long-term performance is expected.

IPO Risk (-): Following Ritter [1984] and Carter and Manaster [1990], the after-market standard deviation of the firm's daily return during the first 30-days post-listing, $[Risk_{i,}]$ is used to proxy for the riskiness of each IPO firm. If the coefficient estimate is negative [positive] and significant, it would then connote that IPOs with greater risk profiles perform worse [better] in the long-run than those with lower risk profiles. A higher early-market return volatility could proxy for the riskiness of the offering in the immediate after-market. Obviously, higher risk would imply a higher probability of under-performance in the long-term. Hence, a negative relationship between IPO risk and long-run performance is expected.

After controlling for these firm level risk factors, the study next considers whether the characteristics of an issuing firm's industry prior to or at the IPO can also determine and/or explain the performance of these firms[107].To explore these possibilities, industry conditions relating to an adjusted IPO firm valuation [IPO surplus value], leverage, equity volatility, profitability, concentration and market-to-book ratio are considered as

[106] Investors place too much emphasis on the short-term prospects of new equity issuances by over-projecting future earnings leading to high market prices and high initial returns; however, if these expectations are not met, the prices are downwardly adjusted leading to lower long-run returns.
[107] See Section 3.3.4, pp.128.

the author seeks to ascertain their predictive and explanatory powers in univariate and multivariate regressions. Equally-weighted industry-specific averages are constructed over all existing public firms within each IPO industry[108]. For an IPO issued in year t, these averages are based on data observed in each firm's fiscal year that ends in the twelve month period from year t-1 to t. The variables, their proxies and envisaged relationship to long-run performance [shown in brackets] are provided below:

IPO Surplus Value (-): A surplus value measure $[sval_i]$ which relates the natural logarithms of the firm's actual market value $[mv_i]$ to its industry and turnover-adjusted market value $\left[amv_i^j\right]$ proxies for an adjusted valuation for each IPO firm to be computed as follows:

$$sval_i = Ln[mv_i] - Ln\left[amv_i^j\right] \ldots\ldots\ldots [4.2]$$

$$amv_i^j = tover_i \times ave\,[mtt]_j \ldots\ldots\ldots [4.3]$$

where $tover_i$ denotes the turnover of firm i at the IPO date and $ave\,[mtt]_j$ refers to the average market-to-turnover ratio of all n firms which belong to the same industry j as

[108] Equal-weighting is used to compute the industry averages as this provides a simple and indicative measure of the value of that characteristic in that industry. A firm's industry is determined by standard industry classification [SIC] codes, as in the first empirical study, and is defined as that industry with at least four mature [age 7 years or more] firms.

firm i[109]. A negative [positive] value of the $[sval_i]$ measure implies that the firm trades at a discount [premium].

Valuation levels and growth expectations may vary significantly between different industries, which are exacerbated during major IPO clusters [Hawawini, 2003]. During these tense market conditions, investors' expectations of the future performance of these firms are high and as of a consequence, these firms are over-valued in the market place at the IPO date. If the coefficient estimate of the $[sval_i]$ variable is negative and significant as expected, it would then show that IPOs for which superb growth prospects are projected frequently may not manage to meet these lofty heights and may as a result perform worse than those for which growth expectations are more modest. Against this backdrop, the coefficient estimate of the surplus value variable is expected to be negative.

Industry Leverage (+): The market leverage ratio serves as a proxy for the industry leverage, where $[i\_lev_i]$ refers to the industry leverage for firm i as at the IPO date. To compute leverage, debt is identified as the sum of the book value of short-term debt and long-term debt. A firm's equity is identified as its market capitalization at the IPO date. The leverage ratio is then the equally-weighted average of each firm's debt

[109] The market value of a firm is computed as the sum of the market value of equity plus the book value of debt. The market-to-turnover ratio is then calculated as the market value of equity divided by the turnover of the firm.

divided by debt plus equity, over all existing public firms in a given industry for firm i in year t. If the coefficient estimate of this variable is positive [negative] and significant, it would then mean that IPO firms from industries with higher leverage perform better [worse] in the long-run than those from industries with low or modest leverage. Based on the findings of Akhigbe, at al [2006] that IPO firms, following the raising of additional capital, could potentially pose an increasing threat to rivals, which is accentuated in industries that are already less concentrated and highly leveraged, a positive relationship between the firm's industry leverage and its long-run performance is predicted and as such, a positive coefficient estimate is expected.

Industry Equity Volatility (-): This is the standard deviation of an industry's twelve monthly stock returns prior to the IPO date, computed as the equally-weighted average over all existing public firms from year t-1 to year t. Hence, $[i\_ev_i]$ refers to the industry equity volatility for firm i as at the IPO date. If the volatility of an IPO firm's industry is a proxy for the riskiness of the industry, then IPO firms from industries with high volatilities should earn higher returns if this risk is priced sufficiently. On the flip side, the higher risk could also imply a higher likelihood of poor market performance in the long-term. This second study leans towards the latter argument and predicts a negative relationship between an IPO firm's industry equity volatility and its long-run performance and as such, expects the coefficient estimate of the equity volatility variable to be negative.

Industry Profitability (+): Profitability is the ratio of net operating income [defined by profit before tax] divided by turnover for each firm in year t-1. An industry's profitability ratio is the equally-weighted average over all existing public firms in a given industry in year t-1. Hence, [i_pr_i] refers to the industry profitability for firm i as at the IPO date. It is a generally accepted fact that investors' perceptions of the future prospects of IPO firms are positively/[negatively] influenced by robust/[weak] industry profit conditions. Against this backdrop, the study predicts a positive relation between industry profitability and IPO long-run performance and as such, expects the coefficient estimate of the industry profitability variable to be positive.

Industry Concentration (+): Industry concentration is computed as the Herfindahl Index [sum of squared market shares of existing firms], where each firm's market share is its market capitalization divided by the total market capitalization of all existing public firms in the given IPO firm's industry in year t. Hence, [i_conc_i] refers to the size-weighted industry concentration for firm i as at the IPO date. If the coefficient estimate of this variable is negative [positive] and significant, it would invariably signify that IPO firms from industries with a higher level of concentration perform worse [better] in the long-run than those from industries with a low or modest level of concentration. The relationship between industry concentration and post-IPO performance is ambiguous. However, this second work leans towards the argument that concentrated industries can provide IPO firms with a more favourable environment to operate and as a result, expects the coefficient estimate of the Herfindahl index variable to be positive.

Industry Market-to-book (-): The industry market-to-book is calculated as the equally-weighted average of the market capitalisation divided by the book value of equity over all existing public firms in a given firm's industry in year t-1. Hence, $[i\_mtb_i]$ refers to the industry market-to-book ratio for firm i as at the IPO date. If the coefficient estimate of this variable is positive [negative] and significant, it would lead us to infer that IPO firms from industries with higher market-to-book ratios perform better [worse] in the long-run than those from industries with low or modest market-to-book ratios. This study leans towards the view that suggests that firms are motivated to go public to take advantage of investor over-valuations in the market place, in line with the 'window of opportunity' hypothesis, which is subsequently corrected in the long-term as information on their true values begin to filter into the market. Following from this, the coefficient estimate of the industry market-to-book variable is expected to be negative.

TABLE 4.1: DESCRIPTION & MEASUREMENT OF VARIABLES

Variable	Description	Measure
$Price_i$	Offer Price	Natural Log of the Offer Price, in year t
OP_i	Offer Proceeds	Natural Log of Offered Shares × share price, in year t
$\mathcal{Log}[1 + age_i]$	Age[110]	Natural Log of [1 + Age], where age is the year [t] of going public less year of incorporation
ME_i	Market Capitalization	Natural Log of Outstanding shares[111] × share price, in year t
TA_i	Total Assets	Natural Log of Total Assets, in year t
MTB_i	Market-to-Book	Market Equity [ME] divided by Book Equity [BE], in year t
PIP_i	Pre-IPO Profit Margin	Operating profit before tax divided by total sales, in year t-1
ROA_i	Pre-IPO Return on Assets	Operating profit before tax divided by total assets, in year t-1
EY_i	Earnings Yield	Earnings per share [Operating profit before tax/Outstanding shares]/share price, in year t
lev_i	Market Leverage	Book Debt [BD] divided by Sum of {Book Debt [BD] + Market Equity [ME]}, in year t
hot_i & $cold_i$	Market Heat	Dummy taking the value 1 for firms going public in hot and cold markets and 0 otherwise

[110] Given that some of the firms may be less than a year old at the IPO date, taking the logarithms would produce negative values. In order to avert this, the study adds 1 to the age.

[111] This is the number of shares issued by each firm comprising the amount on offer and amount retained by the old shareholders.

Table 4.1 - CONT'D		
UW_i	Underwriter Reputation	Gross proceeds for each underwriter divided by total proceeds for the sample period
mv_i	Market Value	Natural Log of Market Equity [ME] + Book Debt [BD], in year t
IR_i	Initial Returns	Sum of the daily returns for the first 30 days post-listing
$Risk_i$	IPO Firm Risk	Standard deviation of an IPO firm's daily returns during the 1^{st} 30 days post-listing.
$\text{Ave}\ [\text{mtt}]_j$	Market-to-turnover	Market Equity [ME] divided by the turnover averaged over all firms in a given industry, in year t
amv_i^j	Assigned Market Value	Firm turnover × Average market-to-turnover ratio
$sval_i$	Surplus Value	Natural Log of Actual Firm Market value [MV] less the Natural log of Assigned Market Value [AMV]
i_lev_i	Industry Leverage[112]	Book Debt [BD] divided by Sum of {Book Debt [BD] + Market Equity [ME]}, in year t
i_conc_i	Industry Concentration	Herfindahl Index [HHI], computed as the sum of firms' squared market shares in year t[113]
i_ev_i	Industry Equity Volatility	Standard deviation of an industry's twelve monthly stock returns, from year t-1 to t
i_pr_i	Industry Profitability	Profit before tax/turnover, in year t-1 averaged over all firms in a given industry
i_mtb_i	Industry Market-to-Book	Market Equity/Book Equity, in year t-1 averaged over all firms in a given industry

[112] The leverage as well as the other industry ratios are equally-weighted averages, over all existing public firms in a given industry for firm i, from year t-1 to year t.

[113] A firm's market share is its market capitalization divided by the total market capitalization of all existing public firms in the given IPO firm's industry.

[4.4] EMPIRICAL ANALYSIS

[4.4.1] Correlation Analysis

Table 4.2 presents the pairwise correlation coefficients between the firm and industry level variables for the sample of IPO firms. Panel A [B] reports the pairwise correlations between the firm [industry] level variables only, while Panel C presents the same across both sets of variables. For the firm risk factors, apart from the size measure variables, underwriter reputation, initial returns, market leverage and IPO risk, all the other variables are not highly correlated. Clearly from the table, all the size measures [i.e. offer price, offer proceeds, market equity, total assets and market value] are shown to be highly and positively correlated, which is not surprising giving the established fact in the literature that large firms tend to be associated with higher offer prices and offer proceeds. The high negative correlation between underwriter reputation and the size measures is an indication that more prestigious underwriters tend to be associated with large and more seasoned firms[114]. This is also due to the fact that prestigious investment bankers tend to certify less risky firms, which are generally large and seasoned firms, in order not to lose their hard-earned reputational capital. The high positive correlation between initial returns and IPO risk is also noted. This suggests

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[114] In this study, the most prestigious underwriter is assigned Rank 1, the next Rank 2 and so on until Rank 109 which denotes the least prestigious underwriter, hence the negative correlation between the underwriter prestige and size variables.

TABLE 4.2: PAIRWISE CORRELATION MATRIX OF FIRM & INDUSTRY RISK FACTORS FOR THE SAMPLE OF IPO FIRMS

The sample is 746 IPO firms that went public over the period January 1999 and December 2006 and 485 firms that went public over the period excluding the 'dotcom' years. The table reports the correlation coefficients between the firm and industry characteristics. The firm characteristics are the natural logarithms of the offer price [LP], age [LA], market value [LMV], underwriter reputation [LU], offer proceeds [LOP], market equity [LME] and total assets [LTA]. The others are market-to-book [MTB], profit margin [PM], return on assets [ROA], market leverage [Lev], earnings yield [EY], initial returns [IR] and IPO risk [Risk]. The industry characteristics are IPO surplus value [SV], profit margin [I_PM], leverage [I_Lev], market-to-book [I_MTB], concentration [I_Conc] and equity volatility [I_EV]. For the firm risk factors, the size measures [i.e. offer price, offer proceeds, market equity, total assets and market value] are shown to be highly correlated. The high positive correlation between the size measures and market leverage on the one hand and initial returns and IPO risk on the other hand is also noted. For the industry risk factors, the high correlation between leverage, concentration, market-to-book and equity volatility is equally noted.

FOR THE ENTIRE PERIOD

PANEL A – FIRM RISK FACTORS ONLY

	LTA	LME	LP	LOP	ROA	PM	LMV	LEV	MTB	EY	LU	LA	IR	Risk
Log TA [LTA]	1.00													
Log ME [LME]	0.77	1.00												
Log Price [LP]	0.63	0.69	1.00											
Log Proceeds [LOP]	0.80	0.82	0.74	1.00										
ROA	0.19	0.12	0.12	0.10	1.00									
Profit Margin [PM]	0.04	0.03	0.01	0.01	0.05	1.00								
Log MV [LMV]	0.81	0.99	0.69	0.83	0.13	0.03	1.00							
Mkt. Lev. [LEV]	0.45	0.10	0.11	0.22	0.08	0.07	0.20	1.00						
MTB	-0.04	0.20	0.12	0.11	0.04	0.01	0.19	-0.08	1.00					
Earnings Yield [EY]	0.18	0.23	0.13	0.10	0.38	0.11	0.23	0.07	0.03	1.00				

PANEL A CONT'D – FIRM RISK FACTORS ONLY

	LTA	LME	LP	LOP	ROA	PM	LMV	LEV	MTB	EY	LU	LA	IR	Risk
Log Reputation [LU]	-0.54	-0.57	-0.50	-0.64	-0.06	0.01	-0.58	-0.14	-0.07	-0.05	1.00			
Log [1+Age] [LA]	0.07	0.15	0.17	0.15	0.02	0.04	0.15	0.01	0.07	0.12	-0.13	1.00		
Initial Ret [IR]	0.00	0.16	-0.01	-0.03	-0.08	0.03	0.15	-0.10	0.07	0.11	0.04	-0.02	1.00	
IPO Risk [Risk]	-0.16	-0.06	-0.14	-0.14	-0.17	0.01	-0.07	-0.17	0.03	-0.10	0.13	-0.07	0.60	1.00

PANEL B - INDUSTRY RISK FACTORS ONLY

	SV	I_Lev	I_MTB	I_PM	I_Conc	I_EV
Surplus Val [SV]	1.00					
I_Leverage [I_Lev]	-0.09	1.00				
I_MTB	-0.18	-0.35	1.00			
I_Profitability [I_PM]	0.09	-0.07	0.17	1.00		
I_Concentration [I_Conc]	0.05	0.41	-0.15	-0.34	1.00	
I_Equity Vol. [I_EV]	0.01	-0.39	0.48	0.04	-0.10	1.00

PANEL C – FIRM AND INDUSTRY RISK FACTORS																				
	LTA	LME	LP	LOP	ROA	PM	LMV	LEV	MTB	EY	LU	LA	IR	Risk	SV	I_Lev	I_MTB	I_PM	I_Conc	I_EV
LTA	1.00																			
LME	0.77	1.00																		
LP	0.63	0.70	1.00																	
LOP	0.81	0.82	0.74	1.00																
ROA	0.18	0.09	0.11	0.08	1.00															
PM	0.05	0.02	-0.03	0.04	0.11	1.00														
LMV	0.81	0.99	0.70	0.83	0.09	0.02	1.00													
LEV	0.44	0.09	0.07	0.21	0.08	0.09	0.19	1.00												
MTB	-0.08	0.23	0.09	0.11	0.05	0.01	0.21	-0.11	1.00											
EY	0.18	0.21	0.12	0.09	0.39	0.13	0.22	0.07	0.03	1.00										
LU	-0.54	-0.57	-0.48	-0.64	-0.03	0.00	-0.57	-0.14	-0.07	-0.05	1.00									
LA	0.06	0.13	0.13	0.12	-0.03	0.07	0.13	0.00	0.04	0.11	-0.09	1.00								
IR	-0.01	0.18	0.00	-0.02	-0.03	0.04	0.16	-0.10	0.12	0.14	0.05	-0.01	1.00							
Risk	-0.16	-0.04	-0.10	-0.11	-0.10	0.00	-0.05	-0.17	0.06	-0.10	0.11	-0.03	0.58	1.00						
SV	-0.16	0.14	0.02	-0.01	-0.16	-0.37	0.10	-0.33	0.15	-0.14	0.01	-0.09	0.11	0.21	1.00					
I_Lev	0.08	0.01	-0.07	-0.02	0.04	0.04	0.03	0.14	-0.07	0.05	0.05	-0.03	-0.09	-0.10	-0.06	1.00				
I_MTB	0.03	0.05	0.13	0.08	-0.02	0.05	0.05	-0.03	0.08	0.01	-0.07	0.08	0.09	0.08	-0.19	-0.35	1.00			
I_PM	-0.08	0.00	0.04	-0.01	-0.02	-0.04	0.00	-0.07	0.11	-0.04	0.01	0.02	0.07	0.12	0.09	-0.06	0.15	1.00		
I_Conc	0.10	0.07	-0.02	0.02	0.03	0.03	0.08	0.10	0.00	0.05	0.05	-0.05	0.00	0.05	0.06	0.42	-0.14	-0.34	1.00	
I_EV	-0.02	0.07	0.18	0.14	-0.03	0.00	0.06	-0.17	0.12	-0.08	-0.08	0.02	0.10	0.23	0.01	-0.39	0.47	0.04	-0.09	1.00

that IPO firms with the most initial returns in the immediate after-market generally tend to exhibit greater after-market return volatility. The table also reveals the relatively high positive correlation between the size measures and market leverage, which suggests that larger and more seasoned IPO firms tend to be associated with higher levels of market leverage. This is against the backdrop of the fact that given the size of these firms, they are better positioned to undertake higher levels of leverage.

For the industry risk factors, leverage, concentration, market-to-book and equity volatility are shown to be relatively highly correlated. The negative correlation between these factors indicates that industries with higher leverage tend to have lower market-to-book and equity volatilities. The positive correlation between market-to-book and equity volatility, on the one hand and the negative correlation between profitability and concentration, on the other hand are also observed. These coefficients signify that industries with higher market-to-book multiples tend to have higher equity volatilities, while industries with lower profitability tend to be less concentrated.

The empirical results from the range of approaches employed in assessing the survivorship of the IPO sample in this third and final study arew next presented. However, before this, the distribution of the initial and holding period returns for the sample by year, industry and IPO market condition is first analysed in the section that follows.

[4.4.2] Distribution of IPO Firms' Returns

Table 4.3 presents the distribution of the initial returns and long-term BHARs for the sample period going from 1999 to 2006 and the sub-period that excludes the technology bubble years [2002-2006] alongside some key offering characteristics. Panels A, B and D present the distribution for both periods by year, industry and IPO market condition respectively, while Panel C presents the distribution by industry exclusively for the sub-period going from 2002 to 2006. This section commences with an analysis for the whole period before proceeding to see how this changes when the 'dotcom' years arte excluded.

Inspection of Panel A reveals that the sample shows clear evidence of clustering. For example, 545 of the 746 sample offers [73.06%] occurred in 2000 and the period going from 2004 to 2006. These years account for 61.53% [£16,619.16m of the £27,011.58m total] of the aggregate gross proceeds which seems to be consistent with the notion of 'hot' markets [Ritter, 1984]. On the basis of the number of the offerings, 2000, 2004 and 2005 seem to be clear contenders for a 'hot market' tag, while 2000, 2002 and 2006 are the candidates if the amount of gross proceeds is used, instead, as the 'hot market' indicator. Clearly, on the basis of the number of offerings and gross proceeds,

TABLE 4.3: DISTRIBUTION OF IPO FIRMS' INITIAL & HOLDING PERIOD ABNORMAL RETURNS ALONGSIDE KEY OFFERING CHARACTERISTICS

The sample is 746 IPOs that went public between January 1999 and December 2006 and 485 IPOs for the sub-period excluding the 'dotcom' years [1999 – 2001], going from January 2002 to December 2006. In Panel A, IPO firms' initial and 5-year value-weighted long-run BHARs are categorized by year, while in Panels B and C, they are categorized by industry. Panel D presents the distribution by the IPO market condition. The average 30-day returns and the value-weighted long-run BHARs, calculated using the 5^{th} matching algorithm [M5] as the benchmark, represent the initial and holding period returns of the IPO firms. The initial returns are calculated for the immediate after-market, going from the first listing day of the IPOs to the 30^{th} day, while the long-run returns have been computed from the second month of trading following the listing day till the fifth anniversary of each of the IPOs. The penultimate and last rows in Panels A, B and C report the averages for the age, initial returns and BHARs for the overall sample period and the sub-period excluding the 'dotcom' years. These rows also report the totals for the number of IPOs and the gross offer proceeds for both periods.

Panel A: By year

Year	No of IPOs	Av Age [Yrs.]	Gross Proc. [£]	Initial returns [%]	BHAR [%]
1999	48	2.44	2,838.06	38.69	-30.55
2000	150	2.58	6,685.24	5.87	-13.44
2001	63	3.38	1,487.08	0.48	47.51
2002	50	4.99	3,932.43	1.92	-136.75
2003	40	3.84	2,134.85	8.88	43.27
2004	138	3.11	2,679.68	13.05	-57.65
2005	152	2.44	3,355.98	10.73	-43.28
2006	105	2.74	3,898.26	18.46	-7.74
1999-2006	**746**	**2.96**	**27,011.58**	**14.89**	**-11.30**
2002-2006	**485**	**3.06**	**16,001.20**	**9.81**	**-6.92**

Panel B: By industry – For the entire period

Industry	No of IPOs	Initial returns [%]	BHAR [%]
Aerospace & Automobiles	6	36.11	-89.21
IT & Computer Services	154	29.20	-49.18
Health & Pharmaceuticals	79	12.38	-13.71
Food Producers & Processors	14	9.27	-29.23
Personal Care & Household Goods	18	9.17	-67.70
Leisure, Hotels & Restaurants	64	16.98	52.09
Chemicals, Mining, Oil & Gas	130	12.68	28.56

Panel B: By industry [Cont'd]

Industry	No of IPOs	Initial returns [%]	BHAR [%]
Construction, Engineering & Electrical	58	13.89	-30.23
Wholesalers & Retailers	27	3.06	-7.26
Media & Entertainment	79	12.10	-41.09
Telecommunications	23	21.65	-43.91
Transport	10	18.95	-93.09
Support Services	84	11.37	27.82
Overall [1999-2006]	**746**	**14.89**	**-11.30**

Panel C: By industry: 2002 – 2006 [Ex. the 'dotcom' years]

Industry	No of IPOs	Initial returns [%]	BHAR [%]
Aerospace & Automobiles	5	5.72	-34.40
IT & Computer Services	69	16.09	-19.98
Health & Pharmaceuticals	57	13.51	-8.85
Food Producers & Processors	12	2.96	-167.94
Personal Care & Household Goods	13	1.58	-48.70
Leisure, Hotels & Restaurants	32	6.10	74.48
Chemicals, Mining, Oil & Gas	118	12.48	31.56
Construction, Engineering & Electrical	46	13.92	-33.73
Wholesalers & Retailers	14	-1.57	39.12
Media & Entertainment	46	10.37	-80.96
Telecommunications	15	10.58	14.50
Transport	5	35.37	-32.29
Support Services	53	8.49	22.94
Overall [2002-2006]	**485**	**9.81**	**-6.92**

Panel D: By IPO market condition				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Initial Ret [%]	BHAR [%]	Initial Ret [%]	BHAR [%]
Hot Market IPOs	19.44	-28.46	12.30	-28.33
Neutral Market IPOs	8.83	-28.64	7.61	-57.65
Cold Market IPOs	6.35	88.90	-4.18	98.07
Difference [Hot – Cold]	13.09 *[3.77***]*	-117.36 *[-7.75***]*	16.48 *[5.45***]*	-126.39 *[-7.37***]*

only 2000 is a hot market, while the choice of 2002, 2004, 2005 and 2006 as 'hot markets' is not so clear-cut. In the same vein, 1999, 2002 and 2003 seem to be clear favourites for a 'cold market' tag on the basis of the number of the offerings, while 2001, 2003 and 2004 are the front-runners if the amount of gross proceeds is used as the 'cold market' indicator. Clearly, on the basis of the number of offerings and gross proceeds, only 2003 is a cold market, while the choice of 1999, 2001, 2002 and 2004 as 'cold markets' is not so unambiguous. In order to overcome the challenge of categorising the years, the age of the firms as of the IPO dates is next examined to see if it can be adopted as the 'hot market' indicator[115]. Clearly, from the same Panel A, the average age of the IPO firms is lowest in 1999, 2000 and 2005 and highest in 2001,

[115] In a booming IPO market, there is a temptation for firms to float their IPOs to take advantage of high market prices occasioned by this market wave. This eventually leads to a situation where a great majority of weak and marginal firms float their offerings within a few years of their start-up. Peristiani and Hong [2004] show that with the 'dotcom' explosion of the late 1990s, the average age of an IPO firm dropped significantly from around seven years to about four years. Against this backdrop, the average age of the IPOs [measured from incorporation date to IPO date] will serve as the most direct measure of market heat.

2002 and 2003. Against this backdrop, 1999, 2000 and 2005 are considered as 'hot market' years, 2001, 2002 and 2003 as 'cold market' years, while 2004 and 2006 are dubbed 'neutral market' years. Following from this, IPOs in the 'hot market' years are tagged 'hot' IPOs, those in the 'cold market' years 'cold' IPOs, while those in the 'neutral market' years are dubbed 'neutral' IPOs.

Over the entire period, a wide variation in the initial and holding period returns is observed. The initial [holding period] returns by year range from 0.48% to 38.69% [-136.75% to 47.51%] respectively. The market for new issues has been known to go through 'cycles'. It is a generally accepted fact that buoyant economic conditions and rising investors' over-optimism in the market place raise the equilibrium prices at which a fixed cohort of firms can float their offerings to the public. These high market prices may become irresistible to many firms [both good and 'poor quality'] as they may decide to go public. If indeed this is the case, it is likely that IPOs issued during 'hot' market periods will perform worse than those issued in 'cold' market periods.

The results from the first two columns in Panel D for the whole period seem to support the conjecture that 'cold' IPOs should record less under-performance relative to the 'hot' IPOs. After 60 months, the long-run BHAR is -28.46% for 'hot' issues and 88.90% for 'cold' issues, suggesting that the 'cold' IPOs actually out-perform the benchmarks for the period in review. The difference in the holding period returns between the 'hot' and 'cold' IPOs is significant at the 1% level, which seems to be consistent with the evidence that firms time their IPOs either after aggressive accounting accruals that creates a divergence between the reported earnings in the IPO year and the cashflows [Teoh, et al, 1998(a and b)] or when its own earnings and indeed valuation has peaked [Ritter, 1991; Jain and Kini, 1994]. In some other cases, they could time the IPOs when the valuations of comparable firms within the industry are its peak thus making equity issuance very attractive [Kim and Ritter, 1999; Loughran and Ritter, 2002; Lowry and Schwert, 2004; Pagano, et al, 1998; Rajan and Servaes, 2003]. The results are not different when the sub-period that excludes the 'dotcom' years are excluded[116]. From the 3rd and 4th columns in Panel D, the 5-year long-run BHAR is -28.33% and 98.07% for 'hot' and 'cold' issues respectively. The difference in the holding period returns between the 'hot' and 'cold' IPOs remains significant at the 1% level. The 'hot' IPOs also tend to exhibit significantly greater initial returns than the IPOs in the other market periods, which is in line with the majority of the evidence in the literature. Expectedly, the 'hot' IPOs have the greatest initial returns and most severe long-run under-performance, which is consistent with the 'fads' hypothesis of Aggarwal and Rivoli

[116] Excluding the 'dotcom' period [1999 – 2001] from the sample leads to a re-classification of the 'hot' and 'cold' periods. Under this re-classification, 2005 and 2006 represent the 'hot' period, 2002 and 2003, 'cold' period and 2004 'neutral' period.

[1990] and the ‘overreaction’ hypothesis of De Bondt and Thaler [1985 and 1989] that suggests the more extreme the initial price movement, the greater is the subsequent price adjustment in the long-term. It is also observed that for both periods, the BHAR results for the ‘neutral’ market IPOs are more negative than those for the ‘hot’ market IPOs which is strange and difficult to explain. This abnormality may partly reflect the difficulty in the initial categorisation of the markets as ‘hot’ or ‘cold’.

When the sample is segmented by industry as shown in Panel B, a wide variation in the long-run performance between the industries for the entire period is equally noticeable. For example, Leisure, Hotels & Restaurants; Chemicals, Mining, Oil & Gas and Support Services stand out as they out-perform the benchmark. The worst performing sectors are Transport, Aerospace & Automobiles and Personal Care & Household Goods, recording under-performances of 93.09%, 89.21% and 67.70% in that order. The IT & Computer Services sector, which was at the heart of the ‘dotcom’ bubble, is the fourth worst performer with an under-performance of 49.18%. The under-performance of IPOs is present in all but three of the thirteen industrial groupings.

There is a marked difference when the ‘dotcom’ years are excluded from the sample as shown in Panel C. An upturn in the performances of the Wholesalers & Retailers and Telecommunications sectors is observed as they join the group of out-performing sectors with 5-year long-run BHARs of 39.12% and 14.50% respectively. The worst performing sectors are now Food Producers & Processors [-167.94%], Media & Entertainment [-80.96%] and Personal Care & Household Goods [-48.70%] in that order. For this sub-period, the under-performance is present in all but five of the thirteen industrial groupings. Over both periods, it is observed that the sample sizes for some of the industries are small. From Panels B and C, the industries with low volume of IPOs [i.e. less than 30 IPOs] are Aerospace & Automobiles, Food Producers & Processors, Personal Care & Household Goods, Wholesalers & Retailers, Telecommunications and Transport. Hence, for these industries, the results must be interpreted with caution.

Overall, a widespread variation in the performances of the firms across the years, IPO market condition and industry is noticeable. The IPO performances across the different market conditions have already been analysed and the worse performance of the 'hot' IPOs was adduced to the fact that many 'poor quality' IPOs take advantage of the opportunity created by this tense market condition to float their offerings. When the true value of these firms is revealed to investors with the passage of time, their values are subsequently adjusted downwards. The disparity in the performance of these firms across industry classifications is of keen interest as this suggests that there may be some industry structure risk factors at play in the market place that determines the initial entry of these firms and their subsequent post-IPO performance. The task in the sections that follow is to explore these ex-ante industry risk factors in order to provide potential IPO investors with additional useful information, beyond that contained in the offer document, which they can use to distinguish firms that are likely to perform from those that are likely to under-perform at the offering stage of these firms.

[4.4.3] Firm and Industry Risk factors and IPO Performance

[4.4.3.1] Analysis of Mean Differences

Prior to conducting detailed regression tests to explore any significant relations between the risk factors and IPO long-run performance, the sample data is first partitioned to check for any general patterns. Table 4.4 presents the average 5-year post-IPO BHARs for the IPO sample grouped into terciles based on a battery of offering, firm and industry characteristics for the entire sample period [1999 – 2006] and the period excluding the technology bubble years [2002 – 2006]. The BHAR returns are equal to an IPO's actual 5-year raw return less the 5-year benchmark return of an appropriate matching firm, where matching has been based on the M5 algorithm as earlier defined in the first empirical study. This section commences with a preliminary analysis for the whole period before proceeding to see how this changes when the 'dotcom years are excluded from the sample.

TABLE 4.4: LONG-TERM ABNORMAL IPO RETURNS BY TERCILES

The sample is 746 IPO firms that went public over the period 1999 to 2006 and 485 firms for the sub-period excluding the 'dotcom' years [2002-2006]. The first 2 columns of the table reports mean values for the characteristics [the age, offering, size and underwriter reputation measures are in logarithms, while the profitability, leverage, market-to-book & industry risk factors are in ratios] and 5-year value-weighted long-run abnormal returns for each IPO tercile over the entire period, while the last 2 columns report the same for the sub-period excluding the 'dotcom' years. In Panels A and B, the firms are grouped into terciles based on a battery of firm and industry characteristics respectively. The reported characteristics are equally-weighted averages over all observations within each tercile. Long-run abnormal returns are computed using the BHAR metric, where an IPO firm's long-term returns are measured for 5 years starting in the 2nd month following listing. The BHAR returns are equal to an IPO's actual 5-year raw return less the 5-year benchmark return of an appropriate matching firm, where matching has been based on the M5 algorithm as earlier defined in the first empirical study. At the bottom of each panel, significance levels [t-stats] for the difference between an item's average in the first and third terciles are reported. ***, **, * indicate significance at the 1, 5 and 10% levels respectively.

PANEL A - FIRM & OFFERING CHARACTERISTICS

PANEL A1 – OFFER PRICE

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Offer Price [T1]	0.17	-20.57	0.14	-33.73
Tercile 2	0.76	-23.90	0.68	-26.08
Most Offer Price [T3]	2.02	-9.15	1.73	-3.29
Difference [T1 – T3]	-1.85	-11.42 *[-1.69*]*	-1.59	-30.44 *[-2.45**]*

PANEL A2 – OFFER PROCEEDS

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Offer Proceeds [T1]	1.55	-18.92	1.34	-11.10
Tercile 2	6.39	-27.46	5.88	-31.26
Most Offer Proceeds [T3]	100.56	-9.99	91.59	-5.16
Difference [T1 – T3]	-99.01	-8.93 [*-0.69*]	-90.25	-5.94 [*-0.36*]

PANEL A3 – MARKET CAPITALIZATION

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Sized [T1]	5.60	-55.39	5.52	-41.30
Tercile 2	23.00	-29.00	21.71	-18.58
Most Sized [T3]	400.36	-9.67	346.22	-5.64
Difference [T1 – T3]	-394.76	-45.72 *[-4.27***]*	-340.70	-35.66 *[-2.23**]*

PANEL A4 – TOTAL ASSETS				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Sized [T1]	2.06	-79.18	2.36	-91.48
Tercile 2	9.40	-69.04	10.30	-113.52
Most Sized [T3]	217.14	12.36	220.33	31.99
Difference [T1 – T3]	-215.08	-91.54 *[-7.27***]*	-217.97	-123.47 *[-7.81***]*

PANEL A5 – MARKET VALUE				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Sized [T1]	6.18	-53.86	6.23	-42.46
Tercile 2	24.95	-23.23	23.67	-11.41
Most Sized [T3]	466.41	-10.00	441.21	-6.05
Difference [T1 – T3]	-460.23	-43.86 *[-3.35***]*	-434.98	-36.41 *[-2.34**]*

PANEL A6 – PROFIT MARGIN [PM]				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Profitable [T1]	-16.64	-58.99	-15.96	-67.51
Tercile 2	-3.70	-42.40	-2.55	-48.01
Most Profitable [T3]	0.34	29.89	0.17	56.16
Difference [T1 – T3]	-16.98	-88.88 *[-7.56***]*	-16.13	-123.67 *[-9.58***]*

PANEL A7 – RETURN ON ASSET [ROA]				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Profitable [T1]	-2.85	-93.97	-3.95	-118.52
Tercile 2	-0.03	-19.55	-0.02	-3.99
Most Profitable [T3]	0.11	29.84	0.09	56.21
Difference [T1 – T3]	-2.96	-123.81 *[-9.23***]*	-4.04	-174.73 *[-10.73***]*

PANEL A8 – EARNINGS YIELD				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Profitable [T1]	-0.20	-50.28	-0.18	-36.69
Tercile 2	-0.01	-53.24	-0.01	-52.22
Most Profitable [T3]	0.06	42.57	0.07	59.81
Difference [T1 – T3]	-0.26	-92.85 *[-6.87***]*	-0.25	-96.50 *[-5.98***]*

PANEL A9 – AGE				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Youngest [T1]	0.22	-26.97	0.21	-36.32
Tercile 2	1.01	-32.11	0.94	-26.52
Oldest [T3]	7.76	18.75	8.01	30.54
Difference [T1 – T3]	-7.54	-45.72 *[-3.49***]*	-7.80	-66.86 *[-4.33***]*

PANEL A10 – MARKET-TO-BOOK [MTB]				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Market-to-Book [T1]	-3.56	-8.64	-1.64	-14.67
Tercile 2	3.28	12.44	3.01	18.80
Most Market-to-Book [T3]	28.48	-25.96	19.78	-16.39
Difference [T1 – T3]	-32.04	17.32 *[1.69*]*	-21.42	1.72 *[0.12]*

PANEL A11 – LEVERAGE				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Levered [T1]	0.00	-54.40	0.00	-74.30
Tercile 2	0.02	29.65	0.03	34.35
Most Levered [T3]	0.22	17.08	0.27	29.91
Difference [T1 – T3]	-0.22	-71.48 *[-6.54***]*	-0.27	-104.21 *[-8.28***]*

PANEL A12 – UNDERWRITER REPUTATION				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Most Prestigious [T1]	10.75	-9.17	11.02	-4.40
Tercile 2	27.08	-12.26	30.34	-15.16
Least Prestigious [T3]	65.74	-37.67	68.79	-30.44
Difference [T1 – T3]	-54.99	28.50 *[2.42**]*	-57.77	26.04 *[2.11**]*

PANEL A13 – INITIAL RETURNS				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Initial Returns [T1]	-0.18	-11.36	-0.13	12.71
Tercile 2	0.08	-17.76	0.07	0.17
Most Initial Returns [T3]	0.42	-4.66	0.32	-33.46
Difference [T1 – T3]	-0.60	-6.70 *[-0.51]*	-0.45	46.17 *[2.99***]*

PANEL A14 – IPO FIRM RISK				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Risky [T1]	0.01	-9.64	0.01	-9.64
Tercile 2	0.03	-7.24	0.03	-10.21
Most Risky [T3]	0.08	-20.94	0.06	10.42
Difference [T1 – T3]	-0.07	11.30 *[1.86*]*	-0.05	-20.06 *[-1.92*]*

PANEL B - INDUSTRY CHARACTERISTICS				
PANEL B1 – PROFITABILITY				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Profitable [T1]	-2.10	-24.45	-2.88	46.61
Tercile 2	0.00	18.69	-0.18	-72.69
Most Profitable [T3]	0.52	-21.28	0.27	26.37
Difference [T1 – T3]	-2.62	-3.17 *[-0.25]*	-3.15	20.24 *[1.90*]*

PANEL B2 – LEVERAGE

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Levered [T1]	0.09	-38.76	0.10	-3.49
Tercile 2	0.17	-5.66	0.18	-18.25
Most Levered [T3]	0.25	16.19	0.27	13.64
Difference [T1 – T3]	-0.16	-54.95 *[-4.77***]*	-0.17	-17.13 *[-1.77*]*

PANEL B3 – MARKET-TO-BOOK

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Market-to-Book [T1]	0.82	-4.40	0.71	46.17
Tercile 2	3.00	-22.34	2.48	-67.41
Most Market-to-Book [T3]	6.13	-6.95	5.95	22.69
Difference [T1 – T3]	-5.31	2.55 *[0.21]*	-5.24	23.48 *[1.83*]*

PANEL B4 – CONCENTRATION

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Concentrated [T1]	0.16	-12.86	0.15	-27.58
Tercile 2	0.22	-29.18	0.23	17.84
Most Concentrated [T3]	0.59	12.12	0.68	7.15
Difference [T1 – T3]	-0.43	-24.98 *[-2.04**]*	-0.53	-34.73 *[-2.29**]*

PANEL B5 – EQUITY VOLATILITY

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	BHAR [%]	Mean	BHAR [%]
Least Volatile [T1]	0.08	-37.74	0.07	-78.84
Tercile 2	0.12	26.28	0.11	61.77
Most Volatile [T3]	0.19	-17.60	0.15	1.84
Difference [T1 – T3]	-0.11	-20.14 *[-1.79*]*	-0.08	-80.68 *[-5.64***]*

PANEL B6 – IPO SURPLUS VALUE				
	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Mean	**BHAR [%]**	**Mean**	**BHAR [%]**
Least Surplus Value [T1]	-1.51	29.79	-1.51	44.19
Tercile 2	0.08	29.18	0.08	-0.34
Most Surplus Value [T3]	2.99	-55.13	2.99	-28.33
Difference [T1 – T3]	-4.50	84.92 *[5.58***]*	-4.50	72.52 *[4.04***]*

Panels A1–A5 categorise the IPO firms by offer price, offer proceeds, market capitalization, total assets and market value respectively. The size measures are expected to impinge positively on the IPO after-market performance given the fact that larger firms signal greater market confidence and stricter monitoring [Lamberto and Rath, 2008]. Also, larger firms with sizeable offerings tend to be linked with lower levels of uncertainty and are also generally less risky[117]. In the same vein, larger firms have better access to public equity markets, have a wider range of product lines and are also more likely to be backed by prestigious underwriters and venture capitalists. The results in Panels A1–A5 for the entire sample period tend to support this conjecture. Panel A1 shows that, after 60 months, the long-run BHAR is -20.57% for IPOs in the lowest offer price tercile and -9.15% for IPOs in the highest offer price tercile, implying that the latter out-performs the former by a significant 11.42% [t-stats: 1.69]. Similarly,

[117] A number of researchers have used offer size as a proxy for asymmetric information [Jegadeesh, et al 1993; Michaely and Shaw, 1994].

from Panel A2, IPOs in the highest offer proceeds tercile are found to out-perform their counterparts in the lowest proceeds tercile by 8.93% [t-stats: 0.69]; however, the difference is statistically insignificant. When the sample is segmented by market capitalization in Panel A3, it is observed that the average BHAR for IPOs in the lowest market capitalization tercile is -55.39% and -9.67% for IPOs in the highest market capitalization tercile, with the difference in the holding period return between the two groups significant at the 1% level. The results are similar when the sample is categorised by total assets and market value in Panels A4 and A5 respectively. IPOs in the highest total assets and market value terciles are found to out-perform their counterparts in the lowest terciles by a highly significant 91.54% [t-stats: 7.27] and 43.86% [t-stats: 3.35] respectively. All the size measure results seem to be consistent with the majority of the evidence in the literature that large firms with sizeable offerings perform better in the long-run. The sub-period results excluding the 'dotcom' years are similar.

Panels A6–A8 group the IPO firms by a range of performance measures spanning profit margin, return on assets [ROA] and earnings yield. These measures are expected to impinge positively on the post-listing market performance of the firms. Going by the findings of Singh and Whittington [1968], Geroski and Jacquemin [1988] and Machin and Van Reenen [1993], IPO firms, which are profitable prior to flotation, are expected to continue to exhibit superior operational and market performance post-listing. The results for the entire sample period tend to support this surmise. Panel A6 shows that, after 60 months, the long-run BHAR is -58.99% for IPOs in the least profit margin tercile and 29.89% for IPOs in the highest profit margin tercile, implying that the latter out-performs the former by a highly significant 88.88% [t-stats: 7.56]. Similarly, from Panel A7, IPOs in the highest ROA tercile are found to out-perform their counterparts in the lowest ROA tercile by a significant 123.81% [t-stats: 9.23]. When the sample is segmented by the earnings yield in Panel A8, it is observed that the average BHAR for IPOs in the lowest earnings yield tercile is -50.28% and 42.57% for IPOs in the highest earnings yield tercile. The high earnings yield IPOs out-perform their low earnings yield counterparts by a huge 92.85% [t-stats: 6.87], which is significant at the 1% level. All the profitability measure results seem to be consistent with the view that firms with the most profitable history prior to listing perform better in the long-term. The results are similar when the 'dotcom' years are excluded from the sample period.

Panel A9 categorises the IPO firms by age. A fledgling firm can launch its IPO without any track record of sustained profitability, which consequently increases the adverse selection costs for investors given the high information asymmetry that surrounds the IPO on the offering day. Conversely, older firms with several years of performance data are expected to be better placed to reduce the uncertainty around their IPOs[118]. Also, since older firms tend to be more established and less speculative with a more stable source of business, they are also expected to perform better in the long-term. The results from Panel A9 seem to support this supposition. After 60 months, the long-run BHAR is -26.97% for the youngest firms [tercile 1] and 18.75% for the oldest firms [tercile 3], with the latter out-performing the former by a highly significant 45.72% [t-stats: 3.49]. The results are consistent with those obtained from excluding the 'dotcom' years. An examination of Panel A10 shows that after 60 months, the holding period return for the IPO firms in the lowest and highest market-to-book terciles is -8.64% and -25.96% respectively, with the firms in the lowest market-to-book tercile out-performing their counterparts by 17.32% [t-stats: 1.69], which is significant at the 10% level. The results indeed show that investors may be overly optimistic about the future performance of IPO firms at the time of issuance and as such, willing to pay higher for the shares of these firms at the offering date; however, more often than not, these expectations are not met as these firms do not operate as well as they are expected to. Thus, investors are forced to revise their initial valuation downwards causing long-run returns to plummet. The result for the sub-period that excludes the technology bubble

[118] Ritter [1991], Jegadeesh, et al [1993], Hoe, et al [2001] and Hensler, et al [1997] use firm age at the IPO date as a proxy for the riskiness of the firm.

years is different, given that the difference in the returns between lowest and highest market-to-book terciles is insignificant [1.72%, t-stats: 0.12].

Panel A11 classifies the IPO firms by leverage. There are two competing views on the relation between leverage and firm performance. One view has it that the presence of leverage could potentially reduce the level of information asymmetry and ex-ante uncertainty around the firm as well as moral hazard costs to investors due to the supervision provided by debt holders. These positive indices are expected to improve the performance of the firm in the long-run. The other view contends that firms with a high level of leverage portend a higher risk since they have to pay a higher portion of their asset earnings to debt holders and as a result are expected to perform poorly in the long-term. The results from Panel A11 seem to be consistent with the former presumption. After 60 months, the holding period return for the least levered firms [tercile 1] is -54.40%, while that for the most levered firms [tercile 3] is 17.08%, with the difference in returns [71.48%, t-stats: 6.54] highly significant. Once again, the results for the sub-period that exclude the technology bubble years are similar.

The IPOs are next categorised by underwriter reputation in Panel A12. Carter and Manaster [1990] document an inverse association between the risk of the IPO firm and the reputation of the investment banker. Chemmanur and Fulghieri [1994] argue that prestigious investment banks gain reputation when they certify IPOs that perform better over the long-term and in order not to jeopardize their prized reputation capital, they tend to avoid smaller and riskier issues [Wolfe, et al, 1994]. After 60 months, the holding period returns for the IPO firms in the least and most prestigious underwriter reputation terciles are -37.67% and -9.17% respectively, with the latter out-performing the former by a significant 28.50% [t-stats: 2.42]. The results indeed show that the certification provided by top notch investment banks is germane to the market performance of new issues of common stock. The result for the sub-period that excludes the technology bubble years is also in line with this proposition.

From Panel A13, it is noticeable that the 5-year BHAR for IPO firms in the least initial returns group is -11.36% and -4.66% for those in the most initial returns category, which tends to imply an insignificant under-performance of the former by 6.70% [t-stats: 0.51]. However, the result for the sub-period that excludes the 'dotcom' years is in line with the 'window of opportunity' and De Bondt and Thaler's [1985] 'overreaction' hypotheses that suggest that investors exaggerate the future prospects of new issues and are willing to pay higher for the firms' stock in the immediate after-market; however, if these expectations are not met, they revise their initial valuation downwards, causing long-term returns to fall. Panel A14 partitions the IPO firms by risk, with the 30-day post-listing market return volatility serving as the proxy. At 60 months, the BHAR is

-9.64% for IPOs in the least risky group, and -20.94% for those in the most risky group. The difference in the holding period return between both groups is significant at the 10% level [11.30%; t-stats: 1.86]. There is an upturn in results when the 'dotcom' years are excluded. The long-term BHAR is -9.64% for IPOs in the least risky group, and 10.42% for those in the most risky group. The difference in the return between both groups is still significant at the 10% level [20.06%; t-stats: 1.92].

The industry structure variables are next examined. From Panel B1, after 60 months, it is observed that the long-run BHAR for IPOs in the least profitable industries [tercile 1] is -24.45% and -21.28% for those in the most profitabile industries [tercile 3]. The difference in the holding period return between both groups is not statistically significant [-3.17%; t-stats: -0.25]. However, when the 'dotcom' years arte excluded, a different picture emerges with the firms in the least profitable industries out-performing those in the most profitable industries by 20.24% [t-stats: 1.90], which is significant at the 10% level. Panel B2 groups the IPO firms by industry leverage. The 5-year BHAR is -38.76% for IPOs in the least levered group and 16.19% for those in the most levered group. The difference in the holding period return between both groups is highly significant [-54.95%; t-stats: -4.77]. This pattern is also evident in the sub-period excluding the 'dotcom' years, albeit at a lower level of significance [10%] as the difference in the long-term BHAR returns between both groups reduces to -17.13% [t-stats: 1.77]. Panel B3 categorises the IPO firms by industry market-to-book. At 60 months, the BHAR is -4.40% for IPOs in the lowest market-to-book group, and -6.95% for those in the highest market-to-book group. The difference in the holding period return between both groups is not significant even at the 10% level [2.55%; t-stats: 0.21]. However, when the 'dotcom' years are excluded, it is observed that firms from industries with the lowest market-to-book out-perform those in the highest market-to-book industries by a significant 23.48% [t-stats: 1.83], which is significant at the 10% level.

The industry concentration effect is next examined in Panel B4. The 5-year BHAR is -12.86% for IPOs in the least concentrated group and 12.12% for those in the most concentrated group. The difference in the holding period return between both groups is significant at the 5% level [-24.98%; t-stats: -2.04]. The results are similar when the 'dotcom' years are excluded. The findings seem to be in tandem with the view that concentrated industries tend to be characterised by less price and market-share wars, which provide a good platform for IPO firms, which are typically smaller, high growth firms, to spot lucrative niches overlooked by the dominant players. The IPO firms are next grouped by industry equity volatility as shown in Panel B5. After 60 months, the BHAR is -37.74% for IPOs in the least equity volatility group and -17.60% for those in the most equity volatility group. The difference in the holding period return between both groups is significant at the 10% level [-20.14%; t-stats: -1.79]. This pattern is also evident in the sub-period excluding the 'dotcom' years, albeit at a higher level of significance [1%] as the difference in the long-term returns between both groups increases to -80.68% [t-stats: -5.64].

Finally, the IPO firms are categorised by an industry-adjusted valuation measure in Panel B6, with the IPO firm surplus value serving as the maesure. Firms with the least surplus value, comprising mainly firms trading at a discount relative to industry peers, are grouped in the first tercile, while firms with the most surplus value, composed of firms trading above their industry-adjusted valuations [i.e. trading at a premium relative to industry peers] are grouped in the third tercile. At 60 months, the BHAR is 29.79% for IPOs in the least surplus value group and -55.13% for those in the most surplus value group. The difference in the holding period return between both groups is highly significant [84.92%; t-stats: 5.58] indicating that IPO firms that trade above their industry-adjusted valuations under-perform those with relatively modest valuations. The results are similar when the 'dotcom' period is excluded from the analysis, as the difference in the long-term returns between both groups remains significant at the 1% level [72.52%; t-stats: 4.04]. Overall, some of the results change when the 'dotcom' period is excluded. More specifically, an upturn in the results for the firm level variables of market-to-book value and initial returns and the industry structure variables of profitability and market-to-book is observed which tends to suggest that the ‘dotcom’ period is driving some of the results.

Thus far, these segmentations have been conducted in order to profile the characteristics of the IPO firms to enable the author to determine firstly, the characteristics of the best and worst performing firms and secondly, if these differences are significant. However, it does not tell us the nature of the relationship of these variables to long-term performance. In the sections that follow, the exact nature of these relationships are explored in univariate and multivariate regression frameworks.

[4.4.3.2] Univariate Regression Analysis

Having garnered an insight into the plausible nature of the relationship of the selected variables to IPO long-term performance, this section performs OLS regression analysis to provide a clearer picture of the nature of these relationships. Table 4.5 reports the univariate regression results of OLS regressions of IPO long-run performance using the 5-year value-weighted M5-matched BHAR as the dependent variable for the sample and a host of firm and industry risk factors as separate explanatory variables. Panel A reports the results for the firm risk factors, while Panel B presents the same for the industry risk factors. The regressions are for a sample of IPOs that went public between 1999 and 2006 and also for the sub-period excluding the ‘dotcom’ years. This

TABLE 4.5: RESULTS OF UNIVARIATE OLS REGRESSIONS OF IPO LONG-RUN PERFORMANCE

This table reports the coefficient estimates & t-values [in parentheses] of OLS regressions of IPO long-run performance using the 5-year value-weighted M5-matched BHAR as the dependent variable for the sample and a host of firm risk factors as the explanatory variables. The regressions are for a sample of IPOs that went public between 1999 and 2006 and also for the sub-period excluding the technology bubble period [2002 – 2006]. M5-matched BHAR returns are equal to an IPO's actual 5-year raw return less the 5-year benchmark return of an appropriate matching firm, where matching has been based on size, market-to-book ratio, pre-IPO performance, turnover growth & earnings yield. The explanatory variables are the natural logarithms of the offer price, market equity, market value, offer proceeds, [1+Age], underwriter reputation [UW] and total assets [TA]. The others are market-to-book [MTB], profit margin, return on asset [ROA], market leverage [Lev], earnings yield, hot and cold dummy variables, 30-day initial returns and IPO firm risk. Panel A reports univariate regression results for the firm risk factors, while Panel B presents the same for the industry risk factors. ***, **, * indicate significance at the 1, 5 & 10% levels respectively. The t-stats have been calculated using Davidson & Mackinnon [1993] robust standard errors.

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

	OVERALL [1999-2006]						2002-2006 [EX. 'DOTCOM' YEARS]					
	Intercept	t-stats	Slope	t-stats	R^2	No of Obs.	Intercept	t-stats	Slope	t-stats	R^2	No of Obs.
Log offer price	-0.5383	*[-6.25***]*	0.3462	*[3.22***]*	0.0102	746	-0.4845	*[-5.04***]*	0.4640	*[3.40***]*	0.0177	485
Log Proceeds	-0.6442	*[-5.91***]*	0.1393	*[3.85***]*	0.0188	746	-0.6137	*[-4.52***]*	0.1799	*[3.82***]*	0.0341	485
Log ME	-0.8012	*[-6.09***]*	0.1411	[4.31***]	0.0244	746	-0.6816	*[-4.21***]*	0.1388	*[3.23***]*	0.0249	485
Log TA	-0.7846	*[-7.58***]*	0.1800	*[5.66***]*	0.0375	746	-0.6860	*[-5.19***]*	0.1745	*[4.42***]*	0.0406	485
Log Mkt. Val	-0.8403	*[-6.24***]*	0.1487	*[4.54***]*	0.0277	746	-0.7257	*[-4.39***]*	0.1469	*[3.47***]*	0.0292	485
Profit Margin	-0.3431	*[-6.48***]*	-0.0005	*[-1.20]*	0.0002	740	-0.2379	*[-3.88***]*	-0.0003	*[-0.83]*	0.0001	482

PANEL A CONT'D – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY												
ROA	-0.3226	*[-6.09***]*	0.0044	*[0.25]*	0.0000	732	-0.2243	*[-3.60***]*	0.0026	*[0.11]*	0.0000	477
Earnings Yield	-0.3157	*[-5.89***]*	0.6123	*[2.49**]*	0.0079	736	-0.2269	*[-3.55***]*	0.5567	*[1.99**]*	0.0067	475
Log [1+Age]	-0.3757	*[-4.64***]*	0.0408	*[0.73]*	0.0006	746	-0.2607	*[-2.83***]*	0.0268	*[0.43]*	0.0003	485
Log UW	0.1411	*[0.90]*	-0.1497	*[-3.24***]*	0.0101	746	0.3482	*[1.99**]*	-0.1796	*[-3.57***]*	0.0175	485
MTB	-0.2965	*[-5.49***]*	-0.0021	*[-3.44***]*	0.0055	716	-0.2222	*[-3.51***]*	-0.0019	*[-1.67*]*	0.0028	471
Lev	-0.3865	*[-6.54***]*	0.6244	*[2.02**]*	0.0041	746	-0.3031	*[-4.28***]*	0.5840	*[1.86*]*	0.0053	481
Hot	-0.1724	*[-2.30**]*	-0.3517	*[-3.44***]*	0.0154	746	-0.1773	*[-2.16**]*	-0.1870	*[-1.74*]*	0.0042	485
Cold	-0.3637	*[-7.37***]*	0.1278	*[0.74]*	0.0013	746	-0.2217	*[-4.61***]*	-0.0768	*[-0.30]*	0.0005	485
Initial Ret	-0.3441	*[-5.99***]*	0.0337	*[0.16]*	0.0001	744	-0.2563	*[-3.54***]*	0.2070	*[0.70]*	0.0013	484
IPO Firm Risk	-0.1967	*[-2.30**]*	-3.4379	*[-2.04**]*	0.0100	744	-0.1812	*[-1.87*]*	-1.7070	*[-0.88]*	0.0013	484

PANEL B – REGRESSIONS INCLUDING THE INDUSTRY LEVEL VARIABLES ONLY												
	OVERALL [1999-2006]						2002-2006 [EX. 'DOTCOM' YEARS]					
	Intercept	t-stats	Slope	t-stats	R^2	No of Obs.	Intercept	t-stats	Slope	t-stats	R^2	No of Obs.
Surplus Value	-0.3167	*[-5.12***]*	-0.0013	*[-0.05]*	0.0000	746	-0.2250	*[-3.16***]*	-0.0110	*[-0.41]*	0.0003	485
I_Profit Margin	-0.3907	*[-6.82***]*	-0.1001	*[-3.35***]*	0.0127	746	-0.3048	*[-4.01***]*	-0.0740	*[-2.13**]*	0.0084	485
I_Leverage	-0.5220	*[-4.40***]*	1.0851	*[1.75*]*	0.0033	746	-0.2824	*[-2.18**]*	0.2573	*[0.42]*	0.0002	485
I_MTB	-0.3537	*[-4.27***]*	0.0049	*[0.23]*	0.0001	746	-0.2963	*[-3.19***]*	0.0206	*[0.85]*	0.0013	485
I_Concentration	-0.4072	*[-5.36***]*	0.2172	*[1.24]*	0.0014	746	-0.2918	*[-3.59***]*	0.1586	*[0.96]*	0.0011	485
I_Equity Volatility	-0.0658	*[-0.47]*	-2.1138	*[-2.08**]*	0.0060	746	-0.3249	*[-2.05**]*	0.8154	*[0.66]*	0.0007	485

section commences with an analysis for the whole period before proceeding to see how this changes when the 'dotcom' years are excluded[119].

In general, preliminary evidence from Panel A is in tandem with the sample segmentations and patterns conducted in the last section. The size measures [i.e. offer price, offer proceeds, market equity, total assets and market value] are all shown to be significantly positively related to IPO long-run performance. For the profitability measures [i.e. profit margin, return on assets, earnings yield], only earnings yield is shown to be significantly positively related to IPO long-run performance. The negative coefficient of the underwriter reputation variable, which indicates a positive relationship to IPO long-run performance[120], suggests that IPOs managed by more prestigious investment bankers tend to have better long-run performance than those underwritten by their less prestigious counterparts. In line with the sample segmentation results, the market-to-book factor is also shown to be significantly negatively associated with subsequent returns of new stock issues, which is generally in line with the majority of the evidence in the literature. In the same vein, the significant positive coefficient of the

[119] Expecting the presence of outliers and its potential impact on the results, the data is closely examined for any extremely large and small values ['outliers']. The examination indeed, reveals the presence of outliers, albeit, few and far between. In particular, these outliers are observed in the firm performance measures of profit margin, return on asset and earnings yield, which are all in ratios. They are also found in the market-to-book, initial returns and IPO firm risk variables. Hence, in the univariate tests that pertain to these variables in this section as well as in the multivariate frameworks, adjustments are made accordingly by excluding them from the regressions.

[120] See Section 4.3.2, pp. 220-221 and Panel F of Table 3.5, pp. 99.

market leverage variable tends to suggest that firms with higher market leverage tend to have better after-market performances which is in tandem with the view in the literature that a higher volume of debt in the capital structure could potentially reduce moral hazard costs to prospective investors and provide a good platform for the firm to improve its market performance.

The negative coefficient of the ‘hot’ market dummy indicates that IPOs issued in ‘hot’ market cycles perform significantly worse than those issued in ‘cold’ and ‘neutral’ markets. Moreover, the ‘cold’ market dummy is shown not to be significantly related to the subsequent stock performance of new stock issues. The 30-day post-listing market return volatility, a proxy for IPO firm risk, is also shown to be negatively associated with IPO long-run performance, suggesting that IPOs with a higher post-listing return volatility exhibit the worse long-run performance. The univariate tests also suggest that the age and initial return variables are not valuable in distinguishing between the best and worst performing IPO firms, given that the coefficients are not significant. By and large, the results are similar when the regressions are performed excluding the ‘dotcom’ years. The only exception is IPO firm risk which is now no longer significantly related to long-run performance.

Performing regressions using the whole sample period, the results from Panel B show that industry risk factors of profitability, leverage and equity volatility are valuable in distinguishing between the best and worst IPO performers, while IPO surplus value, market-to-book and concentration are shown to be insignificant. The negative value for the industry profitability variable lays credence to the fact that IPO firms from industries with higher profitability or better profit conditions perform worse in the long-run than those from industries with low or modest profitability, contrary to the author's expectations. It was expected that the robust profit conditions of an IPO firm's industry should help reduce the adverse selection costs facing investors as they build their investment opportunity sets, against the backdrop of the fact that not much is known about the IPO firms at their offering stages. However, the results may indicate that despite the fanciful industry conditions that may prevail at the IPO date, investors may have some reservations about the IPO firms which may make them not value these firms properly in the market place.

The positive sign of the industry leverage variable indicates generally that IPO firms from industries with a higher leverage perform better in the long-run than those from industries with a low or modest leverage, in line with the author's expectations. The results suggest that following the raising of additional capital which reduces an IPO firm's leverage ratio and in some cases actual debt burden when the offer proceeds are used to partially offset or fully repay any lingering debt burden, the IPO firm could then be a real competitive threat to rivals in an industry that is highly leveraged.

The negative sign of the industry equity volatility measure generally implies that IPO firms from industries with higher equity volatilities perform worse in the long-run than those from industries with low volatilities, in line with the author's expectations. The high equity volatility of an IPO firm's industry should increase the riskiness of the offering and the consequent likelihood of poor performance in the long-term. When the regressions are re-estimated excluding the 'dotcom' period, only the industry profitability measure is found to be significant amongst the raft of industry conditioning risk factors in predicting long-run IPO performance. Thus far, these variables have been studied in isolation in univariate frameworks to enable us to determine the nature of their relationships to IPO long-term performance. However, this process does not control for other germane variables that may be associated with this long-term performance. Hence, in the section that follows, the impact of these variables are examined in multivariate frameworks that control for these other variables.

[4.4.3.3] Multivariate Regression Analysis

Once again, using the 5-year BHARs as the dependent variable and the firm and industry risk factors as the independent variables, OLS regressions are conducted to determine their explanatory powers in a multivariate framework. In order to minimise the impact of cross-correlations and multicollinearity, the number of variables are limited in the regressions. This section of the study includes all relevant variables in the regressions and estimate several models that systematically exclude variables that are highly correlated as revealed by the correlation analysis performed in Section 4.4.1[121]. Table 4.6 reports the OLS regressions of IPO long-run performance using the 5-year value-weighted M5-matched BHAR as the dependent variable for the sample and a host of firm and industry risk factors as the explanatory variables. The regressions are for a sample of IPOs that went public between 1999 and 2006 and also for the sub-period excluding the 'dotcom' period [2002-2006]. The regressions are first estimated

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[121] This study adopts this approach, in line with the majority of the literature and amid a range of other procedures in the econometrics literature [e.g. variable transformation, which could make the error terms serially correlated and heteroscedastic and the use of orthogonal variables], since it is relatively easier and more straightforward. Moreover, this procedure is not harmful to the unbiasedness and efficiency of the parameter estimates [Gujarati, 2003]. The study's cut-off point for collinearity is 0.24. On a related note, the low explanatory power of the models, as captured by the coefficient of determination [i.e. R^2], is noted across the models. However, the author is not really concerned about this given that the intent of this study, and indeed other studies in the literature in this regard, is to determine the direction and significance of the relationship between the variables included in the models and long-term performance, as captured by the parameter estimates. The reported values for the R^2 are generally in line with the literature [Bhabra and Pettway, 2003; Gao, et al, 2006; Goergen, et al, 2007; Chan, et al, 2008; Thomadakis, 2010; Levis, 2011].

TABLE 4.6: RESULTS OF MULTIVARIATE OLS REGRESSIONS OF IPO LONG-RUN PERFORMANCE

This table reports the coefficient estimates & t-values [in parentheses] of OLS regressions of IPO long-run performance using the 5-year value-weighted M5-matched BHAR as the dependent variable for the sample and a host of firm risk factors as the explanatory variables. The regressions are for a sample of IPOs that went public between 1999 and 2006 and also for the sub-period excluding the technology bubble period [2002 – 2006]. M5-matched BHAR returns are equal to an IPO's actual 5-year raw return less the 5-year benchmark return of an appropriate matching firm, where matching has been based on size, market-to-book ratio, pre-IPO performance, turnover growth & earnings yield. The explanatory variables are the natural logarithms of the offer price, market equity, market value, offer proceeds, [1+Age], underwriter reputation [UW] and total assets [TA]. The others are market-to-book [MTB], profit margin, return on asset [ROA], market leverage [Lev], earnings yield, hot and cold dummy variables, 30-day initial returns and IPO firm risk. Panel A reports multivariate regression results for the firm risk factors, while Panel B presents the same for the industry risk factors. Panel C reports multivariate regression results for both the firm and industry risk factors.***, **, * indicate significance at the 1, 5 & 10% levels respectively. The t-stats have been calculated using Davidson & Mackinnon [1993] robust standard errors.

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

	OVERALL [1999 – 2006]		2002 – 2006 [EX. 'DOTCOM' YEARS]	
	Model 1	Model 2	Model 1	Model 2
Intercept	0.3731	-0.7202	0.5107	-0.8977
	[1.81]*	*[-4.13***]*	*[1.69*]*	*[-3.00***]*
Log Mkt. Val		0.1817		0.2299
		*[5.25***]*		*[4.27***]*
Earnings Yield	0.5224	0.3055	0.4531	0.1860
	*[2.26**]*	*[1.23]*	*[1.66*]*	*[0.66]*
Log [1+Age]	0.0288	0.0109	-0.0340	-0.0529
	[0.50]	*[0.20]*	*[-0.41]*	*[-0.68]*
Log UW	-0.1458		-0.1969	
	*[-3.19***]*		*[-3.15***]*	
MTB	-0.0023	-0.0032	-0.0052	-0.0085
	*[-3.86***]*	*[-5.20***]*	*[-1.17]*	*[-1.75*]*

PANEL A CONT'D – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY				
Lev	0.0970		0.1617	
	[0.24]		*[0.32]*	
Hot	-0.2990	-0.3714	-0.1531	-0.1452
	*[-2.81***]*	*[-3.68***]*	*[-1.06]*	*[-1.01]*
Initial Ret		-0.0671		0.3463
		[-0.32]		*[0.73]*
IPO Firm Risk	-1.7306		0.0543	
	[-1.02]		*[0.02]*	
R^2	**0.0437**	**0.0649**	**0.0332**	**0.0730**
No of Obs.	**701**	**701**	**440**	**440**

PANEL B – REGRESSIONS INCLUDING THE INDUSTRY LEVEL VARIABLES ONLY						
	OVERALL [1999 – 2006]			2002 – 2006 [EX. 'DOTCOM' YEARS]		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	-0.1299	-0.1529	-0.4550	-0.3511	-0.4342	-0.4838
	[-0.82]	*[-0.95]*	*[-1.96**]*	*[-2.20**]*	*[-2.62**]*	*[-2.11**]*
Surplus Value	0.0249	0.0110	0.0285	0.0073	-0.0026	0.0092
	[0.97]	*[0.44]*	*[1.10]*	*[0.28]*	*[-0.10]*	*[0.34]*
I_Profit Margin	-0.1679		-0.1590	-0.1695		-0.1643
	*[-3.66***]*		*[-3.98***]*	*[-2.76***]*		*[-3.20***]*
I_Leverage			1.1712			0.5769
			[1.45]			*[0.75]*
I_MTB	0.0775	0.0611	0.0865	0.0490	0.0375	0.0529
	*[2.85***]*	*[2.20**]*	*[3.02***]*	*[1.61]*	*[1.19]*	*[1.66*]*
I_Concentration	-0.1773	0.1989		-0.0629	0.3344	
	[-0.55]	*[0.64]*		*[-0.19]*	*[1.12]*	
I_Equity Volatility	-3.6892	-3.3717	-3.2424	-1.0758	-0.0148	-1.0024
	*[-3.04***]*	*[-2.72**]*	*[-2.64**]*	*[-0.80]*	*[-0.01]*	*[-0.74]*
R^2	**0.0337**	**0.0142**	**0.0358**	**0.0271**	**0.0066**	**0.0277**
No of Obs.	**746**	**746**	**746**	**485**	**485**	**485**

PANEL C – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES												
	OVERALL [1999-2006]						2002-2006 [EX. 'DOTCOM' YEARS]					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.4657	0.5090	0.2158	-0.6113	-0.6096	-0.8150	0.3572	0.3180	0.2727	-0.7269	-0.8714	-0.7719
	[1.80]*	*[1.98**]*	*[0.66]*	*[-2.58**]*	*[-2.55**]*	*[-2.60**]*	*[1.07]*	*[0.95]*	*[0.69]*	*[-2.14**]*	*[-2.39**]*	*[-1.87*]*
Log Mkt. Val				0.1978	0.2009	0.1929				0.1835	0.1945	0.1820
				*[5.06***]*	*[5.07***]*	*[4.97***]*				*[3.68***]*	*[3.76***]*	*[3.68***]*
Earnings Yield	0.4999	0.5003	0.4858	0.2322	0.2370	0.2212	0.5201	0.4937	0.5090	0.3442	0.3129	0.3279
	*[2.18**]*	*[2.18**]*	*[2.17**]*	*[0.98]*	*[1.00]*	*[0.93]*	*[1.75*]*	*[1.69*]*	*[1.74*]*	*[1.20]*	*[1.10]*	*[1.13]*
Log [1+Age]	0.0366	0.0340	0.0392	0.0104	0.0079	0.0152	-0.0152	-0.0129	-0.0130	-0.0369	-0.0347	-0.0329
	[0.60]	*[0.55]*	*[0.64]*	*[0.18]*	*[0.14]*	*[0.26]*	*[-0.20]*	*[-0.17]*	*[-0.17]*	*[-0.51]*	*[-0.47]*	*[-0.44]*
Log UW	-0.1613	-0.1683	-0.1644				-0.1662	-0.1885	-0.1680			
	*[-3.43***]*	*[-3.56***]*	*[-3.49***]*				*[-2.98***]*	*[-3.34***]*	*[-2.98***]*			
MTB	-0.0028	-0.0032	-0.0029	-0.0040	*-0.0043*	*-0.0040*	0.0001	0.0003	0.0001	-0.0002	0.0001	-0.0002
	*[-2.18**]*	*[-2.70***]*	*[-2.21**]*	*[-3.11***]*	*[-3.63***]*	*[-3.11***]*	*[0.09]*	*[0.41]*	*[0.06]*	*[-0.17]*	*[0.06]*	*[-0.19]*
Lev	0.1433	0.0848	0.0903				0.3423	0.2493	0.3123			
	[0.30]	*[0.18]*	*[0.19]*				*[0.66]*	*[0.49]*	*[0.63]*			
Hot	-0.3297	-0.3941	-0.3119	-0.3880	-0.4570	-0.3755	-0.2278	-0.1944	-0.2151	-0.2554	-0.2208	-0.2462
	*[-2.59**]*	*[-3.23***]*	*[-2.38**]*	*[-3.21***]*	*[-3.95***]*	*[-3.01***]*	*[-1.41]*	*[-1.17]*	*[-1.27]*	*[-1.57]*	*[-1.31]*	*[-1.44]*
Initial Ret				0.0069	-0.0128	0.0087				0.0474	0.0538	0.0306
				[0.04]	*[-0.07]*	*[0.05]*				*[0.11]*	*[0.13]*	*[0.07]*

PANEL C CONT'D – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES												
IPO Firm Risk	-1.2147	-1.5534	-1.3547				-1.4535	-1.2253	-1.5837			
	[-0.77]	*[-0.99]*	*[-0.88]*				*[-0.49]*	*[-0.41]*	*[-0.57]*			
Surplus Val	0.0701	0.0624	0.0713	0.0493	0.0415	0.0483	0.0311	0.0188	0.0306	0.0174	0.0078	0.0134
	*[2.38**]*	*[2.10**]*	*[2.40**]*	*[1.89*]*	*[1.57]*	*[1.84*]*	*[0.98]*	*[0.59]*	*[0.94]*	*[0.61]*	*[0.27]*	*[0.45]*
I_Profit Margin	-0.1334		-0.1260	-0.1362		-0.1196	-0.1613		-0.1550	-0.1506		-0.1340
	*[-2.80***]*		*[-3.10***]*	*[-2.97***]*		*[-3.01***]*	*[-2.70***]*		*[-3.08***]*	*[-2.63**]*		*[-2.80***]*
I_Leverage			0.8973			0.4445			0.3118			-0.1267
			[1.08]			*[0.53]*			*[0.40]*			*[-0.16]*
I_MTB	0.0787	0.0682	0.0854	0.0768	0.0662	0.0812	0.0502	0.0404	0.0518	0.0533	0.0437	0.0510
	*[2.96***]*	*[2.52**]*	*[3.08***]*	*[2.86***]*	*[2.42**]*	*[2.84***]*	*[1.61]*	*[1.26]*	*[1.61]*	*[1.74*]*	*[1.40]*	*[1.59]*
I_Conc.	-0.1749	0.1146		-0.3594	0.0771		-0.0882	0.2984		-0.2482	0.0981	
	[-0.53]	*[0.38]*		*[-1.14]*	*[-0.26]*		*[-0.25]*	*[0.95]*		*[-0.77]*	*[0.34]*	
I_Equity Vol.	-2.8679	-2.5687	-2.5238	-3.2107	-2.9286	-2.9805	-1.7221	-0.5899	-1.6035	-1.9583	-0.8665	-1.8383
	*[-2.37**]*	*[-2.08**]*	*[-2.02**]*	*[-2.78***]*	*[-2.48**]*	*[-2.48**]*	*[-1.03]*	*[-0.33]*	*[-0.93]*	*[-1.14]*	*[-0.48]*	*[-1.04]*
R^2	**0.0748**	**0.0635**	**0.0758**	**0.1008**	**0.0889**	**0.0992**	**0.0575**	**0.0396**	**0.0576**	**0.0774**	**0.0618**	**0.0762**
No of Obs.	**701**	**701**	**701**	**701**	**701**	**701**	**440**	**440**	**440**	**440**	**440**	**440**

with the firm risk factors only [Panel A], then the industry risk factors only [Panel B] and finally both factors combined [Panel C].

Market value is selected as the only measure of size, while the the other size measures [i.e. market equity and total assets] as well as the offering characteristics related to size [i.e. offer price and offer proceeds] are excluded entirely from the regressions due to the high correlation between them. In the same vein, earnings yield is also selected as the sole performance measure, while return on assets and profit margin are excluded entirely[122]. Hence, only the following firm risk factors are included in the multivariate framework: 'hot' market dummy, market leverage, market value, market-to-book, earnings yield, underwriter reputation, age, initial returns and IPO risk. Controlling for the relatively observed high correlation between market value and underwriter reputation, market value and market leverage and finally, initial returns and IPO risk, the firm regressions are estimated firstly, with the selected firm risk factors excluding market value and initial returns and secondly, with all the firm risk factors excluding market leverage, underwriter reputation and IPO risk. For the industry regressions, three different models are estimated to account and control for the observed high correlation between industry factors of leverage, market-to-book, equity volatility and

[122] In unreported regressions that adopt the excluded size [i.e. market equity and total assets] and performance measures [i.e. return on assets and profit margin] as the alternatives, the results are similar.

concentration on the one hand as well as profitability and concentration on the other hand. Combining both firm and industry risk factors in the same regression and accounting for the inter-dependencies and cross-correlations inevitably leads to estimating six different models in a multivariate framework that includes both set of factors.

Just like in the last section, this section starts with an analysis for the whole period before proceeding to see how this changes when the 'dotcom' years are excluded. For the firm risk factors, the results from Panel A for the whole period show that only market value, market-to-book, earnings yield, underwriter reputation and the 'hot' market dummy are significantly related with 5-year post–IPO returns. The results seem to be consistent with the univariate results reported earlier and in line with the author's expectations. The results are also generally in tandem with the results from the sample segmentations previously reported and also consistent with the majority of the evidence in the literature. More specifically, the significant positive sign on market value is consistent with the argument that larger firms are generally less risky and better placed than small firms to perform better in the long-run. Market-to-book is significantly negatively related to long-run performance with the result consistent with the 'market overreaction' and 'window of opportunity' hypotheses. The positive sign on the performance factor is also consistent with the expectation that IPO firms with a track record of strong positive earnings are less risky and as such better placed to perform better in the future. By choosing to go public when their operating performance is good, investors are forced to raise their expectations of superior future performance, more especially when this performance is sustained in the post-IPO years.

Underwriter reputation is also shown to be significantly positively related to IPO long-run returns, given the negative sign of the coefficient estimate[123]. This is not a surprise given the established fact that successful firms tend to be underwritten by more prestigious investment bankers. Finally, the 'hot' dummy is shown to be another valuable distinguishing factor between the best and worst performing IPO firms. The significant negative coefficient indicates that IPOs issued in periods of intense and profound market activity ['hot' markets], perform worse that those issued in other periods. When the regressions are re-estimated for the sub-period that excludes the 'dotcom' years in order to isolate the impact of the 'technology bubble', the results are broadly similar. The only difference now is the 'hot' market dummy, which is no longer significant as an explanatory factor in post-IPO stock returns.

For the industry risk factors, the results from Panel B for the whole period show that profitability, market-to-book and equity volatility are significantly related with 5-year

[123] See Section 4.3.2, pp. 220-221 and Panel F of Table 3.5, pp. 99.

post–IPO returns across the three models. The results seem to be consistent with the univariate results and sample segmentations reported earlier. However, when the regressions are re-estimated for the period excluding the ‘dotcom’ years, equity volatility ceases to be significant as a valuable explanatory factor of post-IPO stock returns. The market-to-book factor is observed to go from being highly significant [at the 1% level] across the three models for the whole period to just being mildly significant [at the 10% level] in only one of the three models in the sub-period that excludes the ‘dotcom’ years. In fact, on the basis of these industry regressions, the profitability factor [consistent at the 1% level] and the market-to-book to a limited extent, stands out as the only significant industry factors across the three models that are robust to the inclusion or exclusion of the ‘dotcom’ years.

Controlling for the firm and industry risk factors simultaneously, the results from Panel C for the whole period show that market value, market-to-book, earnings yield, underwriter reputation, the ‘hot’ market dummy as well as industry risk factors of IPO surplus value, profitability, market-to-book and equity volatility are significantly related with 5-year post–IPO returns across the six models. More specifically, on the one hand, market-to-book, the ‘hot’ market dummy and industry risk factors of profitability and equity volatility are shown to be negatively related with subsequent IPO returns across the six models. On the other hand, size [market value], performance [earnings yield], underwriter reputation[124] and industry risk factors of surplus value and market-to-book are shown to be positively related with long-term returns[125].

The results are generally consistent with the sample segmentations and univariate regression results performed in earlier sections and also in line with the majority of the evidence in the literature. More specifically, the size result, which is in line with the author's expectations, suggests that large firms with sizeable offerings perform better in the long-run. The performance result is consistent with the view that firms with a profitable history prior to listing perform better in the long-term, which also meets with the author's expectations. The market-to-book result, consistent with the author's expectations, show that investors may be overly optimistic about the future performance of high market-to-book firms at the time of issuance; however, more often than not, these expectations are not met as these firms do not operate as well as they are expected to. The negative coefficient of the underwriter reputation variable, which indicates a positive relationship to long-term performance and in tandem with the author's expectations, suggests that IPOs managed by more prestigious investment bankers tend to have better long-run performance than those underwritten by their less prestigious counterparts. Expectedly, the 'hot' IPOs have the most severe long-run

[124] See Section 4.3.2, pp. 220-221 and Panel F of Table 3.5, pp. 99.

[125] Earnings yield is significant in three of the six regressions while IPO firm surplus value is significant in four of the six regressions.

under-performance, which tends to suggest that many of these IPOs issued in these tense market conditions are of ‘poor quality’.

For the industry risk factors, the negative sign of the profitability variable suggests that IPO firms from industries with higher profitability or better profit conditions perform worse in the long-run than those from industries with low or modest profitability, which is quite surprising and contrary to the author’s expectations[126]. The market-to-book result, which is also against the author’s expectations, suggests that investors have high expectations of the future value of the firms based on the growth opportunities that abound in the industry which cause them to value the stocks highly. Consequently, these firms take advantage of these opportunities by going public to raise the capital needed to finance the huge investment outlay, which eventually shows up in the future operating and stock performance of these firms. Expectedly, the negative value for the equity volatility factor generally implies that IPO firms from industries with higher equity volatilities perform worse in the long-run than those from industries with low volatilities.

The positive sign in the IPO surplus value factor indicates that firms trading above their industry-adjusted valuations [i.e. those firms trading at a premium relative to industry peers] perform better than their counterparts, which seems to be contrary to the author’s expectations and also at variance with the sample segmentation results. In

[126] See Section 4.4.3.2, pp. 264.

univariate regressions, this variable is not a valuable factor in predicting or explaining IPO long-run performance. However, when the study controls for other firm and industry risk factors that are germane to post-IPO outcomes in multivariate frameworks, the ensuing result indicates that firms that trade at a premium relative to industry peers perform better in the long-term. The results imply that investors are confident that the present performance and the growth opportunities available to the IPO firm in the industry and reflected in the current stock prices will be sustained in the future, which in turn cause them to revise upwards their expectations of future superior performance.

When the 'dotcom' period is excluded and the regressions are re-estimated, size [market value], performance [earnings yield], underwriter reputation and the industry risk factors of profitability and market-to-book to a limited extent[127], are found to be the significant variables. The strong, overwhelming and pervading relationship between firm size, underwriter reputation, industry profitability and IPO long-run performance is observed as the results are significant at the 1% level across the models and robust to the inclusion or exclusion of the 'dotcom' years. The firm level variables of market-to-book and 'hot' market as well as industry structure variables of IPO surplus value and equity volatility cease to be significant. More specifically, the aforementioned variables

[127] The industry market-to-book goes from being highly significant across the six models for the whole period to just being mildly significant [at the 10% level] in only one of the six models when the 'dotcom' years are excluded.

go from being highly significant [all at the 1% level] for the entire period to being insignificant when the ‘dotcom’ years are excluded. The lack of robustness of these evidences clearly shows that the ‘dotcome’ period is massively influencing the results. The explanation for this is not difficult to gauge as this historic period was characterised by a massive demand for capital, high equity volatilities and ‘hot’ markets as both good and poor quality firms rushed to the market to raise capital on the back of brimming investors’ optimism and misevaluations in the market place that drove industry and market values to all-time highs.

On the evidence of these results, the central hypothesis of this second study that industry–structure variables cannot foreshadow the long-term performance of IPOs is rejected. The results show that, after controlling for specific firm and industry risk factors that have been shown to be germane to the after-market performance of new stock issues, size [market value], performance [earnings yield], market-to-book, underwriter reputation, the ‘hot’ IPO market dummy as well as industry risk factors of IPO surplus value, profitability, market-to-book and equity volatility can be important predictors of post-IPO stock performance. However, when the study further controls for the effect of the ‘dotcom’ bubble, only size, performance, underwriter reputation, industry profitability and industry market-to-book to a limited extent, remain as the significantly distinguishing factors between the best and worst performing IPO firms.

Clearly, not all IPOs are bad investments as there are significant variations in the cross-sectional performance of these firms. In fact, the results from this second empirical study confirm the results from the first empirical study that suggests that size, amongst others, could be a key risk factor in the post-IPO performance of issuing firms given that value-weighted performance did not produce a strong and consistent under-performance finding. The study also finds that the profile of under-performing IPO firms can be determined based on a set of observable firm and industry characteristics at the time of the IPO. Under-performance tends to restricted to small, high market-to-book firms with an unprofitable trading history, issued in hot IPO markets, underwritten by less prestigious investment bankers and trading below their industry-adjusted valuations [i.e. trading at a discount relative to industry peers]. These under-performing firms also tend to be located in more profitable and low market-to-book industries with high equity volatilities. On the evidence of these results, IPO managers, their investment bankers and potential IPO investors can foreshadow the long-run performance of these firms based on a battery of firm and industry – conditioning factors at the time of the IPO.

[4.5] SUMMARY AND CONCLUSIONS

[4.5.1] Summary

Several studies in the literature have analysed the relationship between certain firm characteristics and the long-run performance of new issues of common stock; however, little has been done to consider whether the characteristics of an issuing firm's industry are also germane, which is startling given the extant literature's widespread handling of other corporate finance issues. The second study seeks to firstly, confirm the results of previous studies on the relationship between these firm characteristics and long-run IPO performance and secondly, explore salient industry–specific conditioning factors prior to or at the time of the offering that could also prove valuable in predicting or explaining the cross-sectional performance of new issuances.

Using the same sample of 746 IPOs in the UK market over the period 1999 – 2006 as in the first empirical study, the economic importance of selected industry-specific risk factors prior to or at the issue date to IPO firms, their investment bankers and potential IPO investors is tested. When doing this, the study controls for and confirms the results of previous studies on the impact of firm-specific risk factors. Size, market-to-book, past performance, underwriter reputation and the 'hot' IPO market are found to be important predictors of IPO performance in a cross-section. The study documents that industry risk factors relating to an adjusted IPO valuation [i.e. IPO surplus value], profitability, leverage, market-to-book, concentration and equity volatility can potentially predict or explain the cross-sectional differences in IPO long-term performance. However, after controlling for other factors that are germane to IPO long-run performance in a cross-section, the findings reveal that only IPO surplus value, industry profitability, industry market-to-book and industry equity volatility can be significant predictors of an IPO's long-term performance.

More specifically, significant negative relationships between industry conditioning risk factors of profitability, equity volatility and IPO long-run performance on the one hand and significant positive relationships between industry structure variables of IPO surplus value, market-to-book and IPO long-term performance on the other hand are found. These results are robust to including controls for other variables known to predict IPO long-term performance. However, apart from firm size, past performance, underwriter reputation, industry profitability and industry market-to-book to a limited extent, the other variables are not robust to the exclusion of the late 1990s technology bubble, which suggests that the 'dotcom' years are driving some of the results. In general, the results suggest that IPOs issued in low market-to-book and profitable industries with high equity volatilities and that also tend to trade below their industry-adjusted valuations [i.e. trading at a discount relative to industry peers] perform worse than other IPOs in the counterpart industries.

[4.5.2] Conclusions

Given that the literature is still shallow on the impact of industry characteristics on the subsequent long-term performance of new issues of common stock, the goal of this study is to identify salient industry conditioning risk factors prior to or at the IPO that could explain and/or predict the long-run performance of IPOs. Put differently, this second empirical study seeks to identify relevant ex-ante firm and industry characteristics prior to or at the IPO that could firstly, help potential investors build their investment opportunity sets and secondly, provide IPO firms and their investment bankers with additional information they could use to time their offerings.

Consistent with existing literature, several firm characteristics that have been shown to be germane to the subsequent performance of new issues arte included in the analysis. To fully understand the role of industry conditioning risk factors, industry-specific averages of some selected industry risk factors are constructed over all existing firms in a given IPO's industry prior to or at the IPO. In this regard, industry risk factors relating to IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility are considered. The impact of industry conditioning risk factors prior to or at the IPO on the post-issue market performance of these firms are also evaluated both in isolation and after controlling for variables that are known to be crucial determinants of the long-term performance of IPO firms.

The study finds that the evidence on size, past performance, underwriter prestige and industry profitability is strong, overwhelming and compelling. The size result shows that firms desirous of transiting to public life should first attain a critical size level in order to withstand the vagaries of the market place. The performance result suggests that firms desirous of going public should first build a track record of profitable performance to enhance their long-run performance prospects, while the underwriter reputation evidence lays credence to the fact that firms underwritten by the most prestigious investment bankers are less likely to under-perform due to their ability to self-select or hand-pick better and quality firms from the pool of firms going public. The industry profitability evidence suggests that, despite fanciful industry conditions that may prevail at the time of the IPO, firms should ensure that they are top quality before they go public. Overall, the results suggest that not all IPOs are bad investments as potential IPO investors can substantially improve their long-run returns if these IPOs are painstakingly selected. A meticulous selection would entail going beyond the offer document prepared by the investment bankers that lists the offering and firm specific risk factors to considering salient characteristics of the IPO firm’s industry. The results also suggest that IPO firms and their investment bankers should consider industry–conditioning factors prevailing at the IPO to provide them with additional information on whether to go ahead with the IPO, or alternatively, withdraw and re-launch at a more auspicious date. To the best of the author's knowledge, this is [1] the first study in the literature that documents the unique relationships between industry risk factors of IPO surplus value, profitability, market-to-book, equity volatility and IPO performance [2] the first study in the UK market that investigates the impact of this raft of industry risk factors on IPO performance.

Conclusively, this work attempts to fill an important void in the literature by identifying relevant industry conditioning risk factors prior to or at the issue date that could be germane to the long-run performance of IPOs, more particularly for the benefit of potential IPO investors. This study's analysis of the impact of key industry risk factors on the long-run performance of IPO firms adds another dimension to the decision-making process of not only potential IPO investors, but also IPO firms and their investment bankers in the timing of the offering. Despite assessing the relation between the industry structure risk factors used in this study and the long-run performance of IPOs, future research is encouraged into identifying other salient industry risk factors that could prove useful to potential IPO investors in distinguishing between firms that are likely to perform from those that are likely to under-perform in the long-run.

CHAPTER 5 - SURVIVORSHIP OF IPOS

[5.1] Introduction

Thus far, this study has followed the sample of IPOs right from their migration from private to public life by assessing their post-listing market performance relative to that of an appropriately matched set of non-issuing control firms. At this juncture, this final part of the study evaluates them on a 'stand-alone' basis to enable the author to delineate the class of firms within the general IPO group that eventually survive and in the process bring to the fore the plethora of risk factors prior to or at the IPO that shapes this critical stage in the life of these firms. For owners and managers of these firms, ensuring survival is crucial in shielding and improving their financial interests in the firm as the failure rate among new issues of common stock is still relatively high[128]. Survival is the definitive performance assessment of a firm since it offers a distinctive test of whether the firm has performed sufficiently to survive the torrid and competitive market place. Due to the tendency of IPO failure to occur within a few years of going public, the reasons for this and the factors that accentuate this tendency is examined in this third and final empirical study.

[128] Average failure rates of up to 40% have been reported for IPOs 3 - 7 years after listing by several authors in the literature [see section 5.5.2.2, pp. 353-354].

The assessment of the likelihood of failure of IPO firms is important to the various stakeholders in the firm that include the firm's investors [i.e. owners], regulators, auditors, investment bankers, board members and executives. The investors are interested in the risk of failure of the firm because it provides them with an additional dimension on stock valuation. The regulators are concerned about the survival of the firm because it provides them with additional information on on how to revise the pre-listing or post-listing requirements for firms that may wish to go to public. The professional and business interests of the other stakeholders are also linked to the survival of the firm in the market place. Given that IPO firms are fundamentally different from public firms that already have a visible track record of performance in the market place, there is a greater uncertainty associated with their valuation and risk of failure [Weber and Willenborg, 2003]. If this risk is not properly identified and measured at the IPO stage, efficient pricing and risk measurement then requires that issuers and their investment bankers should offer commensurate discounts to compensate unsuspecting investors for losses on new issues that subsequently fail in the post-IPO years [Lewis, et al, 2000].

Subsequent to the offering, the success or failure of an IPO should be of grave concern to reputable investment bankers who may not want to be associated with failed offerings in order to maintain their hard-earned reputational capital; alike, for IPO investors who may not also want to lose their prized investments. Hence, any information prior to or at the IPO that could be germane to the likelihood of survival of IPOs would prove invaluable to these stakeholders. Several studies in the literature have analysed the relationship between certain firm characteristics and the survival of new issues; however, only a few others have studied the impact of industry conditioning risk factors on IPO survival. By and large, the amount of published research on this area is still limited. This provides the springboard for this study as it seeks to identify salient industry conditioning risk factors prior to or at the IPO that can foreshadow the likelihood of survival of IPO firms. Realistically, a firm's ultimate survival in the market place is not only a function of the firm, industry and market conditions around its IPO date, but also on the market and industry conditions subsequent to the issue[129]. However, the author's goal in this third empirical study is to determine if one can predict the survival of new issues by using only that information that would be available to the issuer, its investment banker or the IPO investor prior to or on the date of the offering[130]. Hence, similar to the second empirical study, the aim of this third empirical study is to firstly, determine the class and profile of IPO firms that

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[129] For example, years after the IPO, dominant players could emerge in an industry that was initially fragmented and competitive, which could lead to less competition, limit growth opportunities and induce severe negative survival effects for the other firms. Similarly, the subsequent entry of new firms into an initially close-knit and highly profitable industry could lead to over-investment and a reduction in the excess rents in that industry with attendant negative competitive and survival effects for the current firms [Akhigbe, et al, 2003; Jain and Kini, 2006].

[130] See footnote 72.

survive by using only that information that would be available to the issuer, its investment banker or the IPO investor prior to or at the IPO; secondly, ascertain if a set of observable firm and industry characteristics prior to or at the IPO can presage the survival likelihood of the issuing firms and; thirdly, provide IPO firms, their investment bankers and potential IPO investors with an initial estimate of the survivability of new stock issues based on ex-ante firm and industry conditions prevailing at the offering date in order to guide them in their decision making process.

This third empirical work attempts to fill an important void in the literature by identifying salient industry risk factors prior to or at the IPO that could be influential to the survival prospects of IPO firms for the benefit of the IPO firms, their investment bankers and potential IPO investors. The empirical analysis in this third part of the study is conducted using a range of approaches. The first stage of the analysis here involves data stripping and univariate analysis to enable us to profile surviving and failing firms and thereafter determine if there are any significant differences in the characteristics of the two groups. In the second stage, the study attempts a non-parametric estimation of the hazard rate [i.e. rate of failure] by tracking the firms in duration time. In the third stage, the cohort of firms are trailed in event time by ascertaining crucial firm and industry risk factors that may impinge on the survival likelihood of these firms, employing binary logit models. In the fourth and final stage and also as a robustness check, this same legion of firms are tracked in calendar time, employing survival models [also known as Cox hazard methodology, failure time methodology, duration time models or event-history analysis] that include the parametric accelerated failure time [AFT] and semi-parametric Cox proportional hazard [CPH] models.

Subsequent to the 5-year performance analysis that was performed in the first empirical study, the post-event window is extended by another year in logistic regressions, as each of the sample firms is tracked for six years after the listing date or until the firm is delisted. In duration models, all firms are tracked from listing date to the earlier of failure date or the last observation date [i.e. 31 December 2012][131], while controlling for those firms that are alive and continue to trade beyond this date, using a censoring indicator. Survivors are defined as firms that continue to operate independently as public limited corporations, with acquired/merged firms included in this category[132]. Consistent with this definition, firms that are delisted for a variety of negative reasons such as bankruptcy/insolvency or liquidation are classified as failures

[131] Failing or uncensored firms are tracked to the date of failure, while surviving or censored firms [i.e. firms that have not yet failed] are trailed to the end of the study period [i.e. 31 December 2012].

[132] This is line with the approach of Bhabra and Pettway [2003]. However, Jain and Kini [1999] treat acquired firms as distinct from firms that continue to operate independenly [survivors] or fail outrightly due to financial distress [non-survivors]. In contrast, Jain and Kini [2000] classify acquired firms as failures based on the findings of some studies that those firms are typically distressed prior to their acquisition [Welbourne and Andrews, 1996].

or non-survivors[133]. The decision to include firms that are acquired/merged in the group of survivors is partly based on the accepted view that shareholders of such firms gain from such arrangements and also partly on the fact that the focus of this study is on IPO firms that continue to operate either as single independent entities and/or whose shareholders do not experience any substantial loss in the value of their investments after the listing date.

Using the same sample of 746 IPOs in the UK market over the period 1999 – 2006 as in the first and second empirical studies, this section of the study tests for the economic importance of selected firm and industry risk factors [already identified and used in the second empirical study], prior to or at the IPO to the issuers, their investment bankers and potential IPO investors. The results show that size, past performance, initial market return volatility [IPO risk], underwriter reputation and the 'hot' IPO market are important predictors of the probability of IPO survival in cross-sectional regressions. The findings also reveal that industry conditioning risk factors relating to profitability and the valuation of the firms relative to industry peers [i.e. IPO surplus value] can be valuable determinants of an IPO's survival prospects. More specifically, this third study finds significant negative relationships between the aforementioned industry risk factors and IPO survival likelihood.

[133] This information was obtained from www.opencorporates.com.

The sensitivity of the findings to several methodologies and the inclusion and exclusion of the late 1990s technology bubble offer mixed findings. There is a strong and compelling evidence that past performance and underwriter prestige are strong survival signals [i.e. positively related to survival] with their relationship to IPO survival robust firstly, to event time regressions that either consider the survival or failure of IPO firms in a fixed time period using a binary operator or duration models that track all sample firms to the last observation date, while controlling for those that have not yet failed using a censoring indicator; secondly, to including controls for other variables known to predict IPO survival probability and; thirdly, to the inclusion or exclusion of the late 1990s technology bubble. Size is found to be statistically significant in all the models employed; albeit, not robust to the exclusion of the 'dotcom' period and the inclusion of the industry risk factors in the empirical design. There is also evidence in the CPH model that suggests that IPO surplus value is a bad survival signal [i.e. negatively related to survival], albeit this evidence, once again, disappears in regressions that exclude the 'dotcom' period. IPO firm risk, 'hot' market and industry profitability are also found to be significantly distinguishing factors in event-time logistic regressions, even though these evidences are not robust to the inclusion or exclusion of the late 1990s technology bubble. The lack of robustness of some of the evidences indicates that the technology bubble period is driving some of the results. The results generally indicate that subsequent to the IPO event, large firms with a profitable trading history, highly volatile initial market returns [IPO risk], issued in less tense market conditions [i.e. periods of low or modest IPO activity], underwritten by more prestigious investment bankers, trading at a discount relative to industry peers [i.e. trading below their industry–adjusted valuations] and from less profitable industries have a higher survival likelihood than their counterparts.

This third empirical study contributes to the literature in four ways; firstly, the unique relationships between industry profitability and the valuation of the IPO firms relative to industry peers [i.e. IPO surplus value] and IPO survival likelihood are first documented in this study; secondly, it is the first to study the impact of industry-specific risk factors on the survival of IPOs in the UK market; thirdly, since the study investigates the survival of newly-listed firms using a set of observable ex-ante firm and industry characteristics prior to or at the IPO date, it provides an initial estimate of the survivability of new stock issues to enable the stakeholders [i.e. IPO firms, their investment bankers and potential IPO investors] to make better and informed decisions at the offering date and; fourthly, given the rate of failure of new listings in the market place, the study helps us to better understand the milieu of factors that tend to prevent the capital market from growing in terms of the number of listed firms. Conclusively, despite using a multi-faceted and comprehensive approach that utilises salient firm and industry information prior to or at the IPO to predict the probability of survival of IPO firms, future research is encouraged into identifying other salient industry risk factors that could prove useful to the various stakeholders in distinguishing between firms that are likely to survive from those that are likely to fail.

The rest of the chapter is organised as follows: Section 5.2 reviews the literature on the relevant issues in firm and industry characteristics and the survivorship of IPOs, while Section 5.3 presents the research questions and testable hypothesis. Section 5.4 describes the methodologies used in assessing IPO survivorship. The empirical analysis and ensuing findings are reported in Section 5.5, while Section 5.6 summarises and concludes the study.

[5.2] Literature Review

The performance of IPOs following listing follows two research streams in the literature. The first focuses on the stock and operating performance of these firms following their IPOs relative to a comparable benchmark, regardless of survival, while the second focuses on the ultimate survival of these firms in a fixed time period post-listing. It is pertinent to point out that the amount of published research on the survivorship of new issues of common stock is limited as the majority of the papers in this area treat survival as a marginal issue rather than the focal point. In addition, the majority of the studies, which have been few and far between, have mainly focussed on the US market.

The positive relationship between firm size and IPO survival likelihood is well documented [Schultz, 1993; Hensler, et al, 1997; Jain and Kini, 1999]. Jain and Martin [2005] also find that small US IPOs exhibit shorter times to failure when compared to large firms, which is consistent with the findings of Bhabra and Pettway [2003] and Dimson and Stolin [2002] in their studies of the survival likelihood of US and UK IPOs respectively. More recent studies by Kooli and Meknassi [2007], Yung, et al [2008], Hamza and Kooli [2010], Raju and Prabhudesai [2012] and Espenlaub, et al [2012] also show that smaller firms have lower survival likelihoods. However, the evidence from Australia seems to be contrary to the majority of the findings in the literature as Rath [2008] and Chancharat, et al [2012] find that the size of the firm [measured by total assets] is negatively related to survival, albeit the former's results suggest that investors should invest in firms that have a large offer size at the offering date[134]. The difference in results between the firm and offer size measures from Rath's [2008] study is hard to explain given the established fact that larger firms, which tend to be

[134] The difference in the Australian results from the other studies, which have been majorly on the US market, could be due to the small size of the samples, which may be connected with the relatively small size of the Australian capital market. The sample sizes for the Rath [2008] and Chancharat, et al [2012] studies are 154 and 125 respectively.

associated with larger offerings, are better placed to withstand tough economic and industry conditions, which in the process ensures longer times to failure.

On a related note, prior research has also shown that low-priced [‘penny’] stocks, which tend to be associated with small firms, are more likely to fail and delist. Seguin and Smoller [1997] examine the likelihood of failure of ‘penny’ and ‘non-penny’ stocks in the US over the period 1974-1988, employing logistic regressions and a 5-year tracking window. They find that ‘penny’ IPO stocks, when compared to ‘non-penny’ stocks, are more likely to end up in financial distress. The results are also in line with those obtained in a similar study in the same market by Bradley, et al [2008]. Fernando, et al [2004] also observe that lower [higher] priced stocks are more [less] likely to fail in the 5 years following the initial listing. In the same vein, Bhabra and Pettway [2003] and Demers and Joss [2007], in studies of US IPOs, find that firms with relatively higher offer prices at the issue date exhibit higher survival likelihoods.

Classifying a firm as a non-survivor if it fails or delists within five years in a study of US IPOs using the logistic regression model, Bhabra and Pettway [2003] find that past profitability is significantly positively associated with the probability of survival. Earlier studies by Jain and Kini [1999], Lewis, et al [2000], Dimson and Stolin [2002] and Peristiani and Hong [2004] also find the same evidence. More recent studies by

Demers and Joss [2007], Chi, et al [2010] and Espenlaub, et al [2012] also document longer times to failure for IPOs with strong pre-listing operating performances. The results suggest that pre-listing profitability levels tend to uphold post-listing operating and market performance levels as firms are motivated to go public at the peak of their performance.

The majority of the studies in the literature document a shorter time to failure for IPO firms with a high level of risk. Several variables have been used in the literature to proxy for the risk and uncertainty that may surround new issues[135]. Using the number of risk factors in the offer document as the proxy, Hensler, et al [1997], Bhabra and Pettway [2003] and Rath [2008] find that IPO risk is an increasing function of the hazard rate of new issues. In the same vein, Jain and Kini [1999], Dimson and Stolin [2002], Chi, et al [2010] document a similar relationship, employing the IPO after-market return volatility as the proxy for the riskiness of the IPO firm. The finding by Van der Goot, et al [2009], using IPO valuation uncertainty as the measure of IPO risk, is also in tandem with the majority of the evidence in the literature.

[135] Some of these proxies are the early market return volatility [computed as the standard deviation of the IPO daily return in the immediate after-market], the number of risk factors in the prospectus and the valuation uncertainty relating to the performance of the firm after the offering {computed as the spread in the valuation of the initial price range [as revealed by potential IPO investors under a process of bookbuilding] divided by the average value of the initial price range}.

Employing logit and survival-duration models on a sample of US IPOs over the period 1975-2005, Chang, et al [2013] investigate firstly, whether 'hot' market IPOs are fundamentally different from 'cold' market IPOs and secondly, whether there are significant differences in the survival probability and time to failure between firms that go public in the first half of a 'hot' market ['pioneers'] and those that go public in the second half ['followers'][136]. They document a higher hazard probability for firms that go public in 'hot' market conditions. They also find that 'pioneers' have a longer time to failure than followers with the negative 'hot' market effect disappearing once they control for the 'followers'. In a study of the delisting experience of a sample of US IPOs that were listed over the period 1973-2004, Yung, et al [2008] find that the volatility in long-run abnormal returns and attrition of new listings increases considerably during 'hot' markets relative to 'cold' markets. More specifically, they find that 'hot market' IPOs are three and half times more likely to delist relative to 'cold market' IPOs when they are tracked within three and five years from their issue date. The findings of Hensler, et al [1997], Hamza and Kooli [2010], Chang, et al [2013] and Espenlaub, et al [2012] are in line with the aforementioned studies as they show that going public in 'hot' market periods accelerates or shortens the time to failure. However, Lewis, et al [2000] find that the hazard rate is higher for older firms and IPOs issued in cold markets in

[136] This is the degradation of issuers' quality in 'hot' markets predicted by Alti's [2005] information-spillover and Khanna, et al's [2008] inelastic investment banking theories.

logistic regressions in a study of US IPOs, contrary to the majority of the evidence in the literature. They rationalize this result on the fact that it is not ‘hot’ market conditions *per se* that increases the hazard rate of IPOs, but rather that more new issues are underwritten by low-quality investment banks as a result of the opportunity created by a buoyant economy and an excessive demand for new issues by investors.

On a related note, firms that take advantage of the transitory opportunities created by ‘hot’ market periods often do not manage to do well in the future. This market period usually results in high equity market levels and in the process leads to a flurry of both ‘good’ and ‘poor’ quality issues in the market. Firms issuing their IPOs in these periods typically have high market-to-book values as they cash in on investors’ over-optimism in the market. Demers and Joss [2007], using the 90-day pre-IPO market return as the market gauge, finds a significant negative relationship between the market level at the time of the listing and the time to failure of IPOs. Van der Goot, et al [2009], employing the average value of the NASDAQ index during the month of offering as the market indicator, also show that the market level at the time of the listing is a bad survival signal [i.e. negatively related to survival].

The positive relationship between the age at the IPO and the survival likelihood of new stock issues is also well documented [Schultz, 1993; Hensler, et al 1997; Jain and

Martin, 2005; Peristiani and Hong, 2004]. These studies rationalize this on the fact that older firms tend to be mature and established with a track record of strong performance in their industries and hence, are less likely to fail after their IPOs. More recent studies by Yung, et al [2008], Demers and Joss [2007] and Espenlaub, et al [2012] document shorter times to failure for young firms with little or no pedigree. However, Lewis, et al [2000] find a contrary result and hinge this on the fact that IPOs issued in 'cold' market conditions, which experience higher failure rates, also tend to be the older IPOs.

The presence of expert informational intermediaries have been shown to have a positive impact on the time to failure of new issues due to the certification services they provide before, during and after the offering. These intermediaries include the underwriter, venture capitalist [VC] and auditor. Jain and Kini [2000], Yung, et al [2008] and Hamza and Kooli [2010] document a higher likelihood of survival for IPO firms with VC-backing and underwritten by prestigious investment bankers. Schultz [1993], Jain and Kini [1999], Kooli and Meknassi [2007] and Lewis, et al [2000] also show that prestigious investment bankers tend to be associated with more successful IPO firms. Developing proxies for the presence of the underwriter, the venture capitalist and the 'big auditor', Demers and Joss [2007] find that these variables are a negative function of the likelihood of failure for these firms. Chou, et al [2007] investigate the impact of expert intermediaries on the post-issue survival of IPOs using a sample of US firms that went public during the period 1991-2001, employing logistic regressions and the CPH model. They document a longer time to failure for IPOs associated with industry specialist auditors as well as those backed by reputable venture capitalists, with their results suggesting that the involvement of these parties help the IPO firms to withstand the vagaries and uncertainties of the market place and thus reduce the likelihood of failure. Howton [2006] finds that firms that are VC-backed and also use more prestigious underwriters are less likely to fail five years after the IPO. Jain and Martin [2005] study the relationship between audit quality, the reputation of the underwriter and the time to failure of new stock listings in the US, using the CPH model. They document a positive relationship between the quality of the auditor, the reputation of the underwriter and IPO survival time. Espenlaub, et al [2012], in a study of UK new stock issues, find that the reputation of the nominated advisor to the IPO firm has a significant impact on the survival of IPOs. More specifically, they find that IPOs backed by more reputable advisors survive longer than those backed by less reputable advisors, employing the AFT model. However, the findings of Rath [2008] and Chancharat, et al [2012] with respect to the investment banker reputation and VC-backing variables are contrary to the majority of the evidence in the literature[137].

[137] See footnote 134.

IPO firms with the greatest level of under-pricing and the most initial returns in the early after-market have also been shown to have shorter times to failure. Demers and Joss [2007] show that high initial returns in the immediate after-market is a bad survival signal [i.e. negatively related to survival]. In the same vein, Raju and Prabhudesai [2012] show that there is a tendency for IPOs which have the greatest under-pricing, generally attributed to information asymmetry and investors' misevaluations in the marketplace, to have lower survival likelihoods. Kooli and Meknassi [2007] and Hamza and Kooli [2010] reach similar conclusions in their studies of the survival profile of US IPOs. However, the findings by Hensler, et al [1997] is at variance with the majority of the evidence in the literature as they show that the most under-priced new stock issues exhibit longer survival times. Schultz [1993] also finds that firms with the most initial returns in the first year post-listing have longer survival times, albeit this relationship disappears in the second and third years. The difference in results could be explained by the signalling model of Deeds, et al [1997] where more informed issuers deliberately under-price new issues in order to send strong signals about the quality and capabilities of the firm in the future.

There have also been some studies on the role of corporate governance characteristics on the survival likelihood of new issues. Howton [2006] examines whether observable ex-ante governance-related firm characteristics available to investors at a firm's IPO date can predict the firm's survival or failure. Using a sample of US firms that went public in 1997 employing logistic regressions, they find that firms that have a CEO-founder, a large stockholder and a more stable board of directors are less likely to fail five years after the IPO. In the same vein, Chandy [2006] studies the impact of post-IPO strategic choices on the survival profile of internet-related firms listed on the US market between 1995 and 1999, using the CPH model. They find that strategic decisions relating to market expansion, entry into alliances and the enlargement and reconstruction of the management team and/or board of directors significantly reduce the hazard rate. Chi, et al [2010] find that failing firms tend to be those with a high likelihood of changing management within the first three years of the IPO. Yang and Ding [2012], using logistic regressions and CPH models on a sample of Chinese IPOs listed over the period 1990-2005, document a negative relationship between the extent of government equity stake in these firms and the hazard rate. They also find that the hazard rate is a positive function of the number of directors in the board. Chancharat, et al [2012] find that the likelihood of survival is a non-monotonic positive function of board independence which suggests there is an optimal level of board independence. They also find that the hazard rate for firms with small or large board sizes is lower than those with moderate sized boards.

Jain and Kini [2000] show that road show success and analyst following significantly improve the survival time of new issues of common stock. Carpentier and Suret [2011] study the impact of pre-listing requirements on the survival of a sample of new issues that came into the Canadian market over the period 1982-2000, using the CPH model. They find that survival probability is significantly lower when the pre-listing requirements are low. Mauer, et al [2013] explore the impact of international trade on the performance and survival of IPO firms using a sample of US IPO firms listed over the period 1986-2010, employing probabilistic and hazard models. They find that IPO firms with export activities around their IPO years have significantly lower valuation uncertainty, stronger long-run performance and higher survival likelihood than those firms with no export activities. Besides the firm characteristics at the time of the IPO, the form and nature of the offering has also been found to be significantly related to survival. Schultz [1993] examines 797 unit and share US IPOs issued over the 1986-1988 period and finds that firms which issue 'bundled' or 'packaged' offerings, comprising a share and an option, are more likely to fail than firms that conduct straight offerings.

There is also some evidence that has shown that firms with low leverage [Bhabra and Pettway, 2003; Demers and Joss, 2007; Chancharat, et al, 2012], least earnings management [Li, et al, 2006], high investor demand prior to the issue[138] [Hamza and Kooli, 2010; Van der Goot, et al, 2009], strong secondary market [Lewis, et al, 2000], high owner stock retention at the IPO [Yang, 2006; Hensler, et al, 1997; Peristiani and Hong, 2004; Espenlaub, et al, 2012], high free cashflows [Van der Goot, et al, 2009] and high R-and-D intensity [Bhabra and Pettway, 2003; Demers and Joss, 2007] tend to have longer times to failure.

The issue of the survival of UK IPOs remains a largely unexplored area. Dimson and Stolin [2002], in an unpublished study, investigate the determinants of common stock delisting on the LSE over the period 1975 - 1998, employing CPH models. To the best of the author's knowledge, the only published UK IPO survival study is that of Espenlaub, et al [2012], who examine the determinants of the survival of IPO firms over a window of five years post-listing of firms listed on the Alternative Investment Segment [AIM] of the LSE over the period 2000-2004[139]. More specifically, they investigate the impact of a battery of firm, offering and market-wide factors on the survivability of new

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[138] This is also captured by the over-subscription ratio, which is the ratio of the aggregate demand for the issue to the total shares on offer. Potential investors provide the underwriter with crucial information on their valuations, via the process of book-building, on how they [i.e. underwriters] can adjust the final offer price to reduce the potential level of under-pricing.

[139] The AIM is the lower tier segment of the LSE that provides a market for small and growing firms that are unable to meet the stringent listing rules of the upper tier Main Market, to list their shares. AIM regulation requires every listed firm to have an approved financial firm that could act as advisors, 'gatekeepers', 'decentralized regulators' and sometimes underwriters.

issues. However, just like the majority of the previous studies, they do not consider whether the characteristics of an IPO firm's industry are also germane to survival.

In summary, it is clear that almost all of the previous studies have either employed event time logistic models or duration-based AFT and CPH survival models in assessing the survival likelihood of new listings. They do not find that one approach is always preferred to the other as they provide in each case the relative merits and demerits of each approach; however, there seems to be a general consensus that the duration models provide better estimates of the survival likelihood function given that they account for the individual differences in the time to failure of the sample firms, in addition to controlling for those firms that are still alive at the end of the last observation date. It is also vital to note that the majority of these studies have mainly focussed on the impact of firm, offering and general market characteristics on this stage of the life of these firms. In this regard, the most researched variables in the literature have been size, underwriter reputation, IPO risk, past performance, IPO market condition, age, venture capital, corporate governance, initial returns/under-pricing, market-to-book/general market level, owner stock retention, auditor quality and leverage in that order. In general, these variables have been found to be significantly related to the survival likelihood of new issues of common stock.

From the foregoing, it does appear that the relationship between industry structure conditions at the IPO and the survival likelihood of new issues has been greatly under-examined in the literature. In fact, the only published studies have been Jain and Kini [1999 and 2008] and Howton [2006]. The earlier of the Jain and Kini studies finds that industry R-and-D intensity is positively related to survival. However, they find no significant evidence to suggest that other industry risk factors of market-to-book and concentration can be used to distinguish surviving firms from failing firms. In the later study, they find that more diversified IPO firms whose pre-IPO industry-adjusted investment in R-and-D intensity is larger exhibit higher survival probabilities and longer times to failure than their counterparts [i.e. less diversified firms with lower pre-IPO industry-adjusted investments in R-and-D intensity]. Howton [2006] also finds no evidence to suggest that industry concentration and industry R-and-D expenditure is significantly related to IPO survival.

Since the focus of this final empirical study is on the impact of industry structure variables on the survivability of new issues, a limited range of the firm and offering characteristics is pre-selected as control variables in the empirical design, just like in the second empirical study. In this regard, size related variables of offer price, offer proceeds, market capitalization, total assets and market value as well as performance related variables of profit margin, return on assets and earnings yield are considered.

The IPO market condition, firm leverage, firm age, market-to-book ratio, underwriter prestige, initial returns and IPO firm risk are also included. These are the variables which the majority of the previous studies have shown to be the most important in the assessment of the survivability of IPOs. VC-backing and auditor quality are not included because the author believes that the underwriter prestige variable provides an adequate proxy and effectively captures the role and impact of expert informational intermediaries on the survivorship of new stock issues. This study also excludes earnings management, analyst recommendations, percentage of ownership retention at the IPO and corporate governance characteristics, as they are outside the scope of this work. The discussion of the choice variables to be used in this third empirical study will be conducted in Section 5.4.2.

[5.3] Research Questions and Hypotheses

Given the findings from the second empirical study which showed that some industry conditioning risk factors prior to or at the IPO can be germane to the long-run performance of new stock issues, this final empirical study now seeks to ascertain whether these same battery of industry risk factors can foreshadow the survivability of these new listings, using the works of Jain and Kini [1999 and 2008] and Howton [2006] as a springboard. Hence, similar to the research questions posed in the second empirical study regarding long-run performance, the author now asks if an IPO firm's industry structure relating to an adjusted firm valuation, concentration, market-to-book, profitability, leverage and equity volatility can foreshadow its survival likelihood[140].

Following from the above, the study will provide answers to the following knotty questions:

- What are the industry characteristics of IPOs that survive or fail?
- Are industry risk factors related to an adjusted firm valuation, market-to-book, leverage, concentration, equity volatility and profitability also associated with the survival of these equity issuances?

Following from the research questions above, the central hypothesis under investigation in this third empirical study is presented below:

Hypothesis – [H_0]: Industry - structure risk factors related to an adjusted IPO firm valuation [i.e. IPO surplus value], market-to-book, profitability, leverage, concentration and equity volatility cannot foreshadow IPO survival likelihood.

[140] See Section 4.2.3, pp. 204-211.

[5.4] Methodology

[5.4.1] Applied Empirical Design

The first stage of the empirical analysis in this final study involves data stripping to enable us to profile surviving and failing firms and thereafter determine if there are any significant differences in the characteristics of both groups. These factors are then compared across the two post-IPO states – survival or non-survival – in calendar time. The mean [median] values are determined for both groups and the pairwise differences are then subjected to significance tests, employing both parametric $[t - ratio]$ and non-parametric $[Wilcoxon\ z]$ test statistics.

In the second stage and as a preliminary analysis, the shape of the hazard function is estimated without employing any of the explanatory variables[141]. Let X be a random variable measuring the duration of an offering on the LSE with duration distribution function: $F(t) = \Pr(T < t)$ and density function $f(t) = dF(t)/d(t)$. Now, the duration data can be described in terms of the likelihood of failing during an infinitesimal time interval $d(t)$, given that it has survived up to time t :

$$\lambda(t) = \frac{f(t)}{S(t)} \approx \frac{\Pr(t \leq T < t + dt | \ T \geq t)}{1 - F(t, X)} \ldots\ldots. [5.1]$$

[141] This is also known as non-parametric estimation of the hazard function.

In the third stage, the IPO firms are tracked in event time using binary logit models and a string of explanatory variables. Following Jain and Kini [2000], a logistic regression analysis that utilizes the coefficients of the independent variables is employed to investigate the probability of occurrence of a dichotomous dependent variable and also permits us to examine the overall effect of the independent variables on the dependent variable. The technique weights the independent variables and creates a score for each firm in order to classify it as a survivor or a failure with the 'survivor category' chosen as the reference class against which the 'non-survivors' are contrasted. More specifically, functions of the form below are estimated:

$$Logit(P_{NS}/P_S \,|\mathcal{X}_i) = \alpha + \sum_{m=1}^{M} \beta_m \mathcal{x}_{m,i} + \mathcal{E}_i \quad \ldots\ldots [5.2]$$

The subscript i indexes the IPO firms, P_S is the probability of the 'survivor' state and P_{NS} is the probability of the 'non-survivor' state. $X_{m,i}$ symbolizes a set of observable ex-ante firm and industry characteristics of the listed firm i prior to or at the IPO date that will be deemed germane to its survival prospects, while β_m are the coefficient estimates. The interpretation of the logistic regression model results in a value that can be interpreted as the conditional probability of failure relative to survival. Apart from the signs, the coefficients from this model are not easy to interpret directly. In order to examine the individual impact of the explanatory variables, $\mathcal{X}_{m,i}$ on the probability of failure, this third study computes 'marginal effects', defined as the partial derivative of the probability of failure relative to survival for each of the explanatory variables, while holding the other predictor variables constant at their means.

Given a standard logistic distribution function:

$$F(w) = L(w) = \mathrm{e}^{\mathrm{w}}/\{1 + \mathrm{e}^{\mathrm{w}}\} \ldots\ldots \text{[5.3]}$$

where, $w = \beta_m x_{m,i}$

The partial derivatives or marginal effects can be derived as:

$$\frac{dL(w')}{dx_{m,i}} = \frac{e^{w'}}{(1+e^{w'})^2}\beta_m \ldots\ldots \text{[5.4]}$$

However, due to the non-linearity of the logit model, the marginal effect is the effect of an infinitesimal [i.e. less than one-unit] change in the predictor variables on the probability of failure. To assess the impact of a one-unit change in the predictor variables, the study turns to the log-odds given by:

$$log\Omega(x) = log\frac{P_{NS}}{P_S} = \beta_m x'_{m,i} \ldots\ldots \text{[5.5]}$$

The effect of one-unit changes in the predictor variables on the log-odds is then given by:

$$\frac{dlog\Omega}{dx_{m,i}} = \beta_m \ldots\ldots \text{[5.6]}$$

However, in terms of the odds rather than the log-odds, equation [5.6] can be written as:

$$\frac{\Omega(x'_{m,i}+1)}{\Omega(x'_{m,i})} = \exp(\beta_m) \text{ .... [5.7]}$$

From equation [5.7], the right-hand side can be interpreted as the change in the odds of failure relative to survival associated with one-unit increases in the explanatory variables. If $\exp(\beta_m) > 1$, then the odds of failure relative to survival are greater by $\exp(\beta_m)$. On the other hand, if $\exp(\beta_m) < 1$, then the odds are smaller by $\exp(\beta_m)$. The quantified percentage change in the odds [i.e. odds effect] is given by $\{100 * [exp(\beta_m) - 1]$. The odd ratios are much more comparable to the time and hazard ratios from the AFT and CPH models respectively.

To perform the logistic regressions, the binary dependent variable is set equal to one if the firm fails within six years of the IPO and zero otherwise. Under this model, positive [negative] parameter estimates indicate factors that increase [decrease] the conditional likelihood of failure relative to survival. However, this technique has some noticeable drawbacks; firstly, it only answers the question of whether the event will occur, but not when it eventually occurs and as such is unable to distinguish between firms that fail within six months of their listing date from those that fail within two years [Lowers, et al, 1999]; secondly, it does not control for those firms that are still trading and have not yet failed by the end of the last observation date and; thirdly, it assumes a steady state for the failure process that is, in most cases, violated [Jain and Kini, 2000]. Despite these drawbacks, it is important to point out that the majority of the studies in the literature have employed this technique [Jain and Kini, 1999; Chou, et al, 2007; Yang, et al, 2008; Bhabra and Pettway, 2003; Kooli and Meknassi, 2007; Demers and Joss, 2007; Chi, et al, 2010; Bhattacharya, et al, 2010; Lewis, et al, 2010; Hamza and Kooli, 2010; Chang, et al, 2012; Yang and Ding, 2012; Raju and Prabhudesai, 2012].

To overcome these problems, survival analysis or hazard models that has its origins in the bio-medical sciences and has been employed in a variety of business applications [Freeman, et al, 1983; Carroll, 1984; Carroll and Delacroix, 1982; Lane, et al, 1986; Keasey, et al, 1990; Chen and Lee, 1993; Bandopadhyaya, 1994; Somers, 1996] is adopted in the fourth and final stage to track IPO survival in duration time. Specifically, this technique provides the following benefits; firstly, it permits an assessment of the conditional probability of failure of an IPO firm given that the firm has survived till the present time; secondly, it allows for a better handling of 'censored data'[142] and time-varying covariates [LeClere, 2000; Shumway, 2001] and; thirdly, it employs estimation techniques that incorporate information from both censored and uncensored data to provide efficient and consistent parameter estimates [Allison, 2000]. In the real world, the IPO market is characterized by situations where firstly, a large number of firms that

[142] Censoring refers to a situation where the event has not yet occurred at the end of the tracking period or the firm has left the sample for reasons other than failure. Therefore, the time to the event is only known for a portion of the sample [LeClere, 2000].

went public are still operational even after the end of the observation period and secondly, different time windows for each of the firms depending on when the firm went public. For instance, in the sample, the firms are tracked until 31 December 2012. Therefore, a firm that went public in 1999 is tracked for 13 years, while a firm that had its IPO in 2006 is tracked for 6 years. Against this backdrop, the most appropriate methodology for the analysis of a duration-dependent behaviour such as IPO survival is the survival or hazard model, also known as the Cox [1972] hazard methodology.

The hazard model is used to perform tests of the theorized variables that may impinge on the survival or time to failure of the IPO firms. The hazard probability is the conditional probability that the IPO, offered for sale at $t = 0$, fails at time t given that it has not failed before time t. Using T, a proxy for IPO survival time, defined as the number of months an IPO remains operational before failure or the end of the observation or tracking period, the hazard probability is given by:

$$H(t;X) = f(t;X)/\{1 - F(t;X)\} \text{ ……. [5.8]}$$

where $\mathrm{F(t;X)}$ is the probability that an IPO with characteristics X has failed before time t and $\mathrm{f(t;X)}$ is the probability density function on T. The general form of the hazard model is given by:

$$T(t;X) = T_0(t)e^{X\beta} \text{ ……. [5.9]}$$

where:

T = length of trading period in months

$T_0(t)$ = baseline hazard function describing the expected pattern of the trading period duration for a pool of IPOs that went public in different periods

X = a vector of independent variables hypothesized to impinge on IPO survival time

β = a vector of model parameters

The baseline hazard function describes the probability distribution for IPOs that fail under standardized conditions. Variation from these conditions affects the baseline function and changes the expected probability distribution for the operational period of a non-surviving IPO. A plethora of hazard models exists, differing from each other in terms of the shape of the hazard function [Kalbfleisch and Prentice, 1980]. In this third empirical study, the choice model is the parametric AFT model. The attraction of this model is that the effect of changes to the independent variables on the hazard probability at any time t can differ according to the length of the post-IPO period [Hensler, et al, 1997]. For example, the impact of underwriter reputation on survival may be less for IPOs that went public in earlier periods compared to those that listed in recent times. The AFT model is given by:

$$T(t;X) = T_0(t)^{\sigma}e^{X\beta} \text{ .... [5.10]}$$

Or alternatively,

$$In\, T(t;X) = \sigma T_0(t) + X\beta, \text{ .... [5.11]}$$

With

$$In\, T_0(t) = Ine^{\omega} = \omega \text{ .... [5.12]}$$

where T, X and β are as defined previously. $T_0(t) = e^{\omega}$ is the baseline hazard function with a specified continuous density, while σ is an ancillary scale parameter that shapes the function. Several functional forms exist for modelling the time to failure of IPOs. The log-logistic model is the model of choice[143] given that the frequency distribution of IPO failure by year for the sample is non-monotonic[144]. The log-logistic baseline hazard function is:

$$T_0(t) = \lambda\rho(\lambda\, t)^{\rho-1}/(1 + (\lambda\, t)^{\rho}) \text{ .... [5.13]}$$

where λ and ρ are density parameters and t is the individual IPO failure time. If $\rho < 1$, the log-logistic function is monotonically decreasing[145]. On the other hand, if $\rho > 1$, the function becomes non-monotonic implying that the conditional probability that an IPO will fail rises in the early post-IPO period to its utmost after which it diminishes, with the most plausible failure period occurring at:

$$t = (\rho - 1)^{1/\rho}/\lambda \text{ .... [5.14]}$$

Equation [5.13] is then estimated with the maximum likelihood method to obtain the parameter estimates, with $\lambda = e^{X\beta}$ and $\rho = 1/\sigma$. The statistical significance of these

[143] It is also possible to use the log-normal distribution. However, results from such a model are most times, not robust to a sample comprising IPO firms with very short survival times. Also, the model does not effectively deal with censored observations, unlike its log-logistic counterpart.

[144] See Figure 5.1, pp. 352.

[145] The density function for the time to failure for the IPOs is non-monotonic $[i.e. \rho > 1]$ rising in the early post-IPO years, reaching its peak in year six and reducing thereafter [See Figure 5.1, pp. 352].

estimates is then determined using a z-statistic computed as the ratio of the parameter estimate to its standard error $\{i.e. z(\lambda) = \frac{\lambda}{SE(\lambda)}; z(\rho) = \frac{\rho}{SE(\rho)}\}$. InL_n is the value of the maximum log likelihood of the estimated model.

A substantial number of the sample firms were still operational at the end of the observation period[146]. In order to control for this, an additional binary variable that denotes whether an observation is right-censored or not is introduced[147]. If the censoring marker is denoted as δ_i, taking the value of 1 for failed firms and 0 for censored observations, the general form of the maximum likelihood function becomes:

$$L = c \prod_{i=1}^{n} f_i(t_i X_i)^{\delta_i} \{1 - F_i(t_i; X_i)\}^{1-\delta_i} \ldots\ldots [5.15]$$

where $f_i(t_i; X_i)$ and $1 - F(t_i; X_i)$ are as defined previously in equation 5.8 and C is a constant term.

Just like in the logit model, the parameter estimates resulting from this model do not lend themselves to easy interpretation. One way to assess the effect of the individual variables on the trading or survival time is to conduct a 'sensitivity analysis', defined as the process whereby the individual explanatory variables are 'shocked' from their

146 At the end of the tracking period [31 December 2012], 568 firms did not experience the event [i.e. these firms continued to trade after 2012] and as such the end-point of these firms is not observed in the event window [See Table 5.4, pp. 350].

147 A right-censored observation is an IPO firm that continues to trade after the end of the observation period. Left-censoring occurs when some firms have started trading before the commencement of the study period, which is not applicable in the data.

means, while holding the other predictor variables constant in order to determine the extent to which survival time is affected by that variable. Typically, the shocks are multiples of the variables' standard deviations from their means [Hensler, et al, 1997; Van der Goot, et al, 2009]. Another way of assessing the impact of the individual variables on survival time is to consider the extent to which changes in the hypothesized predictor variables accelerate or decelerate the time to failure, given by the time ratios. Similar to the hazard ratio in the CPH model, the time ratio is calculated as $exp(\beta)$, while the quantified percentage change on survival time or time to failure is computed as $\{100 * [exp(\beta) - 1]\}$. A positive [negative] value of β, which corresponds to time ratios $[exp(\beta)]$ greater [less] than one, indicates that increasing values of the explanatory variable increases [decreases] the survival time or time to failure [Bradburn, et al, 2003].

Overall, under this model, positive [negative] parameter estimates indicate factors that increase [decrease] the trading period or time to failure, which in turn increase [decrease] the probability of survival and decrease [increase] the failure rate. A number of studies in the literature have employed this technique [Hensler, et al, 1997; Kooli and Meknassi, 2007; Van der Goot, et al, 2009; Yang, 2006; Raju and Prabhudesai, 2012; Espenlaub, et al, 2012].

Under the AFT model, the study has assumed a functional form for the underlying survival distribution[148]. However, the model parameters can be estimated by relaxing this assumption. In this regard and also to ensure robustness, the semi-parametric CPH model is employed to assess the conditional probability of failure [i.e. the hazard rate], given that the IPO firm has survived up to the present time. Specifically, the CPH technique provides the following benefits; firstly, the baseline hazard function can assume any functional form which broadens its applicability [Jain and Kini, 2008] and secondly, it allows for both discrete and continuous measurement of event times making it relatively easier to integrate time dependent variables [Jain and Kini, 1998; Allison, 2000].

Under the CPH model, the survival likelihood from one period to another is taken as a function of the hazard rate. For the sample, the hazard rate can be defined as the rate at which an IPO firm, alive at time t, has failed at time $t + h$, where h is an infinitesimal time interval. Hence, the hazard rate can be viewed as the spot change from a survivor state to a non-survivor state. Therefore, the lower the mortal force, the less likely the IPO firm will fail. In terms of the probability density and cumulative density function, the hazard function, $H(t)$ is given as:

[148] The evidence from Figure 5.1 [see pp. 352] indeed suggests that the survival distribution for the sample data approximates the log-logistic form.

$$H(t,X) = \frac{f(t,X)}{1-F(t,X)} \quad \text{……. [5.16]}$$

where $F(t,X)$ is the probability that an IPO firm, listed at time, $t = 0$, with characteristics X has failed before time t and $\mathrm{f(t,X)}$ is the probability density function.

The general form of the hazard model is given by:

$$H(t,X) = H_0(t)\exp(X\beta) = h_o(t).\exp(\textstyle\sum_{k=1}^{p}\beta_k X_k) \quad \text{……. [5.17]}$$

where $h_0(t)$ is the baseline hazard rate, X represents a $(1 \times p)$ vector of explanatory variables and β is a $(p \times 1)$ vector of parameters to be estimated with the method of partial likelihood. If the baseline hazard function is eliminated from equation [5.17], the likelihood function has the following form:

$$H(t,X) = \prod_{i=1}^{k} \frac{\exp(X_i\beta)}{\sum_{j\in R_i}\exp(X_j\beta)} \quad \text{……. [5.18]}$$

where k is the number of time periods, X_i is the vector of covariates associated with the IPO firms observed at time i and R_i is the risk set at time i, representing the time-varying cohort of firms at risk for the event occurring at any point after time i. Firms that have experienced the event will be included in the numerator of equation [5.18], while the entire cohort of firms at the risk of experiencing the event just before the last time period k will be included in the denominator.

The coefficient estimate, β under this variant of the survival model represents the hazard rate and is interpreted as the increase in the log hazard ratio for a one-unit increase in the explanatory variable, while holding the other predictor variables constant. The relative hazard rate or the hazard ratio is computed as $exp(\beta)$, while the quantified percentage change on the hazard rate is calculated as $\{100 * [exp(\beta) - 1]\}$. A negative [positive] value of β, which corresponds to a hazard ratio $[exp(\beta)]$ less than one [greater than one], indicates that increasing values of the explanatory variable lowers [increases] the risk of failure and increases [reduces] the survival time [Vittinghoff, et al, 2005].

Under this model, positive [negative] parameter estimates indicate factors that increase [decrease] the force of mortality which consequently reduce [increase] the trading period or time to failure and in turn, increase [decrease] the hazard rate and decrease [increase] the probability of survival. The concept underlying the CPH model is similar to that of the logistic model and as such, the signs of the parameter estimates from both models are expected to be the same. A substantial number of studies have employed the CPH technique [Jain and Kini, 2000; Chou, et al, 2007; Jain and Martin, 2005; Demers and Joss, 2007; Carpentier and Suret, 2011; Peristiani and Hong, 2004; Hamza and Kooli, 2010; Yang and Ding, 2012; Chancharat, et al, 2012; Van der Goot, et al, 2009; Chandy, 2006; Rath, 2008; Dimson and Stolin, 2002].

It is pertinent to note that the AFT and CPH models share some similarities. They can be employed to model hazard rates and can both be estimated by the method of maximum likelihood. However, they also differ in some respects; firstly, the CPH model is defined in the proportional hazard metric, while the AFT technique is set out in the accelerated time metric; secondly, the CPH model has no intercept since it is undetectable from the data, while the AFT model has an intercept and; thirdly, there is a flipping of the signs of the coefficients when there is a switch from the AFT to the CPH model due to the fact that the time acceleration parameter under the former corresponds to $\exp(-X\beta)$, while the hazard rate under the latter is scaled by $\exp(X\beta)$.

In summary, the logistic and CPH models track factors that impinge on the probability of failure or hazard rate of firms, while AFT models focus on those that increase the trading period or time to failure. Following from this, the signs of the coefficient estimates from the AFT model are expected to be opposite to those of the logistic and CPH models. Given that the majority of the studies in the literature have employed the event-time logistic model, this third study uses this technique as the baseline model. However, in order to reduce model bias which becomes more likely when one technique is favoured over the others and to also give the greatest possible level of depth and robustness to the results, the duration-based AFT and CPH models are also employed to assess the survivability of IPOs.

[5.4.2] Variable Selection and Expectations

Table 5.1 provides a summary of the variables that are under consideration in this third empirical study and their expected relationship to survival probability[149]. A brief explanation of the justification for each variable and its expected relationship with survival [shown in brackets] follows.

Hot Market Condition (-): Specifically, this study wants to investigate whether the issue period has an effect on the survival prospects of issuing firms. During periods of high IPO issuing activity [‘hot markets], there is the temptation for fledgling, marginal and poor quality firms to go public to take advantage of the opportunity created by intense investor optimism and a booming demand for capital in the market place. Following the findings of Yung, et al [2008], Fama and French [2004], Chi, et al [2010], Hamza and Kooli [2010], Chang, et al [2013] and Espenlaub, et al [2012] that IPOs issued in ‘hot’ market conditions are more likely to fail than those issued in other market conditions, a negative relationship between the ‘hot’ market dummy and survival is expected. The ‘hot’ market indicator for firm i is denoted as $[hot_i]$.

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[149] See Table 4.1, pp. 228 for the definitions and measurements of the variables. The author points out that the categorisation of some of the variables could differ from industry to industry. For example, the definition of a large [size] or an old [age] firm could differ, where firms in different industries have different sizes and lifespans. The author has not controlled for these effects since they are not expected to affect the results.

Age (+): Young firms tend to have very little trading history and also not yet strong enough to withstand the vicissitudes of the industry and indeed the market place. Also, they tend to be uncertain about their future prospects and are also less likely to have the requisite managerial expertise to withstand the vagaries of the market place. On the other hand, older firms tend to be mature and established with a track record of sales and positive earnings in their industries because they have been operating for several years. Hence, these firms are less likely to fail after their IPOs. Hensler, et al [1997], Yung, et al [2008], Demers and Joss [2007], Jain and Martin [2005], Peristiani and Hong [2004] and Espenlaub, et al [2012] document a positive relationship between the age of the firm at the IPO and the likelihood of survival. Therefore, firm age at the offering date is expected to be positively related with survival. The age variable is denoted as $\mathcal{Log}[1 + age_i]$.

Size (+): The size of a firm is a crucial factor in its competitiveness and likelihood of survival in the market place[150]. Larger firms tend to be associated with larger offerings which, more often than not, are indicators of market confidence. They are also subject to greater market scrutiny, command a great analyst following and also tend to be favoured by informed investors. Hensler, et al [1997], Jain and Kini [1999], Bhabra and Pettway [2003], Kooli and Meknassi [2007], Jain and Martin [2005], Hamza and Kooli

[150] See Section 3.3.4, pp. 124-125.

[2010], Raju and Prabhudesai [2012] and Espenlaub, et al [2012] find that large firms have better survival prospects than smaller firms. Against this backdrop, a positive relationship is expected between the size of the firm and the likelihood of survival. The offer price $[Price_i]$, offer proceeds $[OP_i]$, market capitalization $[ME_i]$, market value $[MV_i]$ and total assets $[TA_i]$ serve as proxies for the size of the firm.

Leverage (+): The exact relationship between leverage and firm performance and by extension, survival is still hazy as there are two contending views in the literature[151]. Hence, the precise nature of the relationship between leverage, performance and firm survival is inconclusive and can only best be determined by specific empirical tests. However, this study leans towards the view that the judicious use of debt can boost the performance and survival likelihood of the firm and hence, a positive relationship is predicted between leverage and survival, which is contrary to the findings of Bhabra and Pettway [2003], Demers and Joss [2007] and Chancharat, et al [2012]. The firm leverage is denoted as $[Lev_i]$.

Pre-IPO Performance (+): IPOs with a stronger record of profitability at the time of the IPO are expected to exhibit superior performance in the long-term which should in turn massively influence the transition to any of the post-IPO states. Jain and Kini [1999], Bhabra and Pettway [2003], Chi, et al [2010], Peristiani and Hong [2004] and Lewis, et

[151] See Section 4.3.2, pp. 218 and Section 4.4.3.1, pp. 253.

al [2000] document a positive association between past profitability and the probability of survival for new issues of common stock. In the light of the above, a positive relationship between pre-IPO performance and the IPO firm's chances of survival is expected. The pre-IPO performance is measured by return on assets $[ROA_i]$, profit margin $[PM_i]$ and the earnings yield $[EY_i]$.

Market-to-book (-): The study next examines if the expectations of strong future earnings built into the prices of these firms and reflected in their market-to-book values at the time of their going public has any impact on the post-IPO outcomes. On the one hand, if investors perceive these firms to be of good quality with a great future, they would value the firms highly and pay the going price to acquire the stock. If this view holds sway, high market-to-book firms are less likely to fail. On the other hand, if poor quality IPOs are issued during periods of high market misevaluations, unsuspecting investors buy into these IPOs and become overly optimistic about their future prospects. However, with the passage of time, the true quality of these firms is revealed via their operating performances and investors are then forced to revise their expectations as the share prices are downwardly adjusted in equilibrium. Extending the link between market-to-book and IPO long-run performance to include post-IPO outcomes, IPO firms with high market-to-book ratios are more likely to fail. This study goes along with this latter view and predicts a negative relationship between the market-to-book ratio and survival likelihood. The firm's market-to-book ratio is denoted as $[MTB_i]$.

Underwriter Reputation (+): Driven by the need to maintain and enhance their reputational capital towards boosting their business volumes, highly prestigious investment bankers provide post-issue monitoring, stabilization and price support services to the IPO firms. They are also able to select quality IPOs from the myriad of new issues that may be in the market at any time due to the experience garnered over the years from handling top-quality issues. Against this backdrop, firms underwritten by them are expected, on average, to have a higher likelihood of survival. The findings of Schultz [1993], Jain and Kini [1999 and 2000], Yung, et al [2008], Kooli and Meknassi [2007], Lewis, et al [2000] and Hamza and Kooli [2010] are in line with this surmise. Hence, a positive relationship between underwriter reputation and IPO survivability is predicted. However, given the study's categorisation of the underwriter reputation variable[152], a negative sign for the coefficient estimate is expected, which indicates a positive relationship to IPO survival. Underwriter market share serves as this study's direct measure of underwriter reputation $[UW_i]$.

Under-pricing/Initial returns (-): The firm's initial return is the level of returns available in the immediate after-market to investors who subscribe to the offer at the IPO date. A

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[152] See Panel F of Table 3.5, pp. 99 and Section 4.3.2, pp. 220-221.

greater level of under-pricing should logically result in a higher level of initial returns to IPO subscribers in the early after-market. There are two competing views on the role of under-pricing as a signal of firm quality. On the one hand, Rock's [1986] adverse selection theory associates poor quality IPOs with a greater level of under-pricing in order to induce uninformed investors to buy the stock. On the other hand, the signalling theory contends that high quality IPOs under-price their shares in order to send signals to potential investors about the capabilities and future values of the firms. However, the majority of the empiricism on under-pricing tends to align more with the adverse selection arguments. Moreover, Kooli and Meknassi [2007], Demers and Joss [2007] and Hamza and Kooli [2010] show that under-pricing is a bad survival signal [i.e. negatively related to survival]. Therefore, this study goes along with the adverse selection arguments and predicts a negative relationship between under-pricing/initial returns and the probability of survival. Initial returns is denoted as $[IR_i]$.

IPO Risk (-): Several researchers have used different proxies of risk in an attempt to capture the uncertainty that surround new stock issues. Rath [2008], Bhabra and Pettway [2003] and Hensler, et al [1997], using the number of risk factors in the prospectus, find that risk is negatively related to the IPO firm's survival likelihood. Following Ritter [1984], Carter and Manaster [1990] and Jain and Kini [1999] who also find that higher risk significantly reduces the survival probability of new issues of common stock, the after-market standard deviation of the firm's daily return during the first 30-days post-listing, $[Risk_{i,}]$ is employed to proxy for the riskiness of each IPO firm. In line with the majority of extant literature, a negative relationship is predicted between IPO risk and the probability of survival.

IPO Surplus Value (-): Purnanandam and Swaminathan [2004], Chang, et al [2010], Corhay, et al [2002] and Xia and Wang [2003] show that IPO valuation at the listing date could presage the long-term performance of new issues. More specifically, they find that over-valued IPOs [i.e. trading at high market-to-book multiples] tend to under-perform in the long-term. This argument between IPO valuation and long-term performance is extended to include an assessment of the chances of survival of an IPO firm based on an industry-adjusted valuation. If the link between the industry-adjusted valuation of an IPO firm and its long-run performance is also extended to include post-IPO outcomes, it is expected that IPO firms trading above their industry-adjusted valuations [i.e. trading at a premium relative to industry peers] will be more likely to fail. Hence, IPO surplus value is expected to be negatively related to survival. The industry-adjusted valuation or IPO surplus value for firm i is denoted as $[sval_i]$.

Industry leverage (+): The precise nature of the relationship between firm leverage and IPO firm performance is still hazy and as such, best addressed empirically. However, the relationship between industry leverage and IPO performance should be less ambiguous. IPO firms in industries that are already less concentrated and highly leveraged are expected to perform better due to the competitive advantage they enjoy from a relatively healthier capital structure following the injection of new equity capital. Once again, if this argument between industry leverage and long-term performance is extended to include post-IPO outcomes, highly leveraged industries are expected to portend positive signals for the survival prospects of IPO firms. Therefore, a positive relationship is predicted between industry leverage and the probability of survival of new issues of common stock. The market leverage ratio serves as a proxy for the industry leverage. The industry leverage for firm i as at the IPO date is denoted as $[i\_lev_i]$.

Industry Equity Volatility (-): If the volatility of an IPO firm's industry is a proxy for the riskiness of the industry, the risk profile of each of the constituent firms in that industry is expected to increase. On the one hand, if this risk is priced sufficiently, then IPO firms from industries with high volatilities should earn higher returns. On the other hand, higher risk could also imply a higher likelihood of poor performance and failure in the long-term. Therefore, if a firm or its industry is seen by its investors to be too risky, then its likelihood of failure will increase. This study leans towards the latter argument and predicts a negative relationship between the equity volatility of an industry and IPO survival. The industry equity volatility for firm i as at the IPO date is denoted as $[i\_ev_i]$.

Industry Profitability (+): High growth and profitable industries, a measure of industry attractiveness, may provide a good platform for IPO firms to survive and grow. They can do this by identifying and utilising profitable niche opportunities, more especially in industries that are less concentrated. Therefore, the likelihood of survival is likely to be positively related to the profitability of an industry. Moreover, prospective investors can use an IPO firm's industry profit conditions to value firms going public and in the process reduce the information asymmetry and uncertainty surrounding the firm's long-term performance and survival prospects. This measure of industry attractiveness is captured by the profitability of the firms currently in the industry. Based on the foregoing, a positive relationship is predicted between industry profitability and IPO survival. The industry profitability for firm i as at the IPO date is denoted as $[i\_pr_i]$.

Industry Concentration (+): This is another measure of industry attractiveness. There are two competing views on the relationship between this risk factor and the performance and survival prospects of IPO firms. In less concentrated [i.e. more competetitive] industries, it is unlikely that a dominant player has emerged which provides a good avenue for new entrants into the industry to deploy their equity capital more productively. In highly concentrated industries which tend to be less competitive because they are dominated by established players, there are fewer opportunities to deploy the IPO firm's equity capital to maximum effect. However, on the balance, it may still provide IPO firms with a more favourable environment to ply their trade due to the fact that firms in this industry tend to avoid aggressive price and market share wars. Clearly, the relation between survival and industry concentration is still unclear and best addressed empirically. Jain and Kini [1999] do not find strong evidence to support the fact that surviving firms are in more concentrated industries than the failing firms. However, this study leans towards their findings and predicts a positive relationship between the probability of survival and industry concentration. The size-weighted industry concentration for firm i as at the IPO date is denoted as $[i\_conc_i]$.

Industry Market-to-book (-): This is a measure of the growth prospects of an industry. There are two competing explanations for the relation between industry market-to-book and the likelihood of going public [Pagano, et al, 1998]. The first explanation suggests that marginal firms are motivated to go public to take advantage of industry and market over-valuations, while the second explanation suggests that investors have high expectations of the future prospects of the firms based on the growth opportunities that abound in the industry which cause them to value the stocks highly. Extending the link between industry market-to-book and the probability of going public to include the

TABLE 5.1: SUMMARY OF VARIABLES & THEIR EXPECTED RELATIONSHIP TO SURVIVAL

Variable	Description	Exp. relationship to survival
$Price_i$	Offer Price	+
OP_i	Offer Proceeds	+
$\mathcal{Log}[1 + age_i]$	Age	+
ME_i	Market Capitalization	+
TA_i	Total Assets	+
MTB_i	Market-to-Book	-
PM_i	Profit Margin	+
ROA_i	Return on Assets	+
EY_i	Earnings Yield	+
lev_i	Market Leverage	+
hot_i	Market Heat	-
UW_i	Underwriter Reputation	+
mv_i	Market Value	+
IR_i	Initial Returns	-
$Risk_i$	IPO Firm Risk	-
$sval_i$	Surplus Value	-
i_lev_i	Industry Leverage	+
i_conc_i	Industry Concentration	+
i_ev_i	Industry Equity Volatility	-
i_pr_i	Industry Profitability	+
i_mtb_i	Industry Market-to-Book	-

likelihood of survival of the IPO firms, the first explanation should result in a higher failure rate, while the second explanation should culminate in a lower hazard rate. This study aligns with the second argument and predicts a negative relationship between the industry market-to-book and the probability of survival. The industry market-to-book ratio for firm i as at the IPO date is denoted as $[i\_mtb_i]$.

In summary, survival time or time to failure is expected to increase with increasing age, size, leverage, pre-IPO operating performance, underwriter reputation and industry risk factors of leverage, profitability and concentration, and decrease with increasing hot markets, market-to-book, initial returns, risk and industry risk factors of IPO surplus value, equity volatility and market-to-book.

[5.5] EMPIRICAL ANALYSIS

[5.5.1] Distribution of Post-IPO States

Table 5.2 provides a distribution of the surviving and non-surviving firms as at the last observation date [i.e. 31 December 2012] by the year of the IPO [Panel A] and industry [Panel B] for the sample of firms that went public over the period 1999 to 2006 and the sub-period excluding the ‘dotcom’ years, going from 2002 to 2006. The fact that the new issues market goes through cycles is well documented. In tense market conditions characterised by high demand for capital and profound investor optimism, firms and

TABLE 5.2: DISTRIBUTION OF POST-IPO STATES FOR THE IPO SAMPLE

The sample is 746 firms that went public over the period January 1999 and December 2006 and a sub-sample of 485 firms that went public over the period excluding the 'dotcom' years [i.e. 2002 and 2006]. The table reports the distribution of the surviving and non-surviving firms as at the last observation date [i.e. 31 December 2012] by the year of the IPO [Panel A] and industry [Panel B]. The definition of industry is based on the standard industry classification [SIC] codes. Survivors are defined as firms that continue to operate independently as public limited corporations, with acquired/merged firms included in this category. Firms that discontinue operations and cease to trade during the observation period are classified as non-survivors.

Panel A

Year	Survivors	%	Non-Survivors	%	Total	%
1999	29	60	19	40	48	100
2000	105	70	45	30	150	100
2001	46	73	17	27	63	100
2002	38	76	12	24	50	100
2003	29	73	11	28	40	100
2004	110	80	28	20	138	100
2005	121	80	31	20	152	100
2006	90	86	15	14	105	100
Overall [1999 - 2006]	**568**	**76**	**178**	**24**	**746**	**100**
2002 – 2006	**388**	**80**	**97**	**20**	**485**	**100**

Panel B: By industry

Industry	Survivors	%	Non-Survivors	%	Total	%
Aerospace & Automobiles	6	100	0	0	6	100
IT & Computer Services	112	73	42	27	154	100
Health & Pharmaceuticals	61	77	18	23	79	100
Food Producers & Processors	9	64	5	36	14	100
Personal Care & Household Goods	9	50	9	50	18	100
Leisure, Hotel & Restaurants	44	69	20	31	64	100
Chemicals, Mining, Oil & Gas	115	88	15	12	130	100
Construction & Engineering	42	72	16	28	58	100
Wholesalers & Retailers	21	78	6	22	27	100
Media & Entertainment	58	73	21	27	79	100
Telecommunications	17	74	6	26	23	100
Transport	6	60	4	40	10	100
Support Services	68	81	16	19	84	100
OVERALL [1999 – 2006]	**568**	**76**	**178**	**24**	**746**	**100**
2002 – 2006 [ex. 'dotcom' years]	**388**	**80**	**97**	**20**	**485**	**100**

their investment bankers take advantage of the transitory opportunity provided by this market condition to float their offerings. Given that this market situation provides a good platform for weaker firms to also go public due to the reduced market scrutiny, it is very possible that firms issuing their shares in this market condition are likely to have lower survival rates compared to other market conditions. However, the results from Panel A do not support this argument. The survival rates of 60%, 70% and 80% for the three ‘hot’ market periods of 1999, 2000 and 2005 respectively compares favourably with the overall average survival rate of 76%. An improvement in the survival rate after 2003 is also observed, which suggests enhanced quality of the issuers in this later period. When the ‘dotcom’ period is excluded from the sample, the survival rate improves further, going from 76% to 80%. Given that a lot of firms failed during this period, excluding this momentous period from the sample is bound to increase the survival rate. This evidence provides some support for the ‘hot market’ argument that firms floating their offerings in periods of high IPO activity [1999 and 2000 of the ‘dotcom’ period are classified as ‘hot’ market years] are likely to under-perform and consequently fail when compared to those firms that go public in ‘cold’ or ‘neutral’ market conditions.

Panel B provides a distribution of the post-IPO states by industry. It is observed that the percentage of the survivors varies from a low of 50% for Personal Care & Household Goods to a high of 100% for Aerospace & Automobiles. Conversely, the percentage of non-survivors varies from a low of 0% for Aerospace & Automobiles to a high of 50% for Personal Care & Household Goods. A closer look at the table also generally reveals that over the entire period, industries with a high volume of IPOs [i.e. sixty or more IPOs] display survival rates fairly comparable with the overall average of 76%. On the flip side, industries with a low volume of IPOs [i.e. less than sixty issues] tend to exhibit failure rates that are generally above the overall average of 24%. These results generally suggest that there may be some industry – specific risk factors at play in the market place that determines the entry and survival of this class of firms.

[5.5.2] Firm and Industry Risk Factors and IPO Survival

[5.5.2.1] Univariate Analysis

Prior to conducting more specific and detailed tests on the possible impact of the selected variables on IPO survival likelihood, preliminary tests are first undertaken to enable the author to gain an insight into the characteristics of the IPO firms and how they could help distinguish firms that are likely to fail from those that are likely to survive. To accomplish this, simple differences in means and medians are employed to ascertain if the characteristics of the surviving and failing group of firms are significantly different.

TABLE 5.3: COMPARISON BETWEEN FIRM & INDUSTRY RISK FACTORS OF THE POST-IPO STATES FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006 and 485 IPOs for the period excluding the ‘dotcom’ years [2002 - 2006]. Panel A presents the differences in mean and median firm and industry risk factors between the survivor and non-survivor IPO firms for the entire sample period [1999 – 2006], while Panel B reports these differences for the period excluding the ‘dotcom’ years [2002 – 2006]. The first four columns present the means, while the last four columns report the medians. The significance tests for differences in means [medians] are conducted using a two-sample t-statistic [Wilcoxon z-statistics]. ***, **, * indicate significance at the 1, 5 & 10% levels respectively.

Panel A: ENTIRE PERIOD [1999 – 2006]

	MEAN				MEDIAN			
	Non-Survivors	Survivors	Mean Diff	t-stat	Non-Survivors	Survivors	Median Diff	Z-stat
Offering Size [£, Log]	1.919	2.290	-0.371	*(-3.12***)*	1.792	2.038	-0.246	*(-2.82***)*
Offer Price [£, Log]	0.512	0.602	-0.090	*(-2.54**)*	0.470	0.588	-0.118	*(-2.28**)*
Total assets [£, Log]	2.050	2.620	-0.570	*(-4.42***)*	1.883	2.433	-0.550	*(-3.52***)*
Market Cap [£, Log]	3.086	3.402	-0.316	*(-2.39**)*	2.923	3.212	-0.289	*(-2.43**)*
Market Val [£, Log]	3.131	3.485	-0.354	*(-2.64**)*	2.956	3.283	-0.327	*(-2.60**)*
5-YR VW BHAR [%]	-53.826	-27.455	-26.371	*(-2.18**)*	-19.643	-15.022	-4.621	*(-2.72***)*
Pre-IPO Profit Margin [%]	-949.697	-469.498	-480.199	*(-1.82*)*	0.000	0.000	0.000	*(-2.32**)*
Pre-IPO ROA [%]	-52.966	-12.173	-40.793	*(-3.52***)*	-4.867	-1.472	-3.395	*(-2.96***)*
Pre-IPO EPS [£]	-0.031	-0.011	-0.020	*(-1.43)*	-0.005	-0.002	-0.003	*(-2.35**)*
Earnings Yield [%]	-8.843	-4.047	-4.796	*(-2.70***)*	-2.001	-0.622	-1.379	*(-2.21**)*
Market Leverage	0.076	0.079	-0.003	*(-0.31)*	0.005	0.011	-0.006	*(-1.80*)*

Panel A CONT'D – ENTIRE PERIOD [1999-2006]								
Market-to-Book [MTB]	10.109	8.298	1.811	*(0.54)*	3.432	2.947	0.485	*(1.08)*
Age @ offering [years]	2.463	3.153	-0.690	*(-1.34)*	0.971	0.836	0.135	*(0.16)*
Underwriter Reputation [Log]	3.322	3.157	0.165	*(2.02**)*	3.296	3.296	0.000	*(1.20)*
Initial Returns [%]	11.186	10.165	1.651	0.59	8.269	7.374	0.895	*(0.66)*
IPO Firm Risk [%]	4.518	4.081	0.437	*(1.24)*	3.288	2.906	0.382	*(0.88)*
Surplus Val [Log]	0.775	0.451	0.324	*(1.51)*	0.412	-0.072	0.484	*(1.50)*
Industry Leverage	0.160	0.173	-0.013	*(-2.15**)*	0.175	0.179	-0.004	*(-1.94*)*
Industry MTB	3.399	3.290	0.109	*(0.52)*	3.051	2.945	0.106	*(0.97)*
Industry Profitability [%]	-24.214	-61.883	37.669	*(2.02**)*	5.158	1.029	4.129	*(3.16***)*
Industry Conc. [HHI] [%^2]	2,706.377	3,368.302	-661.925	*(-3.17***)*	2,072.857	2,206.143	-133.286	*(-2.69***)*
Industry Equity Volatility [%]	13.234	12.731	0.503	*(2.02**)*	12.227	12.065	0.162	*(0.63)*

Panel B: PERIOD EXCLUDING THE 'DOTCOM' YEARS [2002 – 2006]

	MEAN				MEDIAN			
	Non-Survivors	Survivors	Mean Diff	t-stat	Non-Survivors	Survivors	Median Diff	Z-stat
Offering Size [£, Log]	1.671	2.207	-0.536	*(-3.49***)*	1.609	1.949	-0.340	*(-3.21***)*
Offer Price [£, Log]	0.452	0.557	-0.105	*(-2.41**)*	0.405	0.539	-0.134	*(-2.31**)*
Total assets [£, Log]	2.064	2.709	-0.645	*(-3.74***)*	1.884	2.489	-0.605	*(-3.25***)*
Market Cap [£, Log]	2.959	3.349	-0.390	*(-2.34**)*	2.857	3.177	-0.320	*(-2.30**)*
Market Val [£, Log]	3.002	3.452	-0.450	*(-2.61**)*	2.883	3.255	-0.372	*(-2.57**)*
5-YR VW BHAR [%]	-51.763	-16.554	-35.209	*(-2.34**)*	-35.546	-13.143	-22.403	*(-0.27)*
Pre-IPO Profit Margin [%]	-1,246.147	-441.273	-804.874	*(-2.06**)*	-0.004	0.000	-0.004	*(-2.72***)*
Pre-IPO EPS [£]	-0.021	0.005	-0.026	*(-1.80*)*	-0.005	-0.002	-0.003	*(-2.21**)*
Earnings Yield [%]	-9.054	-2.789	-6.265	*(-2.80***)*	-2.865	-0.511	-2.354	*(-2.47**)*
Pre-IPO ROA [%]	-55.639	-12.453	-43.186	*(-3.17***)*	-5.413	-1.130	-4.283	*(-2.91***)*

Panel B CONT'D – PERIOD EXCLUDING THE 'DOTCOM' YEARS [2002-2006]								
Market Leverage	0.098	0.098	0.000	*(-0.01)*	0.007	0.021	-0.014	*(-1.34)*
Market-to-Book [MTB]	7.811	6.592	1.219	*(0.42)*	3.426	2.755	0.671	*(1.13)*
Age @ offering [years]	2.236	3.268	-1.032	*(-1.37)*	0.923	0.773	0.150	*(0.14)*
Underwriter Reputation [Log]	3.486	3.194	0.292	*(2.64**)*	3.526	3.434	0.092	*(2.23**)*
Initial Returns [%]	10.229	8.191	2.038	*(0.76)*	7.785	6.859	0.926	*(0.92)*
IPO Firm Risk [%]	3.381	3.351	0.029	*(0.09)*	2.547	2.653	-0.106	*(-0.77)*
Surplus Mkt. Val [Log]	0.545	0.274	0.271	*(0.95)*	-0.105	-0.216	0.111	*(0.93)*
Industry Leverage	0.173	0.182	-0.009	*(-1.17)*	0.180	0.180	0.000	*(-0.89)*
Industry MTB	3.095	2.892	0.202	*(0.76)*	2.945	2.461	0.484	*(1.09)*
Industry Profitability [%]	-62.521	-100.634	38.113	*(2.64**)*	-1.593	-16.718	15.125	*(2.18**)*
Industry Conc. [HHI] [%^2]	2,924.956	3,671.565	-746.609	*(-2.36**)*	1,887.318	2,206.143	-318.825	*(-2.64**)*
Industry Equity Volatility [%]	10.531	10.998	-0.467	*(2.64**)*	9.984	11.025	-1.041	*(-1.43)*

(a) Outliers [i.e. extremely large and small values] in the data have been excluded from the computation of the measures of central tendency; hence, the reported means and medians for both periods are based on adjusted data (b) The profit margins look odd and at a great variance from the other performance measures. Over the period, quite a number of the firms posted very small turnovers, while recording substantial operating losses. The adjusted sample mean turnover and profit margin for the full period are about £55m and -750% respectively, which belies the true sample distribution. More specifically, nearly half of the firms [357 out of the 746 total] posted turnovers of less than £1m, while 258 firms out of the 357 sub-total [about 72%] posted turnovers of less than £0.1m. The 357 firms recorded operating pre-tax (losses)/profits of between -£36m and £65m. For these firms, the adjusted mean profit margin ranges from -41,650% to 4,643%. A similar analogy also applies to the industry profitability measure.

Table 5.3 reports the mean and median values of these characteristics as well as the differences between these values for the two post-IPO states. Panel A presents these values for the entire sample period, while Panel B reports same for the period excluding the 'dotcom' years. Significance tests for differences between the mean and median values for both groups are performed, using parametric $[t - ratio]$ and non-parametric $[Wilcoxon\ z]$ test statistics respectively. This section commences with an analysis for the whole period before proceeding to see how this changes when the 'dotcom' years are excluded.

Clearly, the results from Panel A show that there are quite a number of significant differences between the surviving and failing firms in the sample. Firstly, failing firms are shown to be significantly smaller than surviving firms as all the pairwise differences in the mean and median values across all the size measures [i.e. market capitalization, total assets and market value] and the offering measures associated with size [i.e. offer price and offer proceeds] are significant, at least at the 5% level. The results also generally indicate that firms need to achieve a critical mass at the time of their going public to substantially improve their chances of surviving the torrid market place. These results are consistent with the majority of the evidence in the literature [Hensler, et al, 1997; Jain and Kini, 1999; Bhabra and Pettway, 2003; Kooli and Meknassi, 2007; Jain and Martin, 2005; Hamza and Kooli, 2010; Raju and Prabhudesai, 2012; Espenlaub, et al, 2012] and also in line with the author's predictions.

It is also observed that the market performance of surviving firms, measured by the 5-year BHAR, is also significantly better than that of the failing firms with the mean and median values significant, at least at the 5% level. The results generally suggest that firms with stronger pre-IPO operating and market performances have a greater likelihood of survival in the market place in the post-IPO years. These results are also in tandem with the majority of the evidence in the literature [Jain and Kini, 1999; Bhabra and Pettway, 2003; Chi, et al, 2010; Peristiani and Hong, 2004] and also in line with the author's surmise. Preliminary evidence from the univariate tests also suggests that there are significant differences in the pre-IPO performance measures between the surviving and failing firms. For example, the differences in the mean and median pre-IPO profit margins between the surviving and failing firms are significant, at least at the 10% level. The mean [median] return on assets for the surviving group is -12.17% [-1.47%] compared to -52.97% [-4.87%] for the failing group, with the differences significant at the 1% level. Similarly, the mean [median] earnings yield of surviving firms is -4.05% [-0.62%] compared to -8.84% [-2.00%] for the failing group, with the differences again significant at least at the 5% level[153].

The study finds that, though the mean difference in the market leverage between the surviving and non-surviving firms is not significant, the median market leverage of the former is significantly higher than that of the latter at the 10% level. This result is in tandem with the view that leverage, in addition to the benefits of increased monitoring provided by debt-holders, could be a potential *'booster'* to the performance and survival of the firm in the market place, if used judiciously. The leverage result is in line with the expectations. Surviving firms are also found to have significantly higher levels of investment banker prestige compared to the failing firms, with the mean difference significant at the 5% level. The results generally suggest that surviving firms tend to be underwritten by more prestigious investment bankers, which is consistent with the majority of the evidence in the literature [Schultz, 1993; Jain and Kini, 1999 and 2000; Yung, et al, 2008; Kooli and Meknassi, 2007; Lewis, et al, 2000; Hamza and Kooli, 2010] and also meets with the author's conjecture. Evidence from this preliminary analysis suggest that information on age, market-to-book, initial returns and IPO risk are not likely to be valuable in distinguishing between the surviving and failing firms.

[153] However, the result for the earnings per share is mixed. The evidence on the mean difference between both groups is weak [t-stats: -1.43], albeit the median difference is shown to be significant at the 5% level.

The results for the industry structure variables are mixed. The industry leverage of the survivor firms is significantly higher than that of the failing firms, with the mean and median differences significant at least, at the 10% level. An explanation for this result could be that industries with higher leverage provide a good platform for an IPO issuer whose competitive position is enhanced following the raising of additional capital which reduces its leverage ratio and in some cases, the actual debt burden. This competitive threat is exacerbated in industries which are already less concentrated and highly leveraged. Therefore, IPO issuers from industries with a higher leverage are more likely to survive than those from industries with a lower leverage. These results are also in line with the author's expectations.

There is also strong evidence to indicate that survivor firms are in less profitable industries than the failing firms, contrary to the author's predictions. The difference in the mean and median measures of the industry profitability factor across both groups is significant, at least at the 5% level. The author's initial conjecture was that the robust profit conditions of an IPO firm's industry should help reduce the adverse selection costs facing investors as they build their investment opportunity sets, against the backdrop of the fact that not much is known about the IPO firms at their initial offering stages. However, the results may indicate that despite fanciful industry profit conditions that may prevail at the IPO date, there may be some firm-specific or idiosyncratic factors that may hamper the operating and market performance of these firms and their ultimate survival in the market place.

There is compelling evidence of a strong association between industry concentration and the survival likelihood of IPO firms, as the mean and median Herfindahl Index [HHI] measures of industry concentration for the surviving firms is significantly higher at the 1% level. The result, which is in line with the author's surmise, indicates that survivor firms are in more concentrated industries, which seems to be in consonance with the view that concentrated industries provide a more conducive environment for IPO firms to ply their trade. The mean industry equity volatility of surviving firms is shown to be significantly lower than that of failing firms, at the 5% level. The results indicate generally that IPO firms from industries with high equity volatilities have a lower likelihood of survival than those from industries with low volatilities, in line with the author's expectations. This result is not surprising as the high volatility of an IPO firm's industry is expected to rub off on the constituent firms and to consequently increase the riskiness of the offering and the likelihood of failure in the long-term. On the evidence of the tests conducted in this section, no significant differences are found in the other industry risk factors of market-to-book and an adjusted IPO firm valuation [i.e. IPO surplus value] between the surviving and failing firms.

To test for the effect of the 'dotcom' period and to also ensure robustness of the results, similar tests are undertaken by excluding this period from the analysis. The results in Panel B show that apart from industry leverage, all the other results are robust to including or excluding this historic period. So far, these univariate tests suggest that size, past operating performance, market performance, investment banker prestige and industry conditioning risk factors of profitability, concentration, equity volatility and leverage to a limited extent, appear to show more potential in distinguishing between firms that are likely to survive from those that are likely to fail. Hence, on the strength of this preliminary evidence, failing firms are smaller, offer less equity at the IPO at a lower offer price, are less profitable, less leveraged and tend to be underwritten by less prestigious investment bankers. They also tend to be located in less concentrated, less leveraged and more profitable industries with higher equity volatilities.

In this section, the characteristics of surviving and failing firms have been profiled to enable the author to determine if the differences in the characteristics between this set of firms are statistically significant. However, it does not say anything about the nature of the association of these variables with IPO survival likelihood. In the sections that follow, the exact nature of these relationships are explored in event and duration models. But first, an estimate of the shape of the hazard function is attempted in calendar time without employing the explanatory variables.

[5.5.2.2] Non-parametric estimation

Having examined the differences in the characteristics of surviving and failing firms, this study next estimates the hazard rate by tracking the cohort of firms in calendar time. Table 5.4 shows the life table of the 746 firms in the sample at the end of the last observation date [i.e. 31 December 2012], from the end of the first anniversary [year 1] to the end of the sixth anniversary [year 6]. It also shows extended anniversaries for the full period [up to the 13th anniversary] and sub-period IPOs [up to the 11th anniversary] because this study is also interested in tracking sample firms that have survived their sixth anniversaries. Panel A reports the life table for the sample of IPO firms for the entire period [1999-2006], while Panel B presents the same for the sample of IPO firms for the sub-period excluding the technology bubble years [2002-2006].

Over the entire period from Panel A, the life table shows that of the 746 firms in the sample, 79 and 178 fail by year 6 and year 13 respectively, corresponding to probabilities of 11% and 24% that a firm will fail within 6 and 13 years of its listing date. For the sub-period excluding the ‘dotcom’ years, the life table in Panel B shows that of the 485 firms in the sample, 65 and 97 fail by year 6 and year 11, corresponding to respective probabilities of 13% and 20% that a firm will fail within 6 and 11 years of its listing date. Hence, the study finds that the probability of failure [survival] for the full and sub-periods are 11% [89%] and 13% [87%] respectively, using a 6-year tracking

TABLE 5.4: LIFE TABLE FOR THE SAMPLE OF IPO FIRMS

The sample is 746 [485] firms that went public over the period 1999 to 2006 [2002 to 2006]. Panels A and B report the life table for the full sample and sub-samples respectively. The table shows the number and proportion of surviving and non-surviving firms as at 31 December 2012, from the 1st anniversary date or interval up to the 13th [in the case of the full period IPOs] and 11th [in the case of the sub period IPOs] intervals. The proportion of terminating or non-surviving firms by the end of each interval is the absolute number terminating in that interval divided by the total number of sample firms [i.e. 746 and 485 for the entire and sub-periods respectively]. The proportion of surviving firms by the end of each interval is simply calculated as 1 minus the proportion terminating in that interval. Cumulative proportion terminating in any particular interval is simply the sum of the proportions terminating in the preceding and current intervals, while cumulative proportion surviving in any particular interval is calculated as 1 minus the cumulative proportion terminating in that interval.

Panel A: ENTIRE PERIOD [1999 – 2006]

Anniv. Year	No entering	No terminating	Prop terminating	Cum Prop terminating	Prop surviving	Cum Prop surviving
1	746	2	0.003	0.003	0.997	0.997
2	744	3	0.004	0.007	0.996	0.993
3	741	6	0.008	0.015	0.992	0.985
4	735	10	0.013	0.028	0.986	0.972
5	725	21	0.028	0.056	0.971	0.944
6	704	37	0.050	0.106	0.947	0.894
7	667	25	0.034	0.139	0.963	0.861
8	642	20	0.027	0.166	0.969	0.834
9	622	15	0.020	0.186	0.976	0.814
10	607	18	0.024	0.210	0.970	0.790
11	589	12	0.016	0.227	0.980	0.773
12	577	7	0.009	0.236	0.988	0.764
13	570	2	0.003	0.239	0.996	0.761
Overall [1999-2006]	**746**	**178**		**0.239**		**0.761**

Panel B: PERIOD EXCLUDING THE 'DOTCOM' YEARS [2002 – 2006]

Anniv. Year	No entering	No terminating	Prop terminating	Cum Prop terminating	Prop surviving	Cum Prop surviving
1	485	2	0.004	0.004	0.996	0.996
2	483	2	0.004	0.008	0.996	0.992
3	481	4	0.008	0.016	0.992	0.984
4	477	5	0.010	0.027	0.990	0.973
5	472	17	0.035	0.062	0.964	0.938
6	455	35	0.072	0.134	0.923	0.866
7	420	14	0.029	0.163	0.967	0.837
8	406	12	0.025	0.188	0.970	0.812
9	394	3	0.006	0.194	0.992	0.806
10	391	2	0.004	0.198	0.995	0.802
11	389	1	0.002	0.200	0.997	0.800
Overall [2002-2006]	**485**	**97**		**0.200**		**0.800**

FIGURE 5.1: IPO FAILURE FREQUENCY SHOWING THE TIME FROM LISTING TO FAILURE BY CALENDAR YEAR FOR THE FULL IPO SAMPLE

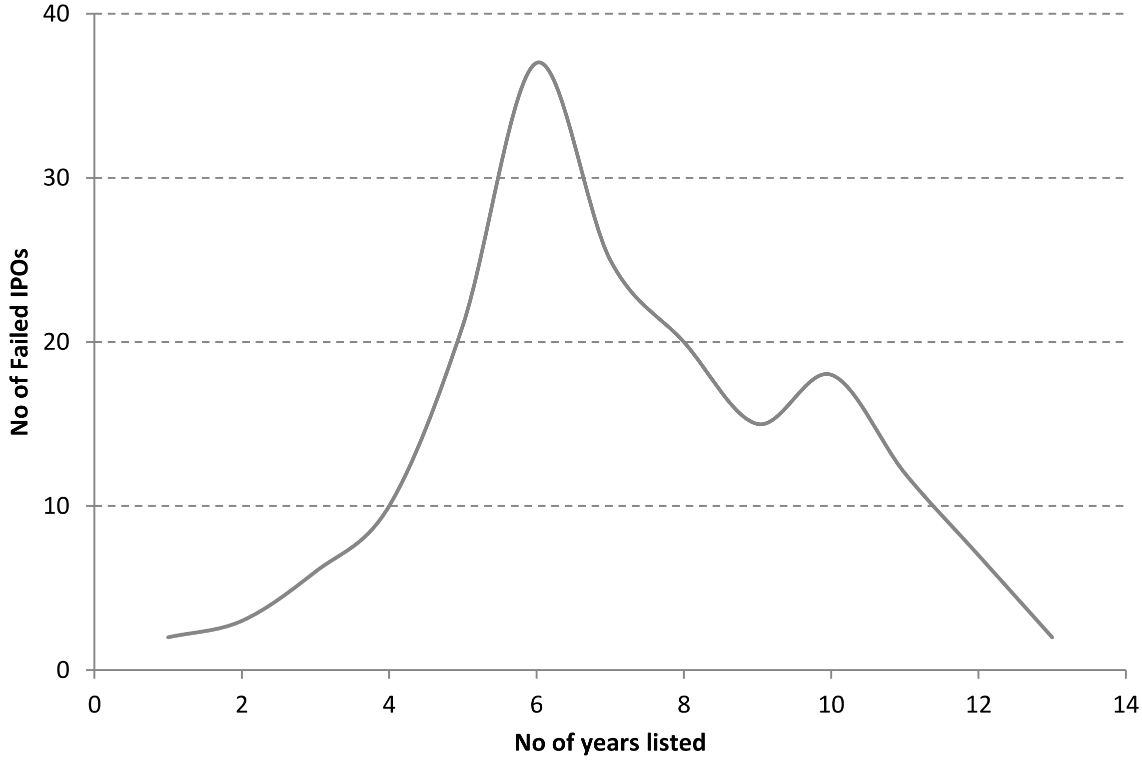


FIGURE 5.2: IPO HAZARD CURVES FOR THE ENTIRE PERIOD [1999 – 2006] & THE PERIOD EXCLUDING THE 'DOTCOM' YEARS [2002 – 2006]

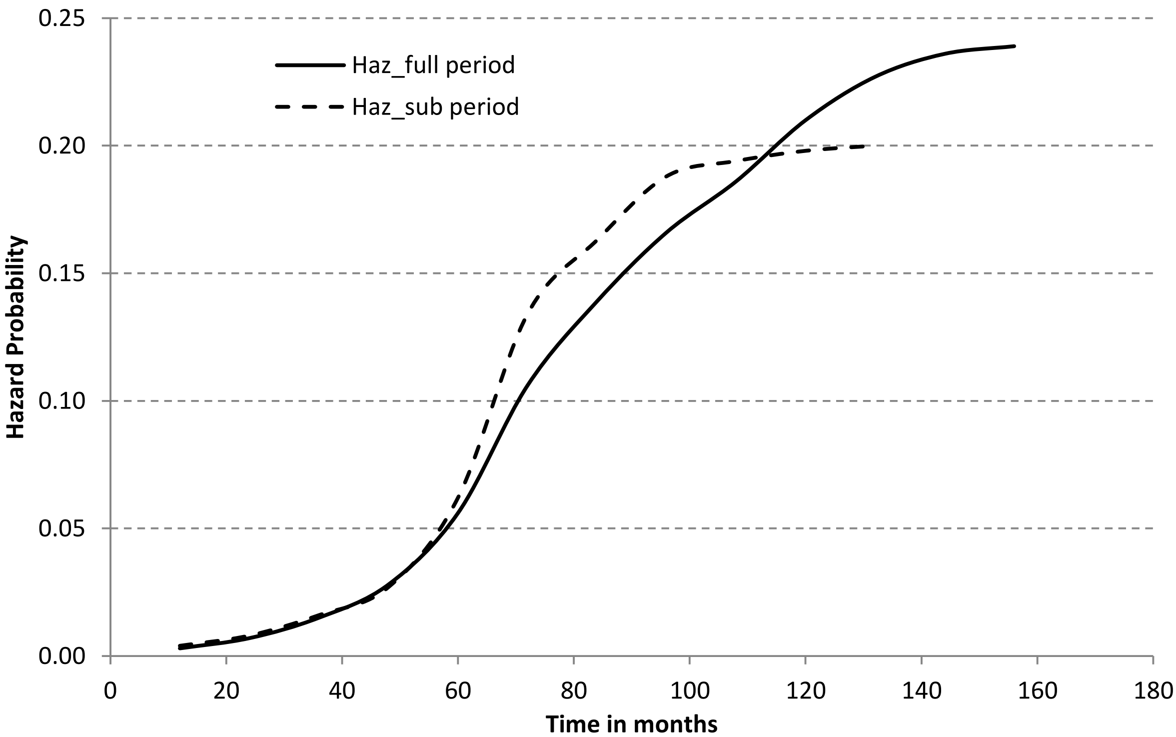
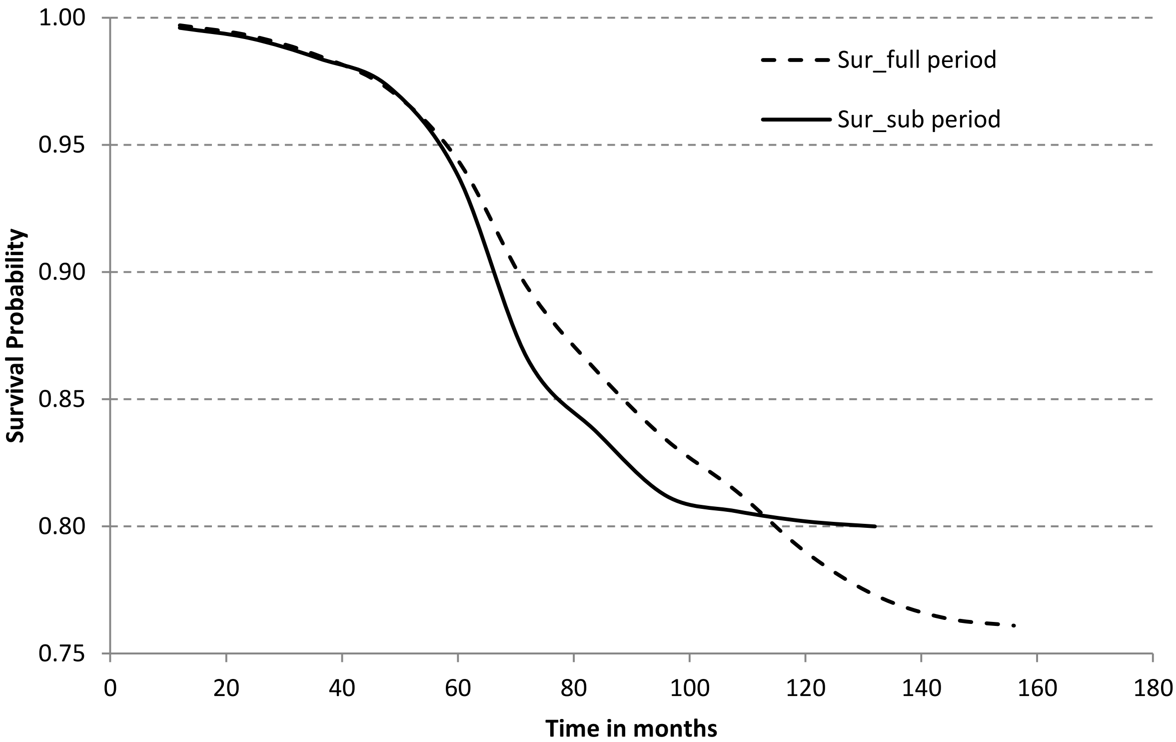


FIGURE 5.3: IPO SURVIVALCURVES FOR THE ENTIRE PERIOD [1999 – 2006] & THE PERIOD EXCLUDING THE 'DOTCOM' YEARS [2002 – 2006]



window for both periods. However, if all the firms in each of the sample periods are tracked for up to their respective maximum anniversaries, the probability of failure [survival] for the full and sub-periods are 24% [76%] and 20% [80%] respectively. The results compare favourably with the majority of the results in the literature. For example, in the US market, Schultz [1993], Bradley, et al [2006], Kooli and Meknassi [2007] find 3-year failure rates of between 6% and 42%. In the same market, Seguin and Moller [1997], Jain and Kini [2000 and 2008], Demers and Joos [2007], Fama and French [2004] and Bhattacharya, et al [2010] find 5-year failure rates of between 9% and 47%. Brown [1970] finds that the average failure rate of firms that went public in the US in the period 1950-60, is around 20% after ten years of listing. Carpentier and Suret [2011] document a 5-year failure rate of 20% for Canadian IPOs, while Rath [2008] documents failure rates of 20% and 29% respectively within 5 and 7 years of listing for Australian new stock issues.

In order to show the the time from listing to failure by calendar year for the full IPO sample, Figure 5.1 is constructed using the first and third columns from Panel A. Clearly from this diagram, the rate of failure rises in the early post-IPO years reaching a peak in the sixth year after which it diminishes. This diagram is in tandem with the fourth column of Panel A which shows the proportion of firms terminating or failing at the end of each anniversary. From this column, the hazard rate rises from 0.003 [0.3%] in the first year and peaks at 0.050 [5%] in the sixth year, after which it decreases. These patterns are not unconnected with the fact that at the early stages of the life of these firms, they struggle to find their footing in their respective industries, hence the high failure or hazard rates. However, a point in time arrives when these firms are able to ride the vagaries of the market place which enable them to establish some kind of foothold. When this threshold is eventually reached [i.e. year 6], the failure rate begins to taper.

Employing the first, fifth and seventh columns from Table 5.4 again, hazard and survival functions are constructed for the entire sample period as well as the sub-period excluding the ‘dotcom’ years over the 6-year and extended windows. Figure 5.2 [5.3] shows the hazard [survival] curve for the entire period and the sub-period that excludes the ‘dotcom’ years. These functions respectively show the hazard and survival probabilities from the date of the offering up to around 13 years post-listing. From both figures, there is no clear-cut difference in these functions for both samples. The hazard function for the full period is for the most part below that of the sub-period excluding the ‘dotcom’ years. This pattern only reverses around month 118 from the time of the listing of the IPOs. Expectedly, the survival function for the full period is for the most part higher than that for the sub-period excluding the ‘dotcom’ years, until month 118, when this pattern reverses as well. In the section that follows, the explanatory variables are introduced into the analysis in order to assess their impact on the probability of failure in an event time framework.

[5.5.2.3] Logit Model

Table 5.5 reports logistic regression results for the IPO sample that controls for various variables known to presage post-IPO outcomes. In this table, results from regressions including the firm level variables only [Panel A] and those including both the firm and industry level variables [Panel B] are reported. In all models, the dependent variable is

TABLE 5.5: LOGISTIC REGRESSION RESULTS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006. The table reports logistic regression results for the IPO sample. In this table, results from firm [firm and industry] logistic regression results for two [six] separate models are reported. In all models, the dependent variable takes a value of 1 if the firm fails within 6 years of the IPO date and 0 otherwise. The firm level independent variables are the natural logarithms of the market value, [1+Age] and underwriter reputation [UW]. The others are market-to-book [MTB], market leverage [Lev], earnings yield, 30-day initial returns, IPO risk and the hot dummy variable. The industry level independent variables are IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility. Panel A reports results including the firm level variables only, while Panel B presents the same including both firm and industry level variables. The z-stats, shown in parentheses, are calculated using Davidson & Mackinnon [1993] robust standard errors. ***, **, * indicate significance at the 1, 5 & 10% levels respectively.

Dependent variable, $y = 1$ if firm fails within 6 years of IPO and $y = 0$ otherwise

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

Independent Variables	**Model 1**	**Model 2**
Intercept	-3.2627	-1.4421
	*[-5.66***]*	*[-5.01***]*
Lev	0.5026	
	[0.58]	
Log Mkt. Val		-0.1420
		[-1.79]*
MTB	-0.0005	-0.0003
	[-0.26]	*[-0.18]*
Earnings Yield	-1.2620	-1.0114
	*[-2.91***]*	*[-2.21**]*
Log UW	0.4220	
	*[3.02***]*	
Log [1+Age]	-0.1515	-0.1518
	[-1.10]	*[-1.12]*
Initial Ret		0.1476
		[0.55]
IPO Risk	-2.7063	
	[-0.97]	
Hot	0.2061	0.1524
	[0.90]	*[0.66]*
Log Likelihood	-266.29	-269.86
Pseudo - R^2	0.04	0.02
N $[y = 1, y = 0]$	701	701

PANEL B – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Intercept	-3.1931	-3.1929	-3.2163	-1.0439	-1.0439	-0.1575
	*[-4.02***]*	*[-4.02***]*	*[-3.85***]*	*[-2.11**]*	*[-2.11**]*	*[-2.15**]*
Lev	1.1982	1.1973	1.0805			
	[1.18]	*[1.19]*	*[1.08]*			
Log Mkt. Val				-0.0937	-0.0937	-0.0966
				[-1.07]	*[-1.07]*	*[-1.10]*
MTB	-0.0007	-0.0007	-0.0009	-0.0007	-0.0007	*-0.0008*
	[-0.26]	*[-0.27]*	*[-0.32]*	*[-0.24]*	*[-0.24]*	*[-0.26]*
Earnings Yield	-1.4238	-1.4237	-1.4541	-1.1927	-1.1925	-1.2111
	*[-3.17***]*	*[-3.17***]*	*[-3.22***]*	*[-2.39**]*	*[-2.38**]*	*[-2.42**]*
Log UW	0.5104	0.5103	0.5005			
	*[3.15***]*	*[3.16***]*	*[3.14***]*			
Log [1+Age]	-0.1808	-0.1808	-0.1795	-0.1835	-0.1836	-0.1806
	[-1.22]	*[-1.22]*	*[-1.20]*	*[-1.25]*	*[-1.25]*	*[-1.22]*
Initial Ret				-0.0784	-0.0785	-0.0761
				[-0.23]	*[-0.23]*	*[-0.23]*
IPO Risk	-6.2055	-6.2086	-6.5460			
	[-1.63]	*[-1.65]*	*[-1.73*]*			
Hot	0.2783	0.2778	0.2782	0.1575	0.1567	0.1631
	[1.07]	*[1.08]*	*[1.07]*	*[0.59]*	*[0.60]*	*[0.61]*
Surplus Val	0.0667	0.0667	0.0581	0.0383	0.0382	0.0340
	[0.98]	*[0.98]*	*[0.88]*	*[0.59]*	*[0.59]*	*[0.53]*
I_Profitability	-0.0016		0.0344	-0.0023		0.0251
	[-0.01]		*[0.36]*	*[-0.02]*		*[0.28]*
I_Leverage			-0.4930			-0.1534
			[-0.27]			*[-0.09]*
I_MTB	0.0252	0.0251	0.0220	0.0185	0.0184	0.0209
	[0.36]	*[0.35]*	*[0.34]*	*[0.24]*	*[0.23]*	*[0.30]*
I_Conc	-0.6971	-0.6936		-0.5546	-0.5495	
	[-0.76]	*[-0.85]*		*[-0.54]*	*[-0.60]*	
I_Equity Vol	-2.3353	-2.3329	-2.3659	-3.9080	-3.9056	-3.9419
	[-0.77]	*[-0.76]*	*[-0.79]*	*[-1.23]*	*[-1.22]*	*[-1.28]*
Log Likelihood	-213.54	-213.54	-213.96	-219.63	-219.63	-219.90
Pseudo - R^2	0.06	0.06	0.06	0.03	0.03	0.03
N $[y=1, y=0]$	701	701	701	701	701	701

TABLE 5.6: DERIVATIVE ANALYSIS OF THE RISK AND ODDS OF FAILURE FROM THE LOGISTIC REGRESSIONS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006. The table reports the coefficients [β], marginal effects and odds ratios of the predictor variables based on the regression specifications that include both the firm and industry level variables reported in Panel B of Table 5.5. These coefficients and the corresponding marginal effects and odds ratios are reported in ranges given that some of the predictor variables have been estimated and found significant in more than one model. The 'marginal effect', is defined as the rate of change of the probability of failure for less than one-unit increases in the predictor variables, while holding the other predictor variables constant. The odds ratio, computed as [$exp(\beta)$], is defined as the odds of failure relative to survival for one-unit increases in the predictor variables. The percentage change in the odds [odds effect] is given by $\{100 * [exp(\beta) - 1]$. A negative [positive] coefficient, which corresponds to an odds ratio of less than one [greater than one], indicates that the odds of failure relative to survival is smaller [larger] by [$exp(\beta)$]. The odds effects have only been reported for the significant variables. * indicates the significant variables, while ** indicates significance in specifications that include only the firm level variables.

Variables	Coefficient	Marginal Effect	Odds Ratio	Odds effect
Lev	1.081 – 1.198	1.081 – 1.198	0.106 – 0.117	
Log Mkt. Val**	-0.142*	-0.016	0.868	*-13.2%*
MTB	-0.001	-0.0000	0.999	
Earnings Yield*	-1.193 – -1.454*	-0.125 – -0.143	0.234 – 0.303	*-69.7% – -76.6%*
Log UW*	0.501 – 0.510*	0.049 – 0.050	1.650 – 1.666	*65.0% – 66.6%*
Log [1+Age]	-0.180 – -0.184	-0.018 – -0.019	0.832 – 0.836	
Initial Ret	-0.076 – -0.079	-0.008	0.925 – 0.927	
IPO Risk*	-6.546*	-0.644	0.001	*-99.9%*
Hot	0.157 – 0.278	0.016 – 0.027	1.170 – 1.321	
Surplus Val	0.034 – 0.067	0.004 – 0.007	1.035 – 1.069	
I_Profitability	-0.002 – 0.034	-0.000 – 0.003	0.998 – 1.035	
I_Leverage	-0.153 – -0.493	-0.016 – -0.049	0.611 – 0.858	
I_MTB	0.018 – 0.025	0.002 – 0.003	1.019 – 1.026	
I_Conc	0.115 – -0.697	-0.058 – -0.068	0.498 – 1.121	
I_Equity Vol	-2.333 – -3.942	-0.229 – -0.414	0.019 – 0.097	

a binary indicator that takes the value of one if the firm fails within six years of the IPO date and zero otherwise. The firm level independent variables are the natural logarithms of size [measured by the market value], Age {measured as [1+Age]} and underwriter reputation [UW]. The others are market-to-book [MTB], market leverage [Lev], past performance [measured by earnings yield], 30-day initial returns, IPO firm risk and the 'hot' dummy variable. The industry level independent variables are IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility.

In order to minimise the impact of cross-correlations and multicollinearity, the study limits the number of variables in the regressions[154]. The author includes all relevant variables in the regressions and estimates several models that systematically exclude variables that are highly correlated as revealed by the correlation analysis performed in Section 4.4.1. Market value is selected as the only measure of size, while the other size measures [i.e. market equity and total assets] and the offering characteristics related to size [i.e. offer price and offer proceeds] are excluded entirely from the regressions. In the same vein, earnings yield is selected as the sole profitability measure, while return on assets and profit margin are excluded[155]. Hence, only the following firm risk factors are included in the regressions including the firm level

[154] The author is using the same data from the second empirical study that has already been adjusted for the presence of extremely large and small values ['outliers'].

[155] In unreported regressions that adopt the excluded size [i.e. market equity and total assets] and performance measures [i.e. return on assets and profit margin] as the alternatives, the results are similar.

variables only: ‘hot’ market dummy, market leverage, market value, market-to-book, earnings yield, underwriter reputation, age, initial returns and IPO risk. Controlling for the relatively observed high correlation between market value and underwriter reputation, market value and market leverage and then initial returns and IPO risk, the study estimates the regressions including only the firm level variables firstly, with the selected firm level risk factors, excluding market value and initial returns and then secondly, with all the firm level risk factors excluding market leverage, underwriter reputation and IPO risk. Combining both firm and industry risk factors and also accounting for the inter-dependencies and cross-correlations in a multivariate framework inevitably leads the author to estimate six different regression models.

It was earlier highlighted in the empirical design in Section 5.4.1 that under the logit model, positive [negative] parameter estimates indicate factors that increase [decrease] the likelihood of failure relative to survival. From Table 5.5, size is found to be significant in regressions that control only for the firm level variables [Panel A] as this evidence disappears completely in regression specifications that control additionally for the industry risk factors [Panel B]. The performance [earnings yield] evidence is present across all specifications regardless of whether industry level variables are included or not in the empirical design. However, it is observed that in specifications that control additionally for the industry level variables excluding leverage, underwriter reputation and IPO risk [model 2 of Panel A and models 4 - 6 of Panel B], the magnitude of the coefficient is smaller. A similar pattern is observed in the underwriter prestige evidence as the size of the coefficient is higher when the study controls additionally for the industry risk factors. IPO risk is found to be only significant in a regression that controls for both the firm and industry level variables excluding size, initial returns and industry concentration [model 3 of Panel B].

Overall, the study finds unassailable evidence that shows that firm level factors of size [market value], past performance [earnings yield] and underwriter prestige continue to be significant in distinguishing between the surviving and failing firms. However, contrary to the author's expectations and the univariate results, IPO risk is found to be significantly negatively related to the probability of failure. The evidence on IPO risk implies that the volatility of an issuing firm's immediate after-market return could proxy for the riskiness of the firm in that industry. If this risk is priced sufficiently, the market performance and ensuing expected returns to investors is expected to increase in the market place. All things being equal, this should rub off positively on the survival of the firm and should consequently reduce the probability of failure.

To assess the effect of the individual variables on the probability of failure or the odds of failure, the study turns to the 'marginal effects' and 'odds ratios' presented in Table

5.6 alongside the coefficients derived from the regression specifications that include the firm and industry level variables from Panel B of Table 5.5. These coefficients and the corresponding marginal effects and odds ratios are reported in ranges given that some of the predictor variables have been estimated and found significant in more than one model. The largest positive effects on IPO survival are provided by IPO risk, past performance, underwriter reputation and size in that order. For infinitesimal [i.e. less than one-unit] increases in IPO risk, past performance and size, the probability of failure reduces by 64.4%, 12.5%-14.3% and 1.6% in that order[156]. This pattern is also observable in the 'odds' figures as the study finds that a one-unit increase in each of these variables reduces the odds of failure by 99.9%, 69.7%-76.6% and 13.2% respectively. For underwriter prestige, an infinitesimal increase in this variable, which would represent a deterioration in underwriter quality going by the author's construction[157], increases the probability of failure by 4.9%-5%. Similarly, a one-unit increase [decrease] in this variable increases [reduces] the odds of failure by 65%-66.6%. This derivative analysis, which is in tandem with the results from Table 5.5, provides further evidence that size, past performance, underwriter reputation and IPO risk are crucial survival signals that potential IPO investors, issuers and investment bankers should take into consideration in their decision making process at the IPO date.

[156] The marginal effects have been converted to percentages to make for better comparisons.

[157] See Panel F of Table 3.5, pp. 99 and Section 4.3.2, pp. 220-221.

Hence, under this model, the probability of failure significantly decreases with increasing firm size [10% level], past performance [at least at the 5% level], underwriter prestige [1% level] and IPO risk [10% level]. More importantly, industry risk factors of IPO surplus value, profitability, leverage, concentration, market-to-book and equity volatility are not found to be valuable predictors of the likelihood of survival or failure of IPO firms, contrary to the preliminary univariate results. In general, these multivariate results suggest that after controlling for other factors that can foreshadow the survival likelihood of IPO firms, firm size, past performance, investment banker prestige and IPO risk appear to show more potential in distinguishing between firms that are likely to survive from those that are likely to fail based on information available at the offering date. On the strength of this enhanced evidence, failing firms are smaller, less profitable, more risky and tend to be underwritten by less prestigious underwriters.

Given the problems already highlighted with this event model technique and to also ensure robustness, this study next undertakes a parametric duration model analysis that replaces the dependent binary variable in the logistic regressions with a duration-specific variable that tracks all sample firms from IPO date to date of failure or last observation date [i.e. 31 December 2012], while simultaneously controlling for those firms that are still surviving by the end of this date, using a censoring indicator.

[5.5.3] Robustness Checks

[5.5.3.1] Parametric Accelerated Failure Time Model

Table 5.7 reports maximum likelihood results of the log-logistic AFT model for the IPO sample. In this table, results from regressions including the firm level variables only [Panel A] and those including both the firm and industry level variables [Panel B] are reported. In all models, the dependent variable is the natural logarithm of the number of months an IPO survives from the listing date to failure date or last observed date [i.e. 31 December 2012], with an additional right-censoring indicator that takes the value of one for those firms that fail within the observation period ['uncensored firms'] and zero for those firms that are still alive as at the last observed date ['censored firms'].

The study earlier highlighted in Section 5.4.1 that under the AFT model, positive [negative] parameter estimates indicate factors that increase [decrease] the trading period or time to failure. From Table 5.7, the size evidence is found across all specifications; albeit, the magnitude of the coefficient is slightly lower when the industry level variables are included in the empirical design. The performance evidence is also largely present across all specifications regardless of whether industry level variables are included or not in the regressions. However, similar to the pattern observed in the logit model, the study finds that in specifications that exclude firm leverage, underwriter reputation and IPO risk [model 2 of Panel A and models 4–6 of Panel B], the magnitude

TABLE 5.7: MAXIMUM LIKELIHOOD RESULTS OF THE LOG-LOGISTIC AFT MODEL OF THE DURATION OF IPOS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between 1999 and 2006. The table reports maximum likelihood results for the log-logistic AFT model. In all models, the dependent variable is the natural logarithm of the number of months from the listing date to the date of failure or the end of the study period [i.e. 31 December 2012], with an additional right-censoring indicator that takes the value of 1 for firms that go bankrupt and fail within the tracking period and zero for censored observations, representing firms that are still alive at the end of the study period. In this table, results from firm [firm and industry] regression results for two [six] separate models are reported. The firm independent variables are the natural logarithms of the market value, [1+Age] and underwriter reputation [UW]. The others are market-to-book [MTB], market leverage [Lev], earnings yield, 30-day initial returns, IPO risk and the hot dummy variable. The industry independent variables are IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility. Panel A reports results including the firm level variables only, while Panel B presents the same for the firm and industry level variables. The z-stats, not shown, have been calculated using Davidson & Mackinnon [1993] robust standard errors. The numbers in parentheses are the p values. ***, **, * indicate significance at the 1, 5 & 10% levels respectively.

Dependent variable, $y =$ natural log of no of months from listing date to failure date or Dec 2012

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

Independent Variables	Model 1	Model 2
Intercept	1.7938	1.6338
	*[0.000***]*	*[0.000***]*
Lev	-0.0630	
	[0.391]	
Log Mkt. Val		0.0169
		*[0.007***]*
MTB	0.0001	0.0001
	[0.582]	*[0.734]*
Earnings Yield	0.0990	0.0692
	*[0.010***]*	*[0.087*]*
Log UW	-0.0336	
	*[0.001***]*	
Log [1+Age]	0.0005	0.0006
	[0.961]	*[0.953]*
Initial Ret		-0.0077
		[0.724]
IPO Risk	0.1881	
	[0.373]	
Hot	-0.0103	-0.0086
	[0.578]	*[0.649]*
Log Likelihood	-166.47	-168.81
N $[y = 1, y = 0]$	701	701

PANEL B – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES						
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Intercept	1.8254	1.8255	1.8066	1.6252	1.6255	1.6138
	*[0.000***]*	*[0.000***]*	*[0.000***]*	*[0.000***]*	*[0.000***]*	*[0.000***]*
Lev	-0.1204	-0.1183	-0.1144			
	[0.174]	*[0.182]*	*[0.198]*			
Log Mkt. Val				0.0162	0.0163	0.0162
				*[0.026**]*	*[0.027**]*	*[0.025***]*
MTB	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
	[0.161]	*[0.143]*	*[0.149]*	*[0.213]*	*[0.198]*	*[0.206]*
Earnings Yield	0.1081	0.1084	0.1100	0.0790	0.0790	0.0800
	*[0.009***]*	*[0.009***]*	*[0.008***]*	*[0.077*]*	*[0.077*]*	*[0.074*]*
Log UW	-0.0423	-0.0423	-0.0421			
	*[0.001***]*	*[0.001***]*	*[0.001***]*			
Log [1+Age]	-0.0002	-0.0001	-0.0002	-0.0001	0.0001	-0.0001
	[0.987]	*[0.996]*	*[0.985]*	*[0.995]*	*[0.992]*	*[0.994]*
Initial Ret				-0.0013	-0.0008	-0.0013
				[0.961]	*[0.976]*	*[0.962]*
IPO Risk	0.3483	0.3616	0.3638			
	[0.240]	*[0.221]*	*[0.211]*			
Hot	-0.0171	-0.0148	-0.0157	-0.0135	-0.0110	-0.0126
	[0.440]	*[0.498]*	*[0.479]*	*[0.549]*	*[0.622]*	*[0.578]*
Surplus Val	-0.0088	-0.0086	-0.0080	-0.0064	-0.0062	-0.0059
	[0.145]	*[0.154]*	*[0.186]*	*[0.251]*	*[0.269]*	*[0.292]*
I_Profitability	0.0044		0.0016	0.0047		0.0029
	[0.63]		*[0.844]*	*[0.617]*		*[0.728]*
I_Leverage			0.1370			0.0905
			[0.378]			*[0.563]*
I_MTB	-0.0046	-0.0044	-0.0043	-0.0041	-0.0038	-0.0039
	[0.427]	*[0.455]*	*[0.454]*	*[0.510]*	*[0.540]*	*[0.506]*
I_Conc	0.0559	0.0458		0.0366	0.0259	
	[0.476]	*[0.527]*		*[0.668]*	*[0.742]*	
I_Equity Vol	0.1077	0.0983	0.1609	0.2308	0.2234	0.2692
	[0.660]	*[0.692]*	*[0.522]*	*[0.365]*	*[0.388]*	*[0.297]*
Log Likelihood	-143.87	-143.99	-143.94	-148.69	-148.82	-148.71
N $[y=1, y=0]$	701	701	701	701	701	701

TABLE 5.8: DERIVATIVE ANALYSIS FROM THE LOG-LOGISTIC AFT REGRESSIONS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006. The table reports the coefficients, time ratios and survival time effects of all the explanatory variables used in the model. The coefficients are the results from the regression specifications that include both the firm and industry level variables as reported in Panel B of Table 5.7. These coefficients and the corresponding time ratios and survival time effects have been reported in ranges given that the predictor variables have been estimated and found significant in more than one model. The time ratio is computed as $exp(\beta)$, while the quantified percentage effect on survival time is calculated as $\{100 * [exp(\beta) - 1]\}$. A positive [negative] value of the coefficient, which corresponds to time ratios $[exp(\beta)]$ greater [less] than one, indicates that increasing values of the explanatory variable increases [decreases] the survival time or time to failure. The survival time effects have only been reported for the significant variables. * indicates the significant variables.

Variables	Coefficient	Time Ratio	Survival Time Effect
Lev	-0.114 – -0.120	0.887 – 0.892	
Log Mkt. Val*	0.016*	1.016	*1.6%*
MTB	0.000	1.000	
Earnings Yield*	0.079 – 0.110*	1.082 – 1.116	*8.2% – 11.6%*
Log UW*	-0.042*	0.959	*-4.1%*
Log [1+Age]	0.000	1.000	
Initial Ret	-0.001	0.999	
IPO Risk	0.348 – 0.364	1.417 – 1.439	
Hot	-0.011 – -0.017	0.983 – 0.989	
Surplus Val	-0.006 – -0.009	0.991 – 0.994	
I_Profitability	0.002 – 0.005	1.002 – 1.005	
I_Leverage	0.091 – 0.137	1.095 – 1.147	
I_MTB	-0.004 – -0.005	0.995 – 0.996	
I_Conc	0.026 – 0.056	1.026 – 1.057	
I_Equity Vol	0.098 – 0.269	1.103 – 1.260	

of the coefficient is much smaller. There is no marked difference in the size of the underwriter prestige coefficient when the study controls additionally for the industry risk factors. Juxtaposing the results from Table 5.7 with the logit results in Table 5.5 from the previous section, firm size, past performance and underwriter prestige continue to be good and strong survival signals [i.e. positively related to survival] as they are significantly positively related to IPO survival across all specifications. These results are in tandem with the logit results and also in line with the author's expectations. However, contrary to the logit results, there is no evidence to support the fact that IPO risk can significantly distinguish between the surviving and failing firms.

To assess the effect of the individual variables on survival time, the study undertakes a transformation of the coefficients of the predictor variables reported in Table 5.7. Hence, Table 5.8 reports the coefficients, time ratios and survival time effects of all the explanatory variables used in the model. The coefficients are the results from the regression specifications that include both the firm and industry level variables as earlier reported in Panel B of Table 5.7. These coefficients and the corresponding time ratios and survival time effects have been reported in ranges given that some of the predictor variables have been estimated and found significant in more than one model. The survival time effects have only been reported for the significant variables. Clearly and expectedly, the largest positive effects on survival time are provided by past performance [earnings yield] and underwriter reputation. A one-unit increase in past performance affects the time ratio with a factor of 1.082-1.116, which is equivalent to an increase of 8.2%-11.6% in survival time. In the same vein, a one-unit increase in the underwriter reputation variable, which would represent a deterioration in underwriter quality going by the author's construction[158], impacts on the time ratio with a factor of 0.959, which corresponds to a decrease of 4.1% in survival time[159]. The only other positive effect is provided by size. A one-unit increase in the size of the firm affects the time ratio with a factor of 1.016, which is equivalent to an increase of 1.6% in the time to failure. This derivative analysis, which is in consonance with the results from Table 5.7, provides further evidence that size, past performance and underwriter reputation are crucial survival signals that potential IPO investors, issuers and investment bankers should take into consideration in their decision making process at the offering date. More particularly, past performance and the reputation of the underwriter are found to be the most important as they provide the largest positive effects on survival time.

Hence, under the AFT model, the time to failure or survival time significantly increases with increasing firm size [at least at the 5% level], past performance [at least at the 10% level] and underwriter prestige [1% level]. More importantly, once again, the study does

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[158] See Panel F of Table 3.5, pp. 99 and Section 4.3.2, pp. 220-221.

[159] Put differently, a one-unit decrease in the underwriter reputation rank, which would represent an improvement in underwriter quality, impacts on the time ratio with a factor of 0.959, which is equivalent to an increase of 4.1% in survival time.

not find that industry risk factors of IPO surplus value, market-to-book, profitability, leverage, concentration and equity volatility can be valuable predictors of the survival time of IPO firms, just like in the logit model. In the next section, the study undertakes another variant of the duration model analysis by replacing the dependent variable in the AFT model with the natural logarithm of the hazard rate.

[5.5.3.2] Semi-Parametric Cox Proportional Hazard Model

Table 5.9 reports partial likelihood results of the semi-parametric CPH model for the IPO sample. In this table, results from regressions including the firm level variables only [Panel A] and those including both the firm and industry level variables [Panel B] are reported. The time to failure is measured as the number of months that elapses between the IPO month and the date of failure or the end of the study period [i.e. 31 December 2012], with an additional right-censoring indicator that takes the value of one for firms that go bankrupt and fail within the tracking period ['uncensored firms'] and zero for 'censored' observations, representing firms that are still alive at the end of the study period. In all models, the dependent variable is the natural logarithm of the hazard rate, where hazard rate is defined as the probability that the firm will fail at time t, given continual listing.

TABLE 5.9: PARTIAL LIKELIHOOD RESULTS OF THE COX PROPORTIONAL HAZARD MODEL OF THE DURATION OF IPOS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between January 1999 and December 2006. The table reports partial likelihood results of the Cox proportional hazard [CPH] model for the duration of the IPOs. The time to failure is measured as the number of months elapsed between the IPO month and the date of failure or the end of the study period [i.e. 31 December 2012], with an additional right-censoring indicator that takes the value of one for firms that go bankrupt and fail within the tracking period and zero for censored observations, representing firms that are still alive at the end of the study period. In all models, the dependent variable is the natural logarithm of the hazard rate, where hazard rate is defined as the probability that the firm will fail at time t given continual listing. In this table, results from firm [firm and industry] regression results for two [six] separate models are reported. The firm independent variables are the natural logarithms of the market value, [1+Age] and underwriter reputation [UW]. The others are market-to-book [MTB], market leverage [Lev], earnings yield, 30-day initial returns, IPO risk and the hot dummy variable. The industry independent variables are IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility. Panel A reports results including the firm level variables only, while Panel B presents the same including both firm and industry level variables. The z-stats, not shown, have been calculated using Davidson & Mackinnon [1993] robust standard errors. The numbers in parentheses are the p values. ***, **, * indicate significance at the 1, 5 & 10% levels respectively.

Dependent variable, y = natural logarithm of the hazard rate

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

Independent Variables	Model 1	Model 2
Lev	0.6417	
	[0.339]	
Log Mkt. Val		-0.1483
		*[0.012**]*
MTB	-0.0006	-0.0002
	[0.767]	*[0.897]*
Earnings Yield	-0.7563	-0.4926
	*[0.010***]*	*[0.109]*
Log UW	0.2877	
	*[0.003***]*	
Log [1+Age]	0.0122	0.0185
	[0.903]	*[0.853]*
Initial Ret		0.1123
		[0.597]
IPO Risk	-1.2696	
	[0.496]	
Hot	0.1182	0.1195
	[0.486]	*[0.475]*
Log Likelihood	-965.66	-967.36
N $[y = 1, y = 0]$	701	701

PANEL B – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES						
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Lev	1.1166	1.1046	1.0791			
	[0.145]	*[0.149]*	*[0.159]*			
Log Mkt. Val				-0.1412	-0.1416	-0.1418
				*[0.034**]*	*[0.034**]*	*[0.033**]*
MTB	-0.0033	-0.0034	-0.0035	-0.0030	-0.0031	-0.0031
	[0.327]	*[0.311]*	*[0.308]*	*[0.381]*	*[0.369]*	*[0.373]*
Earnings Yield	-0.8394	-0.8394	-0.8426	-0.5554	-0.5530	-0.5579
	*[0.007***]*	*[0.007***]*	*[0.006***]*	*[0.090*]*	*[0.091*]*	*[0.089*]*
Log UW	0.3521	0.3515	0.3496			
	*[0.001***]*	*[0.001***]*	*[0.001***]*			
Log [1+Age]	0.0237	0.0225	0.0219	0.0269	0.0252	0.0264
	[0.824]	*[0.834]*	*[0.838]*	*[0.799]*	*[0.812]*	*[0.804]*
Initial Ret				0.0637	0.0618	0.0663
				[0.798]	*[0.804]*	*[0.790]*
IPO Risk	-2.6698	-2.7463	-2.7521			
	[0.244]	*[0.231]*	*[0.232]*			
Hot	0.1750	0.1587	0.1676	0.1688	0.1510	0.1641
	[0.367]	*[0.403]*	*[0.388]*	*[0.380]*	*[0.422]*	*[0.395]*
Surplus Val	0.0769	0.0756	0.0700	0.0570	0.0550	0.0528
	[0.082]*	*[0.087*]*	*[0.112]*	*[0.180]*	*[0.193]*	*[0.215]*
I_Profitability	-0.0347		-0.0092	-0.0361		-0.0208
	[0.678]		*[0.906]*	*[0.663]*		*[0.789]*
I_Leverage			-1.2019			-0.7952
			[0.417]			*[0.589]*
I_MTB	0.0414	0.0394	0.0382	0.0347	0.0326	0.0342
	[0.362]	*[0.381]*	*[0.398]*	*[0.510]*	*[0.476]*	*[0.459]*
I_Conc	-0.5172	-0.4415		-0.3232	-0.2464	
	[0.373]	*[0.418]*		*[0.587]*	*[0.662]*	
I_Equity Vol	-1.1368	-1.0690	-1.6244	-2.0081	-1.9384	-2.3688
	[0.583]	*[0.605]*	*[0.453]*	*[0.325]*	*[0.342]*	*[0.270]*
Log Likelihood	-771.40	-771.48	-771.49	-775.57	-775.67	-775.58
N $[y=1, y=0]$	701	701	701	701	701	701

TABLE 5.10: DERIVATIVE ANALYSIS FROM THE COX PROPORTIONAL HAZARD REGRESSIONS FOR THE IPO SAMPLE

The sample is 746 IPOs that went public between 1999 and 2006. The table reports the coefficients, hazard ratios and hazard rate effects of all the explanatory variables used in the model. The coefficients are the results from the regression specifications that include both the firm and industry level variables as reported in Panel B of Table 5.9. These coefficients and the corresponding hazard ratios and hazard rate effects have been reported in ranges given that the predictor variables have been estimated and found significant in more than one model. The coefficient estimates represent the hazard rates, interpreted as the increase in the log hazard ratio [i.e. the risk of failure] for a one-unit increase in the explanatory variables, while holding the other predictor variables constant. The relative hazard rate or the hazard ratio is computed as $exp(\beta)$, while the quantified percentage effect on the hazard rate is calculated as $\{100 * [exp(\beta) - 1]\}$. A negative [positive] coefficient, which corresponds to hazard ratios less [greater] than one, indicates that increasing values of the predictor variable lowers [increases] the risk of failure and increases [reduces] the survival time. The hazard rate effects have only been reported for the significant variables. * indicates the significant variables.

Variables	Coefficient	Hazard Ratio	Hazard Rate Effect
Lev	1.079 – 1.117	2.942 – 3.054	
Log Mkt. Val*	-0.141 – -0.142*	0.868 – 0.868	*-13.2%*
MTB	-0.003 – -0.004	0.997 – 0.997	
Earnings Yield*	-0.553 – -0.843*	0.431 – 0.575	*-42.5% – -56.9%*
Log UW*	0.350 – 0.352*	1.419 – 1.421	*41.9% – 42.1%*
Log [1+Age]	0.022 – 0.027	1.022 – 1.027	
Initial Ret	0.062 – 0.066	1.064 – 1.069	
IPO Risk	-2.670 – -2.752	0.064 – 0.069	
Hot	0.151 – 0.175	1.163 – 1.191	
Surplus Val*	0.076 – 0.077	1.079 – 1.080	*7.9% – 8.0%*
I_Profitability	-0.009 – -0.036	0.965 – 0.991	
I_Leverage	-0.795 – -1.202	0.301 – 0.451	
I_MTB	0.033 – 0.041	1.033 – 1.042	
I_Conc	-0.246 – -0.517	0.596 – 0.782	
I_Equity Vol	-1.069 – -2.369	0.134 – 0.343	

It was already highlighted in Section 5.4.1 that under this model, positive [negative] parameter estimates indicate factors that increase [decrease] the force of mortality which consequently increase [decrease] the hazard rate or the probability of failure. From Table 5.9, no noticeable difference is observed in the magnitude of the coefficient of the size variable in Panels A and B. The performance evidence is largely present across all specifications regardless of whether or not industry level variables are included in the regressions. However, just like in the previous models, the study finds that in specifications that exclude firm leverage, underwriter reputation and IPO risk [model 2 of Panel A and models 4 – 6 of Panel B], the magnitude of the coefficient is much smaller. The size of the underwriter prestige coefficient is also noticeably higher when the study controls additionally for the industry risk factors, just like in the logit model. The results are generally in tandem with the AFT and logit results reported earlier. Expectedly, the signs of the coefficient estimates for the significant parameters are the same as those obtained from the logit model. This is not surprising given the fact that both models track the likelihood of failure; one [logit], from an event time perspective and the other [CPH], from a duration time standpoint. More particularly, the study finds that firm size, past performance and underwriter prestige continue to be good and strong survival signals [i.e. positively related to survival], just like in the other models, as they are significantly negatively related to the hazard or mortality rate. In addition and unlike in the previous models, firms trading above their industry – adjusted valuations [i.e. those firms with positive IPO surplus values or trading at a premium relative to industry peers] are found to have higher hazard rates, which is in line with the author's expectations.

To assess the effect of the individual variables on the hazard rate or risk of failure and by extension, on survival time, the study undertakes a transformation of the coefficients of the predictor variables reported in Table 5.9. Table 5.10 reports the coefficients, hazard ratios and hazard rate effects of all the explanatory variables used in the model. The coefficients are the results from the regression specifications that include both the firm and industry level variables as earlier reported in Panel B of Table 5.9. These coefficients and the corresponding hazard ratio and hazard rate effects have been reported in ranges given that the some of the predictor variables have been estimated and found significant in more than one model. The hazard rate effects have only been reported for the significant variables as earlier revealed from Table 5.9.

Clearly and expectedly, the largest positive effects on survival time are provided by past performance [earnings yield] and underwriter reputation. A one-unit increase in past performance affects the hazard rate with a factor [i.e. hazard ratio] of 0.431-0.575, which is equivalent to a decrease of 42.5%-56.9% in the risk of failure. In the same vein, a one-unit increase in the underwriter reputation variable, which would represent a deterioration in underwriter quality going by the author's construction[160], impacts on the risk of failure with a factor of 1.419-1.421, which corresponds to an increase of 41.9%-42.1% on the hazard rate[161]. The only other positive effect on survival is provided by size. A one-unit increase in the size of the firm affects the hazard rate with a factor of 0.868, which is equivalent to a decrease of 13.2% in the risk of failure. IPO surplus value provides the only negative effect on survival time as a one-unit increase in this variable impinges on the hazard rate with a factor of 1.079-1.080, which is equivalent to an increase of 7.9%-8% in the risk of failure. This derivative analysis, which is in consonance with the results from Table 5.9, provides further incontrovertible evidence that size, past performance and underwriter reputation are crucial survival signals that potential IPO investors, issuers and investment bankers should take into consideration in their decision making process at the offering date. The study also finds that under this model, the valuation of IPO firms relative to industry peers captured by the IPO surplus value emerges as another vital survival signal which the stakeholders should also pay attention to.

Hence, under the CPH model, the hazard rate or the probability of failure significantly decreases with increasing firm size [at least at the 5% level], past performance [at least

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[160] See Panel F of Table 3.5, pp. 99 and Section 4.3.2, pp. 220-221.

[161] Put differently, a one-unit decrease in the underwriter reputation variable, which would represent an improvement in underwriter quality, impacts on the risk of failure with a factor of between 1.419 and 1.421, which is equivalent to a decrease of between 41.9% and 42.1% in the hazard rate.

at the 10% level] and underwriter prestige [1% level] and increases with increasing industry–related measure of IPO surplus value [10% level]. More particularly, past performance and the underwriter prestige are found to be the most important as they provide the largest positive effects on survival time. More importantly and just like in the previous models, industry risk factors of market-to-book, profitability, leverage, concentration and equity volatility are found not to be significant.

[5.5.3.3] Exclusion of the late 1990s technology bubble

The study next undertakes a further robustness check by excluding the 'dotcom' period [1999 – 2001] from the sample period. Tables 5.11 – 5.16 report the respective regression and derivative analysis results for the logit, AFT and CPH models that exclude this historic period. For Tables 5.11, 5.13 and 5.15, Panel A reports the firm level regression results, while Panel B presents the same for regressions that include the firm and industry level variables. From the logit results in Table 5.11, the performance evidence is also found to be largely present across all the specifications regardless of whether or not the industry factors are included in the regressions; albeit, the coefficients are much higher when the study controls additionally for the industry factors. A similar pattern is observed in the underwriter prestige evidence as the size of

TABLE 5.11: LOGISTIC REGRESSION RESULTS FOR THE IPO SAMPLE EXCLUDING THE 'DOTCOM' YEARS

The sample is 485 IPOs that went public between January 2002 and December 2006. The table reports logistic regression results for the IPO sample that excludes the 'dotcom' years. In this table, results from firm [firm and industry] logistic regression results for two [six] separate models are reported. In all models, the dependent variable takes on a value of 1 if the firm fails within 6 years of the IPO date and 0 otherwise. The firm independent variables are the natural logarithms of the market value, [1+Age] and underwriter reputation [UW]. The others are market-to-book [MTB], market leverage [Lev], earnings yield, 30-day initial returns, IPO risk and the hot dummy variable. The industry independent variables are IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility. Panel A [B] reports results including the firm level variables only [firm and industry level variables]. The z-stats, shown in parentheses, are calculated using Davidson & Mackinnon [1993] robust standard errors. ***, **, * indicate significance at the 1, 5 & 10% levels respectively.

Dependent variable, $y = 1$ if firm fails within 6 years of IPO and $y = 0$ otherwise

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

Independent Variables	Model 1	Model 2
Intercept	-3.3112	-1.5058
	*[-4.77***]*	*[-4.16***]*
Lev	0.3653	
	[0.37]	
Log Mkt. Val		-0.1364
		[-1.43]
MTB	0.0010	0.0012
	[0.47]	*[0.56]*
Earnings Yield	-1.9182	-1.8446
	*[-2.80***]*	*[-2.49**]*
Log UW	0.4336	
	*[2.58***]*	
Log [1+Age]	-0.0497	-0.0385
	[-0.31]	*[-0.25]*
Initial Ret		0.5190
		[1.17]
IPO Risk	-2.2749	
	[-0.43]	
Hot	0.3130	0.3501
	[1.12]	*[1.27]*
Log Likelihood	-189.37	-191.75
Pseudo - R^2	0.05	0.04
N $[y = 1, y = 0]$	440	440

PANEL B – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES						
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-3.8158	-3.7513	-4.1140	-2.0478	-1.9177	-2.4642
	*[-4.23***]*	*[-4.05***]*	*[-4.31***]*	*[-3.20***]*	*[-2.99***]*	*[-3.48***]*
Lev	0.9293	1.0319	0.7944			
	[0.79]	*[0.90]*	*[0.68]*			
Log Mkt. Val				-0.0877	-0.0924	-0.0942
				[-0.83]	*[-0.91]*	*[-0.88]*
MTB	0.0046	0.0042	0.0044	0.0036	0.0035	0.0033
	[0.69]	*[0.62]*	*[0.67]*	*[0.55]*	*[0.53]*	*[0.50]*
Earnings Yield	-2.3630	-2.3331	-2.4665	-2.4473	-2.3927	-2.5417
	*[-3.43***]*	*[-3.37***]*	*[-3.50***]*	*[-3.31***]*	*[-3.22***]*	*[-3.40***]*
Log UW	0.5007	0.5127	0.4869			
	*[2.66***]*	*[2.74***]*	*[2.62***]*			
Log [1+Age]	-0.1294	-0.1382	-0.1191	-0.1106	-0.1184	-0.0976
	[-0.74]	*[-0.79]*	*[-0.67]*	*[-0.63]*	*[-0.68]*	*[-0.55]*
Initial Ret				0.1105	0.0756	0.1130
				[0.22]	*[0.15]*	*[0.23]*
IPO Risk	-8.5738	-9.0011	-8.8647			
	[-1.27]	*[-1.32]*	*[-1.38]*			
Hot	0.7872	0.7504	0.8290	0.7402	0.6977	0.7920
	*[2.29**]*	*[2.13**]*	*[2.48**]*	*[2.14**]*	*[1.96*]*	*[2.32**]*
Surplus Val	0.0388	0.0492	0.0371	0.0186	0.0326	0.0243
	[0.46]	*[0.59]*	*[0.47]*	*[0.23]*	*[0.41]*	*[0.31]*
I_Profitability	0.1737		0.1985	0.2076		0.2234
	[1.26]		*[1.63]*	*[1.50]*		*[1.84*]*
I_Leverage			1.2664			1.8105
			[0.56]			*[0.82]*
I_MTB	0.0232	0.0336	0.0266	0.0305	0.0433	0.0399
	[0.30]	*[0.41]*	*[0.36]*	*[0.37]*	*[0.49]*	*[0.51]*
I_Conc	-0.3138	-0.6820		-0.1464	-0.6016	
	[-0.34]	*[-0.75]*		*[-0.15]*	*[-0.60]*	
I_Equity Vol	3.6479	2.7157	4.0488	3.5061	2.4672	3.8409
	[0.97]	*[0.70]*	*[1.11]*	*[0.92]*	*[0.61]*	*[1.02]*
Log Likelihood	-150.57	-151.28	-150.52	-154.76	-155.79	-154.50
Pseudo - R^2	0.09	0.09	0.09	0.07	0.06	0.07
N $[y = 1, y = 0]$	440	440	440	440	440	440

TABLE 5.12: DERIVATIVE ANALYSIS FROM THE LOGISTIC REGRESSIONS FOR THE IPO SAMPLE EXCLUDING THE 'DOTCOM' YEARS

The sample is 485 IPOs that went public between January 2002 and December 2006. The table reports the coefficients $[\beta]$, marginal effects and odds ratios of the predictor variables based on the regression specifications that include both the firm and industry level variables reported in Panel B of Table 5.11. These coefficients and the corresponding marginal effects and odds ratios are reported in ranges given that some of the predictor variables have been estimated and found significant in more than one model. The odds ratio, computed as $[exp(\beta)]$, is defined as the odds of failure relative to survival for one-unit increases in the predictor variables. The 'marginal effect', is defined as the effect on the probability of failure for less than one-unit increases in the predictor variables, while holding the other predictor variables constant. The percentage change in the odds [odds effect] is given by $\{100 * [exp(\beta) - 1]$. A negative [positive] coefficient, which corresponds to an odds ratio of less than one [greater than one], indicates that the odds of failure relative to survival is smaller [larger] by $[exp(\beta)]$. The odds effects have only been reported for the significant variables. * indicates the significant variables.

Variables	Coefficient	Marginal Effect	Odd Ratio	Odds effect
Lev	0.794 – 1.032	0.090 – 0.119	2.213 – 2.806	
Log Mkt. Val	-0.088 – -0.094	-0.011 – -0.011	0.910 – 0.916	
MTB	0.003 – 0.005	0.000 – 0.001	1.003 – 1.005	
Earnings Yield*	-2.333 – -2.542*	-0.268 – -0.304	0.085 – 0.097	*-90.3% – -92.1%*
Log UW*	0.487 – 0.513*	0.055 – 0.059	1.627 – 1.670	*62.7% – 67.0%*
Log [1+Age]	-0.098 – -0.138	-0.012 – -0.016	0.871 – 0.907	
Initial Ret	0.076 – 0.113	0.009 – 0.014	1.079 – 1.120	
IPO Risk	-8.574 – -9.001	-0.975 – -1.035	0.000 – 0.000	
Hot*	0.698 – 0.829*	0.085 – 0.095	2.009 – 2.291	*100.9% – 129.1%*
Surplus Val	0.019 – 0.049	0.002 – 0.006	1.019 – 1.050	
I_Profitability*	0.223*	0.027	1.250	*25.0%*
I_Leverage	1.266 – 1.811	0.144 – 0.217	3.548 – 6.114	
I_MTB	0.023 – 0.043	0.003 – 0.005	1.023 – 1.044	
I_Conc	-0.146 – -0.682	-0.018 – -0.078	0.506 – 0.864	
I_Equity Vol	2.467 – 4.049	0.300 – 0.461	11.789 – 57.329	

TABLE 5.13: MAXIMUM LIKELIHOOD RESULTS OF THE LOG-LOGISTIC AFT MODEL FOR THE IPO SAMPLE EXCLUDING THE 'DOTCOM' YEARS

The sample is 485 IPOs that went public between January 1999 and December 2006. The table reports maximum likelihood results for the log-logistic AFT model for the IPO sample that excludes the 'dotcom' years. In all models, the dependent variable is the natural logarithm of the number of months from the IPO listing date to the date of failure or the end of the study period [31 December 2012], with an additional right-censoring indicator that takes the value of one for firms that go bankrupt and fail within the tracking period and zero for censored observations, representing firms that are still alive at the end of the study period. In this table, results from firm [firm and industry] regression results for two [six] separate models are reported. The firm independent variables are the natural logarithms of the market value, [1+Age] and underwriter reputation [UW]. The others are market-to-book [MTB], market leverage [Lev], earnings yield, 30-day initial returns, IPO risk and the hot dummy variable. The industry independent variables are IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility. Panel A reports results including the firm level variables only, while Panel B presents the same including both firm and industry level variables. The z-stats, not shown, have been calculated using Davidson & Mackinnon [1993] robust standard errors. The numbers in parentheses are the p values. ***, **, * indicate significance at the 1, 5 & 10% levels respectively.

Dependent variable, $y =$ natural log of no of months from listing date to failure date or Dec 2012

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

Independent Variables	Model 1	Model 2
Intercept	1.8112	1.6291
	*[0.000***]*	*[0.000***]*
Lev	-0.0173	
	[0.852]	
Log Mkt. Val		0.0156
		[0.056]*
MTB	-0.0000	-0.0001
	[0.900]	*[0.679]*
Earnings Yield	0.1378	0.1230
	*[0.004***]*	*[0.020**]*
Log UW	-0.0433	
	*[0.005***]*	
Log [1+Age]	-0.0011	-0.0014
	[0.934]	*[0.915]*
Initial Ret		-0.0396
		[0.333]
IPO Risk	0.2416	
	[0.622]	
Hot	-0.0172	-0.0222
	[0.486]	*[0.366]*
Log Likelihood	-105.90	-109.09
N $[y = 1, y = 0]$	440	440

PANEL B – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.8721	1.8709	1.9216	1.6742	1.6655	1.7374
	*[0.000***]*	*[0.000***]*	*[0.000***]*	*[0.000***]*	*[0.000***]*	*[0.000***]*
Lev	-0.0815	-0.0872	-0.0626			
	[0.460]	*[0.424]*	*[0.565]*			
Log Mkt. Val				0.0131	0.0137	0.0139
				[0.169]	*[0.143]*	*[0.142]*
MTB	-0.0001	-0.0001	-0.0001	-0.0002	-0.0002	-0.0001
	[0.856]	*[0.869]*	*[0.886]*	*[0.744]*	*[0.739]*	*[0.804]*
Earnings Yield	0.1502	0.1505	0.1564	0.1484	0.1479	0.1520
	*[0.001***]*	*[0.001***]*	*[0.001***]*	*[0.007***]*	*[0.008***]*	*[0.011**]*
Log UW	-0.0554	-0.0554	-0.0524			
	*[0.002***]*	*[0.002***]*	*[0.003***]*			
Log [1+Age]	0.0066	0.0066	0.0050	0.0059	0.0058	0.0040
	[0.652]	*[0.649]*	*[0.730]*	*[0.700]*	*[0.703]*	*[0.795]*
Initial Ret				0.0004	0.0008	-0.0003
				[0.993]	*[0.987]*	*[0.995]*
IPO Risk	0.7355	0.7426	0.7661			
	[0.216]	*[0.215]*	*[0.174]*			
Hot	-0.0416	-0.0401	-0.0481	-0.0430	-0.0411	-0.0502
	[0.196]	*[0.217]*	*[0.122]*	*[0.190]*	*[0.218]*	*[0.117]*
Surplus Val	-0.0091	-0.0095	-0.0094	-0.0069	-0.0075	-0.0083
	[0.255]	*[0.231]*	*[0.219]*	*[0.355]*	*[0.313]*	*[0.259]*
I_Profitability	-0.0069		-0.0092	-0.0102		-0.0110
	[0.570]		*[0.376]*	*[0.413]*		*[0.297]*
I_Leverage			-0.2394			-0.3026
			[0.225]			*[0.123]*
I_MTB	-0.0071	-0.0074	-0.0077	-0.0079	-0.0084	-0.0091
	[0.285]	*[0.269]*	*[0.228]*	*[0.257]*	*[0.241]*	*[0.175]*
I_Conc	0.0219	0.0394		-0.0012	0.0246	
	[0.799]	*[0.608]*		*[0.989]*	*[0.762]*	
I_Equity Vol	-0.1394	-0.0948	-0.2176	-0.1337	-0.0718	-0.2065
	[0.699]	*[0.790]*	*[0.537]*	*[0.723]*	*[0.852]*	*[0.577]*
Log Likelihood	-85.86	-86.03	-85.24	-91.55	-91.93	-90.51
N $[y=1, y=0]$	440	440	440	440	440	440

TABLE 5.14: DERIVATIVE ANALYSIS FROM THE LOG-LOGISTIC AFT REGRESSIONS FOR THE IPO SAMPLE EXCLUDING THE 'DOTCOM' YEARS

The sample is 485 IPOs that went public between January 2002 and December 2006, excluding the 'dotcom' years. The table reports the coefficients, time ratios and survival time effects of all the explanatory variables used in the model. The coefficients are the results from the regression specifications that include both the firm and industry level variables as reported in Panel B of Table 5.13. These coefficients and the corresponding time ratios and survival time effects have been reported in ranges given that the predictor variables have been estimated and found significant in more than one model. The time ratio is computed as $exp(\beta)$, while the quantified percentage effect on survival time is calculated as $\{100 * [exp(\beta) - 1]\}$. A positive [negative] value of the coefficient, which corresponds to time ratios $[exp(\beta)]$ greater [less] than one, indicates that increasing values of the explanatory variable increases [decreases] the survival time or time to failure. The survival time effects have only been reported for the significant variables. * indicates the significant variables.

Variables	Coefficient	Time Ratio	Survival Time Effect
Lev	-0.063 – -0.087	0.916 – 0.939	
Log Mkt. Val*	0.016*	1.016	*1.6%*
MTB	0.000	1.000	
Earnings Yield*	0.148 – 0.156*	1.159 – 1.169	*15.9% – 16.9%*
Log UW*	-0.052 – -0.055*	0.946 – 0.949	*-5.1% – -5.4%*
Log [1+Age]	0.004 – 0.007	1.004 – 1.007	
Initial Ret	0.000 – 0.001	1.000 – 1.001	
IPO Risk	0.736 – 0.766	2.087 – 2.151	
Hot	-0.040 – -0.050	0.953 – 0.961	
Surplus Val	-0.007 – -0.010	0.991 – 0.993	
I_Profitability	-0.007 – -0.011	0.989 – 0.993	
I_Leverage	-0.239 – -0.303	0.739 – 0.787	
I_MTB	-0.007 – -0.009	0.991 – 0.993	
I_Conc	-0.001 – 0.039	0.999 – 1.040	
I_Equity Vol	-0.072 – -0.218	0.804 – 0.931	

TABLE 5.15: PARTIAL LIKELIHOOD RESULTS OF THE COX PROPORTIONAL HAZARD MODEL FOR THE IPO SAMPLE EXCLUDING THE ‘DOTCOM’ YEARS

The sample is 485 IPOs that went public between January 2002 and December 2006. The table reports partial likelihood results of the Cox proportional hazard model for the IPO sample that excludes the ‘dotcom’ years. The time to failure is measured as the number of months elapsed between the IPO month and the date of failure or the end of the study period [31 December 2012], with an additional right-censoring indicator that takes the value of one for firms that go bankrupt and fail within the tracking period and zero for censored observations, representing firms that are still alive at the end of the study period. In all models, the dependent variable is the natural logarithm of the hazard rate, where hazard rate is defined as the probability that the firm will fail at time t given continual listing. In this table, results from firm [firm and industry] regression results for two [six] separate models are reported. The firm independent variables are the natural logarithms of the market value, [1+Age] and underwriter reputation [UW]. The others are market-to-book [MTB], market leverage [Lev], earnings yield, 30-day initial returns, IPO risk and the hot dummy variable. The industry independent variables are IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility. Panel A [B] reports results including the firm level variables only [firm and industry level variables]. The z-stats, not shown, have been calculated using Davidson & Mackinnon [1993] robust standard errors. The numbers in parentheses are the p values. ***, **, * indicate significance at the 1, 5 & 10% levels respectively.

Dependent variable, $y =$ natural logarithm of the hazard rate

PANEL A – REGRESSIONS INCLUDING THE FIRM LEVEL VARIABLES ONLY

Independent Variables	Model 1	Model 2
Lev	0.2548	
	[0.760]	
Log Mkt. Val		-0.1494
		[0.079]*
MTB	0.0002	0.0007
	[0.953]	*[0.808]*
Earnings Yield	-1.2495	-1.0534
	*[0.003***]*	*[0.018**]*
Log UW	0.3919	
	*[0.005***]*	
Log [1+Age]	0.0193	0.0202
	[0.886]	*[0.880]*
Initial Ret		0.3777
		[0.402]
IPO Risk	-1.8059	
	[0.673]	
Hot	0.0374	0.0931
	[0.875]	*[0.691]*
Log Likelihood	-506.35	-508.98
N $[y = 1, y = 0]$	440	440

PANEL B – REGRESSIONS INCLUDING THE FIRM & INDUSTRY LEVEL VARIABLES						
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Lev	0.8126	0.8542	0.6333			
	[0.388]	*[0.362]*	*[0.503]*			
Log Mkt. Val				-0.1135	-0.1173	-0.1238
				[0.221]	*[0.201]*	*[0.181]*
MTB	0.0018	0.0017	0.0015	0.0021	0.0021	0.0018
	[0.792]	*[0.804]*	*[0.826]*	*[0.755]*	*[0.750]*	*[0.799]*
Earnings Yield	-1.5013	-1.4984	-1.5285	-1.4106	-1.4033	-1.3942
	*[0.001***]*	*[0.002***]*	*[0.001***]*	*[0.005***]*	*[0.005***]*	*[0.004***]*
Log UW	0.4770	0.4841	0.4588			
	*[0.002***]*	*[0.001***]*	*[0.002***]*			
Log [1+Age]	-0.0480	-0.0513	-0.0337	-0.0469	-0.0490	-0.0263
	[0.742]	*[0.724]*	*[0.818]*	*[0.747]*	*[0.736]*	*[0.858]*
Initial Ret				-0.0278	-0.0252	-0.0424
				[0.958]	*[0.962]*	*[0.935]*
IPO Risk	-6.4677	-6.4053	-7.1218			
	[0.231]	*[0.234]*	*[0.173]*			
Hot	0.2580	0.2381	0.3220	0.2670	0.2492	0.3264
	[0.376]	*[0.413]*	*[0.263]*	*[0.350]*	*[0.384]*	*[0.117]*
Surplus Val	0.0834	0.0872	0.0865	0.0619	0.0682	0.0743
	[0.159]	*[0.138]*	*[0.136]*	*[0.265]*	*[0.214*	*[0.180]*
I_Profitability	0.0681		0.0985	0.0891		0.1048
	[0.534]		*[0.320]*	*[0.419]*		*[0.298]*
I_Leverage			2.2278			2.6526
			[0.232]			*[0.150]*
I_MTB	0.0633	0.0673	0.0659	0.0739	0.0792	0.0824
	[0.251]	*[0.225]*	*[0.199]*	*[0.185]*	*[0.159]*	*[0.116]*
I_Conc	-0.2701	-0.4462		-0.0873	-0.3132	
	[0.677]	*[0.461]*		*[0.893]*	*[0.611]*	
I_Equity Vol	1.0944	0.6371	1.9077	1.1001	0.5653	1.7423
	[0.722]	*[0.835]*	*[0.527]*	*[0.719]*	*[0.854]*	*[0.565]*
Log Likelihood	-405.76	-405.96	-405.15	-410.86	-411.19	-409.85
N $[y = 1, y = 0]$	440	440	440	440	440	440

TABLE 5.16: DERIVATIVE ANALYSIS FROM THE COX HAZARD REGRESSIONS FOR THE IPO SAMPLE EXCLUDING THE 'DOTCOM' YEARS

The sample is 485 IPOs that went public between January 2002 and December 2006, excluding the 'dotcom' years. The table reports the coefficients, hazard ratios and hazard rate effects of all the explanatory variables used in the model. The coefficients are the results from regressions that include both the firm and industry level variables as reported in Panel B of Table 5.15. These coefficients and the corresponding hazard ratios and hazard rate effects have been reported in ranges given that the predictor variables have been estimated and found significant in more than one model. The coefficients represent the hazard rates, interpreted as the increase in the log hazard ratio [i.e. the risk of failure] for a one-unit increase in the explanatory variables, while holding the other predictor variables constant. The relative hazard rate or the hazard ratio is computed as $exp(\beta)$, while the quantified marginal effect on the hazard rate is calculated as $\{100 * [exp(\beta) - 1]\}$. A negative [positive] coefficient, which corresponds to hazard ratios $[exp(\beta)]$ less than one [greater than one], indicates that increasing values of the predictor variable lowers [increases] the risk of failure and increases [reduces] the survival time. The hazard rate effects have only been reported for the significant variables. * indicates the significant variables, while ** indicates significance in specifications that include only the firm level factors.

Independent Variables	Coefficient	Hazard Ratio	Hazard Rate Effect
Lev	0.633 – 0.854	1.884 – 2.349	
Log Mkt. Val**	-0.149*	0.861	*-13.9%*
MTB	0.002 – 0.002	1.002 – 1.002	
Earnings Yield*	-1.394 – -1.529*	0.217 – 0.248	*-75.2% – -78.3%*
Log UW*	0.459 – 0.484*	1.582 – 1.623	*58.2% – 62.3%*
Log [1+Age]	-0.026 – -0.051	0.950 – 0.974	
Initial Ret	-0.025 – -0.042	0.958 – 0.975	
IPO Risk	-6.405 – -7.122	0.001 – 0.002	
Hot	0.238 – 0.326	1.269 – 1.386	
Surplus Val	0.062 – 0.087	1.064 – 1.091	
I_Profitability	0.068 – 0.105	1.070 – 1.110	
I_Leverage	2.228 – 2.653	9.279 – 14.191	
I_MTB	0.067 – 0.082	1.065 – 1.086	
I_Conc	-0.087 – -0.446	0.640 – 0.916	
I_Equity Vol	0.565 – 1.908	1.760 – 6.738	

the coefficient is higher when the study controls additionally for the industry risk factors. The 'hot' IPO market evidence emerges in specifications that control additionally for a raft of industry factors; however, the coefficient and by extension, the evidence is the least when firm leverage, underwriter reputation, IPO risk, industry profitability and industry leverage are excluded from the specifications [model 5 of Panel B]. The industry profitability variable is only marginally significant in a regression framework that excludes firm leverage, IPO risk, underwriter reputation and industry concentration [model 6 of Panel B]. When juxtaposed with the results for the entire period reported in Table 5.5, the results from Table 5.11 present mixed findings. Past performance and underwriter prestige continue to be negatively related to the probability of failure as they are statistically significant across all specifications. The 'hot' IPO market dummy and industry profitability variables turn the corner as they also become significantly distinguishing factors, while the IPO risk evidence disappears.

For an assessment of the dynamics in the marginal and odds effect under the logit model for both periods, the results from Table 5.12 are juxtaposed with those from Table 5.6. The study observes a reduction in the risk and odds of failure for the past performance [earnings yield] variable when the 'dotcom' period is excluded from the sample. For instance, the marginal effect rises from 12.5%-14.3% in the full period to 26.8%-30.4% in the sub-period. Similarly, the odds effect for a one-unit increase in the performance variable surges from 69.7%-76.6% in the full period to 90.3%-92.1% in the sub-period excluding the 'dotcom' years. However, there is no marked difference in the change in the risk and odds of failure for the underwriter prestige variable between the two periods. The 'hot' market indicator and the industry profitability factor emerge as bad survival signals [i.e. negatively related to survival] when the 'dotcom' period is excluded. A one-unit increase in the former increases the failure odds by 100.9%-129.1%, while an equivalent increase in the latter raises the odds of failure by 25%.

From the AFT results in Table 5.13, the size evidence is found to be only present in a firm specification that does not include the industry level variables in the empirical design [model 2 of Panel A]. The performance evidence is also largely present across all specifications regardless of whether industry level variables are included or not in the empirical design; albeit, the coefficients are much higher when the study controls additionally for the industry level variables. In addition, similar to the pattern observed in the full period, the study finds that in specifications that exclude firm leverage, underwriter reputation and IPO risk [model 2 of Panel A and models 4 – 6 of Panel B], the magnitude of the coefficient is also smaller. There is no marked difference in the size of the underwriter prestige coefficient when the study controls additionally for the industry risk factors. Comparing the results in Table 5.13 with the results for the entire period earlier reported in Table 5.7, past performance and underwriter prestige continue to remain good and strong survival signals [i.e. positively related to survival], as these variables are significantly positively related to IPO survival time across all the regressions. However, the size evidence disappears and is only marginally significant at the 10% level in a multivariate framework that does not include the industry risk factors.

For an assessment of the dynamics in the survival time effect for both periods under the AFT model, the results from Table 5.8 are juxtaposed with those from Table 5.14. Generally, the study finds that the effects of the significant predictor variables on survival time are more when the ‘dotcom’ period is excluded from the sample. For instance, the survival time effect for a one-unit increase in past performance [earnings yield] jumps from 8.2%-11.6% in the full period to 15.9%-16.9% in the sub-period. In the same vein, the effect on survival time for a one-unit improvement in the quality of the underwriter increases from 4.1% in the full period to 5.1%-5.4% in the sub-period. There is no change in the survival time effect for the size variable for both periods.

The pattern observed in the AFT results in Table 5.13 is also evident in the CPH model results presented in Table 5.15. The size evidence is only present in a firm specification that does not include the industry level variables in the empirical design [model 2 of Panel A]. The performance evidence is also largely present across all specifications regardless of whether industry level variables are included or not in the empirical design; albeit, the coefficients are much higher when the study controls additionally for the industry risk factors. In addition, similar to the pattern observed in the full period, the study finds that in specifications that exclude firm leverage, underwriter reputation and IPO risk [model 2 of Panel A and models 4 – 6 of Panel B], the magnitude of the coefficient is also smaller. The size of the underwriter prestige coefficient is also found to be higher when the study controls additionally for the industry risk factors, just like in the full period. Comparing the results in Table 5.15 with the results for the entire period earlier reported in Table 5.9, the evidence on past performance and underwriter prestige continue to be irresistible with the variables, once again, significant across both set of regressions in Panels A and B, while the evidence on IPO surplus value disappears. The size evidence disappers and is now only observed marginally at the 10% level in a multivariate framework that does not include the industry risk factors.

For an assessment of the dynamics in the hazard effect for both periods under the CPH model, the results from Table 5.10 arte compared with those from Table 5.16. Generally, the effect of the significant predictor variables on the risk of failure is found to be more when the 'dotcom' period is excluded from the sample. For instance, the percentage reduction in the risk of failure for a one-unit increase in past performance [earnings yield] jumps from 42.5%-56.9% in the full period to 75.2%-78.3% in the sub-period. Similarly, the effect on the hazard rate for a one-unit improvement in the quality of the underwriter increases from 41.9%-42.1% in the full period to 58.2%-62.3% in the sub-period. The study also observes that the hazard rate effect for the size variable increases from 13.2% in the full period to 13.9% in the sub period. In general, the study finds from all the models employed that excluding IPOs issued in the 'dotcom' period from the sample reduces the probability and risk of failure and consequently increases survival time for the cohort of firms, which is in tandem with the earlier findings from Sections 5.5.1 and 5.5.2.2.

Table 5.17 presents a summary of the significance of the findings from the various models used to test the null hypothesis of zero relationship between the selected industry risk factors and IPO survival[162]. Overrall, firm level factors of size, past performance, underwriter prestige, IPO risk and 'hot' market and industry conditioning risk factors relating to IPO surplus value and profitability are found to be significant across the three models and both periods. The study does not find the other firm level factors as well as the industry risk factors relating to leverage, concentration, market-to-book and equity volatility to be significant in any of the models employed. Clearly,

[162] It is important to note that a factor that reduces the hazard rate or probability of failure of a firm under the CPH and logit models respectively will invariably increase the same firm's trading period, survival time or time to failure under the AFT model.

TABLE 5.17: SUMMARY OF THE SIGNIFICANCE OF THE FINDINGS FROM THE VARIOUS MODELS USED TO TEST THE NULL HYPOTHESIS OF ZERO RELATIONSHIP BETWEEN THE SELECTED INDUSTRY RISK FACTORS & IPO SURVIVAL

	FULL PERIOD [1999 – 2006]		
MODEL	VARIABLE	SIGNIFICANCE LEVEL	MARGINAL IMPACT
LOGIT	(+) SIZE* (+) PAST PERFORMANCE (+) UNDERWRITER PRESTIGE (+) IPO RISK	10% AT LEAST 5% 1% 10%	-13.2% -69.7% to -76.6% 65.0% to 66.6% -99.9%
AFT	(+) SIZE (+) PAST PERFORMANCE (+) UNDERWRITER PRESTIGE	AT LEAST 5% AT LEAST 10% 1%	1.6% 8.2% to 11.6% 4.1%
CPH	(+) SIZE* (+) PAST PERFORMANCE (+) UNDERWRITER PRESTIGE (-) IPO SURPLUS VALUE	5% AT LEAST 10% 1% 10%	-13.2% -42.5% to -56.9% 41.9% to 42.1% 7.9% to 8.0%
	PERIOD EXCLUDING THE DOTCOM YEARS [2002 – 2006]		
LOGIT	(+) PAST PERFORMANCE (+) UNDERWRITER PRESTIGE (-) HOT MARKET (-) INDUSTRY PROFITABILITY	AT LEAST 5% 1% AT LEAST 10% 10%	-90.3% to -92.1% 62.7% to 67.0% 100.9% to 129.1% 25.0%
AFT	(+) SIZE* (+) PAST PERFORMANCE (+) UNDERWRITER PRESTIGE	10% AT LEAST 10% 1%	1.6% 15.9% to 16.9% -5.1% to -5.4%
CPH	(+) SIZE* (+) PAST PERFORMANCE (+) UNDERWRITER PRESTIGE	10% AT LEAST 5% 1%	-13.9% -75.2% to -78.3% 58.2% to 62.3%

(a) The signs behind the variables indicate the relationship to survival (b) The figures in the third column specify the significance level in ascending order, with 10% and 1% being the lowest and highest levels respectively (c) The figures in the fourth column in the logit, AFT and CPH models indicate the quantified percentage impact on the odds, survival time and risk of failure respectively for one-unit increases in the predictor variables found to be significant in the models (d) * indicates significance in regression frameworks that controls only for the firm level factors without the industry level factors (e) The logit [AFT] model results indicate relationship to probability of failure [time to failure] in event [duration] time, while the CPH results depicts relationship to the hazard rate in duration time.

past performance and underwriter prestige, in line with the author's surmise, are found to be strong and overwhelming survival signals with the evidences robust firstly, to all the variants of the survival models employed and secondly, to the inclusion or exclusion of the late 1990s technology bubble. Expectedly, the size evidence also appears to be relatively strong as it is largely present in the three models. However, in regressions that exclude the 'dotcom' period and control additionally for the industry risk factors, this evidence disappears. The evidences on IPO risk and IPO surplus value are only present in the logit and CPH models respectively for the whole period as they disappear in regression frameworks that exclude the 'dotcom' period. The risk evidence is against the author's supposition, while the IPO surplus value evidence meets the author's conjecture. The 'hot' market and the industry profitability evidences are only present in logit models that also exclude this momentous period. The former is in tandem with the author's presumption, while the latter is contrary to the author's prediction. The lack of robustness of the evidences on IPO risk and 'hot' market as well as industry structure variables of IPO surplus value and profitability suggest that the 'dotcom' period is driving some of the results.

It is also observed that the largest positive effect on survival time is provided by IPO risk, past performance, underwriter prestige and size in that order. For example, under the logit model for the entire period, a one-unit increase in IPO risk, past performance and size reduces the odds of failure by 99.9%, 69.7%-76.6% and 13.2% respectively. For the underwriter prestige variable, a one-unit increase [decrease], which represents a deterioration [improvement] in underwriter quality going by the author's construction[163], increases [reduces] the odds of failure by 65%-66.6%. These patterns are also generally observable under the logit model for the period excluding the 'dotcom' years as well as the AFT and CPH models for both periods as the study finds that the largest positive effects are provided by past performance, underwriter prestige and size in that order. The largest negative effect on survival time is provided by the 'hot' market, industry profitability and IPO surplus value variables in that order. For example, a one-unit increase in the 'hot' market and industry profitability risk factors under the logit model for the period excluding the technology bubble years increases the odds of failure by 100.9%-129.1% and 25% respectively. A similar increase in the IPO surplus value variable under the CPH model for the entire period increases the risk of failure by 7.9%-8.0%.

Against this backdrop, the central hypothesis of this third empirical study that industry–structure variables cannot foreshadow the survival likelihood of IPOs is rejected as the study finds industry profitability and IPO surplus value to be significant factors that can distinguish between surviving and failing firms. On the evidence of these results, IPO

[163] See Panel F of Table 3.5, pp. 99 and Section 4.3.2, pp. 220-221.

managers, their investment bankers and potential IPO investors can foreshadow the survival likelihood of these firms based on a battery of firm and industry conditioning risk factors prior to or at the IPO. The study finds that failing firms are restricted to small firms with an unprofitable trading history, less volatile initial market returns, issued in hot IPO markets, underwritten by less prestigious investment bankers, trading above their industry–adjusted valuations [i.e. trading at a premium relative to industry peers] and also tend to be located in more profitable industries.

[5.6] SUMMARY AND CONCLUSIONS

[5.6.1] Summary

Several studies in the literature have analysed the relationship between certain firm characteristics and the survival of new issues of common stock; however, little has been done to consider whether the characteristics of an issuing firm's industry are also germane, which is startling given the extant literature's widespread handling of other corporate finance issues. The study seeks to confirm the results of previous studies on the relationship between these firm characteristics and the survival of IPOs and also to explore salient industry conditioning risk factors at the time of the offering that could also prove valuable in predicting the probability of survival of new issuances.

Using the same sample of 746 IPOs in the UK market over the period 1999 – 2006 as in the previous two studies, this final study tests for the economic importance of selected firm and industry risk factors prior to or at the IPO to the issuing firms, their investment bankers and potential IPO investors. In the process, the study confirms the results of previous studies on the impact of firm-specific risk factors. The results show that size, past performance, underwriter reputation, highly volatile initial market returns [IPO risk] and the 'hot' IPO market are important predictors of the probability of IPO survival in cross-sectional regressions. This study identifies industry risk factors relating to industry-adjusted IPO valuations, profitability, leverage, market-to-book, concentration and equity volatility as potential determinants of the likelihood of survival of IPO firms. However, after controlling for all possible factors that may predict IPO survival in a cross-section, the findings reveal that industry conditioning risk factors of IPO surplus value and profitability can be valuable predictors of an IPO's survival prospects. More specifically, the study finds significant negative relationships between IPO surplus value, industry profitability and IPO survival likelihood. However, it does not find that the other industry risk factors of leverage, concentration, market-to-book and equity volatility can foreshadow the likelihood of IPO survival.

The sensitivity of the findings to several methodologies and the inclusion and exclusion of the late 1990s technology bubble offer mixed findings. There is a strong and compelling evidence that past performance and underwriter prestige are strong survival signals [i.e. positively related to survival] with their relationship to IPO survival probability robust firstly, to event time regressions that either considers the survival or failure of IPO firms in a fixed time period using a binary operator or duration models that track all sample firms to the last observation date, while controlling for those that have not yet failed using a censoring indicator; secondly, to including controls for other variables known to predict IPO survival probability and; thirdly, to the inclusion or exclusion of the late 1990s technology bubble. The size evidenceis found in all the models employed; albeit, not robust to the exclusion of the 'dotcom' years and the inclusion of the industry risk factors in the empirical design. There is also evidence in the CPH model that suggests that IPO surplus value is a bad survival signal [i.e. negatively related to survival], albeit, this evidence, once again, disappears in regressions that exclude the 'dotcom' period. IPO firm risk, 'hot' market and industry profitability are also found to be significantly distinguishing factors in event-time logistic regressions, even though these evidences are not robust to the inclusion or exclusion of the late 1990s technology bubble. The lack of robustness of some of the evidences indicates that the technology bubble period is driving some of the results. The results generally indicate that subsequent to the IPO event, large firms with a profitable trading history, highly volatile initial market returns, issued in less tense market conditions [i.e.

periods of low or modest IPO activity], underwritten by more prestigious investment bankers, trading below their industry–adjusted valuations [i.e. trading at a discount relative to industry peers] and from less profitable industries have a higher survival likelihood than their counterparts.

[5.6.2] Conclusions

Given that the literature is still shallow on the impact of industry characteristics on the likelihood of survival of new stock issues, the goal of this study is to identify salient industry risk factors prior to or at the IPO that can be germane to the survivorship of IPO firms. Put differently, this study seeks to identify relevant industry characteristics at the time of the IPO that could be useful to the managers of these firms and their investment bankers on the likely future implications of going ahead with the IPO. Consistent with existing literature, the study includes in the analysis several firm risk factors that have been shown to be germane to the survival or failure of new issues. To fully understand the role of industry risk factors, industry-specific averages of some selected industry risk factors are constructed over all existing firms in a given IPO's industry prior to or at the IPO. In this regard, industry conditions relating to IPO surplus value, profitability, leverage, market-to-book, concentration and equity volatility are considered.

The study evaluates the impact of these industry conditioning risk factors on the post-issue survival likelihood of IPO firms both in isolation and after controlling for variables that are germane to their survival prospects. More particularly, the evidence here on past performance and underwriter prestige is strong, overwhelming and compelling. The former suggests that firms desirous of going public should first build a track record of profitable performance to enhance their long-run survival prospects, while the latter lays credence to the fact that firms underwritten by prestigious investment bankers are less likely to fail due to their ability to hand-pick better and quality firms from the pool of firms going public. Overall, this work attempts to fill an important void in the literature by identifying salient industry risk factors prior to or at the IPO that could be influential to the survival prospects of IPO firms for the benefit of the managers of the IPO firms, their investment bankers and potential IPO investors. The results also suggests that IPO firms and their investment bankers should consider industry conditioning risk factors prevailing at the time of the IPO, particularly those relating to profitability and the valuation of the IPO firm relative to industry peers, to provide them with additional information on whether to go ahead with the IPO, or alternatively, withdraw and re-launch at a more auspicious date. To the best of the author's knowledge, this is [1] the first study that documents the unique relationships between industry risk factors of IPO surplus value, profitability and IPO survival and [2] the first in the UK market that investigates the impact of a raft of industry risk factors on the survival of IPOs.

Conclusively, despite using a multi-faceted and comprehensive approach that utilises salient firm and industry information prior to or at the IPO to predict the probability of survival or failure of IPO firms, future research is encouraged into identifying other salient industry risk factors that could prove useful to the various stakeholders in distinguishing between firms that are likely to survive from those that are likely to fail.

CHAPTER 6 - SUMMARY AND CONCLUSIONS

[6.1] Introduction

The majority of the findings in the literature reveal the prevalence of long-run under-performance of new issues of common stock. However, these findings have come under increasing attack in the finance literature by notable authors who contend that these findings are to a lesser extent, a function of the market investigated, the period and sample size and to a large extent, the methodology, benchmark and weighting schemes employed. This informs the motivation in the first part of this study as it seeks to critique the validity, reliability and robustness of the documented long-run under-performance of new issues of common stock using a fresh sample of 746 IPOs in the UK market over the period 1999 – 2006 and stepwise matching algorithms that selects the matching firms from the general population on the basis of key firm risk factors that includes three new factors – pre-IPO performance, turnover growth and earnings yield – employing a refined matching technique and a battery of methods. The IPO performance results are compared across five different horizons with the results of a set of matching firms selected according to the six stepwise matching algorithms as earlier defined. More importantly, the use of stepwise matching algorithms that selects the matching firms from the general population on the basis of key firm risk factors that includes three new risk factors – pre-IPO performance, turnover growth and earnings yield – employing a distance metric matching technique is first documented in this study.

In the course of analysing the performance of these new issues, the study finds that the under-performance is more prevalent in some groups of IPOs than others. Hence, in the second part of the work, the study tests for the economic importance and significance of key firm and industry risk factors that may predict or explain this cross-sectional variation. When doing this, the study controls for and confirms the results of previous studies on the impact of firm-specific risk factors. In the final part, these firms are tracked for an extended period in event and calendar time in order to explore the significance of this same battery of firm and industry risk factors on the survival likelihood of these firms.

[6.2] Main Findings

The findings from the first empirical study reveal that, indeed, in line with the majority of extant research, IPOs are poor investments either in event time methodologies or calendar time techniques that rebalance the IPO stocks in monthly portfolios, using the equally-weighted technique. However, the evidence is mixed when a value-weighted performance measure is adopted. Under this scenario in event-time methodologies, the under-performance is also largely evident; however, when the risk-adjusted performance of the IPO stocks is tracked in calendar time, under-performance is found to be non-existent in some cases, and at best, weak in others. This pattern of results is robust to the inclusion or exclusion of the late 1990s technology bubble. The results also show that the scale of the under-performance, which varies substantially and in some cases disappears altogether across the matching board, is sensitive to firstly, the choice of empirical method; secondly, the choice of matching firms in the benchmark portfolio; thirdly, the method of cumulating abnormal returns; fourthly, the weighting scheme employed; fifthly, the horizon over which it is measured and; sixthly, the inclusion or exclusion of the late 1990s technology bubble. The study also documents a novel finding. It is found that in almost all the cases, the observed under-performance is least, and in some cases evaporates, when the matching algorithm includes industry as an additional risk factor, which tends to suggest that a matching criterion that includes the industry of the firms is vital in the matching process as it ensures that issuing and non-issuing firms are fairly similar, thus making for better comparisons. In general, the findings show that firstly, after adjusting for market, size, book-to-market, pre-IPO performance, turnover growth, earnings yield and industry effects, the evidence for under-performance and by extension, against market efficiency is strong under the equally-weighted approach; secondly, the under-performance and the evidence against market efficiency is not as strong, may not even exist and in some cases, weak under a value-weighted performance approach and; thirdly, no unique 'IPO effect' is established in the market place under the value-weighted performance approach.

Employing only that information that is available prior to or at the IPO date, the results from the second empirical study indicate that firm size, market-to-book, past performance, underwriter reputation and the 'hot' IPO market are important predictors of IPO performance in a cross-section, in line with the majority of extant literature. The study also documents that industry risk factors relating to IPO surplus value, profitability, market-to-book and equity volatility can help distinguish the best performing from the worst performing firms. These results are robust to including controls for variables known to predict IPO long-term performance. However, apart from firm size, past performance, underwriter reputation, industry profitability and industry market-to-book to a limited extent, they are not robust to the exclusion of the late 1990s technology bubble, which suggests that those years are driving some of the results. The findings suggest that investing in IPOs may not be poor investments after all and that investors should be able to improve their long-run returns by strategically investing in well-selected IPOs after due consideration of relevant firm and industry information prior to or at the IPO date.

In the final part of the study and equally using only information that is available prior to or at the IPO date, the study confirms that firm risk factors of size, past performance, initial market return volatility [IPO risk], underwriter reputation and the ‘hot’ IPO market are important predictors of the probability of IPO survival in cross-sectional regressions, in line with the majority of extant literature. The findings also reveal that industry risk factors of IPO surplus value and profitability can be valuable determinants of an IPO’s survival prospects. More specifically, the study finds significant negative relationships between IPO surplus value, industry profitability and IPO survival likelihood. More importantly, these industry effects are first documented in this study, to the best of the author’s knowledge.

The sensitivity of the findings to several methodologies and the inclusion and exclusion of the late 1990s technology bubble presents mixed findings. There is a strong and compelling evidence that past performance and underwriter prestige are strong survival signals [i.e. positively related to survival] with their relationship to IPO survival probability robust firstly to, event time regressions that either considers the survival or failure of IPO firms in a fixed time period using a binary operator or duration models that track all sample firms to the last observation date, while controlling for those that have not yet failed using a censoring indicator; secondly, to including controls for other variables known to predict IPO survival probability and; thirdly, to the inclusion or exclusion of the late 1990s technology bubble. Size is found to be statistically significant in all the models employed; albeit, not robust to the exclusion of the ‘dotcom’ years and the inclusion of the industry risk factors in the empirical design. Ther is also have evidence in the CPH model that suggests that IPO surplus value is a bad survival signal [i.e. negatively related to survival], albeit this evidence, once again, disappears in regressions that exclude the ‘dotcom’ period. IPO firm risk, ‘hot’ market and industry profitability are also found to be significantly distinguishing factors in event-time logistic regressions, even though these evidences are not robust to the inclusion or exclusion of the late 1990s technology bubble. The lack of robustness of some of these evidences, once again, indicates that the technology bubble period is driving some of the results.

[6.3] Policy Implications

Overall, this work attempts to fill an important void in the literature by firstly, re-assessing the robustness of the under-performance finding of IPO stocks with respect to a variation of the empirical method and choice of matching criteria towards determining if it is really an anomaly that challenges the efficient market hypothesis and secondly, identifying salient industry risk factors that could be influential to the long-run performance and survival prospects of these firms for the benefit of the managers of the IPO firms, their investment bankers and potential IPO investors.

The intent of this study at the onset was to determine if a ‘unique’ IPO effect indeed exists in the market place. The results from the first empirical suggest that when the stocks are stacked in equal proportions in the investor’s portfolio, a strong and unique ‘IPO effect’ exists, which disappears and is at best, weak under a value-weighted measure of performance. The equally-weighted results also generally imply, on the one hand, that investors who are unable to subscribe to the offer in the primary market due to over-subscription and therefore hoping to find some succour in the secondary market might be disappointed as a long-term investment in this set of IPOs from the second month of trading following the listing of these stocks relative to a similar investment in a set of comparable firms selected according to the six matching algorithms consistently produces an inferior performance across the horizon and matching board. On the other hand, a similar investment in a basket of IPO stocks stacked in proportion to their market values does not produce a strong and consistent under-performance finding.

Using only that information that is available prior to or at the IPO date, the results from the second part of the study suggest that large firms with a profitable trading history, low market-to-book, issued in less tense market conditions [i.e. periods of low or modest IPO activity], underwritten by more prestigious investment bankers, trading at a premium relative to industry peers [i.e. trading above their industry-adjusted valuations] and from less profitable and high market-to-book industries with low equity volatilities perform better than their counterparts in the long-term. Consequently, these results generally indicate that not all IPOs are bad investments as potential IPO investors can substantially improve their long-term returns if these IPOs are painstakingly selected. A meticulous selection would entail going beyond the offer document prepared by the investment bankers that lists the offering and firm specific risk factors to considering salient characteristics of the IPO firm's industry. The search for value by investors drives them to considering only stocks that would substantially improve their wealth position in the short and long-term. However, this value can only be delivered by firms with a track record of consistent positive financial performance in the market place which should reflect in the share price and translate to consistent dividend payments and capital appreciation. However, at the time of the IPOs of these firms, information on them is not available which makes the investment decision more complex for investors as they are forced to rely solely on the offer document. More times than often, these firms 'window-dress' as they paint glowing financial projections in the prospectus that never materialise. Unsuspecting investors, in their search for value, are fooled to believing these projections as they part with their hard-earned money. The author avers that investors can substantially reduce the uncertainty that surrounds new issues and in the process improve their long-run returns if they also consider relevant industry information at the time of the IPO.

On the evidence of the results from the third part of the study, the profile of non-surviving IPO firms can be determined based on a set of observable firm and industry characteristics prior to or at the IPO. The study finds that failing firms are restricted to small firms with an unprofitable trading history, less volatile initial market returns, issued in 'hot' IPO markets, underwritten by less prestigious investment bankers, trading at a premium relative to industry peers [i.e. trading above their industry–adjusted valuations] and also tend to be located in more profitable industries. On the evidence of these results, IPO managers, their investment bankers and potential IPO investors can foreshadow the survival likelihood of these firms based on a battery of firm and industry risk factors at the time of the IPO. The results from the third part of the study also suggest that IPO firms and their investment bankers should consider industry conditioning risk factors prevailing at the time of the IPO, particularly those relating to profitability and the valuation of the IPO firm relative to industry peers, to provide them with additional information on whether to go ahead with the IPO, or alternatively, withdraw and re-launch at a more auspicious date. If the conditions of the IPO firm's industry are not conducive, the firm can actually withdraw its offering during the period between the intention to float being publicised and the commencement of the offer period. Alternatively, the firm could consider other equity capital options like a private placement exercise or better still, douse the unfavourable industry conditions that may prevail at the originally intended flotation date by listing by introduction with a view to a flotation at a later date.

[6.4] Limitations and Future Research

Despite the fact that the greatest possible level of depth and robustness has been given to these results, the author warns that the results only hold for the sample size and period used here as this may change if a different and/or a larger sample were to be employed. Also, given the scope of this study, the impact of the delisting and failure of IPO firms on industry rivals' after-market performance as well as investors' sentiments towards that industry regarding subsequent IPOs has not been investigated. Hence, an examination of the impact of the delisting and failure of IPO firms on [1] industry rivals after-market performance and [2] investors' sentiments towards that industry regarding subsequent IPOs could be a lush area for future research.

Since the focus of the second and third parts of the study is on the impact of industry structure variables prior to or at the IPO on the long-run performance and survival likelihood of issues of ordinary equity, a limited range of the variables that have been shown to be germane to the performance and survivability of new listings are pre-selected as the control variables in the empirical design. Earnings management, analyst recommendations, percentage of ownership retention at the IPO and corporate governance characteristics have been excluded as they are outside the scope of this work. Hence, future research is encouraged into controlling for these variables to enable a more robust assessment of the performance and survival likelihood of IPO firms.

In the real world, a firm's ultimate survival in the market place is not only a function of the prevailing conditions around its IPO date but also on conditions subsequent to the issue. However, given that the author's goal in the final part of this study is to provide an initial estimate of the survivability of these new listings by using only that information that would be available to the issuer or the IPO investor prior to or at the offering date, conditions subsequent to the IPO date have not been considered. It is important to note that industry conditions are in a state of flux with its attendant impact on the performance and eventual survival of firms. Against this backdrop, a consideration of time-varying industry conditions subsequent to the IPO date on the performance and survivability of new stock issues would be another productive area for future research.

Prior research has mainly focussed on the impact of [1] firm and offering characteristics usually contained in the offer document on the decision of investors on whether or not to invest in IPOs at the offering date and [2] market timing and the cost of going public on the decision by IPO firms and their investment bankers to float, delay or withdraw an equity offering. This study’s analysis of the impact of key industry risk factors on the performance and survival likelihood of IPO firms adds another dimension to the decision-making process of potential IPO investors, IPO firms and their investment bankers prior to or at the issue date. On the part of the IPO firms and their investment bankers, the timing of the going public decision and the possibility and consequences of an early or late entry is a fruitful area for future research.

Conclusively, despite using a multi-faceted and comprehensive approach that utilises salient firm and industry information prior to or at the IPO to re-assess the performance and survival likelihood of IPO firms, future research is encouraged into identifying other salient firm and industry risk factors that could be used in selecting the control firms from the general population in re-assessing IPO long-run performance and also help in distinguishing between firms that are likely to survive from those that are likely to fail.

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APPENDIX 1: CAPM & FAMA-FRENCH-CAHART 4-FACTOR REGRESSIONS ON THE IPO & CONTROL FIRM PORTFOLIO MATCHED ON VARIOUS ALGORITHMS OVER THE PERIOD JANUARY 1999 & DECEMBER 2006

This table reports the coefficient estimates and t-values [in parentheses] of equally and value-weighted ordinary least squares [OLS] regressions. In all regressions, the discrepancy between the IPO firms' portfolio monthly return [IPO] and the monthly return of the designated control portfolio benchmark [Match] is the dependent variable. The sample comprises 746 firms going public between 1999 and 2006 and 485 firms going public for the sub-period 2002 and 2006 [excluding the 'dotcom' period] and their matching mature control firms [firm age since IPO is at least 7 years]. The explanatory variables are the monthly excess return of the value-weighted FTSE All-Share index over 3-month Treasury Bills rate [RMRF], the return of a zero-investment size portfolio [SMB], the return of a zero-investment book-to-market portfolio [HML] and the return of a zero-investment momentum portfolio [MOM]. Panels A1 – A6 and B1 – B6 report the respective coefficient estimates and t-values [in parentheses] of equally and value-weighted OLS regressions for the entire period [1999 – 2006] and the period excluding the dotcom years [2002 – 2006] respectively. The first two columns presents the results for the CAPM regressions, while the last two columns present Fama-French 3-factor [FF3F] regressions with Cahart's [1997] momentum factor.***, **, * indicate significance at the 1, 5 and 10% levels respectively.

ENTIRE PERIOD [1999 – 2006]

PANEL A1 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\,1}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0146 [-3.01***]	-0.0106 [-1.37]	-0.0161 [-4.01***]	-0.0117 [-1.86*]
RMRF	0.2586 [2.35**]	0.6004 [3.43***]	0.2996 [3.22***]	0.5804 [3.99***]
SMB			0.4481 [4.86***]	0.8635 [5.99***]
HML			-0.4648 [-5.19***]	-0.8191 [-5.84***]
MOM			0.1638 [1.99**]	0.0666 [0.5178]
R^2	0.0316	0.0787	0.3743	0.4213

PANEL A2 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\,2}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0150 [-3.39***]	-0.0119 [-1.33]	-0.0159 [-4.31***]	-0.0148 [-2.07**]
RMRF	0.2982 [2.99***]	0.7179 [3.55***]	0.3141 [3.67***]	0.6846 [4.15***]
SMB			0.4279 [5.05***]	1.1624 [7.11***]
HML			-0.4342 [-5.27***]	-0.8283 [-5.22***]
MOM			0.0958 [1.27]	0.1400 [0.96]
R^2	0.0539	0.0773	0.3746	0.4458

PANEL A3 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\ 3}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0157 [-3.40***]	-0.0110 [-1.21]	-0.0167 [-4.20***]	-0.0138 [-1.86*]
RMRF	0.2186 [2.09**]	0.6586 [3.18***]	0.2426 [2.63***]	0.6267 [3.64***]
SMB			0.4070 [4.45***]	1.1489 [6.73***]
HML			-0.4251 [-4.79***]	-0.8324 [-5.02***]
MOM			0.1121 [1.37]	0.1380 [0.91]
R^2	0.0237	0.0617	0.3156	0.4144

PANEL A4 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\ 4}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0159 [-3.67***]	-0.0120 [-1.41]	-0.0175 [-4.78***]	-0.0149 [-2.15**]
RMRF	0.2111 [2.16**]	0.6573 [3.42***]	0.2291 [2.71***]	0.6246 [3.90***]
SMB			0.4578 [5.45***]	1.0941 [6.88***]
HML			-0.3601 [-4.41***]	-0.7411 [-4.80***]
MOM			0.1307 [1.74*]	0.1377 [0.97]
R^2	0.0256	0.0714	0.3429	0.4185

PANEL A5 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\ 5}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0155 [-3.66***]	-0.0101 [-1.12]	-0.0166 [-4.38***]	-0.0134 [-1.82*]
RMRF	0.2144 [2.24**]	0.6736 [3.30***]	0.2322 [2.65***]	0.6430 [3.80***]
SMB			0.3625 [4.17***]	1.1663 [6.94***]
HML			-0.3336 [-3.95***]	-0.7779 [-4.77***]
MOM			0.1012 [1.30]	0.1612 [1.07]
R^2	0.0282	0.0666	0.2646	0.4190

PANEL A6 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\ 6}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0127 [-3.08***]	0.0011 [0.09]	-0.0150 [-3.83***]	-0.0055 [-0.47]
RMRF	0.1500 [1.60]	0.3957 [1.46]	0.2095 [2.31**]	0.5218 [1.93*]
SMB			0.2616 [2.91***]	0.7593 [2.84***]
HML			-0.1619 [-1.86*]	-0.2824 [-1.09]
MOM			0.2185 [2.73***]	0.5545 [2.32**]
R^2	0.0111	0.0081	0.1692	0.1144

2002 – 2006 PERIOD [EXCLUDING THE 'DOTCOM' YEARS]

PANEL B1 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\ 1}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0195 [-4.01***]	-0.0069 [-1.14]	-0.0214 [-4.29***]	-0.0059 [-0.94]
RMRF	0.0108 [0.10]	0.3066 [2.31**]	-0.0054 [-0.05]	0.3048 [2.09**]
SMB			0.0918 [0.61]	0.0726 [0.38]
HML			0.2201 [1.48]	-0.1512 [-0.81]
MOM			0.1203 [1.00]	-0.0700 [-0.46]
R^2	0.0001	0.0403	0.0010	0.0196

PANEL B2 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\ 2}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0203 [-4.25***]	-0.0102 [-1.27]	-0.0208 [-4.23***]	-0.0100 [-1.23]
RMRF	0.1302 [1.24]	0.5396 [3.07***]	0.0805 [0.70]	0.5634 [2.99***]
SMB			0.0077 [0.05]	0.5932 [2.43**]
HML			0.1852 [1.26]	-0.3885 [-1.61]
MOM			-0.0144 [-0.12]	0.0307 [0.16]
R^2	0.0052	0.0747	0.0002	0.1059

PANEL B3 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\,3}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0199 [-4.08***]	-0.0100 [-1.25]	-0.0196 [-3.87***]	-0.0096 [-1.18]
RMRF	0.1172 [1.10]	0.5314 [3.04***]	0.0703 [0.60]	0.5521 [2.94***]
SMB			-0.0360 [-0.24]	0.5655 [2.33**]
HML			0.1008 [0.67]	-0.3986 [-1.66]
MOM			-0.0722 [-0.59]	0.0072 [0.04]
R^2	0.0019	0.0733	0.0224	0.1021

PANEL B4 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\,4}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0192 [-3.68***]	-0.0106 [-1.32]	-0.0194 [-3.60***]	-0.0105 [-1.30]
RMRF	0.1409 [1.23]	0.5254 [2.98***]	0.0778 [0.62]	0.5353 [2.84***]
SMB			-0.0245 [-0.15]	0.5985 [2.45**]
HML			0.1938 [1.21]	-0.3466 [-1.43]
MOM			-0.0543 [-0.42]	0.0220 [0.11]
R^2	0.0049	0.0707	0.0375	0.1023

PANEL B5 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\,5}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Intercept [alpha]	-0.0165 [-4.58***]	-0.0087 [-1.18]	-0.0171 [-4.55***]	-0.0086 [-1.19]
RMRF	0.0614 [0.77]	0.5454 [3.40***]	0.0470 [0.54]	0.5915 [3.52***]
SMB			0.0180 [0.16]	0.7023 [3.23***]
HML			0.0945 [0.85]	-0.4855 [-2.25**]
MOM			0.0255 [0.28]	0.0670 [0.38]
R^2	0.0058	0.0920	0.0161	0.1618

PANEL B6 - DEPENDENT VARIABLE – $[R_{pt}^{ipo} - R_{pt}^{match\ 6}]$

	CAPITAL ASSET PRICING MODEL		FF-CAHART-4F MODEL	
	Eq. Weighted	**Val. Weighted**	**Eq. Weighted**	**Val. Weighted**
Intercept [alpha]	-0.0159 [-5.00***]	-0.0160 [-1.93*]	-0.0176 [-5.55***]	-0.0141 [-1.67*]
RMRF	0.0058 [0.08]	0.4989 [2.74***]	-0.0034 [-0.04]	0.5584 [2.85***]
SMB			0.2105 [2.21**]	0.3396 [1.34]
HML			0.1151 [1.22]	-0.5531 [-2.20**]
MOM			0.1162 [1.52]	-0.0617 [-0.30]
R^2	0.0001	0.0590	0.0591	0.0777