Corporate Finance Dynamics: Evidence from India

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This thesis is dedicated to my parents

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Abstract

The capital structure and corporate payout decisions of firms have puzzled the minds of academics for the best part of half a century. The recurring nature of such salient decisions ensue that firms' financial policies do not manifest themselves in arbitrary or random patterns, but evolve following dynamic trends that are still far from being fully understood. Accordingly, in this thesis we investigate the corporate dynamics of firms' capital structure and corporate payout policies with the purpose of providing new evidence on the existing disparities within the corporate finance literature. Specifically, the content of this thesis contributes on a number fronts as it presents one theoretical and two empirical essays on the dynamics of firms' financial policies, wherein we incorporate the uniqueness of India's emerging market context to conduct our empirical analysis.

In the first chapter of this thesis we use Monte Carlo experiments to furnish an extensive appraisal of the dynamic panel estimators commonly employed in the corporate finance literature, where a specific emphasis is placed on the impact of estimator choice on the reported speed of financial policy adjustment. The results from the chapter uncover that the least squares dummy variable corrected estimator of Kiviet (1995) and the quasi-maximum likelihood fixed-effect estimator of Hsiao et al. (2002) are the least biased and most statistically robust estimators across a range of experiments. In contrast, our experiments expose that the popular generalised method of moments estimators of Arellano and Bond (1991) and Blundell and Bond (1998) are highly sensitive to the degree of dynamic persistence, the extent of unobserved cross-sectional heterogeneity and the level of panel unbalancedness. In doing so, our first chapter underscores the seriousness of estimator choice in the analysis of financial policy dynamics. Moreover, based on our findings, the chapter puts forward the claim that the high proliferation of generalised method of moments estimators in the corporate finance literature has been partly at fault for the disparate empirical evidence concerning financial policy adjustment speeds.

In the second chapter of this thesis we analyse how Indian listed firms facing asymmetric adjustment costs transition towards their capital structure target over the course of the business cycle. Bringing together the cross-sectional and time-series elements of autoregressive heterogeneity, the chapter finds the adjustment speeds of Indian firms to be pro-cyclical, thus, supporting the notion that more prosperous macroeconomic conditions help to alleviate the market frictions associated with capital adjustment costs. Complementary to these findings, the chapter uncovers that firms with the highest earnings and greatest growth opportunities adjust significantly quicker to their capital structure target over the business cycle, while, conversely, firms with limited internal financial funds and limited growth opportunities adjust significantly slower and are more servery impacted by the capital market shocks induced by macroeconomic downturns. All things considered, the evidence presented in this chapter provides the first empirical evidence of Indian listed firms' adjustment asymmetries over the course of the business cycle.

Finally, in the third chapter of this thesis we investigate if the dividend decisions of Indian listed firms are influenced by the actions and characteristics of their industry peers. Drawing from the spatial econometric literature, the chapter presents the first empirical evidence of proximity related peer effects as we discover that the dividend decisions made by local industry peers bear the greatest economic influence on the dividend decisions made by Indian listed firms. The chapter finds that the informational content embedded within peer dividend decisions is economically more important for dividend increases and dividend decreases than any other firm or industry related characteristics. Moreover, the empirical evidence suggests that the tangible decisions of peers prove most economically meaningful in periods of heighten macroeconomic uncertainty, when the opaqueness of firms own information is likely to be most severe. Accordingly, the evidence of proximity related peer effects put forward in our final chapters presents a clear criticism of the extant literature that has predominately focused on the role of firm-specific factors on corporate payout decisions.

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List of Abbreviations

AS-GMM	Ahn and Schmidt Generalised Method of Moments
DPF	Dynamic Panel Fractional
FD-GMM	First Difference Generalised Method of Moments
FE	Fixed Effect
GMM	Generalised Method of Moments
LD	Longest Difference
LD4	Lag Difference Four
LSDVC	Least Squares Dummy Variable Correction
MDR	Market Debt Ratio
OLS	Ordinary Least Squares
QML	Quasi-Maximum Likelihood
SEBI	Securities and Exchange Board of India
SOA	Speed of Adjustment
SYS-GMM	System Generalised Method of Moments
2SLS	Two Stage Least Squares

Chapter 1

Introduction

1.1 Motivation and Background

The capital structure and corporate payout policies of firms are the most debated financial policies in the corporate finance literature. Managers must repeatedly make important decisions regarding the composition of their firm's capital structure, the amount of profit they should return to investors, and the form in which such payment, if any, should be delivered. The dynamic and reoccurring nature of such salient decisions mean that the financial policies of firms do not simply manifest themselves in arbitrary or random fashions but evolve to follow consistent and distinct dynamic patterns (Allen and Michaely 2003; Graham et al. 2015). Understanding why these patterns occur and the factors that determine them is not only important in the traditional sense, i.e. for value maximisation, but also, because both financial policies are related to, and interact with, a number of equally salient corporate decisions, such as corporate investment.

In the pursuit of corporate expansion, managers must choose how best to finance their current set of positive investment opportunities by weighing up the costs and benefits of internal and external funds. Accordingly, managers must decide the proportion of internally generated earnings that should be returned to shareholders and the remaining amount that should be reinvested back into the firm. Moreover, when the use of external funding is required, managers must analyse the trade-offs between debt and equity as they consider the optimal composition of their capital structure. Subsequently, the interdependent nature of firms' financial policies and their close proximity with long-term operations mean that the implications of such decisions not only effect a firm's future growth, but, at the aggregate level, have also consequential effects on the prosperity of a country's long-term economic performance. It is for these reasons why the capital structure and corporate payout policies of firms have received substantial attention from academics over the past 60 years as researchers have seeked to clarify the underlying mechanism that govern corporate financial policy dynamics.

Since Modigliani and Miller (1958) and Modigliani and Miller (1963) irrelevance theorems, an abundance of theoretical, anecdotal and empirical evidence has emerged in relation to both financial policies. The theoretical literature has clearly delineated - under the assumption of imperfect capital markets - that frictions such as taxation, agency costs and asymmetric information all play important roles in determining a firm's capital structure and corporate payout policy. Moreover, theoretical studies have conjectured that such market imperfections are indeed the underlying mechanisms that govern financial policy dynamics and regulate the speed in which firms adjust their capital structure and corporate payout policy (Kumar 1988; Fischer et al. 1989).

Accordingly, researchers have sought to validate these claims which has resulted in an enormous literature on the determinants of firms' financial policies and a rich literature relating to the speed and motives behind why firms adjust their capital structure and corporate payout policies. As a result, scholars have uncovered and reached consensus on a number important financial policy behaviours. For instance, it is almost unequivocally agreed that managers concern themselves with the stability of their dividend payout with markets seemingly placing a premium on stable payout policies. Subsequently, the persistence observed in firms' dividend payout is the by product of managers smoothing their dividends payments (Lintner 1956; Brav et al. 2005). Moreover, the leading consensus on capital structure advances that firms hold capital structure targets of which they adjust towards and re-balance over time (Graham and Harvey 2001; Leary and Roberts 2005). Nonetheless, more than 60 years on from the original irrelevance theorems, there are still a number of deeply contentious issues that the literature has yet to resolve.

Despite the importance of capital structure and corporate payout policy dynamics, there is still little agreement regarding both the rate in which firms adjust their corporate financial policies and which factors determine the propensity of such of transitions. More explicitly, many studies have provided conflicting evidence over the speed in which firms adjust/smooth their capital structure and dividend payout policies and there remains limited consensus on why some firms adjust their financial policies quicker than others. In addition to both these contested disputes, there exists little evidence on why many of the most salient capital structure and corporate payout decisions made by firms often coincide with the decisions of their industry counterparts. It is indeed these three ongoing and unresolved issues that this thesis has been motivated to investigate. Accordingly, this thesis has endeavored to contribute towards the vast literature on capital structure and corporate payout dynamics by using the combination of theoretical simulation-based analysis and an empirical analysis of Indian listed firms.

1.2 Importance and Institutional Context of India

In the pursuit to further the literature's understanding of capital structure and corporate payout policy, many studies in recent years have looked to analyse the corporate financial policies of firms residing in emerging markets (e.g., Öztekin and Flannery 2012 and Öztekin 2015). Emerging markets provide unique empirical environments to test the existing contests of finance theories. Prior to the last decade, the vast majority of empirical studies focused on the financial policies of firms residing in developed bank-based (e.g., Germany and Japan) and/or market-based (e.g., the UK and the US) economies. However, in such cases, the very market imperfections that bring theoretical relevance to the capital structure and corporate payout policies of firms are often trivial due to such economies having well developed capital markets, strong legal systems and high levels of information dispersion.

In contrast, emerging markets, by their very definition, only offer a proportion of such full functioning features. Emerging economies are often characterised by underdeveloped infrastructure, low levels of information dispersion, illiquid capital markets and/or weak legal systems (Khanna and Palepu, 2010). Moreover, they are often highly exposed to global macroeconomic shocks due to their strong reliance on external capital flows (Aguiar and Gopinath, 2007). Consequently, the examination of firms residing in emerging markets is not only important for domestic managers, investor and policy makers, but more broadly, for the finance literature as whole. The analysis of firms of which are exposed to more pervasive market frictions are ultimately going to provide new insights on the dynamic nature of firms and their financial decisions. These are the main reasons why this thesis has focused the content of its empirical analysis on the capital structure and corporate payout policies of Indian listed firms.

True to type, India as an emerging market has gone under drastic economic change over the past three decades. Prior the early 1990's, India's economy was characterised by high levels of corruption, low levels of information dispersion, strong trade protectionism and many sectors where dominated by inefficient state-owned enterprises (Khanna and Palepu 1997; Khanna and Palepu 2000). Moreover, strict reserve requirements on banks and high interest rates meant credit dispersion was uncharacteristically low, while equity markets where largely illiquid due to a lack of transparency and poor investor protection (Rodrik and Subramanian 2005; Mohan and Kapur

2015). In the early 1990's, India's balance of payments crisis invoked vast sectoral privatisation and numerous regulatory reforms as the government liberalised the economy in an attempted to improve private sector efficiency and flexibility. As a result, over the last two decades, successful reforms have meant India's economy has sustained stable and consistent economic growth of roughly 6-7% per annum and has risen from the tenth largest economy in terms of purchasing power parity in 1990 to the third largest economy behind China and the US (World Bank, 2018).

One of the major contributing factors to India's economic success over the last two decades has been the liberalisation and development of its financial sector. The partial reduction of regulatory capital requirements has given India's banks greater autonomy over their lending decisions resulting in substantial credit growth to households and firms. Moreover, significant improvements to the infrastructure of India's capital markets alongside the removal of restrictive listing regulations has led to the number of listed companies increasing drastically from roughly 2,500 in 1991 to more than 5,000 in 2019. Furthermore, the introduction and transition of legislative authority to the Securities and Exchange Board of India (hereafter, SEBI) from 1988 to 1992, has resulted in a number of precise and independently motivated regulatory reforms - e.g. Clause 49 - that have significantly improved the level of corporate governance in India (Dharmapala and Khanna, 2012). In fact, the comparison of security market regulation provided by La Porta et al. (2006) shows India is in the top three countries for corporate disclosure requirements marginally behind the US and Singapore and fifth in the world for liability standards. Consequently, for much of the last two decades, India's minority shareholder protection has been comparable to that of a developed bank-based or market-based economy and has been considered far ahead of many of its emerging market counterparts (World Bank, 2018).

Accordingly, the significant structural changes and economic reforms that have led to India's advanced and well developed financial system not only makes the corporate financial decisions of Indian listed firms of supreme empirical interest but also empirically auspicious. Indeed, it is the contrast and juxtaposition of India's developed financial sector yet residing issues of corruption, regional inequality and limited information dispersion that makes India's emerging market context an ideal laboratory to analyse the market imperfections that influence and govern the capital structure and corporate payout dynamics of firms.

1.3 Research Questions and Contributions

The purpose of this thesis is to bring clarity to the ongoing disputes and unanswered issues relating to the capital structure and corporate payout dynamics of firms. In particular, based on the outlined motivations for this thesis, the content of this document has devoted its attention to the following three important questions: i) Why do many researchers provide conflicting evidence on the speeds in which firms adjust their financial policies?, ii) Which factors are dominant in determining the rate in which firms adjust their financial policies? and iii) Why do some of the most salient financial decisions made by firms often coincide with the decisions of their industry counterparts? To address these questions, this thesis contributes on a number of fronts by providing both theoretical and empirical evidence.

To investigate the first research question, chapter 2 uses Monte Carlo simulations as a means to examine the economic importance of estimator choice in the context of the corporate finance literature. In particular, by placing specific emphasis on the dynamic partial adjustment model commonly used in the capital structure and corporate payout literature, chapter 2 investigates, via a range of fixed-parameter experiments, how the type of econometric estimator employed by researchers can impact the implied speed of financial policy adjustment.

To answer the second and third research questions, the thesis employs the uniqueness of India's emerging market context to provide new and robust empirical evidence on the capital structure and corporate payout dynamics of firms. Chapter 3 directly addresses the second research question as it examines the underlying mechanisms that determine a firm's capital structure adjustment process. Using the theoretical guidance from chapter 2, chapter 3 adopts the most up-to-date and accurate econometric methods to investigate how firms facing asymmetric adjustment costs transition towards their capital structure target over the course of the business cycle.

Chapter 4 addresses the final research question of this thesis by analysing why the financial decisions made by firms often coincide with the decisions of their industry counterparts. Specifically, chapter 4 investigates to what end are the dividend decisions of Indian listed firms influenced by the dividend decisions of their industry peers. Motivated by the spatial econometric literature, chapter 4 places specific focus on the importance of geographical proximity in the manifestations of peer effects. To elaborate on the contributions made by each chapter in this thesis, the summary and contributions of each essay are presented in the following sub-sections.

1.3.1 Chapter 2: An Investigation of Dynamic Panel Data Models in Empirical Corporate Finance

Chapter 2 investigates the estimation of dynamic panel data models in the empirical corporate finance literature. Since the seminal work of Lintner (1956), researchers have utilised dynamic partial adjustment models as means of evaluating the rate at which firms adjust/smooth their capital structure or corporate payout policy. However, while the stylised approach has proved immensely popular amongst academics, the resulting evidence has yielded vastly disparate economic conclusions about the rate in which firms adjust their financial policies (e.g., Fama and French 2002 and Flannery and Rangan 2006).

In the pursuit to clarify such contests, chapter 2 analyses, explicitly, the implications of estimator choice on the speed of financial policy adjustment. In detail, chapter 2 uses Monte Carlo simulations to furnish a systematic analysis of nine dynamic panel estimators commonly employed in the empirical corporate finance literature. Using multiple evaluative metrics, chapter 2 contributes to the literature by providing an account of each estimator across a range of settings experienced by researchers. In particular, the chapter examines how the degree of dynamic persistence, the panel dimensions, the level of cross-sectional heterogeneity and the severity of panel unbalancedness all impact the accuracy of dynamic panel estimators. Accordingly, chapter 2 presents a clear and comprehensive picture on how the choice of econometric method can significantly effect the estimation of the autoregressive coefficient and, in turn, the implied speed of financial policy adjustment.

The findings of chapter 2 expose a number of important results. The chapter uncovers that the degree of dynamic persistence in the dependent variable is a key driver of estimator performance, with highly persistence data inducing the most biased outcomes and the least precise estimates of the autoregressive coefficient. In addition, the chapter illustrates that the common varying characteristic's of corporate finance data sets, such as: panel dimensions, cross-sectional heterogeneity and panel unbalancedness, as well as the degree of censoring in the dependent variable, all pose unique problems for researchers employing dynamic panel data models.

Crucially, the study establishes that, on average, the least squares dummy variable correction estimator of Kiviet (1995) and the quasi-maximum likelihood fixed-effect estimator of Hsiao et al. (2002) most accurately and most consistently estimate the autoregressive coefficient in dynamic panel data models. Moreover, in special cases, when the dependent variable of interest is censored, the chapter finds the dynamic panel fractional estimator of Elsas and Florysiak

(2015) to be most proficient. In contrast, the chapter reports that the popular generalised method of moments estimators of Arellano and Bond (1991) and Blundell and Bond (1998) are highly sensitive to changes in dynamic persistence, cross-sectional heterogeneity and the level of panel unbalancedness. In each case, the generalised method of moments estimators prove to be biased and inconsistent, thus, resulting in spurious estimates of the speed of financial policy adjustment.

Accordingly, chapter 2 presents a systematic econometric review on how the choice of estimator can impact the reported speed of financial policy adjustment. In doing so, the chapter contributes to literature by showing why many studies have yielded conflicting conclusions on the speed of capital structure adjustment and the rate of dividend payout smoothing. Moreover, perhaps most importantly, the analysis conducted in chapter 2 provides guidance on the best econometric practice for future research. Such recommendations bear importance not only for the corporate finance literature, but also, for a range of disciplines concerned with the correct estimation of dynamic panel data models.

1.3.2 Chapter 3: Leverage Dynamics over the Business Cycle: Evidence from India

The first empirical investigation of this thesis evaluates how firms facing asymmetric adjustment costs transition towards their capital structure target over the course of the business cycle. Studies have shown that firm-specific and macroeconomic factors impact the rate in which firms' adjust towards their optimal capital structure, however, evidence has rarely been provided on the duality of such effects, especially in an emerging market context. Moreover, the recent theoretical (Hackbarth et al. 2006 and Bhamra et al. 2010) and empirical (Strebulaev and Yang 2013 and Halling et al. 2016) evidence on the leverage dynamics of firms over the course of the business cycle have yielded vastly disparate conclusions with academics disagreeing on the cyclical nature of corporate leverage. Accordingly, chapter 3 sets out to clarify such ambiguities by bringing together both elements of the firm-specific and macroeconomic adjustment cost literature to present a comprehensive analysis of how Indian listed firms manage their corporate leverage over the course of the business cycle.

The chapter builds on the recent work of Halling et al. (2016) by proposing a single-step model specification that allows for the simultaneous estimation of firm-specific adjustment costs over high and low macroeconomic growth regimes. Furthermore, in accordance with guidance presented in chapter 2, the chapter employs the dynamic panel fractional estimator of Elsas and

Florysiak (2015) to account for the fractional nature of corporate leverage and to provide the most precise estimates of the true speed of capital adjustment.

The chapter uncovers that macroeconomic performance plays a pivotal role in the capital structure adjustment process with the adjustment speeds of Indian listed firms proving pro-cylcial over the sample period. Accordingly, our findings support the notion that more prosperous macroeconomics conditions help to alleviate the adjustment costs induced by capital market frictions and imperfections making the adjustment costs faced by firms in high growth periods significantly less. Furthermore, the chapter reveals that firms with the highest potential growth opportunities and firms with the highest earnings adjust quicker towards their capital structure target over the course of the business cycle, yet, most proactively manage their corporate leverage in periods of economic prosperity due to lower implied adjustment costs.

All in all, chapter 3 contributes to the literature as it provides the first evidence of firm-specific adjustment asymmetries for Indian listed firms over the business cycle. In doing so, the chapter contributes to the recent debates on the cyclical nature of corporate leverage dynamics by providing complementary evidence of pro-cyclical adjustment speeds from a new emerging market context. Moreover, from a methodological perspective, the use of the most up-to-date and accurate econometric method ensures that the results presented in the chapter provide the most precise estimates of the autoregressive coefficient. Consequently, the documentation of adjustment speed heterogeneity put forward in this chapter can be considered more precise than many of the bias approaches previous employed by the literature, e.g., Fama and French (2002), Flannery and Rangan (2006), and Kayhan and Titman (2007), to name but a few.

1.3.3 Chapter 4: Dividend Decisions, Peer Effects and Geographical Proximity: Evidence from India

The corporate payout policy literature has long concerned itself with the dividend decisions made by firms. However, since Fama and French (2001) illustrated the growing behavioural trends of corporate payout policies, little insight has been provided into why the dividend payout decisions of firms often coincide with the decisions of their peers. Motivated by such observations, chapter 4 addresses the final research question of this thesis by investigating if the dividend decisions of Indian listed firms are influenced by the dividend decisions of their industry counterparts.

The econometric analysis presented in chapter 4 expands upon the contemporaneous studies of Adhikari and Agrawal (2018) and Grennan (2019) who investigate the role of peer behaviour on the corporate payout policies of US listed firms. Drawing from the the spatial econometrics literature, chapter 4 proposes a new measure of peer influence based on the geographical distance between firms' headquarters. In doing so, the study makes a sizable contribution to the literature by offering the first empirical evidence of proximity based peer effects. Supplementary to this, the chapter also adds to the growing literature on peer influence in corporate finance by presenting the first empirical analysis of corporate payout peer effects in an emerging market context.

Using an instrumental variable approach to overcome the inherent simultaneity issues of peer effect analysis, the chapter reveals that the dividend decisions made by Indian listed firms are significantly influenced by dividend decisions of their industry counterparts. More precisely, we find local industry peers bear the greatest economic influence on the dividend decisions made by Indian listed firms, an effect we attribute to imperfect information and local competition for investors and market share. The chapter shows that the informational content embedded within peer dividend decisions is economically more important for dividend increases and dividend decreases than any other firm or industry related characteristics. Moreover, the empirical evidence suggests that the tangible decisions of peers prove most economically meaningful in periods of heighten macroeconomic uncertainty, when the opaqueness of firms own information is likely to be most severe.

In the conclusion of our final chapter, we provide a number of robustness tests to illustrate the stoutness of our empirical contributions. In particular, we examine the validity of our results to randomised peer definitions, various standard error structures, potential omitted factors and extended radius measures. In doing so, we illustrate that our findings are not a product of latent common factors attributable to the choice of reference group structure nor are they driven by specific error structures, omitted variable bias or arbitrary distance measures.

1.4 Structure of the Thesis

The remainder of the thesis is organised as follows. Chapter 2 investigates the estimation of dynamic panel data models in the empirical corporate finance literature. Chapter 3 presents an analysis of the leverage dynamics of Indian listed firms over the course of the business cycle. Chapter 4 examines if the dividend decisions of Indian listed firms are influenced by the actions and/or characteristics of their industry counterparts. Finally, chapter 5 concludes the thesis, offers some policy implications and identifies areas for on going and future research.

Chapter 2

An Investigation of Dynamic Panel Data Models in Empirical Corporate Finance

Abstract: *Dynamic panel data models have become increasingly prominent in the empirical corporate finance literature. However, estimation of the lagged dependent variable in combination with the firm individual effect leads to a number of econometric issues. While several methodologies exist to overcome such complexities, there is little consensus on the appropriate method of estimation for the corporate finance setting. In this chapter, we examine this issue by analyzing a range of dynamic panel estimators via Monte Carlo experiments. Our simulations find the least squares dummy variable corrected estimator of Kiviet (1995) and the quasi-maximum likelihood fixed-effect estimator of Hsiao et al. (2002) to be the most robust estimators across a range of experiments. Comparatively, the popular generalized method of moments estimators prove to be highly sensitive to changes in dynamic persistence, cross-sectional heterogeneity and panel unbalancedness. Thus, leading us to question the reliability of previous empirical studies that employ said methods.*

2.1 Introduction

Dynamic panel data models play a natural role in the corporate finance literature as researchers seek to understand the dynamic behavior of firms and their corporate policies. Numerous studies on cash holdings (e.g., Ozkan and Ozkan 2004 and Bates et al. 2009), capital structure (e.g., Flannery and Rangan 2006 and Frank and Goyal 2009), corporate payout policy (e.g., Short et al. 2002 and Leary and Michaely 2011) and investment decisions (e.g., Bond and Meghir 1994 and Guariglia and Yang 2016) have all employed some form of dynamic panel data model.

However, the estimation of dynamic panel data models can be difficult for a number of reasons. First, datasets in the corporate finance literature typically consist of a large number of firms (N), over a small, and often infrequent, number of years (T). Subsequently, the traditional pooled ordinary least squares (hereafter, OLS) estimator is considered inadequate for such a setting, as the OLS estimator fails to account for the time-invariant differences among firms ; resulting in biased estimates of the autoregressive coefficient. Furthermore, it has long been known that due to the correlation between the lagged dependent variable and the fixed-effect component, the fixed-effect or within-transformation (hereafter, FE) estimator also produces biased estimates of the autoregressive coefficient when the panel length, T, is short (Balestra and Nerlove 1966; Nerlove 1967; Nerlove 1971; Nickell 1981).

The economic implications of cross-sectional heterogeneity and finite sample bias are of significant relevance in the capital structure and coporate payout policy literature, as often researchers look to employ dynamic partial adjustment model specifications. Here, the autoregressive coefficient is of central interest as researchers aim to evaluate the rate at which firms adjust towards their optimal corporate financial target. For example, in the capital structure literature, the seminal work of Fama and French (2002) employ the OLS estimator and report the speed of adjustment (hereafter, SOA) for US firms to be 10% per annum. Conversely, Flannery and Rangan (2006) via the FE estimator report the rate of adjustment for US firms to be considerably higher, at roughly 34%. Consequently, failing to account for such econometric complexities can often engender spurious economic conclusions.

In order to address the methodological issues associated with cross-sectional heterogeneity and finite sample bias, researchers have turned to more advanced econometric techniques. Lemmon et al. (2008) employ the system-generalized method moments (hereafter, SYS-GMM) estimator of Blundell and Bond (1998) and report the SOA for US firms to be around 25% annually. Huang and Ritter (2009) adapt the longest difference (hereafter, LD) estimator of Hahn et al. (2007) and find the rate of adjustment to range between 12%-21%. While Öztekin and Flannery (2012) use the least squares dummy variable corrected (hereafter, LSDVC) estimator of Kiviet (1995) and report the SOA for US firms to be closer to 27%. However, despite the rich array of econometric methods employed throughout the corporate finance literature, the complexities of dynamic panel data models have lead to little consensus on the true SOA.

The purpose of this chapter is to understand the implications of estimator choice in the context of the corporate finance literature. In particular, this chapter places a specific emphasis on the dynamic partial adjustment model seen in the capital structure and corporate payout policy literature in order to stress the economic implications of estimator choice. To this end, we examine the statistical properties for a range of dynamic panel estimators by conducting a series of Monte Carlo experiments. In detail, we investigate the statistical properties of nine different dynamic panel estimator, namely: the OLS estimator, the FE estimator, the first difference-GMM (hereafter, FD-GMM) estimator of Arellano and Bond (1991), the non-linear GMM estimator of Ahn and Schmidt (1995) (hereafter, AS-GMM), the SYS-GMM estimator of Blundell and Bond (1998), the lag difference four (hereafter, LD4) estimator of Huang and Ritter (2009), the LSDVC estimator of Kiviet (1995), the quasi-maximum likelihood (hereafter, QML) fixed effect estimator of Hsiao et al. (2002) and lastly, in a unique cases, we examine the dynamic panel fractional dependent variable (hereafter, DPF) estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015), which is explicitly designed for cases when the dependent variable is censored between zero and one. In doing so, this chapter not only provides an account of the problems associated with dynamic panel data models but more importantly, provides guidance on the econometric best practice for the corporate finance literature.

Previous Monte Carlo simulations, such as Arellano and Bond (1991) and Kiviet (1995), have mainly focused on small panel data designs resulting in experiments inconsistent with that of the corporate finance setting. We address this issue by focusing our panel data design more specifically on large N and short T panel dimensions. Indeed, we are not the first to venture down this avenue, with a number of recent studies, namely: Flannery and Hankins (2013), Zhou et al. (2014) and Dang et al. (2015), all examining the performance of dynamic panel estimators in the context of corporate finance. Our study strengthens this growing body of literature by making a number noteworthy contributions.

First, our study overcomes the limitations of Flannery and Hankins (2013) and Dang et al. (2015) by systematically analyzing estimator performance across multiple evaluative metrics over multiple levels of dynamic persistence. Therefore, our study provides a more thorough and complete examination of dynamic panel estimators in the corporate finance setting. Our second contribution is the coverage of two dynamic panel estimators, namely: the AS-GMM and QML estimators, that, to the best of our knowledge, have been overlooked by the literature on corporate finance based simulations. We argue that failure to acknowledge such estimators could be costly for the number reasons. First, Dang et al. (2015) reports that out of the GMM-estimators the FD-GMM estimator often estimates the autoregressive coefficient with the least amount of bias. However, the work of Ahn and Schmidt (1995) documents through asymptotic efficiency experiments that the AS-GMM estimator outperforms the FD-GMM estimator. Parallel to this argument, the work of Hsiao et al. (2002) and Phillips (2017) show the QML estimator to outperform the popular GMM-estimators, therefore, highlighting it's importance in dynamic panel analysis. Finally, we contribute to the literature by exploring multiple simulation experiments relevant to the corporate finance setting. Not only does our study validate the experiments of previous simulations, we evaluate properties of estimators in untested environments. For example, to date, only Flannery and Hankins (2013) have considered the impact of panel unbalancedness in the corporate finance setting. We expand on their contribution by examining multiple levels of unbalancedness, thus, providing a more complete and comprehensive analysis of said issue.

Our results indicate that the LSDVC and QML estimators are generally the most robust and resilient methods of estimation for dynamic panel data models in the empirical corporate finance setting. We find that these estimators estimate the autoregressive coefficient with the least amount of bias across simulations, thus, most accurately estimating the SOA. Among the two, the LSDVC estimator performs well in cases of heightened cross-sectional heterogeneity, whereas the QML estimator outperforms the LSDVC estimator in cases of short and unbalanced panels. Nonetheless, in special cases, where the dependent variable is censored between zero and one, we find the DPF estimator to be the most appropriate estimator, with the degree of estimator bias being associated with the proportion of censoring in the dependent variable.

Our simulation experiments also document that the FD-GMM and SYS-GMM estimators are highly sensitive to a range of problems associated with the corporate finance literature, with the autoregressive coefficient proving to be unreliable and unpredictable across simulations. Of note, the FD-GMM estimator performs unfavourably in short and unbalanced panels, while the performance of SYS-GMM estimator is largely hindered when the degree of cross-sectional heterogeneity is high. Our findings are consistent with Flannery and Hankins (2013), Zhou et al. (2014) and Dang et al. (2015) as we report the robustness of the LSDVC estimator. Furthermore, our addition of the QML estimator proves to be crucial for discussion on dynamic panel estimators as well as our understanding of the true SOA. Finally, the growing evidence on the frailties of the GMM estimators leaves us with concern on the accuracy of forgone empirical studies that employ said approaches. The remainder of this chapter is as follows. In Section 2.2 we provide a review of the dynamic partial adjustment model as well as a brief summary of each dynamic panel estimator. In Section 2.3 we discuss our data and experiment design and introduce the data generating process used for our simulations as well as our six proposed experiments. In Section 2.4 we report our findings from our experiments. In Section 2.5 we outline the empirical implications of our results and in Section 2.6 we conclude the chapter.

2.2 Dynamic Panel Data Models in Empirical Corporate Finance

2.2.1 Model Specification

The corporate policies set by firms typically result in a decision based on an optimal corporate target. These targets have frequently been examined by dynamic panel data models in the empirical corporate finance literature with corporate financial policies regarding capital structure and dividend payout typically employing some form of dynamic partial adjustment model (see, for example, Fama and French 2002; Flannery and Rangan 2006; Lemmon et al. 2008; Antoniou et al. 2008; Andres et al. 2009; Pindado et al. 2012; Faulkender et al. 2012). Motivated by Lintner (1956), the dynamic partial adjustment model uses the lagged dependent variable to approximate the firms movement from their current corporate position to their corporate target. The traditional partial adjustment model is specified as follows:

$$y_{i,t} - y_{i,t-1} = \theta(y^*_{i,t} - y_{i,t-1}) + \eta_i + \upsilon_{i,t} \tag{2.1}$$

where $y_{i,t}$ and $y^*_{i,t}$ denote the actual (observed) and optimal (unobserved) corporate policies of firm i at time t, η_i is the time-invariant individual (firm) effect and $\upsilon_{i,t}$ is the idiosyncratic error term. In the dynamic model, (2.1), the optimal corporate policy can be considered a tightening or a loosening of the previous corporate policy, therefore, the firm's current position can be considered either above or below the optimal target. Accordingly in (2.1), firms' attempt to adjust towards their optimal corporate policy due to the benefits associated with being located at the target level. The SOA (θ) reflects the rate of adjustment (per time period) and is arguably bound between 0 and 1. An estimate of $\theta = 0$ reflects no SOA and thus no adjustment towards an optimal corporate policy. Alternatively, an estimate of $\theta = 1$ implies an immediate adjustment from the firm's current position to the optimal corporate policy.

The empirical obstacle of equation (2.1) is that the optimal corporate policy - for example, the optimal amount of debt or dividend payout - is not directly observed. However, it can be argued that the optimal corporate policy is deterministic on a set of firm-specific characteristics ($X_{i,t}$). One can therefore define the relationship as follows:

$$y^*_{i,t} = \Omega' X_{i,t} \tag{2.2}$$

given equation (2.2), a two-stage approach is arguably the most intuitive method for estimating the dynamic panel model in equation (2.1). However, such two-stage approaches are often susceptible to the generated regressor problem, resulting in invalid inference in the second-stage (Pagan, 1984)[1]. As a result, a number of studies adopt a one-stage approach[2], which involves substituting equation (2.2) into equation (2.1) and thus takes the following form:

$$y_{i,t} = (1-\theta)y_{i,t-1} + \theta\Omega' X_{i,t} + \eta_i + \upsilon_{i,t} \tag{2.3}$$

defining $\lambda = 1 - \theta$ and $\beta = \theta\Omega$, we obtain the following:

$$y_{i,t} = \lambda y_{i,t-1} + \beta' X_{i,t} + \eta_i + \upsilon_{i,t} \tag{2.4}$$

Finally, equation (2.4) can be considered the baseline specification used to investigate the corporate policy decisions made by firms. The above dynamic partial adjustment model allows for the joint single-stage estimation of the SOA: $\hat{\theta} = 1 - \hat{\lambda}$ and the long run parameter coefficients for target policy determinants: $\hat{\Omega} = \hat{\beta}/1 - \hat{\lambda}$. The majority of empirical studies focus on estimating the SOA as researchers aim to investigate the frictions associated with the adjustment process. For example, in the capital structure literature, the recent work of Öztekin and Flannery (2012) documents the importance of institutional factors in determining the SOA. They find that firms with often high adjustment speeds are located in countries with low levels of information asymmetry, with anglosphere countries generally adjusting the quickest. In addition, Cook and Tang (2010), Dang et al. (2014) and Drobetz et al. (2015) all report the positive association between the rate of adjustment and the business cycle. With regards to the dividend literature and firm-specific characteristics, Aivazian et al. (2006) show that firms with public debt ratings smooth their dividends more and adjust their dividends more slowly to increased earnings. Similarly, Leary and Michaely (2011) find that older, larger firms, and firms with less volatile earnings report slower speeds of adjustment. Finally, Michaely and Roberts (2011) show that public firms smooth dividends significantly more than their private listed counterparts.

However, despite such inferences, the type of econometric method used to estimate the partial adjustment model can potentially result in biased and inconsistent estimates of autoregressive coefficient, λ, which in turn translates into spurious and misleading adjustment speeds. Therefore, in order to ensure that the above inferences are valid, and not driven by the choice of estimator, one must first be confident that the estimator of choice is able to adequately estimate the true SOA. Thus, it is here where this chapter makes its most important contribution as we evaluate the economic implications of estimator choice in the context of the corporate finance setting.

[1] In short, two-stage approaches fail to account for suitable standard error adjustment in the second-stage, often resulting in invalid inference and over-rejection of the null hypothesis. For further reading see Kripfganz and Schwarz (2019) on second-stage standard-error correction.

[2] See, for example, Flannery and Rangan (2006), Antoniou et al. (2008) and Dang et al. (2012).

2.2.2 Dynamic Panel Estimators

2.2.2.1 Traditional Estimators

A number of econometric methods have been used by researchers to estimate the dynamic partial adjustment model in equation (2.4). Two traditional approaches that have been implemented in the corporate finance literature are the OLS and FE estimators. Nonetheless, it is well recognized that both the OLS and FE estimators can yield biased and inconsistent estimates of the autoregressive coefficient (Wooldridge, 2010) and as a consequence, can result in inaccurate conclusions about the true SOA. Starting with former, the OLS estimator fails to account for the time-invariant individual (firm) effect, η_i. Baltagi (2008) states that since $y_{i,t}$ is deterministic on η_i in (2.4), it follows that $y_{i,t-1}$ is also a function of η_i. Therefore, in the event that η_i is in fact different from zero, the assumptions of the OLS estimator are violated as $y_{i,t-1}$ is correlated with η_i, i.e. $E[y_{i,t-1}\eta_i] \neq 0$. This violation results in the OLS estimator producing upwardly biased and therefore inconsistent estimates of λ, and thus, the underestimation of the SOA.

In an attempt to mitigate this issue, other empirical studies have turned to the FE estimator which accounts for η_i by using the following data transformation:

$$y_{i,t} - \bar{y}_i = \lambda(y_{i,t-1} - \bar{y}_{i,-1}) + \beta(X_{i,t} - \bar{X}_i) + (\eta_i - \bar{\eta}_i) + (\upsilon_{i,t} - \bar{\upsilon}_i) \tag{2.5}$$

which can be re-written as:

$$\tilde{y}_{i,t} = \lambda\tilde{y}_{i,t-1} + \beta\tilde{X}_{i,t} + \tilde{\upsilon}_{i,t} \tag{2.6}$$

The demeaning process of equation (2.5) transforms the data allowing for the removal of η_i, as seen in equation (2.6). However, despite the data transformation, the FE approach can still yield biased estimates of the coefficient λ. Nickell (1981) illustrates that the data transformation introduces a correlation between $\tilde{y}_{i,t-1}$ and $\tilde{\upsilon}_i$, as by its very definition, $\bar{\upsilon}_i$ contains elements of $\upsilon_{i,t-1}$ which is correlated to $y_{i,t-1}$. In addition to this, $\upsilon_{i,t}$ is also correlated with $\bar{y}_{i,-1}$ as the latter also contains elements of $y_{i,t}$. Nickell (1981) documents that both sources of correlation are bias of order $1/T$. Therefore, when T is small and fixed and N is large the FE estimator produces downwardly biased estimates of the coefficient λ, thus, the overestimation of the SOA. Whereas, when $T \to \infty$, the proportions of $\upsilon_{i,t-1}$ and $y_{i,t}$ are small relative to their respective averages and therefore the bias associated with the FE estimator is negligible.

Consequently, while the FE estimator may be suitable for fields with large T panel dimensions, topics investigated in the empirical finance literature are typically hindered by short panels. For example, in the context of the capital structure literature, Flannery and Hankins (2013) show that Compustat North America, arguably the richest dataset of its kind, has a median annual panel length of 11 years ($T = 11$). However, Judson and Owen (1999) show that the FE estimator can still be severely biased when $T = 30$. Furthermore, it is consistent to suggest, that databases with coverage of emerging markets (in our case India) may have shorter and less rich samples. In fact, in Chapter 3 and Chapter 4, our two samples of panel data consists of an average panel length of 11 and 8 years, respectively. It is for these reasons that researchers within the empirical corporate finance literature have considered more advanced methods of estimation in order to obtain unbiased estimates of the true SOA.

2.2.2.2 Generalized Method of Moments Estimators

In order to ameliorate the finite-sample bias associated with the FE estimator, many authors have adopted more advanced econometric methods such as GMM estimators, namely that of the FD-GMM estimator of Arellano and Bond (1991) and the SYS-GMM estimator of Blundell and Bond (1998). A good starting point for this discussion is the instrumental variable estimator of Anderson and Hsiao (1981) which removes η_i by taking the first-difference of (2.4):

$$y_{i,t} - y_{i,t-1} = \lambda(y_{i,t-1} - y_{i,t-2}) + \beta(X_{i,t} - X_{i,t-1}) + (\eta_i - \eta_i) + (\upsilon_{i,t} - \upsilon_{i,t-1}) \tag{2.7}$$

defining the difference operator as $\Delta = (1 - L)$ where L is the lag operator, equation (2.7) can be simply written as:

$$\Delta y_{i,t} = \Delta y_{i,t-1} + \beta \Delta X_{i,t} + \Delta \upsilon_{i,t} \tag{2.8}$$

This first-difference transformation eliminates η_i similar to that of the FE estimator. However, estimation of (2.8) can still yield biased and inconsistent estimates due to the correlation between $\Delta y_{i,t-1}$ and $\Delta \upsilon_{i,t}$, as $y_{i,t-1}$ is clearly a function of $\upsilon_{i,t-1}$. In order to remove this correlation, Anderson and Hsiao (1981) propose an instrumental variable approach where they suggest two possible instruments for $\Delta y_{i,t-1}$: the level instrument $y_{i,t-2}$ or the lagged difference $\Delta y_{i,t-2}$, where the former is considered superior as it induces smaller variance and requires one less observation (Arellano, 1989). However, despite the proposed solution, this just-identified equation lacks efficiency due to its restrictive specification[3].

To address this problem, the FD-GMM estimator exploits a larger number of instruments available within the data. Arellano and Bond (1991) stipulate that additional instruments can

[3]Note: We do not examine the performance of the Anderson and Hsiao (1981) estimator in our experiments as it can be considered a restricted instrument model. See Wintoki et al. (2012) for Monte Carlo experiments regarding restricted instruments.

be employed if one takes advantage of the moment conditions that exist between $y_{i,t}$ and $\upsilon_{i,t}$. To illustrate, we consider (2.8), where $t = 3$:

$$\Delta y_{i,3} = \Delta y_{i,2} + \beta \Delta X_{i3} + \Delta \upsilon_{i3} \tag{2.9}$$

from here the available valid instrument is $y_{i,1}$ since it is correlated with $\Delta y_{i,2}$ and not correlated with $\Delta \upsilon_{i3}$. Continuing in this fashion, when $t = 4$ we have:

$$\Delta y_{i,4} = \Delta y_{i,3} + \beta \Delta X_{i4} + \Delta \upsilon_{i4} \tag{2.10}$$

here, the available valid instruments consist of $y_{i,2}$ and $y_{i,1}$ for $\Delta y_{i,3}$ as both level instruments are correlated with $\Delta y_{i,3}$ and remain uncorrelated with $\Delta \upsilon_{i4}$. Following this process it is clear that when $t = T$ the set of valid GMM instruments are $(y_{i,1}, y_{i,2}, ..., y_{i,T-2})$ for $\Delta y_{i,t-1}$ and thus by utilizing the moment conditions, $E[y_{i,t-k} \Delta \upsilon_{i,t}] = 0$, where $t = 3, ..., T$ and $k = 2, ..., t-1$, the total number of instruments available can be defined as $T(T-1)/2$, where the GMM-style instrument matrix, Z_i, is defined follows:

$$Z_i = \begin{pmatrix} y_{i,1} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i,1} & y_{i,2} & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & y_{i,1} & \dots & y_{i,T-2} \end{pmatrix} \tag{2.11}$$

Arellano and Bond (1991) show that by incorporating a larger number of instruments the FD-GMM estimator can produce unbias and consistent estimates of λ and more importantly, accurate estimates of the true SOA. Note however that the FD-GMM estimator has been found to perform poorly in finite samples when the level instruments are only weakly correlated with that of the first differences. This is often the case when i) λ is highly persistent and/or ii) the variance of η_i is large relative to the variance $\upsilon_{i,t}$ (Blundell and Bond, 1998). For example, when λ is highly persistent, the differenced variables experience a sizable loss of variation which results in the GMM-style instruments having limited explanatory power, often referred to as the weak instrument problem.

To get around these issues two alternative GMM-estimators have been proposed, the AS-GMM estimator of Ahn and Schmidt (1995) which uses additional non-linear moment conditions and the more popular SYS-GMM estimator of Blundell and Bond (1998). Starting with the former, Ahn and Schmidt (1995) suggest that there are $T-2$ additional moment conditions that are ignored by the FD-GMM estimator. Under the assumptions that $\upsilon_{i,t}$ is homoskedastic and uncorrelated with η_i and $y_{i,1}$ the additional moment conditions hold: $E[\upsilon_{i,T} \Delta \upsilon_{i,t}] = 0$

where $t = 3, ..., T-1$. These additional moment conditions can be combined with the moment conditions of the FD-GMM estimator by adding further columns to the instrument matrix Z_i, with the total amount valid instruments now defined as $T(T-1)/2 + (T-2)$. Ahn and Schmidt (1995) asymptotic efficiency experiments confirm that the non-linear moment conditions increase performance when λ is highly persistent and/or the variance of η_i is large relative to $\upsilon_{i,t}$. Despite the merits of the FD-GMM and AS-GMM-estimators, the first-differencing approach is not without its econometric shortcomings. As highlighted by Griliches and Hausman (1986), the differencing approach may exacerbate the impact of measurement errors on the dependent variable. Furthermore, given the model of interest is conceptually in levels, differencing may reduce the variation of explanatory variables as well as the statistical power of tests (Levine et al., 2000).

To improve on the proprieties of the above GMM-estimators Blundell and Bond (1998) propose the SYS-GMM estimator that introduces another set of moment conditions, however, this time by utilizing the moment conditions associated with the level equation (2.4). Instead of removing η_i by first differencing, they consider using instruments in first-differences which are clearly orthogonal to η_i. Therefore, by considering the following moment conditions, $E[\Delta y_{i,t-k} \upsilon_{i,t}] = 0$, where $t = 3, ..., T$ and $k = 1, ..., t-2$, the set of valid instruments for t=T are $(\Delta y_{i,2}, ..., \Delta y_{i,t-1})$ for $y_{i,t-1}$. Thus, by utilizing a system of first-differenced, (2.8), and level, (2.4), equations Blundell and Bond (1998) report that the SYS-GMM estimator can largely improve on the FD-GMM estimator when the λ is highly persistent and in asymptotic variance comparisons they find that the SYS-GMM is considerably more efficient than the AS-GMM estimator. Nonetheless, Bun and Windmeijer (2010) document that the SYS-GMM estimator can still be affected by the weak instrument problem when autoregressive coefficient is highly persistent. Furthermore, when the number of instruments exceeds the size of the sample, such proliferation can result in reductions in consistency and efficiency (Roodman, 2009). It is because of such shortcomings that a small number recent empirical studies have employed a range of alternative estimators in order to estimate the true SOA.

2.2.2.3 Alternative Estimators

A number of alternative estimators have been tested in the context of corporate finance via Monte Carlo experiments and empirical applications. To accompany the previously discussed estimators, in this chapter we test the performance of four additional estimators, namely: the fourth-period difference estimator (LD4) of Huang and Ritter (2009) that was adapted from the LD estimator of Hahn et al. (2007) for unbalanced panels. The LSDVC estimator of Kiviet

(1995) which was similarly adapted for unbalanced panels by Bruno (2005), the QML estimator of Hsiao et al. (2002) and finally in special cases, where the dependent variable is fractional, we examine the DPF estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015).

To illustrate the LD4 estimator we start with the LD estimator of Hahn et al. (2007). They propose an IV-style approach that is argued to be favourable when λ is highly persistent and also suitable for cases of second-order serial correlation. In the fashion of Anderson and Hsiao (1981), the LD-estimator uses differencing to remove the time-invariant individual (firm) effect η_i, however, unlike equation (2.8) which employs first differencing, Hahn et al. (2007) propose using the longest possible difference available, therefore when $t = 30$ we have:

$$y_{i,30} - y_{i,2} = \lambda(y_{i,t-29} - y_{i,1}) + \beta(X_{i,30} - X_{i,2}) + (\eta_i - \eta_i) + (\upsilon_{i,30} - \upsilon_{i,2}) \tag{2.12}$$

from here it is evident that $y_{i,1}$ is correlated with $(y_{i,29} - y_{i,1})$ however remains uncorrelated with $(\upsilon_{i,30} - \upsilon_{i,2})$. Furthermore, drawing from Ahn and Schmidt (1995), Hahn et al. (2007) propose that the residuals from equation (2.12) can also be used as instruments. Based on two stage least squares, the LD estimator first estimates equation (2.12) using only $y_{i,1}$ as an instrument. Thereafter, one predicts the residual and uses both $y_{i,1}$ and the residual as instruments, this process is then repeated where finally the estimates of the third iteration are reported. Whilst the simulations of Hahn et al. (2007) show the LD estimator to be unbias when λ is highly persistent, the long difference approach is not suitable for the short nature of unbalanced panels commonly encountered in empirical corporate finance.

To address this obstacle, Huang and Ritter (2009) in the capital structure literature propose adapting the LD estimator by using equal differencing intervals for all firms:

$$y_{i,t} - y_{i,t-k} = \lambda(y_{i,t-1} - y_{i,t-k-1}) + \beta(X_{i,t} - X_{i,t-k}) + (\eta_i - \eta_i) + (\upsilon_{i,t} - \upsilon_{i,t-k}) \tag{2.13}$$

they experiment with four different differencing intervals, $K = 4, 8, 18$ and 28, however their study shows that the SOA varies considerably across estimates, from 11.5% to 21.1%. They associate this sensitivity to the differencing length set and the panel length requirements this imposes on the dataset. For example, their full sample consists of an unbalanced panel of 111,413 observations. However, for $K = 4$ the estimation procedures uses $61,145$ observations whereas for $K = 28$ only $2,099$ observations are available. Therefore, due to this limitation we shall only consider the LD4 estimator seen in similar Monte Carlo experiments of Flannery and Hankins (2013), Dang et al. (2015) and Zhou et al. (2014), where $K = 4$.

The estimators discussed thus far have primarily focused on using instruments in order to alleviate the correlation between the transformed lagged dependent variable and the transformed error term. However, the LSDVC estimator of Kiviet (1995) proposes a data-dependent correction of the fixed-effect bias. The LSDVC estimator has further been extended Bun and Kiviet (2003) and Bruno (2005) in order to allow for heteroskedasticity and unbalanced panels. In practice, the LDSVC estimator first estimates the biased coefficients of the least squares dummy variable estimator and thereafter subtracts the approximated bias correction. In order to estimate the degree of bias, information on the unknown population parameters λ and σ_v^2 from equation (2.4) are required. Thus, to approximate the population parameters and make the correction feasible, estimates from consistent estimators are proposed, with the FD- and SYS-GMM estimators being natural choices (Bruno, 2005)[4]. Despite the previous simulations of Kiviet (1995), Judson and Owen (1999), Bruno (2005), Flannery and Hankins (2013), Zhou et al. (2014) and Dang et al. (2015) all documenting the favourable properties of the LSDVC estimator, to date, only a few empirical studies have employed the methodology empirically, namely: Öztekin and Flannery (2012), Wintoki et al. (2012) and Dang et al. (2015).

While the LSDVC estimator first estimates the biased parameters and thereafter provides an approximated correction, the QML estimator of Hsiao et al. (2002) is designed to avoid such bias in the first place. To recapitulate, the two main econometric issues in fixed-effects dynamic panel data models - given the time-series panel dimension, T, is fixed - are i) the introduction of the time-invariant individual (firm) effect which increases with the number of cross-sectional units often referred to as the incidental parameter problem and ii) the initial value problem, whereby the initial observation is correlated with the time-invariant (firm) individual effect, however, the initial observation of each cross-section is rarely observed. As outlined by Anderson and Hsiao (1981), both the incidental parameter problem and the initial value problem result in the violation of the standard regularity conditions of the maximum likelihood estimator, thus resulting the in inconsistent estimates. To circumvent this bias, Hsiao et al. (2002) propose a transformed likelihood function which maximises a system of two equations based on one first differenced equation and one projection equation used to obtain the initial values[5]. More specifically, starting from first difference equation of (2.8), Hsiao et al. (2002) show that the correlation between the initial first difference and the residual can be dealt with by estimating the joint distribution of

[4]Note: In our forthcoming simulations we use the SYS-GMM estimator for parameter identification.

[5]Note: In spirit, the QML estimator of Hsiao et al. (2002) can be considered as a form of limited-information maximum likelihood estimator that is a special case of a full information maximum-likelihood approach with many cross-equation restrictions.

$\Delta y_i = (\Delta y_{i,1}, \Delta y_{i,2}, ..., \Delta y_{i,T})$ conditional on the regressors, x_{it}. Subsequently, in order to obtain a representation of the initial observation, Hsiao et al. (2002) suggest the projection of $\Delta y_{i,1}$ by using all leading differences of all x_{it}'s as shown below:

$$\Delta y_{i,1} = \alpha + \sum_{s=1}^{T} \Delta x_{i,s} \pi_s + \xi_1 \tag{2.14}$$

given the proposed transformed likelihood function, the system of equations formed by equation (2.8) for the time periods $t \geq 2$ and equation (2.14) for $t = 1$ can be maximised. As illustrated by Hsiao et al. (2002) in the comparison to the GMM style estimators, the QML estimator does not struggle with the weak instrument problem often leading to biased estimates in the GMM style estimators and also includes additional information in the form of equation (2.14) leading to sizeable efficiency gains. Nevertheless, despite its suitability to the corporate finance setting and the rapidly growing theoretical literature in this area in recent years - e.g. Kruiniger (2013), Hayakawa and Pesaran (2015), Phillips (2015), Kripfganz (2016) and Phillips (2017) - there has been relatively little empirical application in comparison to the GMM style estimators (Hayakawa and Pesaran, 2015)

Our final estimator for discussion is the DPF estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015) which is designed specifically for dynamic panel data models with a fractional dependent variable. In the corporate finance literature, the dependent variable of interest is often fractional and therefore bound between $[0, 1]$. In such cases, the aforementioned econometric estimators are often inappropriate due to the distributional assumptions imposed the dependent variable. Thus, failing to account for the fractional nature of the dependent variable may result in biased estimates of the autoregressive coefficient (Loudermilk, 2007). The DPF estimator builds on the doubly-censored Tobit estimator of Loudermilk (2007), which not only takes the fractional and lagged dependent variable into account but also the time-invariant individual (firm) effect. Thus, in order to estimate equation (2.4), the DPF estimator defines the dependent variable as latent ($y^{\#}_{i,t}$) with two possible corner solutions, as shown below:

$$y_{i,t} = \begin{cases} 0 & \text{if } y^{\#}_{i,t} \leq 0, \\ y^{\#}_{i,t} & \text{if } 0 < y^{\#}_{i,t} < 1, \\ 1 & \text{if } y^{\#}_{i,t} \geq 1. \end{cases} \tag{2.15}$$

Given the fractional nature of the dependent variable and the so called incidental parameters problem, it is not possible to remove the time-invariant individual (firm) effect from the explanatory variables coefficients (Baltagi, 2008). Thus, Elsas and Florysiak (2011) and Elsas and

Florysiak (2015) propose modelling explicitly the conditional distribution for the time-invariant individual (firm) effect, whereby η_i depends on the mean of the regressors and the initial observation of the dependent variable, as shown below:

$$\eta_i = \psi_0 + \psi_1 y_{i0} + \psi_2 \bar{X}_i + \epsilon_i \tag{2.16}$$

where ϵ_i is the error term and y_{i0} is initial observation of the dependent variable used to deal with the initial condition problem in nonlinear dynamic panel estimators (Wooldridge, 2005). Furthermore, unlike the estimator of Loudermilk (2007), that includes all observations of X_{it} in the fixed effect specification, the DPF estimator encompasses Mundlak (1978) style devices, $\bar{X}_i$, which are simply defined as $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$. This approach not only allows for correlation between the regressors and the fixed-effects component but is also robust to unbalanced panels. In sum, the DPF estimator can be considered the combination of a type one, doubly censored Tobit model and the correlated random-effects estimator, with the inclusion of two additional regressors, y_{i0} and $\bar{X}_i$. The simulations performed by Elsas and Florysiak (2011), Elsas and Florysiak (2015) and Dang et al. (2015) all show the DPF estimator to be preferable when the dependent variable of interest is fractional.

2.3 Data Generation and Experiment Design

2.3.1 Data Generating Process

In this section we introduce the parameter definitions and the data generating process (hereafter, DGP) used for our Monte Carlo experiments. First let us consider the following dynamic data panel model:

$$y_{i,t} = \lambda y_{i,t-1} + \beta x_{i,t} + \eta_i + \nu_{i,t} \tag{2.17}$$

$$x_{i,t} = \rho x_{i,t-1} + \xi_{i,t} \tag{2.18}$$

$$\nu_{i,t} \sim N(0, \sigma_\nu^2) \tag{2.19}$$

$$\xi_{i,t} \sim N(0, \sigma_\xi^2) \tag{2.20}$$

Starting with main parameter of interest, λ, the degree of persistence in the dynamic parameter has been found to differ across countries, stages of the business cycles, firms and the type corporate policy. Furthermore, previous simulations by the likes of Arellano and Bond (1991) and Kiviet (1995) have all reported varying levels of bias associated with different levels of persistence. Subsequently, in our experiments we consider three different values of λ in order to encapsulate different degrees of dynamic persistence. Following Arellano and Bond (1991) we set $\lambda = 0.2$ (low persistence), $\lambda = 0.5$ (moderate persistence) and $\lambda = 0.8$ (high persistence). We set β=1-λ which means that changes to λ only effect the relationship between x and y in the short run and the long run relationship is kept at unity ($\frac{\beta}{1-\lambda}$). Kiviet (1995) and Bruno (2005) generate the time-invariant component in equation (2.17) by assuming $\eta_i \sim N(0, \sigma_\eta^2)$ and $\sigma_\eta = \mu(1-\lambda)\sigma_\nu$ and therefore $E[x_{i,t}\eta_i] = 0$. However, such a setting is unrealistic of firm corporate data as η_i is likely to be correlated with explanatory variables. Therefore, we follow Dang et al. (2015) and Elsas and Florysiak (2015) and set η_i to be correlated with the explanatory variable, $x_{i,t}$, as this is more fitting for data of interest and our empirical analysis in later chapters. We define $\eta_i = \mu(1-\lambda)\sigma_\nu z_i$, where $z_i = (\bar{x_i} - \bar{x}) + 1$ and $\bar{x_i}$ and $\bar{x}$ are the within and overall means, respectively. Finally, we set $\sigma_\nu^2 = 1$ and in equation (2.18) we set $\rho = 0.5$ across all simulations.

Regarding the DGP, the traditional approach implemented by the likes of Arellano and Bond (1991) and more recently Flannery and Hankins (2013) and Zhou et al. (2014), utilize the autoregressive nature of equation (2.17) and equation (2.18), whereby one determines the panel time dimension as $\mathrm{T}=\mathrm{T}_0+\mathrm{T}_1$, where T_0 is the desired panel length and T_1 is the initial generating process[6]. Given the initial process length, one assigns arbitrary values to both $y_{i,0}$ and $x_{i,0}$ (often zero) and thereafter discards all T_1 observations once the DGP is complete. However, this DGP requires the waste of a large set of random numbers determined by the dimensions N and T_1, as well as being prone to the slow convergence problem (Kiviet, 1995).

For our DGP, we follow the more efficient procedure designed by McLeod and Hipel (1978) for time series simulations and adopted by Kiviet (1995), Bun and Kiviet (2003), Bruno (2005) and Dang et al. (2015) for the panel data setting. Formally following Kiviet (1995), we set L as the lag operator for equation (2.17) and define:

$$y_{i,t} = \lambda L y_{i,t} + \beta x_{i,t} + \eta_i + \nu_{i,t} \tag{2.21}$$

factorizing and rearranging we have:

$$y_{i,t} = \frac{\beta}{(1-\lambda L)} x_{i,t} + \frac{\eta_i}{(1-\lambda L)} + \frac{\nu_{i,t}}{(1-\lambda L)} \tag{2.22}$$

following the same process for $x_{i,t}$ we can define $y_{i,t}$ as the combination of an AR(2) and AR(1) processes:

$$y_{i,t} = \frac{\beta}{(1-\lambda L)(1-\rho L)} \xi_{i,t} + \frac{\eta_i + \nu_{i,t}}{(1-\lambda L)} = \beta \varphi_{i,t} + \psi_{i,t} + \frac{\eta_i}{(1-\lambda L)} \tag{2.23}$$

[6]Where T_1 is set $T_1 = 10$ in Flannery and Hankins (2013) and Zhou et al. (2014).

where $\varphi_{i,t} = (\rho + \lambda)\varphi_{i,t-1} - \rho\lambda\varphi_{i,t-2} + \xi_{i,t}$ and $\psi_{i,t} = \lambda\psi_{i,t-1} + \nu_{i,t}$. We can obtain the initial start values for the AR(1) process by drawing from the randomly generated $\xi_{i,t}$ and $\nu_{i,t}$:

$$x_{i,0} = \xi_{i,0}(1 - \rho^2)^{-1/2} \tag{2.24}$$

$$\psi_{i,0} = \nu_{i,0}(1 - \lambda^2)^{-1/2} \tag{2.25}$$

and finally we obtain the initial values of the AR(2) process as:

$$\varphi_{i,0} = \xi_{i,0} var(\varphi_{i,t})^{1/2} \tag{2.26}$$

$$\varphi_{i,1} = \varphi_{i,0} corr(\varphi_{i,t}, \varphi_{i,t-1}) + \xi_{i,1} var(\varphi_{i,t})^{1/2} + \{1 - corr[(\varphi_{i,t}, \varphi_{i,t-1})^2]\}^{1/2} \tag{2.27}$$

where the var($\varphi_{i,t}$), corr($\varphi_{i,t}, \varphi_{i,t-1}$) and corr($\varphi_{i,t}, \varphi_{i,t-2}$) are defined as:

$$var(\varphi_{i,t}) = \sigma_\xi^2[1 - (\lambda + \rho)corr(\varphi_{i,t}, \varphi_{i,t-1}) + \lambda\rho corr(\varphi_{i,t}, \varphi_{i,t-2})]^{-1} \tag{2.28}$$

$$corr(\varphi_{i,t}, \varphi_{i,t-1}) = \frac{\lambda + \rho}{1 + \lambda\rho} \tag{2.29}$$

$$corr(\varphi_{i,t}, \varphi_{i,t-2}) = \frac{(\lambda + \rho)^2}{1 + \lambda\rho} - \lambda\rho \tag{2.30}$$

As we can see, this DGP avoids both the waste of random numbers and the slow convergence problem as the initial values for the AR(1) and AR(2) processes are generated via a combination of random numbers ($\xi_{i,0}$ and $\nu_{i,0}$) and defined parameter values (namely, λ and ρ)[7]. To maintain the rigor of Kiviet (1995), Bun and Kiviet (2003), Bruno (2005) and Dang et al. (2015), we control for two specific elements, namely the factor loading of the time-invariant individual (firm) effect, η_i, denoted as μ, and the signal-to-noise ratio, we denote as ζ.

The loading factor measure reflects the impact of η_i on the dependent variable, $y_{i,t}$, with respect to the error competent, $\nu_{i,t}$. By rearranging the individual effect we can define $\mu = ((1 - \lambda)^{-1}\sigma_\eta)/\sigma_\nu$ and therefore when the size of the individual effect, $(1 - \lambda)^{-1}\sigma_\eta$, is equal to that of the error, σ_ν, the loading factor equals unity. However, when the size/impact of the individual effect is bigger than that of the error, the loading factor increases and causes greater bias in the estimator performance (Kiviet 1995 and Dang et al. 2015). The signal-to-noise ratio measures the variance ratio of the explanatory regressors with respect to the error term. Defining the latent variable, $z_{i,t} \equiv \beta\varphi_{i,t} + \psi_{i,t} = y_{i,t} + \eta_i/(1 - \lambda)$ one can define the signal-to-noise ratio as $\zeta = \sigma_s^2/\sigma_v^2$ where σ_s^2 is variance of the signal $s_{i,t} = z_{i,t} - \nu_{i,t}$. From this, previous studies of Kiviet (1995), Bruno (2005) and Dang et al. (2015) have found the level of the signal noise to impact the level of parameter bias in the autoregressive coefficient, yet, the outcome of which is often mixed.

[7] For further discussion see Kiviet (1995).

2.3.2 Experiment Design

In order to investigate the performance of dynamic panel estimators we propose six different simulation experiments. First, however, we simulate our benchmark simulation where the controlling parameters are set to match that of a typical dataset found in the empirical corporate finance literature. Therefore, we set the panel dimensions to $N = 500$ and $T = 12$ to represent Compustat North America. Furthermore, we consider three values of λ: $\lambda = 0.2, 0.5, 0.8$ and set $\beta = 1 - \lambda$, $\rho = 0.5$, $\mu = 1$ and $\zeta = 5$ with a repetition rate of $R = 500$[8].

For our first two experiments, we test i) the impact of changes in time series length (T) and ii) the impact of changes in cross-section size (N), as the asymptotic bias of dynamic panel estimators depends on the relative rates of both T and N dimensions (Alvarez and Arellano, 2003). Thus, for experiment one we test two different values of T: $T = 6$ and $T = 18$. For experiment two we test two different values of N: $N = 100$ and $N = 250$. For our next set of experiments we evaluate i) the impact the time-invariant individual (firm) effect and ii) the impact of changes in the signal-to-noise ratio (ζ). With previous studies such as Kiviet (1995) and Dang et al. (2015) finding that dynamic panel bias increases with increased values of μ and mixed outcomes when values of ζ are high. Therefore in experiment three we test two variations of η_i: i) when there is zero correlation between $x_{i,t}$ and η_i and ii) when $\mu = 3$ to evaluate the impact of increased cross-sectional heterogeneity. For experiment four we test two different values of ζ: $\zeta = 2$ and $\zeta = 8$, similar to Kiviet (1995).

In our final two experiments, we test both i) the impact of panel unbalancedness and ii) the impact of different levels of censored data. Elsas and Florysiak (2015) argue that estimating dynamic panel data models within empirical corporate finance is challenging as i) corporate panel data on companies is typically unbalanced and ii) many variables of interest are in fact censored between [0,1][9]. Thus, for experiment five we test three levels of panel unbalancedness (ω): $\omega = 50\%$ (high unbalancedness), $\omega = 70\%$ (moderate unbalancedness) and $\omega = 90\%$ (low unbalancedness). Finally, for experiment six we test the degree of censoring, (C), in the dependent variable, where we choose three levels of censoring: $C \approx 30\%$, $C \approx 20\%$ and $C \approx 10\%$.

In order to assess the relative performance of each estimator Flannery and Hankins (2013) propose the root mean squared error. However, as pointed out by Dang et al. (2015), focusing

[8]Other studies such as Dang et al. (2015) set $R = 1000$, however, due to the computational demands of the LSDVC estimator we set the $R = 500$, consistent with that of Flannery and Hankins (2013) and Zhou et al. (2014).

[9]For example, debt-to-capital, cash-to-asset and repurchase ratios are all prominent fractional dependent variables.

solely one evaluative method can result in narrow conclusions. The authors find the root mean squared error is likely to favour the SYS-GMM estimator over FD-GMM estimator, despite on average, the SYS-GMM estimator producing more biased estimates. For this reason we employ a number of evaluative metrics, namely: coefficient bias (Bias)[10], the standard deviation of bias (SD)[11], the root mean square error (RMSE) [12] and a wald test (Wald), which is the average non-rejection frequency where the null hypothesis set to equality[13].

Finally, to supplement our assessment, we draw from Zhou et al. (2014) who document the trade-off between bias and variance. In fact, they claim that this relationship is analogous to that the mean-variance (return-risk) trade-off of modern portfolio theory. Thus, in order visualize the relationship between bias and variance we utilize non-parametric kernel (bias) density plots for each estimator. Where the preferred estimator can be considered one with a narrow bandwidth and a centering close to zero.

2.4 Monte Carlo Experiments

2.4.1 Benchmark Simulations

We begin our analysis with our benchmark simulations, Table 2.1 reports the simulation statistics for λ, Table 2.2 reports the simulation statistics for β, Table 2.3 reports the inferred rate of adjustment and finally Figure 2.1 illustrates the bias density plots for the parameter λ[14].

Starting with Table 2.1, the performance of the traditional estimators are consistent with the work of Kiviet (1995) and Judson and Owen (1999) as we find the OLS (FE) estimator to consistently overestimate (underestimate) the autoregressive coefficient. Furthermore, we document the level of bias for the OLS (FE) estimator decreases (increases) with the level of persistence, with the highest level of bias reported being 0.194 (-0.112) when $\lambda = 0.2$ (0.8). Regarding the other evaluative metrics, we find both estimators to have relatively low levels of SD, however, both the OLS and FE estimators perform poorly in RMSE and Wald. Alarmingly, the FE estimator reports the only non-zero Wald value of 2.6% when $\lambda = 0.2$. Thus, out of the 500 repetitions, the FE estimator was only able to estimate the true value of λ (at the

[10]Bias= $\frac{1}{R}\sum_{i=1}^{R}(\hat{\lambda}_i - \lambda)$, where $\hat{\lambda}_i$ is the estimated autoregressive coefficient and λ is set in the DGP.

[11]SD=$\sqrt{\frac{1}{R}\sum_{i=1}^{R}(\hat{\lambda}_i - \bar{\lambda})^2}$ where $\hat{\lambda}_i$ is the estimated autoregressive coefficient and $\bar{\lambda}$ is the average bias.

[12]RMSE=$\sqrt{\frac{1}{R}\sum_{i=1}^{R}(\hat{\lambda}_i - \lambda)^2}$ where $\hat{\lambda}_i$ is the estimated autoregressive coefficient and λ is set in the DGP.

[13]$H_0 : \hat{\lambda}_i = \lambda$ where $\hat{\lambda}_i$ is the estimated autoregressive coefficient and λ is set in the DGP.

[14]For brevity, in later experiments we shall only report the simulation statistics and bias density plots for λ in the main text. All other corresponding Table's can be found in the appendix.

5% significance level) 13 times. Finally, in terms of β (Table 2.2), the OLS estimator reports moderate levels of bias while the FE estimator generally performs well.

Moving on to the GMM estimator, we find, unsurprisingly, that the FD-, AS- and SYS-GMM estimators outperform the traditional estimators in terms of bias, for example when $\lambda = 0.5$ we report bias of -0.010, -0.003 and 0.018, respectively. Consistent with Blundell and Bond (1998) we document that all three estimators increase in bias as the level of persistence increases, with negligible bias at low to moderate levels of λ. Yet, when λ is highly persistent the degree of bias becomes moderate, especially in the FD- and SYS-GMM estimators, with reported bias of -0.044 and 0.038, respectively. In general, all three estimators perform well across SD, RMSE and Wald with the SYS-GMM estimator notably outperforming the FD-GMM estimator in RMSE consistent with Dang et al. (2015). Furthermore, while in most cases all evaluative metrics worsen as λ increases, the SD for SYS-GMM estimator remains relatively low. As a result, the combination of increased bias and low SD when $\lambda = 0.8$ leads to the SYS-GMM estimator performing poorly in the Wald test. Again, similar to the traditional estimators, our baseline simulations prove consistent with the existing literature of Arellano and Bond (1991), Flannery and Hankins (2013) and Dang et al. (2015) who all illustrate the positive relationship between persistence and bias in the GMM estimators. Such reductions in performance across metrics is largely attributable to the weak instrument problem which is caused by the reduction in information as λ approaches unity (Bun and Windmeijer, 2010). Moreover, the number of moment conditions increases at the order of T^2 which can in turn induce severe bias in finite samples (Ziliak, 1997).

Looking at the alternative estimators, we find the performance of the LD4 estimator to be inversely affected by the degree of dynamic persistence. So much so, at low to moderate levels of persistence, the LD4 estimator performs worse than the traditional estimators across most evaluative metrics. However, when $\lambda = 0.8$, the LD4 estimator outperforms both the FD- and SYS-GMM estimators in terms of bias, consistent with the work Dang et al. (2015). Looking at β, the same relationship follows with degree of persistence, however, even when $\lambda = 0.8$ the LD4 estimates β with sizable bias. Thus, when λ is highly persistence the LD4 estimator might be advantageous in estimating the true autoregressive coefficient, but, at the cost of inconsistent and biased values of β. Finally, we find the LSDVC and QML estimators to be superior across all values of λ, with the performance of both estimators being weakened by the degree of dynamic persistence. However, unlike the GMM-estimators, we see the LSDVC and QML estimators still estimate λ with negligible bias when $\lambda = 0.8$. While the performance of the

LSDVC estimator is unsurprising given the work of Flannery and Hankins (2013), Zhou et al. (2014) and Dang et al. (2015) we are, to the best of our knowledge, the first to document the estimator properties of the QML estimator in the corporate finance setting. As documented in Section 2.2.2.3, the QML estimator boasts a number of auspicious qualities with respect to the GMM estimators in that it has the advantage of having a fixed number of orthogonality conditions independent of the sample size. Moreover, it also has the advantage of increased information, making the full use of all available information in the sample, subsequently yielding more effieinct estimates. Furthermore, our benchmark simulations indicate that the performance of the QML estimator edges the LSDVC estimator. Overall our simulations results regarding the QML estimator support the parallel studies of Kruiniger (2013), Hayakawa and Pesaran (2015) and Phillips (2017) and compliment those in the corporate finance setting of Flannery and Hankins (2013) and Dang et al. (2015).

To visualize the impact of dynamic persistence in Table 2.1, Figure 2.1 illustrates the role of λ and its influence on bias and SD. It is clear that when the degree of persistence is low, the GMM and alternative estimators (apart from the LD4 estimator) are centred close to zero, with the LSDVC and QML estimators having the most narrow bandwidths. However, as the degree of persistence increases to $\lambda = 0.8$, the density and bandwidths of the aforementioned estimators worsens considerably (especially in the GMM-estimators) resulting in a wider bias curves and less consistent estimates.

In sum, we find the degree of dynamic persistence to have a significant impact on the properties of estimators, where in most cases, higher levels of persistence result in increased estimator bias. Our benchmark simulations indicate that the OLS and FE estimators are inadequate methods of estimation as both estimators produce severely biased estimates of the autoregressive coefficient, λ. The economic implications (Table 2.3) of the OLS and FE estimators reflect their inability to estimate the true SOA. For example, where the SOA$=20\%$ the OLS and FE estimator, on average, determine the SOA to be 13.56% and 31.20%, respectively. We find the GMM and alternative estimators to be more suitable for corporate finance setting, however, the GMM and LD4 estimators prove highly sensitive to the degree of persistence. Overall, the LSDVC and QML estimators provide the most accurate estimates for the SOA, even when $\lambda = 0.8$, the implied SOA is 21.00% and 20.98%, respectively. In what follows, we examine the role of the dynamic panel estimators over a number of experiments as we look to analyze the impact of various fixed parameters.

Table 2.1: Benchmark Simulations (λ)

	$\lambda = 0.2$				$\lambda = 0.5$				$\lambda = 0.8$			
Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
OLS	0.194	0.008	0.194	0.000	0.144	0.006	0.144	0.000	0.064	0.004	0.065	0.000
FE	-0.025	0.007	0.026	0.026	-0.045	0.007	0.045	0.000	-0.112	0.009	0.112	0.000
FD-GMM	-0.001	0.016	0.016	0.914	-0.010	0.019	0.022	0.880	-0.044	0.037	0.057	0.648
AS-GMM	0.002	0.014	0.014	0.896	-0.003	0.015	0.016	0.908	-0.014	0.024	0.028	0.760
SYS-GMM	0.007	0.010	0.012	0.806	0.018	0.012	0.022	0.538	0.038	0.012	0.039	0.078
LD4	0.215	0.070	0.226	0.006	0.104	0.055	0.117	0.100	0.016	0.041	0.044	0.422
LSDVC	-0.003	0.007	0.007	1.000	-0.006	0.007	0.010	1.000	-0.010	0.010	0.014	1.000
QML	-0.001	0.007	0.007	0.964	-0.004	0.007	0.008	0.914	-0.010	0.010	0.014	0.822

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ and $\mu = 1$ and all reported simulations are configured for $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 2.2: Benchmark Simulations (β)

	$\beta = 0.8$				$\beta = 0.5$				$\beta = 0.2$			
Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
OLS	0.051	0.008	0.052	0.000	0.032	0.006	0.033	0.000	0.019	0.004	0.019	0.010
FE	0.008	0.007	0.010	0.782	0.008	0.006	0.009	0.710	0.003	0.005	0.005	0.896
FD-GMM	-0.001	0.016	0.016	0.928	0.002	0.013	0.022	0.934	0.006	0.011	0.057	0.876
AS-GMM	-0.003	0.015	0.014	0.912	-0.002	0.012	0.016	0.910	0.000	0.009	0.028	0.918
SYS-GMM	-0.002	0.009	0.012	0.910	-0.002	0.007	0.022	0.908	-0.001	0.006	0.039	0.896
LD4	-0.629	0.058	0.226	0.000	-0.340	0.033	0.117	0.000	-0.116	0.011	0.044	0.000
LSDVC	0.001	0.007	0.007	1.000	0.001	0.006	0.010	1.000	0.001	0.005	0.014	1.000
QML	0.001	0.007	0.007	0.946	0.001	0.006	0.008	0.952	0.000	0.005	0.014	0.956

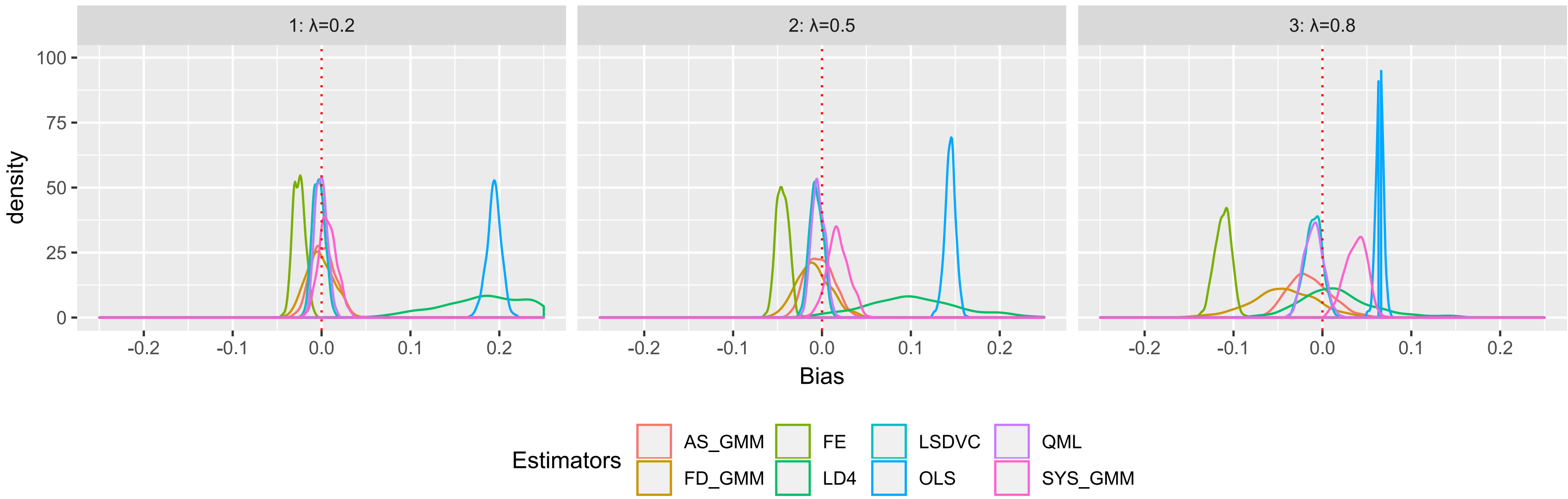
Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\lambda = 1 - \beta, \rho = 0.5, \zeta = 5$ and $\mu = 1$ and all reported simulations are configured for $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 2.3: Benchmark Simulations: Implied Speed of Adjustment

True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
80.00%	60.60%	82.55%	80.15%	79.82%	79.28%	58.48%	80.33%	80.06%
50.00%	35.57%	54.46%	50.97%	50.27%	48.20%	39.61%	50.65%	50.41%
20.00%	13.56%	31.20%	24.41%	21.44%	16.24%	18.39%	21.00%	20.98%

Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Figure 2.1: Benchmark Simulations: Bias Density Plots



Source: Author's own calculation.

2.4.2 Experiment One: The Impact of Changes in Time Series Length

The results from experiment one can be found in Table 2.4. Holding N and all other parameters fixed, we investigate the impact of panel length by setting $T = 6$ and $T = 18$. First, we find both the OLS and FE estimators to be sensitive to panel length. While, both estimators report performance improvements when $T = 18$, the OLS and FE estimator remain severely biased at their unfavored degrees of persistence. These findings echo that of Judson and Owen (1999) who observe when $T = 30$ the OLS and FE estimators can still be servery biased[15]. In economic terms, when the SOA is equal to 50% and $T = 6$, the OLS (FE) estimator, on average, estimates the SOA at 32.95% (61.40%), whereas when $T = 18$, the estimated SOA is 36.40% (53.72%). Thus, reiterating the OLS and FE estimators inability to estimate the true SOA.

Regarding the GMM-estimators, we find that when the panel length reduces to $T = 6$, the performance of the FD- and SYS-GMM estimators seriously deteriorates in terms of bias and RMSE. Alternatively, the AS-GMM estimator performs relatively well in terms of bias across all degrees of persistence, however, displays a sizable increase in SD relative to our benchmark simulations. Furthermore, the LD4 estimator also performs poorly when $T = 6$, with ample increases in bias, SD and RMSE. Note, that while the LD4 estimator performs uncharacteristically well when $\lambda = 0.5$, this is distorted by extreme outliers, with an estimated range of $[0.086, 1.742]$. Further emphasising our use and contribution of multiple evaluative metrics.

Finally, the LSDVC and QML estimators perform relatively well at low and moderate levels of persistence when $T = 6$, with reported bias of -0.004 and -0.010, respectively. However, when $\lambda = 0.8$ we find that the bias for the LSDVC and QML estimators increases to moderate levels of -0.032 and -0.029, respectively. Thus, on average, both estimators overestimate the true SOA by roughly 3%.

Overall, our simulations clarify that T has considerable performance implications for dynamic panel estimators. Moreover, short panel length hinders the performance estimators over all evaluative metrics, especially bias and SD. The impact of T is most clearly summarized in Figure 2.2 as we document a dramatic difference in bandwidth and centering for both levels of T relative to our benchmark simulations. The implications of this experiment shows that use a-priori sub-sampling over different time periods is likely exacerbate finite sample bias. Thus, providing insightful guidance for our forthcoming empirical chapters.

[15] In additional (unreported) simulations we test $T = 30$ and find that the OLS and FE estimators are still moderately biased. For example, for $\lambda = 0.8$ we find the FE estimator to produce bias of 0.035 whereas Judson and Owen (1999) report 0.066.

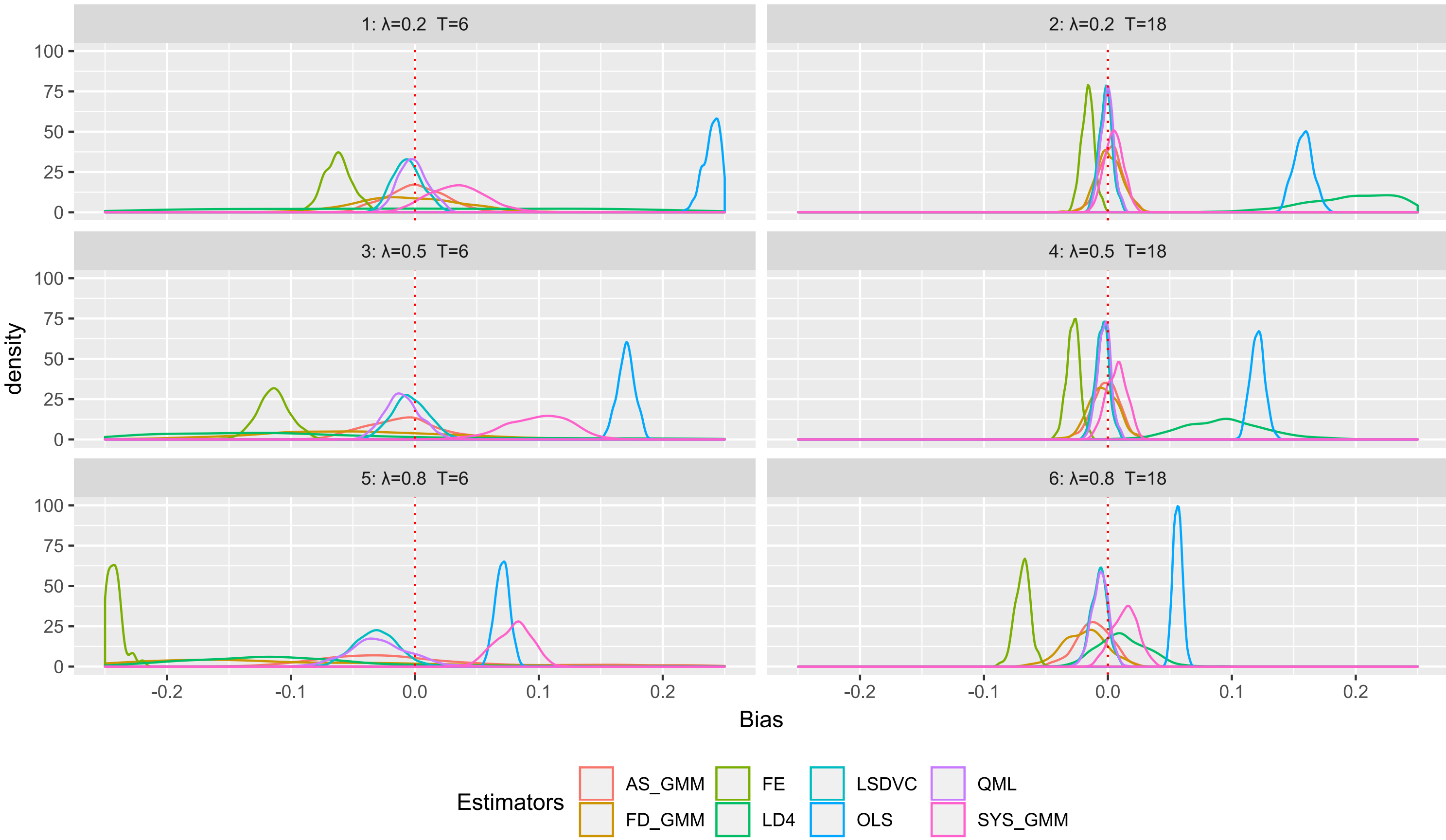
Table 2.4: Experiment One: The Impact of Changes in Time Series Length

		$T = 6$				$T = 18$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.243	0.009	0.243	0.000	0.158	0.008	0.158	0.000
	FE	-0.062	0.011	0.063	0.000	-0.016	0.005	0.017	0.112
	FD-GMM	-0.005	0.041	0.041	0.946	0.001	0.010	0.010	0.864
	AS-GMM	0.001	0.024	0.024	0.956	0.002	0.010	0.010	0.836
	SYS-GMM	0.034	0.023	0.041	0.534	0.005	0.007	0.009	0.748
	LD4	0.249	0.752	0.792	0.460	0.211	0.047	0.216	0.002
	LSDVC	-0.006	0.012	0.013	1.000	-0.002	0.005	0.006	1.000
	QML	-0.001	0.012	0.012	0.952	0.000	0.005	0.005	0.936
$\lambda = 0.5$	OLS	0.171	0.007	0.171	0.000	0.121	0.006	0.121	0.000
	FE	-0.114	0.013	0.115	0.000	-0.028	0.005	0.028	0.000
	FD-GMM	-0.051	0.081	0.095	0.882	-0.004	0.012	0.012	0.860
	AS-GMM	-0.003	0.050	0.051	0.890	-0.001	0.011	0.011	0.832
	SYS-GMM	0.099	0.026	0.103	0.018	0.007	0.008	0.011	0.682
	LD4	-0.003	0.319	0.318	0.292	0.094	0.033	0.100	0.018
	LSDVC	-0.004	0.014	0.015	1.000	-0.005	0.005	0.007	1.000
	QML	-0.010	0.014	0.017	0.896	-0.003	0.005	0.006	0.916
$\lambda = 0.8$	OLS	0.071	0.006	0.071	0.000	0.056	0.004	0.056	0.000
	FE	-0.274	0.017	0.274	0.000	-0.069	0.006	0.069	0.000
	FD-GMM	-0.232	0.198	0.305	0.696	-0.019	0.017	0.025	0.640
	AS-GMM	0.002	0.084	0.084	0.758	-0.011	0.014	0.018	0.706
	SYS-GMM	0.080	0.014	0.081	0.000	0.014	0.010	0.017	0.420
	LD4	-0.055	0.193	0.201	0.222	0.012	0.020	0.023	0.482
	LSDVC	-0.032	0.017	0.036	1.000	-0.007	0.007	0.010	1.000
	QML	-0.029	0.025	0.038	0.790	-0.006	0.007	0.009	0.848

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ and $\mu = 1$ and all reported simulations are configured for $N = 500$ with a repetition rate of $R = 500$.

Figure 2.2: Experiment One: Bias Density Plots



Source: Author's own calculation.

2.4.3 Experiment Two: The Impact of Changes in Cross-section Size

While the number of cross-section in the corporate finance literature is often large, it is common practice in the literature to divide firms into sub-samples (often based on firm-specific characteristics), in an attempt to evaluate the economic size or significance of the desired relationship[16], in our case, the SOA. In order to evaluate the econometric implications of such actions, we evaluate the impact of reduced cross-section size on estimator performance by setting $N = 100$ and $N = 250$. The results from our simulations can be found in Table 2.5.

Starting with the traditional estimators, we find the OLS and FE estimators to display little to no change in terms of bias and RMSE for reduced levels of N, yet, we document increased levels of SD relative to our benchmark simulations. Comparatively, the results for the GMM-estimators indicate that all evaluative metrics are affected by the number of cross-sections. We find the FD- and AS-GMM estimators to increase in bias, SD and RMSE as N becomes small, with the FD-GMM estimator reporting severe bias of -0.089 when $\lambda = 0.8$. Alternatively, relative to our benchmark simulations, the SYS-GMM estimator reports lower levels of bias when $N = 100$, however, at the cost of a significant increase in SD, with SD more than doubling across all degrees of persistence. For the alternative estimators, we find LD4 estimator to exhibit a reduction in performance across all evaluative metrics as N becomes small, with the LD4 now estimating λ with moderate bias of 0.048 when $N = 100$ and $\lambda = 0.8$. Finally, the LSDVC and QML estimators continue to be the most robust in terms of bias, however, as N becomes small both estimator display moderate levels of SD and RMSE.

Overall, we find the cross-sectional size of the panel has notable implications for the SD and RMSE of estimators with the GMM and LD4 estimators also displaying changes in bias. Regarding the SOA, the increase in SD reduces the consistency and therefore the likelihood of the estimator estimating the true SOA. For example when $\lambda = 0.8$ and $N = 100$ the LSDVC and QML estimator have a SD of 0.022 and 0.024, whereas relative to our benchmark simulations, where $N = 500$, the SD of both estimators is 0.010. The implications of which suggest that, on average, given one standard deviation, the LSDVC and QML estimators will be roughly estimate 2.2% and 2.4% either side of their estimated SOA of 20.85% and 20.93%, respectively. In conclusion, given the type of estimator, authors should be cautious when using sub-samples or small N datasets, with the instrument based estimators particularly displaying sensitive results to the size of N.

[16]See Kisgen (2006), Elsas and Florysiak (2011), Dang et al. (2012) Elsas and Florysiak (2015), and Guariglia and Yang (2016) for examples in the dynamic panel corporate finance literature.

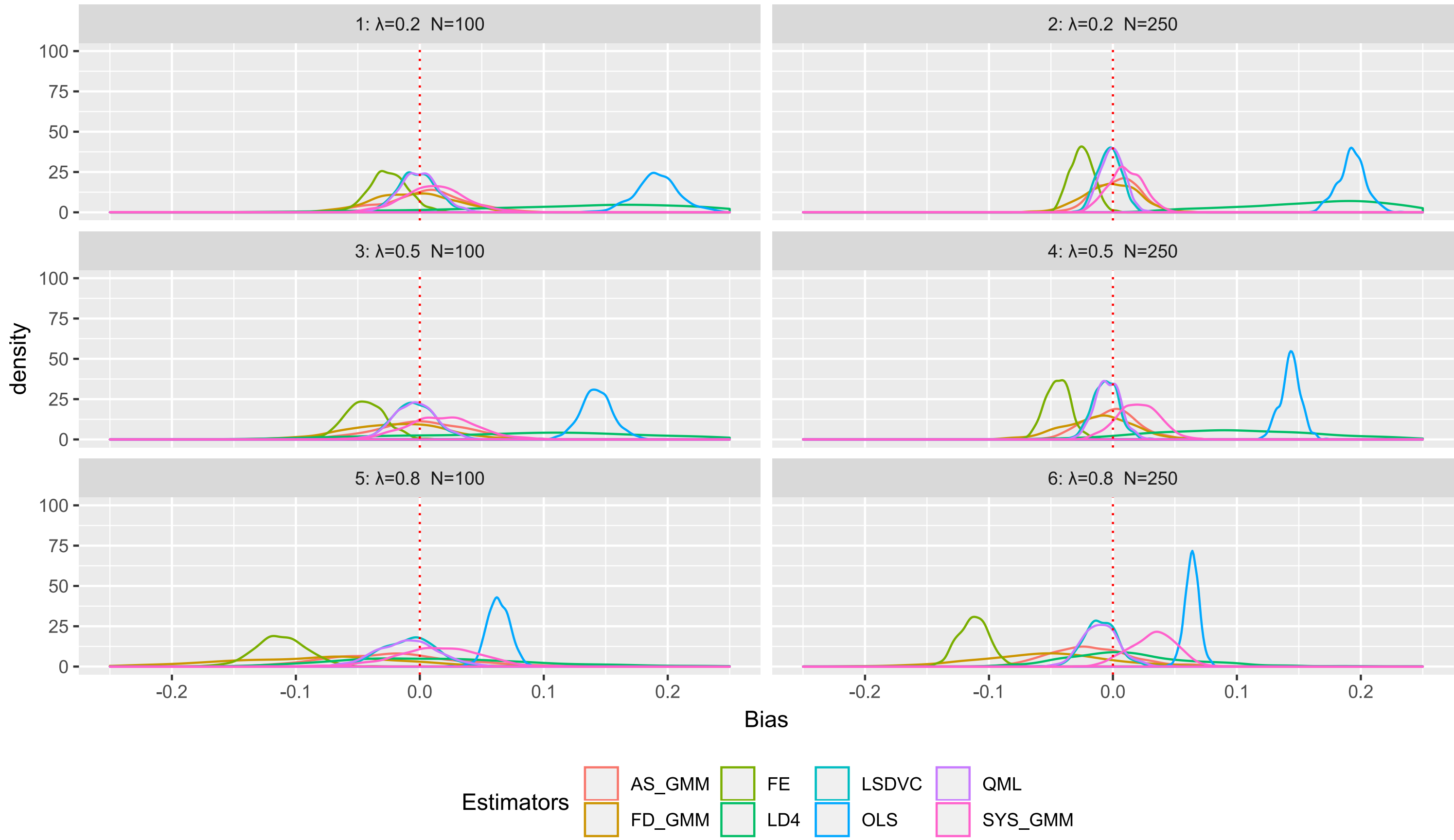
Table 2.5: Experiment Two: The Impact of Changes in Cross-sectional Size

		$N = 100$				$N = 250$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.191	0.018	0.192	0.000	0.193	0.011	0.193	0.000
	FE	-0.025	0.015	0.029	0.584	-0.025	0.009	0.027	0.242
	FD-GMM	-0.005	0.032	0.032	0.732	-0.001	0.021	0.021	0.888
	AS-GMM	0.005	0.033	0.033	0.590	0.004	0.018	0.019	0.884
	SYS-GMM	0.012	0.024	0.027	0.572	0.010	0.014	0.017	0.758
	LD4	0.239	0.176	0.297	0.290	0.223	0.098	0.244	0.088
	LSDVC	-0.002	0.016	0.016	1.000	-0.003	0.009	0.010	1.000
	QML	0.000	0.016	0.016	0.940	0.000	0.009	0.009	0.958
$\lambda = 0.5$	OLS	0.143	0.013	0.143	0.000	0.143	0.008	0.144	0.000
	FE	-0.044	0.016	0.047	0.194	-0.044	0.010	0.046	0.006
	FD-GMM	-0.020	0.040	0.045	0.670	-0.012	0.028	0.030	0.826
	AS-GMM	0.001	0.036	0.036	0.602	-0.001	0.022	0.022	0.846
	SYS-GMM	0.018	0.028	0.033	0.504	0.020	0.017	0.026	0.546
	LD4	0.126	0.149	0.195	0.354	0.108	0.079	0.134	0.244
	LSDVC	-0.004	0.017	0.018	1.000	-0.006	0.010	0.012	1.000
	QML	-0.004	0.017	0.017	0.936	-0.004	0.010	0.011	0.938
$\lambda = 0.8$	OLS	0.064	0.009	0.064	0.000	0.064	0.006	0.064	0.000
	FE	-0.112	0.021	0.114	0.000	-0.112	0.013	0.113	0.000
	FD-GMM	-0.089	0.074	0.115	0.408	-0.058	0.050	0.076	0.610
	AS-GMM	-0.023	0.053	0.058	0.466	-0.017	0.033	0.038	0.690
	SYS-GMM	0.014	0.034	0.037	0.454	0.032	0.018	0.037	0.296
	LD4	0.048	0.142	0.150	0.410	0.020	0.067	0.070	0.462
	LSDVC	-0.009	0.022	0.024	1.000	-0.010	0.013	0.017	1.000
	QML	-0.009	0.024	0.026	0.914	-0.010	0.015	0.018	0.898

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ and $\mu = 1$ and all reported simulations are configured $T = 12$ with a repetition rate of 500.

Figure 2.3: Experiment Two: Bias Density Plots



Source: Author's own calculation.

2.4.4 Experiment Three: The Impact of The Time-Invariant Individual Effect

In Table 2.6, we evaluate two distinct settings for the time-invariant individual (firm) effect. In setting one, we analyze the impact of zero correlation between the regressor and the time-invariant individual (firm) effect. We set $\eta_i \sim N(0, \sigma_\eta^2)$ where $\sigma_\eta = \mu(1-\lambda)\sigma_\nu$ and we maintain $\mu = 1$ to allow for direct comparison with our benchmark simulations. For our second set of simulations, we analyze the impact of increased cross-sectional heterogeneity on estimator performance. Here we revert to our default definition of the fixed-effect component, whereby $x_{i,t}$ is correlated η_i, and we set $\mu = 3$. Thus, proportionately the variance of η_i is set three times larger than the variance of $\nu_{i,t}$.

Starting with the first set of simulations, we find the OLS estimator to reduce in bias and RMSE across all degrees of persistence, while comparatively, the FE estimator remains unaffected by the change in definition. Similar to Dang et al. (2015), we document that both the FD- and SYS-GMM estimators display favourable properties when η_i is uncorrelated with x_{it}, especially when $\lambda = 0.8$, where the SYS-GMM estimator reports minimal bias of -0.005. In terms of the alternative estimators, the LD4 estimator displays marginal gains across all evaluative metrics whereas the LSDVC estimator reacts unfavourably, with deterioration in bias and RMSE, especially when the degree dynamic persistence is high. Finally, in comparison to the benchmark simulations, the QML estimator is relatively unaffected across all metrics and therefore can be considered robust to different types of time-invariant individual (firm) effects, both correlated and uncorrelated.

Regarding the second set of simulations, we report, unsurprising, that the OLS estimator performs poorly at high levels of cross-sectional heterogeneity, with extreme bias and RMSE of 0.497 when $\lambda = 0.2$. Furthermore, given the SYS-GMM estimator does not completely deal with the η_i in the system-equation (Wintoki et al., 2012), we also report heightened levels of bias of 0.093 when $\lambda = 0.8$. Comparatively, the FD-GMM estimator displays opposing behaviour in terms of bias (consistent with Dang et al. 2015), however, at the cost of increased SD and RMSE, relative to our benchmark simulations. Regarding the alternative estimator, while the LD4 estimator reports increases over all evaluative metrics, the LSDVC estimator performs favourable to heightened levels of cross-sectional heterogeneity, with reductions in bias and RMSE. Finally, the QML estimator remains unaffected to changes μ, and therefore continues to be robust across simulation settings.

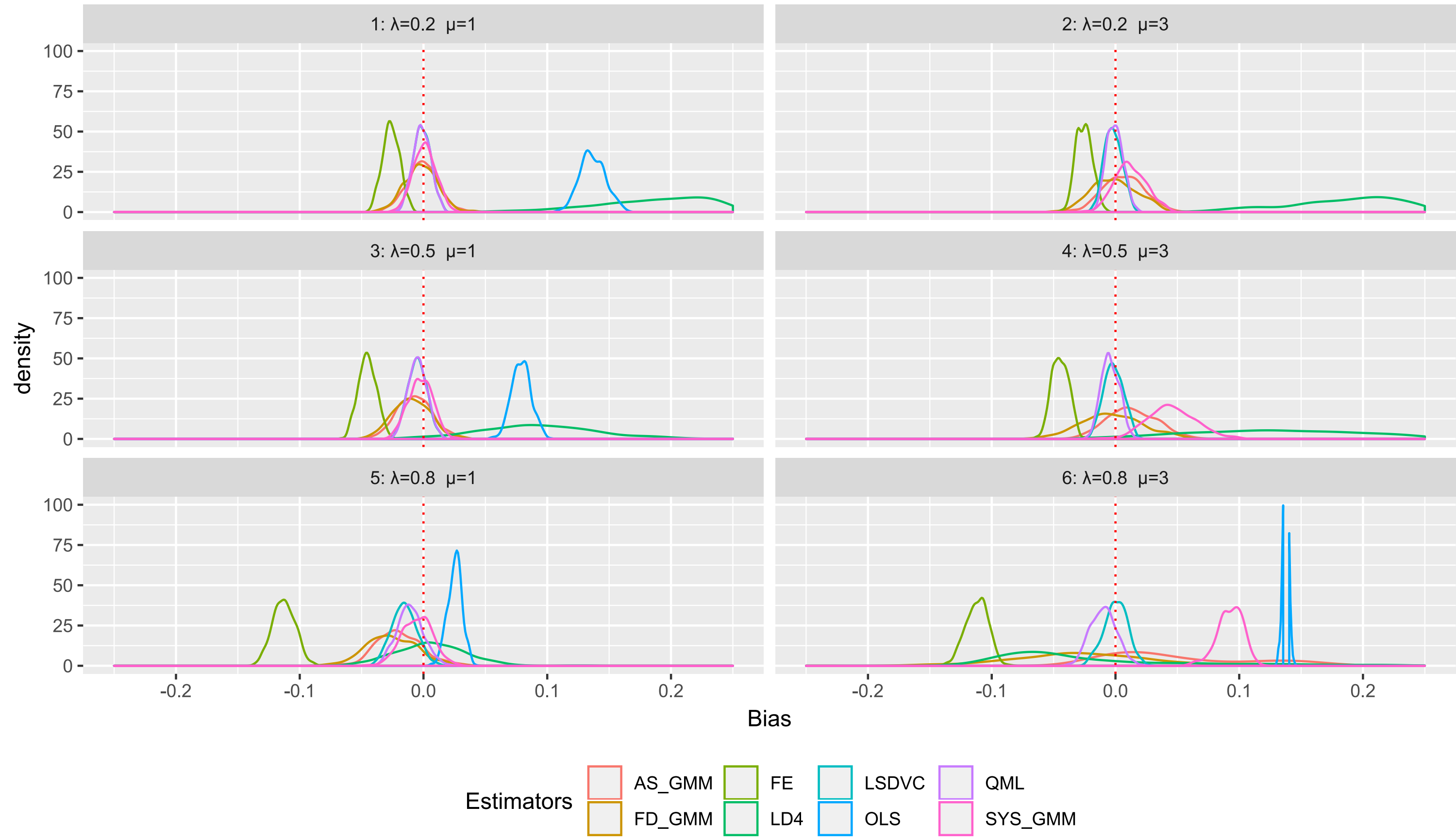
Table 2.6: Experiment Three: Varying Factor Loading

		$\mu = 1$				$\mu = 3$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.137	0.010	0.137	0.000	0.497	0.007	0.497	0.000
	FE	-0.026	0.007	0.027	0.038	-0.025	0.007	0.026	0.026
	FD-GMM	-0.002	0.013	0.013	0.912	-0.001	0.018	0.018	0.896
	AS-GMM	-0.001	0.013	0.013	0.902	0.007	0.017	0.018	0.844
	SYS-GMM	0.001	0.009	0.009	0.902	0.012	0.013	0.018	0.732
	LD4	0.215	0.065	0.225	0.010	0.306	0.300	0.428	0.004
	LSDVC	-0.001	0.007	0.007	1.000	-0.002	0.007	0.007	1.000
	QML	-0.001	0.007	0.007	0.932	-0.001	0.007	0.007	0.964
$\lambda = 0.5$	OLS	0.079	0.008	0.079	0.000	0.328	0.004	0.328	0.000
	FE	-0.045	0.007	0.046	0.000	-0.045	0.007	0.045	0.000
	FD-GMM	-0.010	0.015	0.018	0.836	-0.003	0.025	0.025	0.902
	AS-GMM	-0.007	0.014	0.016	0.854	0.013	0.020	0.024	0.742
	SYS-GMM	-0.002	0.010	0.010	0.898	0.045	0.019	0.049	0.132
	LD4	0.094	0.048	0.106	0.108	0.259	0.213	0.335	0.068
	LSDVC	-0.005	0.008	0.009	1.000	-0.002	0.008	0.008	1.000
	QML	-0.005	0.007	0.009	0.892	-0.004	0.007	0.008	0.914
$\lambda = 0.8$	OLS	0.025	0.006	0.026	0.010	0.138	0.002	0.138	0.000
	FE	-0.113	0.009	0.113	0.000	-0.112	0.009	0.112	0.000
	FD-GMM	-0.026	0.020	0.033	0.652	-0.030	0.053	0.061	0.860
	AS-GMM	-0.020	0.018	0.027	0.684	0.050	0.058	0.076	0.496
	SYS-GMM	-0.005	0.012	0.013	0.864	0.093	0.010	0.093	0.000
	LD4	0.006	0.028	0.029	0.524	0.071	0.214	0.225	0.092
	LSDVC	-0.016	0.010	0.018	1.000	0.000	0.009	0.009	1.000
	QML	-0.011	0.010	0.015	0.816	-0.010	0.010	0.014	0.822

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\beta = 1 - \lambda, \rho = 0.5$ and $\zeta = 5$ and all reported simulations are configured $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Figure 2.4: Experiment Three: Bias Density Plots



Source: Author's own calculation.

All in all, we report that the likely correlation present between x_{it} and η_i in the corporate finance setting will have a significant effect on estimator performance, with most estimators performing preferably in cases of zero correlation. Furthermore, given the correlation between x_{it} and η_i, the degree of cross-sectional heterogeneity has a detrimental effect on estimator performance, with all evaluative metrics proving sensitive μ. The implications on bias and SD are visualized in Figure 2.4 with only the LSDVC and QML estimators showing any degree of reliability when $\lambda = 0.8$ and $\mu = 3$. Thus, the LSQVC and QML estimators remain most favourable methods, regardless of η_i.

2.4.5 Experiment Four: The Impact of Changes in Signal Noise

In Table 2.7, we investigate estimator performance by varying the explanatory properties of the single regressor, $x_{i,t}$, relative to that of the residual. Therefore, following Kiviet (1995), we set $\zeta = 2$ and $\zeta = 8$ to represent low and high levels of explanatory power.

We report the bias of the OLS and FE estimators to have opposing reactions to the level of ζ, with the OLS (FE) estimator increasing (decreasing) in bias and RMSE when ζ increases. For the GMM-estimators, we find variation in ζ has little impact at low to moderate levels of persistence, however, when $\lambda = 0.8$, the performance of the GMM-estimators deteriorates considerably. Out of the three estimators, the AS-GMM estimator is preferable, as we document low levels of dynamic bias, while comparatively, the FD-GMM estimator performs least favourable with the level of bias being three times larger when $\zeta = 8$ (-0.048) relative to when $\zeta = 2$ (-0.011), consistent with Kiviet (1995). Finally, both the LSDVC and QML estimators display significant increases in SD as ζ increases, however, similar to Bruno (2005) and Dang et al. (2015) we find the LSDVC estimator to reduce in bias for high values of ζ, whereas, the QML estimator displays a negligible increase in bias.

In sum, we find that higher levels of explanatory power in the regressor generally result in increased bias, with only the FE and LSDVC estimators displaying the opposite effect. However, the degree of induced parameter bias is negligible in comparison to our previous experiments, with the LSDVC and QML estimators continuing to estimate the SOA with considerable accuracy. Finally, in Figure 2.5 we document significant increases in density's for the LSDVC and QML estimators, as ζ increases, with the density in some cases more then doubling in height. Thus, reiterating the performance superiority of the LSDVC and QML estimators.

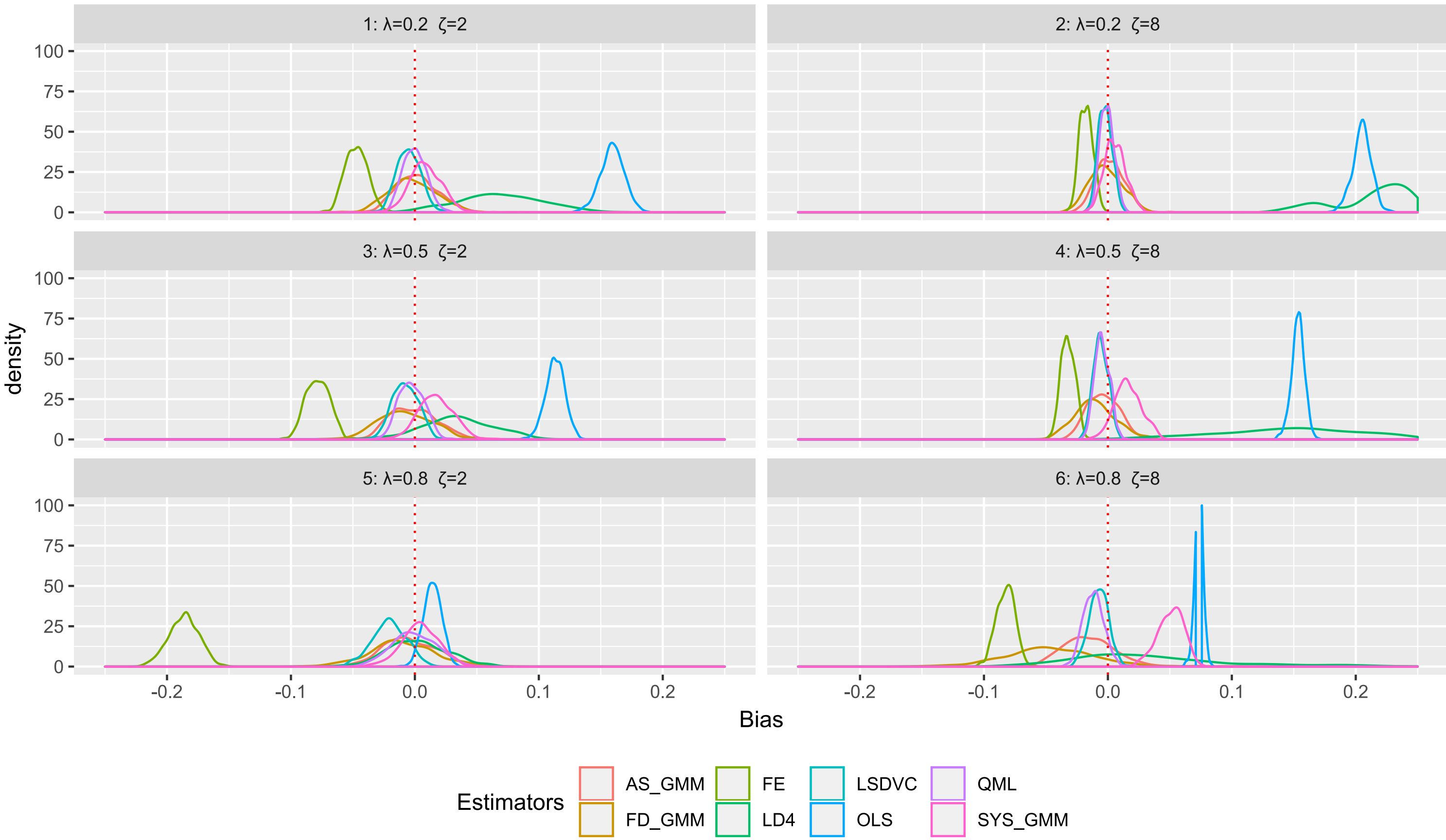
Table 2.7: Experiment Four: Varying Signal Noise

	Estimator	$\zeta = 2$ Bias	SD	RMSE	Wald	$\zeta = 8$ Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.159	0.009	0.160	0.000	0.205	0.008	0.205	0.000
	FE	-0.047	0.009	0.048	0.000	-0.018	0.005	0.018	0.124
	FD-GMM	-0.002	0.019	0.019	0.900	-0.001	0.013	0.013	0.920
	AS-GMM	0.002	0.017	0.017	0.904	0.002	0.011	0.012	0.894
	SYS-GMM	0.009	0.013	0.016	0.812	0.006	0.009	0.010	0.818
	LD4	0.069	0.035	0.077	0.304	0.461	0.158	0.487	0.000
	LSDVC	-0.005	0.009	0.011	1.000	-0.002	0.006	0.006	1.000
	QML	0.000	0.009	0.009	0.968	-0.001	0.005	0.006	0.960
$\lambda = 0.5$	OLS	0.113	0.008	0.113	0.000	0.153	0.005	0.154	0.000
	FE	-0.078	0.010	0.079	0.000	-0.032	0.006	0.033	0.000
	FD-GMM	-0.008	0.022	0.024	0.912	-0.010	0.017	0.020	0.860
	AS-GMM	-0.001	0.019	0.019	0.922	-0.004	0.013	0.013	0.888
	SYS-GMM	0.017	0.014	0.022	0.658	0.016	0.011	0.019	0.520
	LD4	0.035	0.029	0.046	0.428	0.170	0.080	0.188	0.044
	LSDVC	-0.008	0.010	0.013	1.000	-0.006	0.006	0.008	1.000
	QML	-0.003	0.010	0.011	0.962	-0.005	0.006	0.007	0.884
$\lambda = 0.8$	OLS	0.014	0.007	0.016	0.498	0.074	0.003	0.074	0.000
	FE	-0.186	0.012	0.187	0.000	-0.083	0.007	0.083	0.000
	FD-GMM	-0.011	0.026	0.028	0.880	-0.048	0.034	0.059	0.568
	AS-GMM	-0.004	0.022	0.022	0.888	-0.014	0.023	0.027	0.694
	SYS-GMM	0.004	0.015	0.016	0.864	0.051	0.011	0.052	0.002
	LD4	0.002	0.024	0.024	0.524	0.044	0.083	0.094	0.314
	LSDVC	-0.021	0.014	0.025	1.000	-0.007	0.008	0.011	1.000
	QML	0.000	0.018	0.018	0.950	-0.012	0.008	0.014	0.676

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\beta = 1 - \lambda, \rho = 0.5$ & $\mu = 1$ and all reported simulations are configured $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Figure 2.5: Experiment Four: Bias Density Plots



Source: Author's own calculation.

2.4.6 Experiment Five: The Impact of Panel Unbalancedness

For our penultimate experiment, we examine the impact of panel unbalancedness on estimator performance. To evaluate this domain, we test three levels of panel unbalancedness: high (50%), moderate (70%) and low panel unbalancedness (90%). The panel data design for this experiment can be found in Table 2.8.

Table 2.8: Unbalanced Panel Design

N	T	$N \cdot T$	$i \leq 200$	$200 < i \leq 400$	$i > 400$	$N \cdot T_i$	ω
500	12	6000	T=4	T=5	T=12	3000	50%
500	12	6000	T=6	T=9	T=12	4200	70%
500	12	6000	T=10	T=11	T=12	5400	90%

We start off by using our baseline DGP for each level of panel unbalancedness. Next, we split the number of cross-sections (firms) into three levels and thereafter remove T number of periods. Therefore, when $\omega = 70\%$, we remove the first 6 time periods for the first 200 cross-sections, for the middle 200 cross-sections we remove the first 3 time periods and we leave the final 100 cross-sections untouched, i.e. $T = 12$. The results from our simulations can be found in Table 2.9. We document for the OLS and FE estimators that all evaluative metrics decrease with respect to ω, with the FE estimator arguably being more severely affected by the degree of panel unbalancedness.

In terms of the GMM-estimators, the relationship is less clear, while SD and RMSE declines with ω, bias at low to moderate levels of dynamic persistence fluctuate at trivial levels. However, when $\lambda = 0.8$ the impact panel unbalancedness is more pronounced, we find the levels of bias in the FD- and AS-GMM estimators to be positively correlated with the severity of panel unbalancedness, with the FD- and AS-GMM estimators reporting moderate to high levels of bias when $\omega = 50\%$. Inconsistent with latter, the SYS-GMM estimator perform favourably in terms of bias and RMSE as ω depreciates, with the SYS-GMM estimator displaying negligible bias of 0.017 when $\lambda = 0.8$ and $\omega = 50\%$. These findings are not dissimilar with Flannery and Hankins (2013), who report the RMSE of the SYS-GMM estimator to be lower than its balanced panel equivalent. Looking at the alternative estimators, we find the bias of the LD4 estimator to be relatively unaffected by the degree of unbalancedness, however, we document large changes in SD and RMSE. In terms of the LSDVC, we document increases in bias, SD and RMSE as the ω decreases consistent with the simulations of Bruno (2005). Finally, the QML estimator shows similar qualities with notable increases across all evaluative metric.

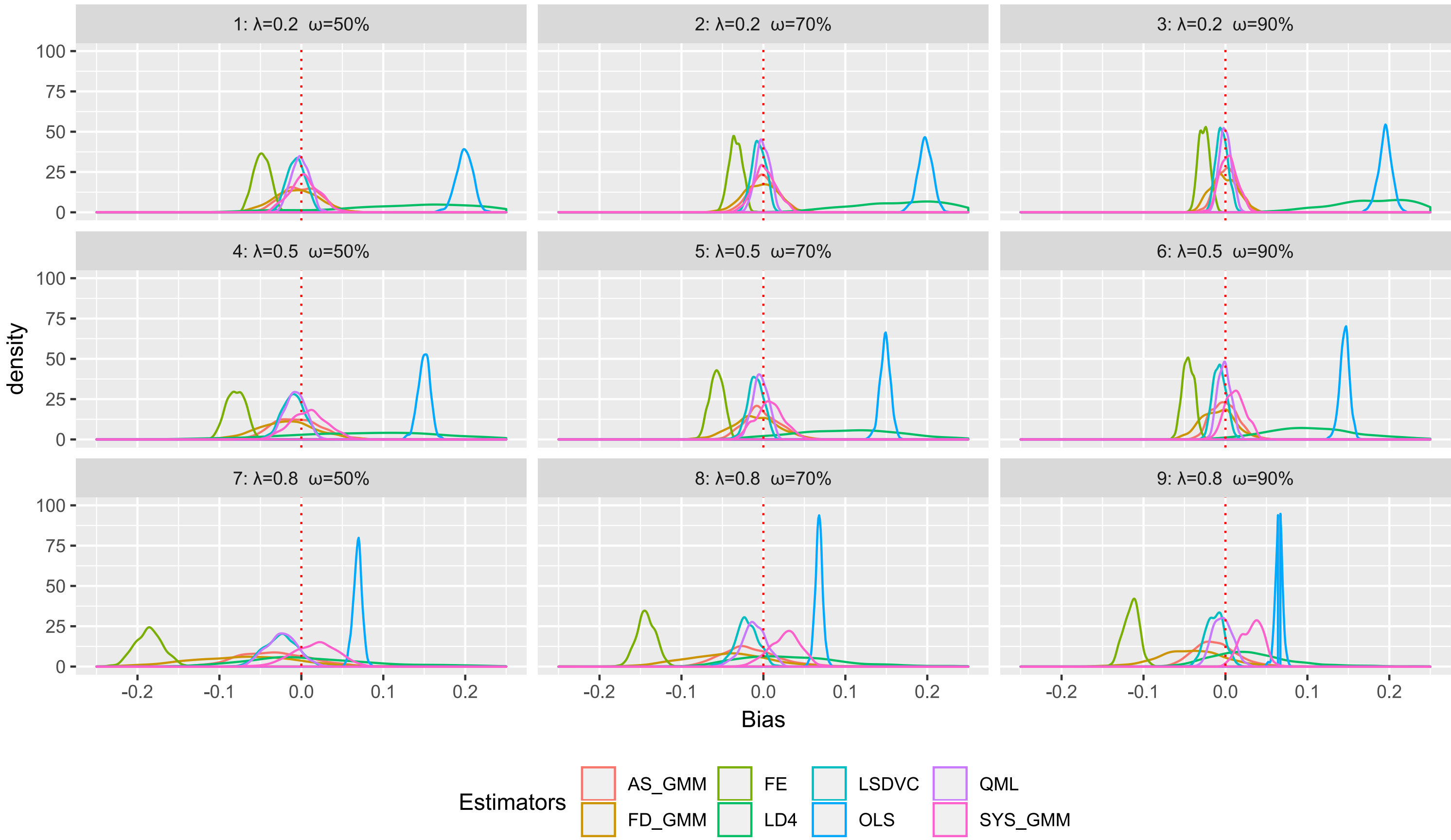
Table 2.9: Experiment Five: Varying Panel Balance

		$\omega = 50\%$				$\omega = 70\%$				$\omega = 90\%$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.199	0.010	0.199	0.000	0.197	0.009	0.198	0.000	0.195	0.008	0.195	0.000
	FE	-0.048	0.010	0.049	0.000	-0.034	0.008	0.035	0.006	-0.026	0.007	0.027	0.032
	FD-GMM	-0.006	0.027	0.028	0.818	-0.003	0.021	0.021	0.896	-0.002	0.016	0.016	0.902
	AS-GMM	0.000	0.023	0.023	0.810	0.001	0.018	0.018	0.884	0.002	0.014	0.014	0.890
	SYS-GMM	0.004	0.018	0.018	0.754	0.002	0.014	0.0144	0.868	0.004	0.011	0.011	0.882
	LD5	0.235	0.175	0.293	0.306	0.228	0.109	0.252	0.084	0.217	0.076	0.230	0.014
	LSDVC	-0.006	0.011	0.013	1.000	-0.006	0.008	0.010	1.000	-0.004	0.007	0.008	1.000
	QML	-0.001	0.011	0.011	0.970	-0.001	0.008	0.008	0.964	0.000	0.007	0.007	0.960
$\lambda = 0.5$	OLS	0.150	0.007	0.150	0.000	0.149	0.006	0.149	0.000	0.145	0.006	0.146	0.000
	FE	-0.080	0.011	0.081	0.000	-0.057	0.009	0.058	0.000	-0.045	0.007	0.046	0.000
	FD-GMM	-0.018	0.035	0.040	0.744	-0.010	0.027	0.029	0.854	-0.009	0.020	0.022	0.886
	AS-GMM	-0.006	0.028	0.029	0.776	-0.001	0.022	0.022	0.870	-0.001	0.016	0.016	0.924
	SYS-GMM	0.009	0.022	0.024	0.718	0.008	0.017	0.018	0.818	0.012	0.012	0.017	0.730
	LD	0.120	0.143	0.187	0.386	0.119	0.087	0.148	0.210	0.109	0.059	0.123	0.104
	LSDVC	-0.010	0.013	0.017	1.000	-0.009	0.010	0.013	1.000	-0.007	0.008	0.011	1.000
	QML	-0.008	0.012	0.015	0.908	-0.004	0.009	0.010	0.946	-0.001	0.008	0.008	0.970
$\lambda = 0.8$	OLS	0.069	0.005	0.069	0.000	0.068	0.004	0.068	0.000	0.065	0.004	0.065	0.000
	FE	-0.186	0.017	0.187	0.000	-0.143	0.012	0.144	0.000	-0.115	0.009	0.115	0.000
	FD-GMM	-0.074	0.064	0.098	0.504	-0.046	0.049	0.067	0.676	-0.042	0.039	0.057	0.670
	AS-GMM	-0.032	0.044	0.054	0.550	-0.016	0.035	0.039	0.756	-0.012	0.026	0.029	0.772
	SYS-GMM	0.017	0.026	0.031	0.562	0.026	0.019	0.032	0.446	0.032	0.013	0.035	0.240
	LD	0.040	0.135	0.141	0.452	0.051	0.098	0.110	0.356	0.032	0.051	0.060	0.328
	LSDVC	-0.025	0.020	0.032	1.000	-0.020	0.014	0.025	1.000	-0.013	0.011	0.017	1.000
	QML	-0.024	0.019	0.030	0.750	-0.011	0.015	0.018	0.892	-0.004	0.012	0.012	0.944

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ and $\mu = 1$ and all reported simulations are configured $N = 500$ with a repetition rate of $R = 500$.

Figure 2.6: Experiment Five: Bias Density Plots



Source: Author's own calculation.

In terms of economic implications, we find the SYS-GMM, LSDVC and QML estimators to estimate, on average, the rate of adjustment with the highest degree of accuracy. For example, when $\omega = 50\%$ and $\lambda = 0.8$ the SYS-GMM, LSDVC and QML estimators estimate the rate of adjustment at 18.34%, 22.51% and 22.37%, respectively. Note, however, the SYS-GMM estimator does produce notably higher levels of SD relative to its counterparts. This trade off is illustrated in Figure 2.6 as we observe the bandwidths of all estimators to be servery impeded by the degree of unbalancedness.

In sum, we find the degree of panel unbalancedness has an influential impact on the properties of estimators, where in most cases, higher levels of unbalancedness result in increased estimator bias, SD and RMSE. We find the LSDVC and QML estimators to continue to perform favourably across all evaluative metrics and produce only moderate levels of bias when the degree of panel unbalancedness is high. Given that panel unbalancedness is almost unavoidable in the empirical corporate finance setting, this experiment provides insightful guidance and postulates that robustness tests of balanced sub-samples may prove to be informative in forthcoming chapters.

2.4.7 Experiment Six: Varying Percentage of Censored Observations

For our final experiment we investigate the impact of fractional data on estimator performance. Many dependent variables in empirical corporate finance are fractional in nature, yet, the estimators assessed so far were originally developed for continuous, unbounded dependent variables. Thus, failing to account for the fractional nature of the dependent variable is likely to result in biased estimates of the autoregessive coefficient (Loudermilk, 2007). In order to evaluate the impact of fractional data we adopt the DGP process of Elsas and Florysiak (2011) and Elsas and Florysiak (2015) outlined below:

$$y^{\#}_{i,t+1} = \lambda y_{i,t} + \beta x_{i,t} + \eta_i + \upsilon_{i,t+1} \tag{2.31}$$

$$\eta_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{x}_i + \phi_i \tag{2.32}$$

$$y^{\#}_{i,0} = \beta x_{i,t} + \alpha_0 + \alpha_2 \bar{x}_i + \phi_i + u_{i0} \tag{2.33}$$

We follow the same experiment design by including three levels of λ: $\lambda = 0.2$, $\lambda = 0.5$ and $\lambda = 0.8$ and we define $\beta = 1 - \lambda$. We set $x_{i,t} \sim U(-0.5, 1)$ and we generate $\upsilon_{i,t}$ independently and randomly by setting $\upsilon_{i,t} \sim N(0, \sigma^2)$. The time-invariant variable, η_i, in equation (2.32), is dependently generated with $\alpha_0 = 0.1$, $\alpha_1 = 0.1$ and $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$. Finally, the initial latent variable, $y^{\#}_{i,0}$, is dependently generated where $u_{i0} \sim N(0, \sigma_u^2)$ and $\sigma_u = 0.01$.

In order to evaluate the degree of censoring in the dependent variable, we follow Dang et al. (2015) by defining $\phi_i \sim N(0, \sigma_\phi^2)$ where we adjust σ_ϕ in order to create three degrees of censoring in the dependent variable: $C \approx 30\%$, $C \approx 20\%$ and $C \approx 10\%$[17]. In effect, the adjustment of σ_ϕ explicitly alters the magnitude of the fixed-effect component relative to that of the residual, thereby impacting the number of firm-year observations that fall outside the unit-interval, resulting in a greater degree of censoring in the dependent variable.

The results for our final experiment can be seen in Table 2.10. Focusing on $\lambda = 0.8$, where we are able to generate all levels of censoring, we see, as expected, that the majority of estimators designed for continuous variables are adversely effected by the degree of censoring. For the traditional estimators, both the OLS and FE estimator remain severely biased irrespective of level of censoring. For the GMM estimators, we find the FD- and AS-GMM estimators to be highly sensitive to the level censoring, with severe bias of -0.161 and -0.148 when $C \approx 30\%$ and negligible bias of -0.015 and -0.014 when $C \approx 10\%$. Comparatively, we find the SYS-GMM estimator to be more robust to degree censoring, with the SYS-GMM estimator displaying marginal differences in bias and SD with respect to changes in σ_ϕ.

For the alternative estimators, we observe polar responses from the LSDVC and QML estimators. We find for the LSDVC (QML) estimator that the level of bias decreases (increases) with the level of censoring, with the LSDVC (QML) estimator reporting negligible bias of 0.008 (-0.016) when $C \approx 30\%$ ($C \approx 10\%$), however, severe levels of bias when $C \approx 10\%$ ($C \approx 30\%$). Alternatively, we document that the DPF estimator, unsurprisingly, performs favourably across all degrees of censoring. Consistent with Elsas and Florysiak (2011), Elsas and Florysiak (2015) and Dang et al. (2015), we find the DPF estimator estimates λ with minimal bias and also performs well across other evaluative metrics.

In sum, we find the degree of censoring to have a significant impact on the properties of estimators, where in most cases, higher levels of censoring results in increased estimator bias. In terms of economic implications, we find the DPF estimator to most accurately estimate the SOA across all levels of censoring, however, at low levels of censoring, i.e. $C \approx 10\%$, other estimators, such as the FD-GMM, AS-GMM and QML estimators all estimate λ with moderate levels of bias. Therefore, given the degree of censoring in the dependent variable one should be cautious on the choice of estimator choice with the DPF proving most favourable out of the estimators trailed in this chapter.

[17]Note: Given the DGP, the degree of censoring in $y^{\#}_{i,t+1}$ is also effected by λ through $x_{i,t}$, therefore for $\lambda = 0.2$ the minimal level of censoring is restricted to $C \approx 25\%$ and $\lambda = 0.2$ to $C \approx 18\%$

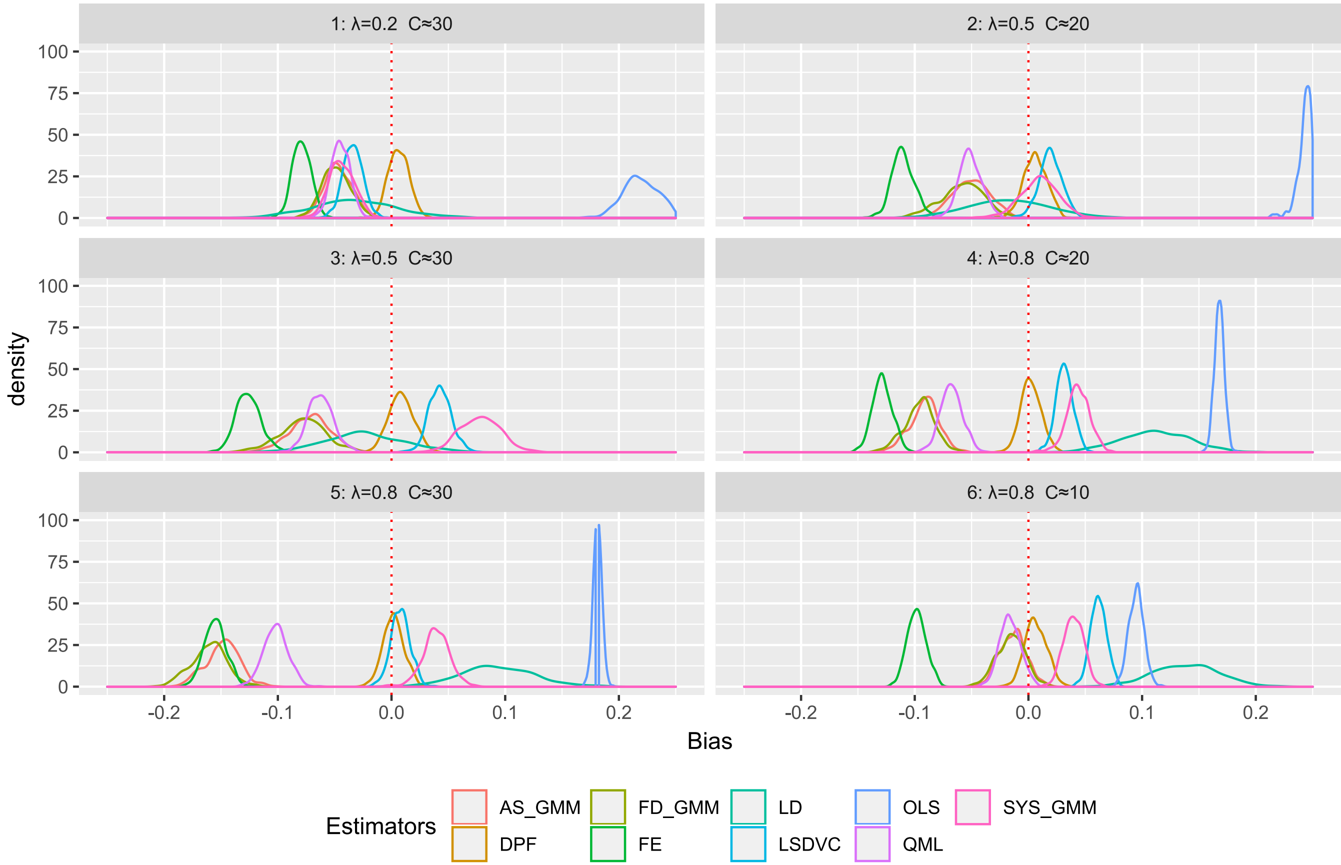
Table 2.10: Experiment Six: Varying Percentage of Censored Observations

		$C \approx 30\%$				$C \approx 20\%$				$C \approx 10\%$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.220	0.016	0.079	0.000								
	FE	-0.079	0.008	0.221	0.000								
	FD-GMM	-0.049	0.012	0.080	0.016								
	AS-GMM	-0.047	0.012	0.050	0.016								
	SYS-GMM	-0.044	0.011	0.048	0.008								
	LD4	-0.033	0.038	0.045	0.876								
	LSDVC	-0.034	0.009	0.050	1.000								
	QML	-0.045	0.008	0.035	0.000								
	DPF	0.006	0.009	0.046	0.872								
$\lambda = 0.5$	OLS	0.395	0.008	0.395	0.000	0.260	0.012	0.260	0.000				
	FE	-0.126	0.011	0.126	0.000	-0.110	0.010	0.111	0.000				
	FD-GMM	-0.078	0.020	0.081	0.010	-0.058	0.019	0.061	0.070				
	AS-GMM	-0.072	0.018	0.074	0.008	-0.051	0.017	0.053	0.088				
	SYS-GMM	0.078	0.018	0.080	0.002	0.010	0.017	0.019	0.756				
	LD4	-0.023	0.035	0.042	0.874	-0.017	0.036	0.040	0.918				
	LSDVC	0.043	0.010	0.044	1.000	0.019	0.010	0.022	1.000				
	QML	-0.062	0.011	0.063	0.000	-0.051	0.010	0.052	0.000				
	DPF	0.008	0.011	0.014	0.852	0.006	0.010	0.012	0.902				
$\lambda = 0.8$	OLS	0.181	0.004	0.181	0.000	0.168	0.004	0.047	0.000	0.095	0.007	0.095	0.000
	FE	-0.155	0.010	0.155	0.000	-0.129	0.009	0.168	0.000	-0.098	0.008	0.099	0.000
	FD-GMM	-0.161	0.016	0.161	0.000	-0.096	0.013	0.129	0.000	-0.015	0.012	0.020	0.720
	AS-GMM	-0.148	0.015	0.149	0.000	-0.092	0.013	0.097	0.000	-0.014	0.012	0.018	0.728
	SYS-GMM	0.039	0.012	0.041	0.016	0.044	0.010	0.092	0.008	0.040	0.009	0.041	0.002
	LD4	0.093	0.032	0.098	0.090	0.111	0.031	0.045	0.026	0.138	0.029	0.141	0.000
	LSDVC	0.008	0.008	0.011	1.000	0.032	0.007	0.116	1.000	0.062	0.007	0.062	1.000
	QML	-0.102	0.011	0.102	0.000	-0.068	0.010	0.033	0.000	-0.016	0.009	0.019	0.546
	DPF	0.002	0.009	0.009	0.940	0.002	0.009	0.068	0.938	0.006	0.009	0.011	0.890

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005), QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002) and finally the DPF estimator is the dynamic panel fractional variable estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\beta = 1 - \lambda$, $\alpha_0 = 0.1$, $\alpha_1 = 0.1$ and $\sigma_u = 0.01$ and all reported simulations are configured $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Figure 2.7: Experiment Six: Bias Density Plots



Source: Author's own calculation.

2.5 Empirical Implications and Implementation

So far in this chapter we have evidenced the performance of a range of dynamic panel estimators subject to various theoretical sample conditions. Prior to concluding, in this section we provide a brief discussion on the empirical implications of our findings. Specifically, throughout the course of this chapter we have documented the economic implications of our dynamic panel estimators by reporting the associated SOA for each simulation. However, in this section, we stress further the empirical implications of such results, and how, with regards to corporate financial policies, the empirical implications for researchers are significant.

One of the main takeaways from our simulation study is that the degree of dynamic persistence is a key driver in estimator performance, with all most all estimators reporting reductions in consistency and efficiency as the autoregressive parameter approaches unity. Not only is this of significant relevance, with most corporate financial policies being highly persistent - e.g., capital structure and corporate payout policy - but also, given the autoregressive coefficient's inverse relationship with the SOA, biased estimates of the autoregressive coefficient when λ is highly persistence also yields the most spurious economic conclusions. To illustrate, let us consider the bias arsing from our first experiment where the time-series length T is reduced to $T = 6$. As shown in Appendix Table A.2.7, when $\lambda = 0.8$ the true SOA of adjustment is 20%, thus, implying that firms, on average, take 5 years to adjust towards their optimal corporate financial policy. From our simulations, the FD-GMM and SYS-GMM report an implied SOA of 43.22% and 12.05% indicating that firms adjust towards their optimal corporate financial policy approximately every 2.3 years and 8.3 years, respectively. In contrast, the preferred LSDVC and QML estimators report implied adjustment speeds of 23.15% and 22.87%, respectively, thus, suggesting that firms adjust towards their optimal corporate policy in approximately 4.4, a considerably more accurate representation of the true SOA.

Despite the superior statistical qualities of the LSDVC and QML estimators, their application in the corporate finance literature is extremely scarce (Flannery and Hankins 2013, Dang et al. 2015 and Hayakawa and Pesaran 2015). Arguably, one of the biggest drawbacks of the LSDVC estimator is a practical one. In order to compute the bias correction and the bootstrapped variance covaraince matrix, the LSDVC estimator has an extremely high computational demand, which when partnered with the size of corporate finance datasets - in some instances more than 100,000 observations - the estimation of the LSDVC estimator on a standard desktop computer becomes almost a perpetual issue. In contrast, the QML estimator does not require such computing power, however, its lack of use may indeed stem from the prior restrictive assumptions imposed by Hsiao et al. (2002) for example, the requirement for idiosyncratic errors to be homoskedastic. Nevertheless, recent progress in the area of fixed-effect QML estimation has seen a number extensions allowing for heteroskedastic errors (Hayakawa and Pesaran, 2015) unbalanced panels (Kripfganz, 2016) and models beyond the AR(1) process (Binder et al., 2005). Subsequently, given the favourable performance of the QML estimator evidenced in this chapter over the GMM estimators and, in certain cases, the LSDVC estimator, we advance its employment for the empirical corporate finance setting and in turn validating its need for inclusion in this chapter and the wider literature.

2.6 Concluding Remarks

The primary aim of this chapter was to investigate the economic implications of estimator choice in the context of the corporate finance literature. We find the autoregressive coefficient to vary across estimator choice and panel data properties. More precisely, our analysis uncovers that the degree of dynamic persistence in the dependent variable is a key driver of estimator performance, with highly persistence data proving most problematic in the corporate finance setting. Furthermore, our study verifies that common varying characteristic's of corporate finance datasets, such as: panel dimensions, cross-sectional heterogeneity and panel unbalancedness, all pose unique problems for researchers employing dynamic panel data models.

Over the duration of this chapter, we find the LSDVC and QML estimators are generally the most robust methods for estimating dynamic panel data models in the corporate finance setting. These estimator, on average, estimate the autoregressive coefficient with the highest degree of accuracy and in turn provide the most concise approximation of the true SOA. Moreover, both estimators display rigor and robustness to changes in key fixed parameters, with the LSDVC estimator performing favourably to high levels of cross-sectional heterogeneity and the QML estimator proving advantageous in cases of small and unbalanced panels.

In contrast, we find at high levels of dynamic persistence the GMM estimators perform poorly across experiments, with the FD- and SYS-GMM estimators proving highly sensitive to changes in key fixed parameters. Thus, the growing evidence on the frailties of the GMM estimators leaves us with concern on the accuracy of forgone empirical studies that employ such approaches, especially when the degree of persistence is high. Finally, in specific cases, when the dependent variable of interest is indeed fractional, our simulations uncover that the DPF estimator is most preferable, with the body of previous estimators being highly sensitive to the degree of censoring in the dependent variable.

All in all, this chapter clearly illustrates how failing to adequately account for dynamic panel data model complexities can give rise erroneous economics conclusions. Subsequently, this chapter presents a comprehensive argument to why much of the capital structure and corporate payout policy literature have yielded vastly disparate economic conclusions on the speed of financial policy adjustment. Going forward, practitioners should strongly consider the LSDVC, QML and DPF estimators as preferable alternatives to the traditional and GMM estimators due to their superior statistical performance. Incorporation of such methods should hopefully bring consensus to one of the oldest empirical debates with corporate finance.

2.7 Appendix

Table A.2.1: Experiment One: The impact of changes in time-series length

		$T = 6$				$T = 18$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.116	0.012	0.117	0.000	0.030	0.006	0.031	0.000
	FE	0.007	0.011	0.013	0.894	0.005	0.005	0.007	0.844
	FD-GMM	0.003	0.032	0.041	0.948	-0.004	0.013	0.010	0.834
	AS-GMM	-0.001	0.022	0.024	0.954	-0.005	0.013	0.010	0.828
	SYS-GMM	0.005	0.014	0.041	0.914	-0.004	0.007	0.009	0.808
	LD4	-0.662	0.665	0.792	0.154	-0.625	0.040	0.216	0.000
	LSDVC	0.002	0.011	0.013	1.000	0.000	0.005	0.006	1.000
	QML	0.001	0.011	0.012	0.956	0.000	0.005	0.005	0.956
$\beta = 0.5$	OLS	0.074	0.009	0.074	0.000	0.018	0.004	0.019	0.010
	FE	0.002	0.009	0.009	0.946	0.006	0.004	0.007	0.730
	FD-GMM	0.017	0.036	0.095	0.916	-0.002	0.010	0.012	0.860
	AS-GMM	-0.002	0.024	0.051	0.930	-0.003	0.010	0.011	0.830
	SYS-GMM	0.008	0.012	0.103	0.860	-0.003	0.006	0.011	0.810
	LD4	-0.284	0.205	0.318	0.048	-0.333	0.022	0.100	0.000
	LSDVC	0.004	0.009	0.015	1.000	0.000	0.004	0.007	1.000
	QML	0.001	0.009	0.017	0.956	0.000	0.004	0.006	0.964
$\beta = 0.2$	OLS	0.038	0.007	0.038	0.000	0.012	0.003	0.013	0.036
	FE	-0.009	0.007	0.011	0.768	0.004	0.003	0.005	0.832
	FD-GMM	0.034	0.034	0.305	0.796	0.001	0.007	0.025	0.886
	AS-GMM	-0.005	0.018	0.084	0.896	-0.001	0.007	0.018	0.856
	SYS-GMM	0.004	0.010	0.081	0.926	-0.003	0.005	0.017	0.832
	LD4	-0.111	0.056	0.201	0.004	-0.114	0.007	0.023	0.000
	LSDVC	0.002	0.007	0.036	1.000	0.000	0.003	0.010	1.000
	QML	-0.001	0.007	0.038	0.954	0.000	0.003	0.009	0.958

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\lambda = 1 - \beta, \rho = 0.5, \zeta = 5$ & $\mu = 1$ and all reported simulations are configured for $N = 500$ with a repetition rate of 500.

Table A.2.2: Experiment Two: The impact of changes in cross-sectional size

		$N = 100$				$N = 250$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.051	0.018	0.054	0.148	0.051	0.011	0.052	0.000
	FE	0.008	0.015	0.017	0.902	0.008	0.009	0.012	0.866
	FD-GMM	0.000	0.034	0.032	0.742	-0.002	0.023	0.021	0.884
	AS-GMM	-0.002	0.037	0.033	0.626	-0.004	0.022	0.019	0.856
	SYS-GMM	-0.002	0.020	0.027	0.648	-0.004	0.013	0.017	0.840
	LD4	-0.651	0.150	0.297	0.000	-0.636	0.082	0.244	0.000
	LSDVC	0.001	0.015	0.016	1.000	0.001	0.009	0.010	1.000
	QML	0.001	0.015	0.016	0.934	0.001	0.009	0.009	0.954
$\beta = 0.5$	OLS	0.032	0.014	0.035	0.286	0.032	0.008	0.033	0.018
	FE	0.008	0.013	0.015	0.888	0.008	0.008	0.011	0.832
	FD-GMM	0.005	0.028	0.045	0.756	0.002	0.020	0.030	0.874
	AS-GMM	-0.002	0.029	0.036	0.640	-0.003	0.018	0.022	0.856
	SYS-GMM	-0.001	0.017	0.033	0.638	-0.003	0.011	0.026	0.832
	LD4	-0.354	0.094	0.195	0.000	-0.342	0.049	0.134	0.000
	LSDVC	0.002	0.013	0.018	1.000	0.001	0.008	0.012	1.000
	QML	0.001	0.013	0.017	0.936	0.001	0.008	0.011	0.958
$\beta = 0.2$	OLS	0.019	0.006	0.020	0.110	0.019	0.010	0.022	0.478
	FE	0.003	0.006	0.007	0.922	0.003	0.010	0.011	0.906
	FD-GMM	0.008	0.015	0.076	0.816	0.013	0.022	0.115	0.678
	AS-GMM	0.000	0.014	0.038	0.852	0.002	0.021	0.058	0.604
	SYS-GMM	-0.002	0.009	0.037	0.854	0.000	0.014	0.037	0.634
	LD4	-0.117	0.018	0.070	0.000	-0.123	0.036	0.150	0.000
	LSDVC	0.001	0.006	0.017	1.000	0.002	0.010	0.024	1.000
	QML	0.000	0.006	0.018	0.954	0.001	0.010	0.026	0.932

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\lambda = 1 - \beta, \rho = 0.5, \zeta = 5$ and $\mu = 1$ and all reported simulations are configured $T = 12$ with a repetition rate of 500.

Table A.2.3: Experiment Three: Varying factor loading

		$\mu = 1$				$\mu = 3$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	-0.061	0.009	0.061	0.000	-0.014	0.010	0.018	0.694
	FE	0.007	0.007	0.010	0.798	0.008	0.007	0.010	0.782
	FD-GMM	-0.001	0.015	0.013	0.922	-0.001	0.016	0.018	0.930
	AS-GMM	-0.002	0.015	0.013	0.914	-0.005	0.017	0.018	0.870
	SYS-GMM	-0.003	0.009	0.009	0.882	-0.003	0.009	0.018	0.908
	LD4	-0.630	0.054	0.225	0.000	-0.708	0.262	0.428	0.006
	LSDVC	0.000	0.007	0.007	1.000	0.000	0.007	0.007	1.000
	QML	0.000	0.007	0.007	0.954	0.001	0.007	0.007	0.946
$\beta = 0.5$	OLS	-0.027	0.006	0.028	0.004	0.007	0.007	0.010	0.810
	FE	0.007	0.005	0.009	0.744	0.008	0.006	0.009	0.710
	FD-GMM	0.001	0.013	0.018	0.916	-0.001	0.014	0.025	0.940
	AS-GMM	-0.001	0.013	0.016	0.910	-0.007	0.014	0.024	0.856
	SYS-GMM	-0.003	0.007	0.010	0.884	-0.002	0.008	0.049	0.902
	LD4	-0.335	0.030	0.106	0.000	-0.434	0.129	0.335	0.000
	LSDVC	0.000	0.006	0.009	1.000	0.002	0.006	0.008	1.000
	QML	0.000	0.006	0.009	0.942	0.001	0.006	0.008	0.952
$\beta = 0.2$	OLS	-0.005	0.004	0.007	0.758	0.017	0.005	0.018	0.028
	FE	0.002	0.004	0.005	0.902	0.003	0.005	0.005	0.896
	FD-GMM	0.003	0.009	0.033	0.910	0.004	0.012	0.061	0.914
	AS-GMM	0.001	0.009	0.027	0.908	-0.010	0.013	0.076	0.682
	SYS-GMM	-0.002	0.006	0.013	0.898	0.000	0.007	0.093	0.900
	LD4	-0.115	0.009	0.029	0.000	-0.128	0.049	0.225	0.000
	LSDVC	0.000	0.004	0.018	1.000	0.004	0.005	0.009	1.000
	QML	0.000	0.004	0.015	0.952	0.000	0.005	0.014	0.956

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\lambda = 1 - \beta, \rho = 0.5$ and $\zeta = 5$ and all reported simulations are configured $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table A.2.4: Experiment Four: Varying Signal Noise

		$\zeta = 2$				$\zeta = 8$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.075	0.011	0.076	0.000	0.044	0.006	0.044	0.000
	FE	0.014	0.011	0.018	0.716	0.005	0.005	0.008	0.820
	FD-GMM	-0.001	0.024	0.019	0.920	0.000	0.013	0.013	0.936
	AS-GMM	-0.004	0.023	0.017	0.892	-0.002	0.012	0.012	0.918
	SYS-GMM	-0.004	0.014	0.016	0.906	-0.001	0.007	0.010	0.918
	LD4	-0.501	0.031	0.077	0.000	-0.844	0.135	0.487	0.000
	LSDVC	0.001	0.011	0.011	1.000	0.001	0.005	0.006	1.000
	QML	0.001	0.011	0.009	0.950	0.001	0.005	0.006	0.944
$\beta = 0.5$	OLS	0.050	0.009	0.051	0.000	0.027	0.005	0.027	0.000
	FE	0.013	0.009	0.016	0.668	0.005	0.004	0.007	0.746
	FD-GMM	0.001	0.020	0.024	0.924	0.002	0.011	0.020	0.926
	AS-GMM	-0.003	0.020	0.019	0.890	-0.001	0.010	0.013	0.922
	SYS-GMM	-0.003	0.013	0.022	0.904	-0.001	0.006	0.019	0.910
	LD4	-0.298	0.021	0.046	0.000	-0.380	0.049	0.188	0.000
	LSDVC	0.001	0.009	0.013	1.000	0.001	0.004	0.008	1.000
	QML	0.001	0.009	0.011	0.956	0.001	0.004	0.007	0.944
$\beta = 0.2$	OLS	0.040	0.015	0.043	0.256	0.015	0.003	0.016	0.006
	FE	0.005	0.018	0.018	0.916	0.002	0.003	0.004	0.902
	FD-GMM	0.005	0.033	0.028	0.916	0.006	0.008	0.059	0.848
	AS-GMM	0.001	0.033	0.022	0.902	0.000	0.007	0.027	0.916
	SYS-GMM	0.000	0.024	0.016	0.904	0.000	0.004	0.052	0.898
	LD4	-0.113	0.021	0.024	0.000	-0.122	0.019	0.094	0.000
	LSDVC	0.001	0.018	0.025	1.000	0.001	0.003	0.011	1.000
	QML	0.001	0.017	0.018	0.958	0.000	0.003	0.014	0.956

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\lambda = 1 - \beta, \rho = 0.5$ and $\mu = 1$ and all reported simulations are configured $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table A.2.5: Experiment Five: Varying Panel Balance

		$\omega = 50\%$				$\omega = 70\%$				$\omega = 90\%$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.043	0.010	0.044	0.014	0.049	0.009	0.049	0.000	0.051	0.008	0.052	0.000
	FE	0.009	0.010	0.013	0.860	0.008	0.008	0.012	0.796	0.008	0.007	0.010	0.798
	FD-GMM	0.003	0.027	0.028	0.834	0.002	0.021	0.021	0.892	0.000	0.017	0.016	0.916
	AS-GMM	0.000	0.024	0.023	0.852	-0.001	0.019	0.018	0.898	-0.003	0.016	0.014	0.916
	SYS-GMM	-0.003	0.015	0.018	0.830	-0.003	0.011	0.014	0.874	-0.002	0.009	0.011	0.898
	LD	-0.646	0.148	0.293	0.000	-0.639	0.091	0.252	0.000	-0.630	0.064	0.230	0.000
	LSDVC	0.001	0.011	0.013	1.000	0.001	0.008	0.010	1.000	0.001	0.007	0.008	1.000
	QML	-0.002	0.011	0.011	0.944	-0.001	0.008	0.008	0.950	0.000	0.007	0.007	0.950
$\beta = 0.5$	OLS	0.026	0.008	0.028	0.082	0.030	0.007	0.031	0.006	0.032	0.006	0.032	0.000
	FE	0.006	0.008	0.010	0.896	0.007	0.007	0.010	0.786	0.007	0.006	0.009	0.742
	FD-GMM	0.007	0.023	0.040	0.786	0.004	0.018	0.029	0.868	0.002	0.014	0.022	0.912
	AS-GMM	0.002	0.020	0.029	0.814	0.000	0.016	0.022	0.908	-0.002	0.013	0.016	0.922
	SYS-GMM	-0.003	0.012	0.024	0.820	-0.002	0.010	0.018	0.874	-0.001	0.008	0.017	0.890
	LD	-0.350	0.088	0.187	0.000	-0.347	0.052	0.148	0.000	-0.341	0.036	0.123	0.000
	LSDVC	0.001	0.009	0.017	1.000	0.001	0.007	0.013	1.000	0.001	0.006	0.011	1.000
	QML	-0.005	0.009	0.015	0.914	-0.002	0.007	0.010	0.938	0.000	0.006	0.008	0.950
$\beta = 0.2$	OLS	0.017	0.006	0.018	0.174	0.018	0.005	0.019	0.032	0.019	0.004	0.019	0.010
	FE	-0.003	0.007	0.007	0.932	0.000	0.006	0.006	0.944	0.002	0.005	0.005	0.896
	FD-GMM	0.014	0.018	0.098	0.702	0.009	0.014	0.067	0.804	0.007	0.011	0.057	0.856
	AS-GMM	0.005	0.015	0.054	0.794	0.003	0.012	0.039	0.862	0.000	0.010	0.029	0.916
	SYS-GMM	0.000	0.010	0.031	0.824	0.000	0.008	0.032	0.868	0.000	0.007	0.035	0.900
	LD	-0.121	0.033	0.141	0.000	-0.122	0.023	0.110	0.000	-0.117	0.013	0.060	0.000
	LSDVC	0.001	0.008	0.032	1.000	0.001	0.006	0.025	1.000	0.001	0.005	0.017	1.000
	QML	-0.008	0.007	0.030	0.804	-0.005	0.006	0.018	0.872	0.000	0.005	0.012	0.954

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\lambda = 1 - \beta, \rho = 0.5, \zeta = 5$ and $\mu = 1$ and all reported simulations are configured $N = 500$ with a repetition rate of $R = 500$.

Table A.2.6: Experiment Six: Varying Percentage of Censored Observations

		$C \approx 25\%$				$C \approx 10\%$				$C \approx 5\%$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	-0.241	0.011	0.242	0.000								
	FE	-0.233	0.010	0.233	0.000								
	FD-GMM	-0.239	0.011	0.050	0.000								
	AS-GMM	-0.238	0.011	0.048	0.000								
	SYS-GMM	-0.239	0.011	0.045	0.000								
	LD4	-0.814	0.017	0.050	0.000								
	LSDVC	-0.230	0.010	0.035	1.000								
	QML	-0.231	0.010	0.046	0.000								
	DPF	0.002	0.007	0.011	0.944								
$\beta = 0.5$	OLS	-0.166	0.010	0.166	0.000	-0.106	0.008	0.107	0.000				
	FE	-0.166	0.009	0.166	0.000	-0.101	0.007	0.102	0.000				
	FD-GMM	-0.172	0.011	0.081	0.000	-0.102	0.009	0.061	0.000				
	AS-GMM	-0.172	0.011	0.074	0.000	-0.102	0.009	0.053	0.000				
	SYS-GMM	-0.143	0.012	0.080	0.000	-0.088	0.009	0.019	0.000				
	LD4	-0.582	0.019	0.042	0.000	-0.592	0.019	0.040	0.000				
	LSDVC	-0.143	0.009	0.044	1.000	-0.084	0.007	0.022	1.000				
	QML	-0.162	0.009	0.063	0.000	-0.097	0.007	0.052	0.000				
	DPF	0.001	0.007	0.014	0.938	0.002	0.006	0.012	0.946				
$\beta = 0.2$	OLS	-0.071	0.006	0.072	0.000	-0.051	0.006	0.052	0.000	-0.024	0.005	0.025	0.000
	FE	-0.070	0.005	0.070	0.000	-0.048	0.005	0.049	0.000	-0.015	0.005	0.015	0.363
	FD-GMM	-0.074	0.007	0.161	0.000	-0.050	0.007	0.097	0.000	-0.011	0.007	0.020	0.490
	AS-GMM	-0.073	0.007	0.149	0.000	-0.050	0.007	0.092	0.000	-0.012	0.007	0.018	0.496
	SYS-GMM	-0.044	0.007	0.041	0.000	-0.026	0.007	0.045	0.014	-0.005	0.006	0.041	0.393
	LD4	-0.398	0.021	0.098	0.000	-0.403	0.022	0.116	0.000	-0.415	0.022	0.141	0.000
	LSDVC	-0.059	0.006	0.011	1.000	-0.036	0.005	0.033	1.000	-0.001	0.005	0.062	1.000
	QML	-0.068	0.005	0.102	0.000	-0.046	0.005	0.068	0.000	-0.010	0.005	0.019	0.500
	DPF	0.002	0.006	0.009	0.934	0.003	0.006	0.009	0.902	0.004	0.005	0.011	0.300

Source: Author's own calculation.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005), QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002) and finally the DPF estimator is the dynamic panel fractional variable estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error and Wald is the non-rejection percentage at the 5% significance level of a Wald test with the null hypothesis set to the equality. Fixed parameters are set to $\lambda = 1 - \beta$,, $\alpha_0 = 0.1$, $\alpha_1 = 0.1$ and $\sigma_u = 0.01$.and all reported simulations are configured $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table A.2.7: Experiment One: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$T = 6$	80.00%	55.73%	86.21%	80.50%	79.87%	76.58%	55.05%	80.59%	80.13%
	50.00%	32.95%	61.40%	55.07%	50.34%	40.06%	50.34%	50.37%	51.01%
	20.00%	12.94%	47.37%	43.22%	19.84%	12.05%	25.47%	23.15%	22.87%
$T = 18$	80.00%	64.23%	81.62%	79.89%	79.76%	79.52%	58.88%	80.19%	80.05%
	50.00%	36.40%	53.72%	50.65%	50.23%	48.68%	39.40%	50.57%	50.36%
	20.00%	14.38%	26.88%	21.88%	21.11%	18.62%	18.82%	20.70%	20.62%

Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Table A.2.8: Experiment Two: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$N = 100$	80.00%	60.85%	82.51%	80.53%	79.49%	78.84%	56.08%	80.18%	80.03%
	50.00%	35.75%	54.42%	52.01%	49.88%	48.23%	37.43%	50.44%	50.38%
	20.00%	13.65%	31.20%	28.85%	22.34%	18.58%	15.16%	20.85%	20.93%
$N = 250$	80.00%	60.72%	82.52%	80.14%	79.64%	78.95%	57.67%	80.27%	80.04%
	50.00%	35.67%	54.45%	51.16%	50.13%	47.95%	39.21%	50.59%	50.41%
	20.00%	13.62%	31.22%	25.76%	21.74%	16.76%	17.96%	21.00%	21.01%

Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Table A.2.9: Experiment Three: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\mu = 1$	80.00%	66.33%	82.62%	80.20%	80.06%	79.91%	58.47%	80.13%	80.13%
	50.00%	42.09%	54.53%	50.96%	50.72%	50.23%	40.61%	50.50%	50.49%
	20.00%	17.47%	31.28%	22.57%	21.97%	20.52%	19.41%	21.56%	21.08%
$\mu = 3$	80.00%	30.33%	82.55%	80.08%	79.33%	78.78%	49.39%	80.19%	80.06%
	50.00%	17.25%	54.46%	50.27%	48.65%	45.45%	24.14%	50.15%	50.41%
	20.00%	6.24%	31.20%	23.01%	15.05%	10.73%	12.91%	19.97%	20.98%

Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Table A.2.10: Experiment Four: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\zeta = 2$	80.00%	64.06%	84.72%	80.16%	79.80%	79.12%	73.10%	80.50%	80.03%
	50.00%	38.68%	57.84%	50.75%	50.11%	48.31%	46.47%	50.76%	50.27%
	20.00%	18.58%	38.65%	21.09%	20.38%	19.55%	19.79%	22.06%	20.05%
$\zeta = 8$	80.00%	59.50%	81.76%	80.15%	79.85%	79.42%	33.88%	80.23%	80.07%
	50.00%	34.66%	53.22%	51.03%	50.36%	48.38%	32.96%	50.57%	50.46%
	20.00%	12.65%	28.25%	24.76%	21.43%	14.94%	15.65%	20.73%	21.17%

Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Table A.2.11: Experiment Five: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\omega = 50\%$	80.00%	60.10%	84.83%	80.59%	79.98%	79.63%	56.50%	80.63%	80.14%
	50.00%	35.02%	58.01%	51.81%	50.57%	49.12%	37.97%	51.00%	50.76%
	20.00%	13.13%	38.62%	27.37%	23.24%	18.34%	15.97%	22.51%	22.37%
$\omega = 70\%$	80.00%	60.25%	83.39%	80.32%	79.87%	79.81%	57.23%	80.56%	80.08%
	50.00%	35.14%	55.70%	51.02%	50.12%	49.24%	38.09%	50.92%	50.36%
	82.00%	13.22%	34.31%	24.62%	21.57%	17.37%	14.93%	22.05%	21.12%
$\omega = 90\%$	80.00%	60.51%	82.62%	80.15%	79.78%	79.61%	58.30%	80.42%	80.00%
	50.00%	43.13%	68.62%	57.37%	53.24%	48.34%	45.97%	52.51%	52.37%
	20.00%	13.47%	31.49%	24.22%	21.20%	16.75%	16.84%	21.29%	20.36%

Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Table A.2.12: Experiment Six: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML	DPF
$C \approx 30\%$	80%	57.98%	87.91%	84.86%	84.68%	84.36%	83.27%	83.41%	84.49%	79.38%
	50%	10.48%	62.60%	57.81%	57.17%	42.19%	52.33%	45.74%	56.24%	49.16%
	20%	1.87%	35.50%	36.06%	34.85%	16.07%	10.70%	19.22%	30.18%	19.82%
$C \approx 20\%$	50%	24.03%	61.05%	55.83%	55.07%	49.03%	51.72%	48.05%	55.11%	49.41%
	20%	3.20%	32.85%	29.60%	29.15%	15.63%	8.85%	16.84%	26.78%	19.78%
$C \approx 10\%$	20%	10.51%	29.83%	21.54%	21.36%	16.02%	6.15%	13.83%	21.62%	19.35%

Source: Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005), QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002) and finally the DPF estimator is the dynamic panel fractional variable estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015).The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Chapter 3

Leverage Dynamics over the Business Cycle: New Evidence from India

Abstract: *In this chapter we investigate the leverage dynamics of Indian listed firms over the business cycle. Using a unbalanced panel of 2,650 Indian listed firms over 1997-2017, we propose a novel single-step model specification that allows for simultaneous estimation of firm-specific and macroeconomic adjustment costs allowing for cross-sectional and time-variant adjustment speeds. Our results show Indian listed firms adjust quicker in periods of high GDP growth (29.80%) relative to low GDP growth (22.90%), of which, firms in the highest quartiles of the market-to-book ratio and profitability adjust asymmetrically, adjusting upwards of 40% in high growth regimes and downwards towards 30% in low growth regimes. Overall, our results provide new evidence of both cross-sectional and time-varying asymmetries in capital structure adjustments in a developing market context, which are consistent with the dynamic trade-off theory.*

3.1 Introduction

Since Modigliani and Miller's (1958) irrelevance theorem, the corporate finance literature has debated the importance of capital structure decisions in the presence of capital market frictions and imperfections (e.g., corporate and personal taxation, imperfect information and agency problems). Naturally, while opinions differ, the leading view of capital structure, the trade-off theory, asserts that firms seek to maintain an optimal capital structure that balances the costs and benefits associated with corporate leverage (Fischer et al. 1989; Flannery and Rangan 2006; Frank and Goyal 2009; Huang and Ritter 2009; Faulkender et al. 2012). Moreover, in the event of target deviation, the trade-off theory posits that value maximising firms seek to re-balance their corporate leverage as they look to return to their optimal capital structure. Yet, if the costs of recapitalization exceed the benefits of readjustment, firms may look to prolong their excursion rather than forcing an immediate return to their target leverage (Leary and Roberts 2005; Strebulaev 2007). The empirical implications of such actions follow that in an dynamic framework, corporate leverage should exhibit mean reversion as firms - of whom often face a gamut of distinct adjustment costs - aim to revert to their optimal capital structure target. Subsequently, an enormous number of empirical studies have attempted to examine the speed in which firms adjust their corporate leverage via dynamic partial adjustment models.

In an attempt to shed light on the divergence of firms' capital structure adjustment speeds, an abundance of empirical studies have approximated the asymmetric adjustment costs faced by firms via a range of firm-specific characteristics, for example: firm size (Drobetz and Wanzenried, 2006), target deviation (Byoun, 2008), the market-to-book ratio (Elsas and Florysiak, 2011), absolute financing deficit (Faulkender et al., 2012) profitability (Dang et al., 2012) and credit ratings (Wojewodzki et al., 2018). While the literature associated with cross-sectional heterogeneity and asymmetric adjustment costs is well established and indeed plentiful, surprisingly little is known about the leverage dynamics of firms over the course of the business cycle (Korteweg and Strebulaev, 2013). Furthermore, the theoretical and empirical evidence in this area has yielded vastly disparate economic conclusions, with theoretical and empirical ambiguities being largely model dependent (Halling et al., 2016). On one hand, Korteweg and Strebulaev (2013) claim that the leverage ratios of US firms evolve pro-cyclically with Cook and Tang (2010), Dang et al. (2014) and Drobetz et al. (2015) all reporting faster adjustment speeds in periods of higher economic growth. On the other hand, the more recent work of Halling et al. (2016) argues that once cyclicality is correctly parameterized, the target leverage ratios of US firms evolve counter-cyclically, with only a small proportion of firms reporting pro-cyclical behaviour.

Given such disparities, the purpose of this chapter is to provide new empirical evidence on the corporate leverage dynamics of firms over the course of the business cycle by investigating the capital structure dynamics of Indian listed firms. Specifically, to contribute new insights to the literature, this chapter brings together both the cross-sectional and time-series elements of the heterogeneous adjustment speed literature to present a systematic investigation of how firms facing opposing adjustment costs adjust their corporate leverage over the business cycle.

Understanding the factors that govern the adjustment of firms corporate leverage is not only important at the firm level for managers and investors, but also, because the ineffective management of corporate leverage can have significant repercussions for the wider economy. For example, in periods of economic downturn, under-leveraged firms with limited internal funds may have to pass up on positive investment opportunities if they are unable to raise external capital due to costly market frictions, thus, slowing the route of macroeconomic recovery. Alternatively, over-leveraged firms that are unable to smoothly adjust their existing debt obligations may expose themselves to heighten financial distress costs which could result in corporate bankruptcy and consequently deeper macroeconomic decline.

Despite the saliency of firms capital structure adjustment process, almost exclusively the majority of the aforementioned studies have focused on the adjustment processes of firms residing developed bank-based and/or market-based economies, where capital market imperfections and frictions are somewhat trivial[1]. In contrast, emerging economies, such as India, are characterised by a more pervasive market failures that make the adjustments costs faced by firms considerably more severe, thus, making the process of leverage adjustment significantly slower (Öztekin and Flannery, 2012). Moreover, over the course of the business cycle, one can hypothesise that the economic pass-through of exogenous macroeconomic shocks to firm-specific adjustment costs is likely to be more pronounced in less developed institutional environments, where capital market frictions, agency problems and information asymmetries are more prevalent and shock absorbing government mechanism are limited. Accordingly, given such premises, this chapter aims to provide new evidence from an emerging market context in an attempt to shed light on leverage dynamics of firms.

Using an unbalanced panel of 2,650 Indian listed firms over the period of 1997-2017 we investigate how three firm-specific measures of adjustment heterogeneity, namely, absolute financing deficit (e.g. Faulkender et al. 2012), the market-to-book ratio (e.g. Elsas and Florysiak 2011) and profitability (e.g. Dang et al. 2012) impact the speed of adjustment over high and low periods of GDP growth, which we classify via OCED business cycle indicator's. We focus of such firm-specific measures for two important reasons. First, variances in said measures reflect some of the most significant adjustment cost asymmetries faced by firms and are therefore three of the most commonly analysed sources of cross-sectional adjustment speed heterogeneity. Second, and more importantly, unlike other potential candidates that have proved prominent in the literature - e.g., firm size, firm age and credit ratings - a firms absolute financing deficit, the market-to-book ratio and level of profitability are largely time-variant, thus, changes in macroeconomic conditions, market confidence and ultimately economic growth are all likely to have direct impacts on

[1]Note: Halling et al. (2016) as a form of robustness test illustrate their findings through an international sample of 18 countries namely, Australia, Austria, Brazil, Canada, France, Germany, India, Italy, Japan, Korea, Mexico, New Zealand, Spain, Sweden, Switzerland, Taiwan, the UK and the US. Therefore while implicitly they assess capital structure dynamics over the business cycle in a developing context, the pooling of firms remains that's we are the first to explicitly assess simultaneous asymmetries.

the levels of such variables and therefore the adjustment costs firms face over the course of the business cycle.

Building on the recent studies of Drobetz et al. (2015) and Halling et al. (2016), this chapter proposes a single-step model specification that allows for the simultaneous estimation of firm-specific adjustment costs over the two proposed macroeconomic regimes, whilst also controlling for heterogeneous leverage targeting and unobserved time-invariant factors. More explicitly, we adapt the traditional dynamic partial adjustment model via a quartile dummy variable approach, accounting for distinct firm-group adjustment costs, and thereafter we extend our specification via a regime switching mechanism to account for both high and low periods of GDP growth. Furthermore, based on the insights of Chapter 2, we estimate our single-step specification via the DPF estimator of Elsas and Florysiak (2015), which not only takes into account the fractional nature of our dependent variable, the market debt ratio, but also, most accurately estimates the true SOA (Elsas and Florysiak 2015; Dang et al. 2015).

To set the scene, we first examine the traditional dynamic partial adjustment model specification and establish the consistently of our three firm-specific measures of asymmetric adjustment cost relative to the existing literature. We find the typical Indian firm adjusts unconditionally towards their optimal target at 26.90% per annum, therefore, closing the gap between sub-optimal and optimal target leverage by approximately one quarter each year. Moreover, consistent with the literature, we find that firms with the highest market-to-book values and profitability levels adjust both significantly and economically faster than their counterparts, closing the distance towards target leverage by greater than one third each year. We document that firms with the highest absolute financing deficit also adjust significantly faster than there better balanced counterparts, however, the economic difference is economically smaller, with such firms only adjusting 3.70% faster.

With out our initial findings in place, we address our main research objective by examining how firms adjust their leverage over the course of the business cycle and how the role of the business cycle effects the adjustment speeds of firms facing opposing firm-specific adjustment costs. We document that the average Indian listed firm to adjust quicker in periods of high GDP growth (29.80%) relative to low GDP growth (22.90%) supporting the pro-cyclical view that more prosperous macroeconomic conditions help to alleviate market frictions corresponding with adjustment costs. In fact, the effect of macroeconomic performance is close to twice the 4% difference reported by Cook and Tang (2010) in the US, therefore, illustrating the greater importance of macroeconomic performance in a developing market context. Next, by combining firm-specific adjustment costs with the regime switching mechanism, we find that the measure of absolute financing deficit displays little conditional sensitivity across macroeconomic regimes. In contrast, our measures of the market-to-book ratio and profitability provide economically the most distinctive results. We report that firms in the highest quartile of the market-to-book ratio and profitability adjust at 43.60% and 41.40% in high growth periods relative to 32.40% and 27.20% in low periods, respectively. Accordingly, these findings suggest the adverse selection costs for such firms, i.e. the cost of issuing (retiring) securities and the relative cost of internal and external finance, decreases the most in periods of economic upturn. Overall, the results presented in this chapter prove that, on average, both cross-sectional heterogeneity in firm-specific characteristics and time-series variation in macroeconomic performance matters for the capital structure adjustment process of Indian listed firms. More precisely, the impact of such macroeconomic shocks are asymmetrically transmitted across firms with the SOA proving pro-cyclical, thus, supporting the work of Cook and Tang (2010), Dang et al. (2014) and Drobetz et al. (2015) and more generally the dynamic trade-off theory.

Based on the analysis undertaken in this chapter, we make two important contributions to the literature. First, our study provides the first evidence of firm-specific adjustment asymmetries for Indian listed firms over the business cycle[2]. At a broader level, the literature on heterogeneous adjustment speeds has predominantly focused on either firm-specific characteristics or macroeconomic conditions, however, it has more widely neglected the role of both factors in conjunction with one another. Therefore, this chapter contributes to the recent work of Dang et al. (2014) and Halling et al. (2016) by assessing both sources of adjustment cost heterogeneity simultaneously. Our second contribution is methodological and manifests itself in two distinct ways. Unlike the proposed approach of Dang et al. (2014), our empirical approach allows for single-step estimation of firm-specific adjustment costs over opposing macroeconomic regimes and is therefore free of the generated regressors problem and associated complexities of accurate second-stage inference. Furthermore, this chapter accounts for the recent econometric advancements in dynamic panel data models by applying the DPF estimator of Elsas and Florysiak (2015). In doing so, we account for the fractional nature of the dependent variable and mechanical mean reversion. Our estimation approach therefore provides the least biased estimates of the autoregressive coefficient and the most accurate estimates of the true SOA. Consequently, our documentation of adjustment speed heterogeneity can be considered more precise than the

[2]Note: While the recent work of Bandyopadhyay and Barua (2016) examines the direct effect of the business cycle on the level of corporate leverage, we are, to the best of our knowledge, the first to examine the adjustment of Indian firms' corporate leverage over the course of the business cycle.

biased approaches previous employed by Fama and French (2002), Flannery and Rangan (2006), Kayhan and Titman (2007), Dang et al. (2012), Dang et al. (2014), Halling et al. (2016) and Baum et al. (2017).

The remainder of the chapter is structured as follows. Section 3.2 provides a brief review of relevant literature. Section 3.3 details our extension of the dynamic partial adjustment model and model predictions. Section 3.4 introduces our dataset and provides summary statistics. Section 3.5 reports our empirical findings. Section 3.6 documents our robustness analysis and Section 3.7 concludes.

3.2 Related Literature

The dynamics of corporate leverage have been a central issue in the corporate finance literature for more than half a century. In the presence of capital market frictions and imperfections three predominate theories have come to light, namely, the trade-off theory, the pecking order theory and the market timing theory. The trade-off theory is premised on the notion of an optimal capital structure, wherein managers look balance the costs and benefits of debt and equity. For example, managers often look to balance the tax benefits of debt against the dead weight cost of bankruptcy resulting in what is often refereed to as the tax-bankruptcy trade-off. In contrast, neither the pecking order or the market timing theory advocate the notion of an optimal capital structure. The former predicts a firms capital structure reflects asymmetric information between firms and financial institutions (Jensen, 1986) where the latter suggests a firms corporate leverage is nothing more than the historic sum of opportunistic managerial dealings in capital markets (Baker and Wurgler, 2002)[3].

In order to find a winner in this horse race, early empirical literature contested the existence of an optimal capital structure. Bradley et al. (1984), Titman and Wessels (1988) and Rajan and Zingales (1995), to name but a few, provided empirical evidence to suggest firms indeed pursue an optimal capital structure and later survey evidence by Graham and Harvey (2001) in the US helped to validate this claim, with more than 80% of firms in their sample agreeing that they actively target an optimal leverage. Similar anecdotal evidence has also been documented in the UK, the Netherlands, Germany, and France (e.g. Brounen et al. 2006).

Accepting the premise that firms hold optimal targets, a large body of literature has investigated the dynamic trade-off theory by examining how quickly firms adjust towards their target

[3]See Frank and Goyal (2009) for an in-depth review of capital structure theory.

leverage in the event of deviation. In the US, Fama and French (2002) found debt-ratios to adjust slowly over time reporting a SOA of 10% per annum. In contrast, Flannery and Rangan (2006) for a similar sample documented the SOA to be closer to 34% while the cross-country comparison of Antoniou et al. (2008) report reasonably fast adjustment speeds in the US (32%), the UK (32%), and France (39%) yet slower speeds in Germany (24%) and Japan (11%)[4]. Despite the collective contributions of the aforementioned studies, they largely failed to consider two important empirical issues, that is, estimator choice and heterogeneity in adjustment costs. Subsequently, the most recent research has divided into two strands in order to address these two empirical affairs.

The first strand of literature has investigated the economic importance of estimator choice. As explicitly examined in Chapter 2, incorrect estimation of dynamic panel data models can give rise to inaccurate estimates of the autoregressive coefficient and therefore spurious rates of adjustment. Accordingly, it is clear from the above studies - which all adopt similar US samples - that the implied SOA is largely subject to the estimation procedure employed. Consequently, the recent work of Flannery and Hankins (2013), Dang et al. (2015), Elsas and Florysiak (2015) and Zhou et al. (2016) have all investigated how to most accurately estimate the true SOA in short dynamic panels with unobserved time-invariant individual (firm) effects.

The second and more prominent strand of literature has examined conditional heterogeneity in adjustment speeds by taking a more complementary perspective towards capital structure theories (e.g., Fama and French 2005 and Barclay and Smith 2005). In accordance with the dynamic trade-off theory, the SOA is economically meaningful reflecting the associated costs of adjustment. However, the incorporation of the traditional dynamic partial adjustment approach implies an unconditional and therefore homogeneous rate of adjustment for all firms in the sample; yet, in many cases, firms face a gamut of distinct market frictions, imperfections and constraints resulting in a unique mix of adjustment costs and consequently different pathways towards target leverage (Fischer et al., 1989). Subsequently, the recent literature has investigated the determinants of adjustment speeds by approximating adjustment costs by firm-specific and macroeconomic characteristics in line with the pecking order and/or the market timing theory.

At the firm level, Byoun (2008) and Faulkender et al. (2012) illustrate how a companies financial status has a first order effect on the SOA, with Faulkender et al. (2012) showing that firms with the greatest financing imbalance, either deficit or surplus, adjust quickest due to

[4]See Appendix Table for a survey of adjustment speeds detailing sample information, the implied SOA and estimation method(s).

a greater desire and lower costs of readjustment. Moreover, Elsas and Florysiak (2015) and Wojewodzki et al. (2018) document a non-monotonic relationship between credit ratings and the SOA, with highly rated firms facing the lowest costs of adjustment while those with the lowest ratings exerting the greatest financial distress costs. Larger firms generally adjust slower due to lower costs of deviation, while firms with substantial investment opportunities often adjust their capital structure mix to ensure the pursuit of profitable investments opportunities (Elsas and Florysiak 2011; Dang et al. 2014). Furthermore, firms with higher profitability levels and greater financial flexibility adjust their capital structure more frequently (Dang et al., 2012) whereas firms with a history of debt-covenant violation often experience greater adjustment costs and in turn, slower speeds of adjustment (Devos et al., 2017). Overall, it is said that well governed firms adjust quicker than their poorly governed counterparts (Chang et al. 2014; Liao et al. 2015).

At the macroeconomic level, both time-invariant and time-variant factors have been to found to have a pronounced effect on a firms leverage and re-balancing dynamics. Starting with the former, Antoniou et al. (2008) suggests firms situated in market-based economies adjust quicker than their bank-based counterparts due to better functioning capital markets and more stringent debt repayments systems. Accordingly, the underlying institutional origins of countries and their legal and financial traditions have a significant effect on how and also the speed in which firms re-balance their capital structure (Öztekin and Flannery 2012; Öztekin 2015). With regards to time-variant factors, Cook and Tang (2010) document the importance of time-series variation in GDP growth, term spread, default spread and dividend yield; with more prosperous macroeconomic conditions in the US resulting in a reduction in market frictions, lower adjustment costs and as a result, faster speeds of adjustment. Analogously, Dang et al. (2014) and Ebrahim et al. (2014) using sub-samples report faster speeds of adjustment in the USA and Malaysia pre-crisis in comparison to crisis/post-crisis periods, respectively. However, in contrast, the recent work of Halling et al. (2016) finds leverage targets to develop counter-cyclically, with only a small proportion of firms reporting pro-cyclical behaviour.

All in all, it is clear from the above discussion, if one is able to accurately estimate the true SOA, that both cross-sectional heterogeneity and time-series variation in macroeconomic performance plays a pivotal role in the way firms re-balance their capital structure to return to their optimal leverage. Nonetheless, the manner in which macroeconomic factors impact the speed of adjustment is far from conclusive. In the next section we introduce how we adapt the traditional dynamic partial adjustment model to account for both firm-specific and macroeconomic induced adjustment costs.

3.3 Research Design

In this section we present our empirical research design. In Section 3.3.1 we outline the model specifications employed in this chapter. In Section 3.3.2 we discuss the predictions for our dynamic partial adjustment model and finally in Section 3.3.3 we debate the merits and short comings of estimation procedures and discuss potential endogeneity concerns.

3.3.1 Dynamic Partial Adjustment Model

The dynamic trade-off theory predicts that the existence of transaction costs, taxation and information asymmetries results in firms being unable to adjustment immediately to their optimal target leverage. In order to evaluate such phenomena we employ a dynamic partial adjustment model. Following the likes of Flannery and Rangan (2006), Antoniou et al. (2008) and Huang and Ritter (2009), the conventional dynamic panel partial adjustment model for a firms' market debt ratio (hereafter, MDR) can be specified as follows[5]:

$$\ell_{i,t} - \ell_{i,t-1} = \psi(\ell^*_{it} - \ell_{i,t-1}) + \upsilon_{it} \tag{3.1}$$

where $\ell_{i,t}$ and $\ell^*_{i,t}$ denote the actual (observed) and target (unobserved) MDR of firm i at time t and $\upsilon_{i,t}$ is a composite error component such that $\upsilon_{i,t} = \eta_i + \eta_t + \epsilon_{i,t}$, where η_i is the firm-specific effect, η_t is the time-specific effect and $\epsilon_{i,t}$ is the idiosyncratic error term with zero mean and constant variance. Accordingly in equation (3.1), firms attempt to adjust towards their optimal preference due to the benefits associated with being located at the target level. The SOA ψ approximates the adjustment rate from the current position to the optimal target. An estimate of $\hat{\psi} = 0$ reflects zero SOA and thus no adjustment towards an optimal target. Alternatively, an estimate of $\hat{\psi} = 1$ implies an immediate adjustment from the firms current MDR to their optimal target.

The main challenge faced to the researcher is that the target MDR, $\ell^*_{i,t}$, is not directly observed. To overcome this issue the literature has advocated two approaches. First, target MDR can be approximated by mean or moving average values. However, it is strenuous to claim that the target MDR is either constant over time or a sole product of historic values (Shyam-Sunder and Myers, 1999). The second, and more preferable approach, is that target leverage can

[5]Previous empirical research has considered both market and book equity ratios to examine the capital structure adjustment process (e.g. Lemmon et al. 2008 and Brav 2009). However, estimates corresponding to the associated ratios can differ widely (Frank and Goyal, 2009). Welch (2004) argued that the book value of equity is largely a plug number used to balance the books. Furthermore, book values can be considered backwards looking and equity values can even be negative for ill managed firms. As a result, Flannery and Rangan (2006) states that on the whole, the finance literature tends to play down the relevance of book debt ratios. Accordingly, in this chapter we focus on the MDR.

be approximated by a unique mix of deterministic firm-specific characteristics ($X_{i,t}$) as shown below:

$$\ell^*_{i,t} = \Omega' X_{i,t} \tag{3.2}$$

where $X_{i,t}$ represents a kx1 vector of explanatory factors determining target MDR and Ω denotes the associated coefficients. Specifically, in this chapter we employ twelve firm-specific controls. Drawing from Flannery and Rangan (2006), Huang and Ritter (2009) and Elsas and Florysiak (2015) we include: profitability, the market-to-book ratio, non-debt tax shields, firm size, asset tangibility, an R&D expenditure indicator and industry medium MDR. In addition, we also control for the direct effect of our remaining measure of adjustment speed heterogeneity, absolute financing deficit, as well as sales growth. Finally, we include a dividend payout indicator to account for adjacent internal governance mechanisms and import and export intensity to control for international exposure.

The pecking order theory advocates that highly profitable firms often exhaust internal funds then the external finance channels of debt and lastly equity. Comparatively, the static trade-off theory proposes a positive relationship due to the tax benefits of debt, however, the dynamic trade-off theory suggests firms rarely accumulate continuous profits (Strebulaev, 2007). Taken together, profitability often predicts a negative empirical relationship. Similarly, growth opportunities and non-debt tax shield also predict a negative relationship as firms with high growth opportunities often want to protect against debt-agency conflicts and assure the security of future investment opportunities; while non-debt related tax shields are a natural substitute to the deductible expenses of debt (Flannery and Rangan, 2006).

Size and asset tangibility are often predicted to be positively associated with MDR as larger more tangible firms are usually more transparent, face fewer adjustment costs and have larger debt capacity. In comparison, firms with R&D expenditure are more likely to have greater intangible assets and are more dependent on equity financing, predicting a negative relationship (Öztekin, 2015). Frank and Goyal (2009) suggest industry medium MDR controls for several factors, including uniqueness, regulations and stock variance. Thus, firms actively converge to industry mean/medium leverage ratio and therefore the general consensus is industry medium MDR is positively associated with a firms MDR.

The effect of absolute financing deficit on target leverage is inherently ambiguous as firms in surplus (deficit) are less (more) likely to require external funds, thus predicting a negative (positive) association with MDR. In contrast, the relationship between sales growth and dividend payout and MDR is somewhat more clear cut. Both variables are expected to be negatively correlated with MDR with dividend payout's naturally operating as an alternative internal governance mechanism that alleviates free cash-flow concerns (Frank and Goyal, 2009). The prediction of export intensity is mixed, on one hand, traditional theory posits that multinational firms are large and diversified and should have higher debt capacity. However, debt capacity of such firms can be expected to be lower because of the additional risks of foreign operations (Aggarwal and Kyaw, 2010). Furthermore, large multinational have been found adopt lower levels of long-term debt, yet, higher level of short-term debt (Doukas and Pantzalis, 2003), thus, the overall effect of export intensity and MDR is ambiguous. Finally, as illustrated in the recent work of Xu (2012), import intensity is often correlated with lower marginal costs and subsequently higher profit levels. Thus, similar to profitability, higher import intensity corresponds to lower debt levels.

Given equation (3.2) and the aforementioned controls, a two-stage approach is arguably the most intuitive method for estimating the dynamic partial adjustment model in (3.1). However, this approach is widely restricted by second stage inference problems (Pagan, 1984). Furthermore, strict estimation of (3.2) would result in time-invariant structural coefficients (Ω), thus, implying the long-run relationship between target MDR and its determinants are homogeneous and time insensitive to changes in macroeconomic performance. According to Halling et al. (2016), this is one of the major empirical issues that have been overlooked the literature, e.g., Fama and French (2002), Flannery and Rangan (2006), Kayhan and Titman (2007), Byoun (2008), Faulkender et al. (2012) and Baum et al. (2017), to name but a few. In an attempt to combat these concerns, we first adopt an alternative one-stage approach, which involves substituting (3.2) into (3.1) as follows:

$$\ell_{i,t} = \lambda \ell_{i,t-1} + \beta' X_{it} + \upsilon_{i,t} \tag{3.3}$$

where $\lambda = 1-\psi$ and $\beta = \psi\Omega$. Equation (3.3) can be considered the unconditional baseline partial adjustment model allowing for simultaneous single-stage estimation of the SOA: $\hat{\psi} = 1 - \hat{\lambda}$ and the long run parameter coefficients for target leverage: $\hat{\Omega} = \frac{\hat{\beta}}{1-\hat{\lambda}}$. While (3.3) avoids concerns of valid second-stage inference, the unconditional specification still implies a constant and therefore homogeneous SOA for all firms. However, as postulated earlier, firms are subject to a constitution of internal and external factors that in turn regulate the rate at which they can adjust. To embody this thinking, we first extend the traditional specification to allow for heterogeneous rates of adjustment between firm-groups which we approximate by our three measures of adjustment heterogeneity, namely, absolute financing deficit, the market-to-book ratio and profitability. We adapt equation (3.3) using a quartile dummy variable approach, as shown below:

$$\ell_{i,t} = (\lambda + \sum_{j=2}^{4} \varphi_j Z_{j,t-1})\ell_{i,t-1} + \beta' X_{i,t} + \upsilon_{i,t} \tag{3.4}$$

where $Z_{j,t}$ is an exogenous discrete variable that categories firms based on our three measures of adjustment cost heterogeneity and the subscript j denotes the quartile group allocated to each firm each year[6]. This conditional additive based approach therefore allows for ease of comparison between firm-groups that may exhibit heterogeneous rates of adjustment. Next, we further extend (3.4) to account for changes in macroeconomic performance. While credit channel theory predicts that the behaviour of leverage is pro-cyclical as firms look to borrow less during economic downturns (Bernanke and Gertler, 1989) similar to Cook and Tang (2010) and Dang et al. (2014), recent findings have found it to be counter-cyclical (Halling et al., 2016). Thus, to evaluate this behavior we extend (3.4) using a regime-switching approach, consisting of two alternative regimes:

$$\ell_{i,t} = [(\lambda + \sum_{j=2}^{4} \varphi_j Z_{j,t-1})\ell_{i,t-1} + \beta' X_{i,t}]_{\cdot RH} + [(\lambda + \sum_{j=2}^{4} \varphi_j Z_{j,t-1})\ell_{i,t-1} + \beta' X_{i,t}]_{\cdot RL} + \upsilon_{i,t} \tag{3.5}$$

where RH and RL represent binary classifications of high and low periods of GDP growth, which we approximate via OCED recession indicators. We adopt the OECD business cycle indicators for three reasons. First, GDP growth can be considered the widest macroeconomic indicator as it resembles all developments in the economy. Second, changes in the business cycle/GDP growth are arguably the most commonly used indicators in the macroeconomic heterogeneous adjustment literature and therefore allows for ease of comparison (e.g. Cook and Tang 2010). Finally, the phase average trend procedure used by the OECD to identify business cycles has been shown to more accurately identify periods of peaks and troughs when compared to other popular trend methods such as Hodrick–Prescott and Band-pass filters (Zarnowitz and Ozyildirim, 2006).

Subsequently, to summarize, Equation (3.5) can be considered our final adaption of the traditional partial adjustment model in equation (3.1), of which there are a number of clear advantages. First, the quartile-dummy variable extension allows for statistical inspection of conditional firm-specific factors effecting the speed of adjustment. Second, the parameterization of such conditional factors over two opposing regimes allow for the simultaneous estimation and cohabitation of both conditional adjustment speeds. Thus, equation (3.5) allows one to draw both economic and statistical inferences about firm-group adjustment asymmetries over

[6] We discuss in detail our predictions for our three measures of firm-specific adjustment costs in Section 3.3.2.

the two regimes, which in turn, may foster different economic and statistical conclusions about the rate and significance of adjustment speeds. Finally, (3.5) allows the long run coefficients to vary across high and low growth periods in line with Halling et al. (2016), thus, capturing the potential contrasting effects of opposing external market conditions.

3.3.2 Predictions of Heterogeneous Adjustment Speeds

The objective of this chapter is to not only evaluate how firm-specific adjustment costs and variances in macroeconomic performance directly effect the SOA, but also, how macroeconomic performance spills into to other channels, resulting in asymmetric effects of firm-specific adjustment costs over the business cycle. In this section we outline the model predictions for our empirical framework detailed previously.

To recapitulate, the dynamic trade-off theory suggests when firms protrude from their target, managers must consider two types of costs i) the explicit cost of issuing and/or retiring securities (i.e. debt and equity) and ii) the cost of target deviation (i.e. the loss of not operating at their optimal capital structure). In this study, we propose three measures of time-variant firm-specific adjustment costs, namely, absolute financing deficit, the market-to-book ratio and profitability. Starting with our first measure, Faulkender et al. (2012) suggests that a firms absolute financing deficit (i.e. operating income after taxes, interest and expected investment) has a first order effect on the SOA. Firms with greater absolute distance from required cash flow face lower costs of adjustment due to the size of adjustment required and the greater benefits received from re-optimization. Subsequently, firms in the upper-quartile of absolute financial deficit are predicted to adjust quicker than their better balanced counterparts.

Our prediction for firms with high market-to-book ratios is also positive. While on one hand, firms with low market-to-book ratios can be larger, more tangible with greater cash flow, this is not systematically always the case. More generally, the literature (e.g., Elsas and Florysiak 2011; Dang et al. 2012 and Dang et al. 2014) suggests firms with high market-to-book ratio's rely more heavily on external financing, either debt or equity, to pursue positive investment opportunities. In addition, these firms often look to issue new equity when market-to-book values are considered high to take advantage of the high firm valuation (Baker and Wurgler, 2002). Taken together, the greater involvement of external finance means high growth firms adjust their leverage mix more frequently allowing for quicker adjustment to their desired target (Drobetz and Wanzenried, 2006). Thus, we expect firms with in the highest quartile of the market-to-book ratio to adjust the quickest.

For our measure of profitability the pecking order theory would suggest that due to the additional costs associated to external financing, more profitable, less constrained firms, will naturally prefer the exhaust internal funds, then debt and finally equity (Myers and Majluf, 1984). Thus, the lack dependence on external financing would suggest that more profitable firms adjust slower. In contrast, more profitable firms with an excess of retained earnings, are more likely to manage their capital structure to balance the benefits of debt and equity. Equally, more profitable firms also face greater incentives to increase debt due to cash flow agency problems (Jensen, 1986) and are also less financial constrained meaning they are able to issue securities at a lower cost. Subsequently, more profitable firms are able to reap the rewards of financial flexibility and adjust their capital structure mix in order to maximize the benefits of optimal target leverage. Thus, in line with the recent findings of Dang et al. (2012) we predict a positive association between profitability and the SOA.

Finally, with regards to the business cycle, macroeconomic variation can effect the SOA through a number of direct and indirect channels. According to Hackbarth et al. (2006), Chen (2010) and Bhamra et al. (2010) firms restructuring thresholds are lower in more prosperous macroeconomic conditions. Specifically, macroeconomic performance directly effects firms leverage ratios via supply side effects as transaction costs vary over the course of the business cycle and also vary in magnitude for different types of external financing channels (i.e. debt and equity). For example, the provisions of external debt is largely conditional on financial institutions, thus, macroeconomics shocks associated to such institutions capitalisation is likely to have a greater impact on the transaction costs of debt. In comparison, the liquidity of secondary markets has also been shown to vary over time (e.g Duffie et al. 2007), thus, macroeconomic shocks effecting consumer confidence and firms market valuations is likely to result in more expensive debt and equity costs. Taken together, contrary to the work of Halling et al. (2016), we predict that macroeconomic performance directly effects the SOA, with more prosperous macroeconomic conditions facilitating faster speeds of adjustment.

While time-series variation in macroeconomic performance may directly effects the SOA via supply side channels, it may also manifests itself indirectly through our firm-specific measures. Naturally, one can consider firms profit levels to be higher in more prosperous macroeconomic conditions, thus, resulting in even greater financial flexibility and desire to operate at an optimal capital structure. Furthermore, in line with market timing theory, firms look to exploit misvaluations by timing their equity and debt issues, that is, issuing equity when stocks are overvalued and debt when equity valuations and interest rates are low. Thus, if firms market deviations from fundamental values are pro-cyclical (i.e. higher market-to-book levels in growth periods) then one would expect more opportunistic managerial behaviour in equity markets and greater leverage adjustment. In light of the presented arguments, we predict high growth periods to correlated with high adjustment speeds, and that indirectly, the extent of adjustment between firm-group's may also be greater in high growth periods.

3.3.3 Empirical Implementation and Endogeneity Concerns

The empirical implementation of dynamic partial adjustment models pose a number of practical and econometric challenges. For instance, the estimation of dynamic partial adjustment models require the inclusion of the lagged dependent variable in order to allow for the analysis of corporate financial policies over time. Furthermore, financial data on firms is regularly unbalanced, especially in emerging market contexts, and, more often then not, the corporate financial policies of interest, in our case, the MDR, is fractional. To complicate the estimation procedure further, it is possible that we also face a number of endogeneity concerns that may induce bias in our forthcoming estimates and ultimately influence our interpretation of true the SOA. Subsequently, prior to discussing the competing merits of opposing estimation procedures, we first outline how we address such potential endogeneity concerns before detailing how alternative estimators accommodate for the econometric challenges we face going forward.

It is to be expected that there are a number of possible observable and unobservable/hard to measure factors that influence a firms capital structure mix which, if omitted, are likely induce estimation bias. As outlined in the Section 3.3.1, to alleviate such concerns, we propose a large set of conditional variables that are regarded to be the most significant and robust in determining a firms capital structure (Frank and Goyal 2009 and Öztekin 2015). Moreover, given the emerging market context of India, we also propose the use of an additional set of observable explanatory variables in order to account for foreign market engagement (import and export intensity) and demand side changes (sales growth). With regards to unobservable/hard to measure factors, Lemmon et al. (2008) shows that a significant proportion of the variance in firms' capital structure (approximately 60%) is attributable to unobserved firm-specific factors. Moreover, given India's emerging market context, and the large number of capital market and regulatory reforms over our sample period, it is possible that such reforms have had, at least in principle, nuanced effects on firms' information environment and transaction costs. Subsequently, given such observations, in our model specification in Section 3.3.1 we propose the use of both firm- and year-specific fixed-effects to help alleviate such omitted variable concerns. With regards to other endogeneity concerns, such as measurement error and reverse causality, it may indeed be the case that measurement error could generate endogeneity bias in our estimates, with financial reporting errors being common in such large datasets, especially in emerging market data, where typically accounting practices are considered less rigorous. To address both these concerns we adopt a strict set of data cleaning rules - outlined in the forthcoming section - and, as specified in equation 3.3, the inclusion of the autorgressive parameter, at least in part, helps to mitigate causality concerns (Leszczensky and Wolbring, 2018).

Given the above practical and econometric concerns, the corporate finance literature has adopted a number of different econometric techniques to estimate the speed in which firms adjust towards their optimal capital structure. For example, the OLS (Fama and French, 2002), the FE (Flannery and Rangan, 2006), the SYS-FMM (Lemmon et al., 2008), the LD4 (Huang and Ritter, 2009) and the LSDVC estimator (Öztekin and Flannery, 2012) have all been employed by previous studies[7]. However, as evidence in Chapter 2, not all estimation procedures are able to accommodate for the econometric issues outlined above, and thus, often fail to accurately estimate the true SOA. For instance, it is well known that the OLS estimator fails to account for the time-invariant differences between firms (firm-fixed effects), thus resulting in omitted variable bias causing upward bias in the autoregressive coefficient and the underestimation of the SOA. To ameliorate such effects, the corporate finance literature has adopted more advanced estimation methods, of which, as evidenced in Chapter 2, the LSDVC and QML estimators prove to be the most reliable when the dependent variable of interest is continuous. However, one practical issue that complicates matters further, is that, with regards to firms' capital structure, the dependent variable of interest, the MDR, is fractional, thus, many of the estimators listed above are inadequate as the do not correctly accommodate for the distribution of the dependent variable (Dang et al. 2015 and Elsas and Florysiak 2015).

A natural candidate to address the fractional nature of the dependent variable is the pooled Tobit estimator, however, similar the OLS estimator, such maximum likelihood procedure fails to account for the time-invariant differences between firms and, due to the incidental parameter problem, is not able to accommodate for such omitted factors without inducing significant bias (Baltagi, 2008). Papke and Wooldridge (2008) develop a semi-parametric approach to circumvent such constraints, thus allowing unobserved firm-specific heterogeneity, however, such estimation procedure doesn't consider specifications that include a lagged dependent variable. In contrast,

[7]Note: See Table A.3.2 for a more complete list of the estimation procedures used in the capital structure literature.

Loudermilk (2007) propose a doubly censored type one tobit model with a lagged dependent variable which controls conditionally for unobserved heterogeneity. Yet, such conditional specification relies on all exogenous variables from all time periods to approximate the time-invariant parameter, therefore, requiring balanced panel data and rendering it not suitable to the corporate finance setting, where entry and exit to the sample is frequent and often partially related to firm's capital structure. Consequently, the main estimator of choice that we embody in this chapter is the DPF estimator chapter of Elsas and Florysiak (2011) and Elsas and Florysiak (2015). The DPF estimator, similar to Loudermilk (2007), models conditionally for unobserved heterogeneity, however, draws from the Mundlak (1978) thus allowing for the unbalanced panel setting ever frequent in the corporate finance setting. Moreover, as evidence in Chapter 2 as well as in Dang et al. (2015) and Elsas and Florysiak (2015), the DPF estimator, in comparison to the aforementioned estimators, most accurately estimates the autoregressive coefficient thus providing the most accurate estimate of the true speed of adjustment. Nevertheless, in what follows, we examine empirically the SOA via a range of dynamic panel estimators and diagnostics tests in section 3.5.1 in order ensure the most accurate estimation of the true SOA. Thus, we shall return to this conversion later.

3.4 Data and Summary Statistics

3.4.1 Data

The dataset used in this chapter is obtained from Prowess, a database maintained by the Centre for Monitoring the Indian Economy (CMIE). Prowess reports firm-level financial, market and governance variables for both listed and unlisted Indian companies in a standardized format, allowing for equal comparison. Regarding the sample data employed in this study, we focus specifically on listed firms with the fiscal year ending March 31st. We therefore excluded all firms with alternative year end dates and removed all biannual reportings. In addition, following the literature (e.g. Flannery and Rangan 2006; Antoniou et al. 2008; Dang et al. 2012) we applied a number of standard data restrictions. First, we excluded all firms operating in financial (NIC64-NIC66) and utility sectors (NIC35-NIC39) since these industries are largely subject to alternative accounting standards. Second, given the dynamic panel data model proposed, we removed all firms with less than three consecutive observations to ensure a panel data structure. Thereafter, we removed all observations that have missing data and winsorized all continuous explanatory variables at the 1st and 99th percentiles to mitigate the effect of outliers and eradicate errors in the data. We excluded the MDR in this final step due to the use of the DPF estimator in later sections (Elsas and Florysiak 2011; Elsas and Florysiak 2015).

Our final sample coverage is from 1997-2017 and consists of 2,650 firms with a total of 30,313 firm-year observations, approximating an average panel length of 11.4 years per firm. Further details regarding the structure of our unbalanced panel and the distribution of firm–year observations can be found in appendix Table A.3.2 and Table A.3.3, respectively.

3.4.2 Summary Statistics and Univariate Tests

Table 3.1 reports summary statistics and contains mean, standard deviation, minimum, 25th percentile, median, 75th percentile and maximum values of the variables used in the our estimation procedure. We find the median leverage, 0.409, to be below the mean leverage, 0.423, and a relatively large cross-sectional differences between the 25th percentile and the 75th percentile. Furthermore, we note that MDR is fractional of which 1,939 observations are left censored (zero) and only 9 observations are right censored (one). In terms of other summary statistics, generally speaking the average firm-year reported an 8.8% profit and 8.7% sales growth. In terms of asset structure, the average firm-year observation consists of roughly 32% tangible assets whereas only 17.7% of the overall sample observations engage in R&D activities. In contrast, we find 56% of the firm-year observations in our sample pay dividends, while firms generally import roughly 12% of raw materials used for production, with the percentage of revenues generated through exports being slightly higher. Table 3.2 presents the correlation matrix of the variables used in the our estimation procedure. In terms of MDR and its determinants, all variables bar non-debt tax shields display correlations reflective of their predicted signs. Regarding the cross-comparison of explanatory variables, only non-debt tax shields displays a potentially concerning correlation with asset tangibility. However, unreported results show the value of the variance impact factor for these two variables to be smaller than 2, thus, it is unlikely that we will find multicollinearity problems between these variables[8]

Prior to our main analysis, we dig deeper into the distribution of our data and use univariate mean tests to understand the capital structure behaviour of firms across our three measures of firm-specific adjustment heterogeneity as well as over opposing macroeconomic regimes[9]. In Table 3.3 we report the mean debt and equity behaviour of firms, conditional on the quartile

[8]Note: In addition to multicollinearity, we address potential nonstationarity concerns by running a series of panel unit-root tests. In appendix Table A.3.5, we report the results from Fisher-type Augmented Dickey-Fuller and Phillips-Perron tests for all continuous variables. We evidence that nonstationarity is not a concern in our panel-data series with all but one test rejecting the null hypothesis at the 1% level.

[9]Note: Our general findings are robust to additional equality of median test

rankings of our three measures of firm-specific adjustment heterogeneity. At a broad level, we find firms actively manage debt more than equity, with changes to debt occurring in more than 90% of observations across all groups. More precisely, we find firms with the highest financial imbalance have lower net debt levels than their counterparts, this is largely down to similar levels of debt increases and decreases. We find firms with the highest market-to-book ratios display the lowest active debt behaviour across all sub-groups, with relatively low debt increases. Comparatively, such firms display the highest proportion of active equity behaviour, of which, roughly one third of the observations report equity issues and 2.3% report buy-backs. Note the difference in means between firms with the lowest market-to-book ratio (Q1) and the highest (Q4) is statistically significant at the 1% level, suggesting that the latter more frequently issue equity to take advantage of high market values. Finally, we report firms with the highest profitability levels have the lowest net debt issues across all groups. Nonetheless, they maintain similar active debt policies as other firm-groups. Interestingly, we find highly profitable firms increase and decrease debt in similar frequencies, 44.9% and 46.9%, respectively. This asymmetric behaviour across firm groups alludes to our earlier prediction that firms with high financial flexibility benefit from being able to adjust their leverage mix freely.

In Table 3.4 we report similar mean statistics over time from 1997-2017, here we also detail domestic GDP growth and the OCED regime indicators of high and low macroeconomic growth[10]. Generally speaking, we observe the level of debt increases to be counter-cyclical with close to 70% of firms increasing their debt around the 1997/1998 Asian crisis. In comparison, roughly one third of firms issue equity in the build up to the 2008/2009 financial crisis. Overall, the mean tests from the two opposing regimes indicate firms generally have lower MDR's in high growth periods, consistent with the recent findings of Bandyopadhyay and Barua (2016).

Finally, in Table 3.5 we report the mean statistics and univariate difference tests for group affiliated and private listed firms and in Figure 3.1 we document the distribution of MDR across both groups from 1997-2017 via box plots. In forthcoming sections we use the structural differences between group-affiliated and private listed firms as an extended form of empirical analysis. Group affiliated firms operate as legal entities and hold similar characteristics as both conglomerates and LBO associations. While on one hand, group affiliated firms can mitigate issues of market failure by utilizing internal group credit channels, on the other hand, group affiliated firms are often owned by one dominant owner and are prevalent to agency issues (Khanna and Palepu, 2000). Apart from sales growth, we find that both MDR and its determinants display a

[10]Note: Further information can be found in notes of Table 3.4.

mean statistical difference across the two groups. Notably, group affiliated firms are statistically larger and have higher leverage ratio's than their private listed counterparts, yet, on average, also have greater growth opportunities. Such summary's are not to dissimilar to Khanna and Palepu (2000), who found well diversified groups have on average higher growth opportunities. In Panel B of Table 3.5 we find the difference in means between group-affiliated and private listed firms to only persist up until 2005, this finding is in line with Bhaumik et al. (2012) who suggested business groups helped alleviate credit constraints for their member firms, but the ability to do so has declined over time.

Table 3.1: Summary Statistics

	Observations	Mean	S.D.	Min	Q1	Median	Q3	Max
1. Market Debt Ratio (MDR)	30,313	0.423	0.308	0.000	0.128	0.409	0.693	1.000
2. Profitability	30,313	0.088	0.092	-0.349	0.041	0.085	0.132	0.496
3. Market-to-Book	30,313	1.086	1.131	0.082	0.529	0.734	1.156	12.942
4. Non-Debt Tax Shields	30,313	0.030	0.022	0.000	0.015	0.026	0.040	0.158
5. Size	30,313	7.543	1.750	3.431	6.322	7.462	8.677	13.154
6. Asset Tangibility	30,313	0.323	0.198	0.002	0.166	0.304	0.460	0.878
7. R&D Expenditure Indicator	30,313	0.175	0.380	0.000	0.000	0.000	0.000	1.000
8. Industry Medium MDR	30,313	0.411	0.188	0.005	0.301	0.411	0.538	0.850
9. Absolute Financing Deficit	30,313	0.076	0.075	0.001	0.026	0.056	0.100	0.541
10. Sales Growth	30,313	0.087	0.416	-2.172	-0.036	0.100	0.238	2.604
11. Dividend Payout Indicator	30,313	0.535	0.499	0.000	0.000	1.000	1.000	1.000
12. Export Intensity	30,313	0.187	0.277	0.000	0.000	0.042	0.265	1.000
13. Import Intensity	30,313	0.133	0.230	0.000	0.000	0.180	1.000	1.000

Source: Prowess - Author's own calculation.

Notes: This table reports the summary statistics for all main text variables. MDR is the sum of short-term and long-term borrowing over the market value of equity plus the sum of short-term and long-term borrowing. Profitability is the ratio of earnings after taxation as ratio of total asset. The market-to-book ratio is the market value of equity plus the sum of short-term and long term borrowing over the book value of total assets. Non-Debt Tax Shields is the ratio of depreciation to total assets. Size is the natural logarithm of total assets. Asset Tangibility is the ratio of fixed assets to total assets. R&D expenditure Indicator is a binary variable that takes the value 1 if the firm reports R&D expenditures or otherwise 0. Industry Medium MDR is industry median MDR calculated based on NIC industry classification. Absolute Financing Deficit is the sum of operating income before depreciation [OIBD] less income taxes, less interest expense, less mean industry investment (CAPEX) based on NIC industry classifications as a proportion of total assets (Faulkender et al., 2012). Sales Growth is the natural logarithm of current sales revenue as a portion of the previous periods sales revenue. Dividend Payout Indicator is a binary variable that takes the value 1 if the firm pays dividends or otherwise 0. Export Intensity is the sum foregin sales revenue over total sales. Import Intensity is the sum of imported raw materials over total raw material costs. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table 3.2: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Market Debt Ratio (MDR)	1.000												
2. Profitability	-0.333	1.000											
3. Market-to-Book	-0.372	0.238	1.000										
4. Non-Debt Tax Shields	0.112	-0.058	0.050	1.000									
5. Size	0.066	0.113	0.124	-0.104	1.000								
6. Asset Tangibility	0.290	-0.099	-0.058	0.567	-0.041	1.000							
7. R&D Expenditure Indicator	-0.120	0.176	0.140	0.028	0.271	0.008	1.000						
8. Industry Medium MDR	0.379	0.052	-0.230	0.083	-0.003	0.251	0.151	1.000					
9. Absolute Financing Deficit	-0.106	0.072	0.143	0.006	-0.142	-0.106	-0.058	-0.105	1.000				
10. Sales Growth	-0.119	0.282	0.098	-0.027	0.009	0.001	0.032	-0.001	0.020	1.000			
11. Dividend Payout Indicator	-0.268	0.469	0.121	-0.039	0.307	-0.052	0.246	0.101	-0.064	0.145	1.000		
12. Export Intensity	-0.064	0.103	0.046	0.015	0.041	-0.052	0.039	-0.072	0.003	0.033	0.089	1.000	
13. Import Intensity	0.139	0.056	-0.053	0.078	0.097	0.131	0.111	0.234	-0.068	0.004	0.079	-0.074	1.000

Source: Prowess - Author's own calculation.

Notes: This table reports the correlation matrix for all main text variables. MDR is the sum of short-term and long-term borrowing over the market value of equity plus the sum of short-term and long-term borrowing. Profitability is the ratio of earnings after taxation as ratio of total asset. The market-to-book ratio is the market value of equity plus the sum of short-term and long term borrowing over the book value of total assets. Non-Debt Tax Shields is the ratio of depreciation to total assets. Size is the natural logarithm of total assets. Asset Tangibility is the ratio of fixed assets to total assets. R&D expenditure Indicator is a binary variable that takes the value 1 if the firm reports R&D expenditures or otherwise 0. Industry Medium MDR is industry median MDR calculated based on NIC industry classification. Absolute Financing Deficit is the sum of operating income before depreciation (OIBD) less income taxes, less interest expense, less mean industry investment (CAPEX) based on NIC industry classifications as a proportion of total assets (Faulkender et al., 2012). Sales Growth is the natural logarithm of current sales revenue as a portion of the previous periods sales revenue. Dividend Payout Indicator is a binary variable that takes the value 1 if the firm pays dividends or otherwise 0. Export Intensity is the sum foregin sales revenue over total sales. Import Intensity is the sum of imported raw materials over total raw material costs. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 3.3: Mean Analysis of Debt and Equity Behaviour by Quartile Rankings

Quantile	MDR	Net Debt Issue	Net Equity Issue	Active Debt	Debt Increase	Debt Decrease	Active Equity	Equity Increase	Equity Decrease
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Absolute Financing Deficit									
Q1	0.453	0.025	0.011	0.959	0.599	0.359	0.237	0.213	0.024
Q2	0.441	0.024	0.013	0.949	0.573	0.376	0.242	0.220	0.022
Q3	0.427	0.024	0.015	0.943	0.559	0.383	0.243	0.221	0.021
Q4	0.369	0.016	0.030	0.937	0.506	0.430	0.286	0.265	0.022
Panel B: Absolute Financing Deficit Difference in Mean Test									
Q4 vs Q1	-0.084^{***}	-0.009^{***}	0.019^{***}	-0.022^{***}	-0.093^{***}	0.071^{***}	0.050^{***}	0.052^{***}	-0.002
Panel C: Market-to-book									
Q1	0.458	0.001	0.010	0.930	0.480	0.450	0.170	0.151	0.019
Q2	0.549	0.027	0.010	0.974	0.603	0.371	0.225	0.202	0.022
Q3	0.462	0.037	0.017	0.970	0.623	0.347	0.284	0.260	0.024
Q4	0.221	0.026	0.031	0.913	0.531	0.382	0.330	0.306	0.023
Panel D: Market-to-book Difference in Mean Test									
Q4 vs Q1	-0.237^{***}	0.025^{***}	0.020^{***}	-0.017^{***}	0.051^{***}	-0.068^{***}	0.160^{***}	0.155^{***}	0.004^{*}
Panel E: Profitability									
Q1	0.514	0.028	0.020	0.928	0.572	0.356	0.211	0.196	0.014
Q2	0.498	0.033	0.017	0.970	0.615	0.355	0.259	0.235	0.024
Q3	0.439	0.031	0.016	0.971	0.602	0.369	0.279	0.255	0.023
Q4	0.239	-0.002	0.016	0.918	0.449	0.469	0.260	0.233	0.027
Panel F: Profitability Difference in Mean Test									
Q4 vs Q1	-0.275^{***}	-0.029^{***}	-0.004^{**}	-0.010^{***}	-0.124^{***}	0.113^{***}	0.049^{***}	0.036^{***}	0.013^{***}

Source: Prowess - Author's own calculation.

Notes: This table reports mean statistics for debt and equity behaviour by quartile rankings conditional on our measures of firm-specific adjustment costs. Panel A reports the mean statistics across quartiles of absolute financing deficit. Panel B reports the difference in mean values between column Q4 and Q1, where the corresponding asterisk represent the p-value associated with the t-test for differences in means. Panel C reports the mean statistics across quartiles of The market-to-book ratio. Panel D reports the difference in mean values between column Q4 and Q1, where the corresponding asterisk represent the p-value associated with the t-test for differences in means. Panel E reports the mean statistics across quartiles of profitability. Panel F reports the difference in mean values between column Q4 and Q1, where the corresponding asterisk represent the p-value associated with the t-test for differences in means. Absolute Financing Deficit is the sum of operating income before depreciation (OIBD) less income taxes, less interest expense, less mean industry investment (CAPEX) based on NIC industry classifications as a proportion of total assets (Faulkender et al., 2012). The market-to-book ratio is the market value of equity plus the sum of short-term and long term borrowing over the book value of total assets. Profitability is the ratio of earnings after taxation as ratio of total asset. Column (1) reports mean MDR which is the sum of short-term and long-term borrowing over the market value of equity plus the sum of short-term and long-term borrowing. Column (2) and (3) report net debt and equity issues where net debt is the first difference of total borrowing over total assets and net equity issue is calculated as cash proceeds from share issues less cash outflows from stock redemption's over total assets (Strebulaev and Yang, 2013). Column (6) and (9) report active debt and equity which is the proportion of non-zero values in the numerator, of which debt and equity increases (column (7) and (10)) and decreases (column (8) and (11)) denote the proportion of positive and negative values in the numerator, respectively. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level . All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 3.4: Distribution of Mean Debt and Equity Behaviour from 1997 to 2017

Year	GDP Growth (1)	Regime Classification (2)	Market Debt Ratio (3)	Net Debt Issue (4)	Net Equity Issue (5)	Active Debt (6)	Debt Increase (7)	Debt Decrease (8)	Active Equity (9)	Equity Increase (10)	Equity Decrease (11)
Panel A: Mean Statistics by Year											
1997	4.72	Low	0.530	0.045	0.016	0.990	0.676	0.314	0.320	0.314	0.006
1998	4.83	Low	0.596	0.050	0.015	0.988	0.687	0.301	0.298	0.294	0.004
1999	6.06	High	0.571	0.024	0.012	0.987	0.595	0.392	0.248	0.247	0.001
2000	7.58	High	0.516	0.017	0.024	0.971	0.571	0.400	0.283	0.279	0.004
2001	2.05	Low	0.538	0.019	0.029	0.960	0.560	0.400	0.307	0.304	0.004
2002	6.42	Low	0.545	0.004	0.010	0.943	0.472	0.471	0.225	0.221	0.003
2003	3.55	Low	0.560	0.009	0.008	0.955	0.486	0.469	0.214	0.212	0.002
2004	8.81	High	0.497	0.010	0.010	0.950	0.488	0.462	0.195	0.190	0.005
2005	8.46	High	0.372	0.021	0.012	0.954	0.544	0.410	0.206	0.189	0.017
2006	9.59	High	0.327	0.036	0.037	0.959	0.586	0.372	0.329	0.301	0.027
2007	9.24	High	0.349	0.051	0.036	0.951	0.640	0.310	0.333	0.303	0.030
2008	8.30	Low	0.352	0.045	0.036	0.949	0.639	0.309	0.341	0.311	0.030
2009	0.19	Low	0.491	0.031	0.015	0.949	0.597	0.352	0.259	0.213	0.046
2010	13.08	High	0.364	0.016	0.020	0.944	0.535	0.410	0.283	0.246	0.037
2011	9.51	High	0.383	0.032	0.023	0.946	0.627	0.319	0.293	0.261	0.032
2012	4.22	Low	0.422	0.029	0.013	0.940	0.606	0.334	0.232	0.203	0.030
2013	5.74	Low	0.453	0.020	0.010	0.939	0.568	0.371	0.220	0.194	0.026
2014	6.36	High	0.447	0.014	0.008	0.931	0.532	0.399	0.208	0.178	0.031
2015	7.37	High	0.382	0.006	0.010	0.926	0.487	0.439	0.206	0.187	0.019
2016	8.61	High	0.362	0.002	0.006	0.925	0.469	0.456	0.173	0.159	0.014
2017	5.82	Low	0.310	0.002	0.007	0.921	0.446	0.475	0.178	0.155	0.022
Panel B: Regime Difference in Mean Test											
Full Sample			0.446	0.024	0.017	0.947	0.560	0.387	0.252	0.230	0.022
Low Regime			0.451	0.025	0.016	0.947	0.571	0.377	0.253	0.230	0.023
High Regime			0.402	0.021	0.018	0.946	0.551	0.395	0.251	0.229	0.022
High Regime vs Low Regime			-0.049^{***}	-0.004^{***}	0.002^{***}	-0.001	-0.020^{***}	0.019^{***}	-0.002	-0.001	-0.001

Source: Prowess - Author's own calculation.

Notes: This table reports the distribution of debt and equity behaviour from 1997 to 2017. Panel A reports the mean values to corresponding column by year. Panel B reports the difference in mean values between column high and low growth regimes, where the corresponding asterisk represent the p-value associated with the t-test for differences in means. Column (1) reports yearly GDP growth for the fiscal year ending the 31st March. Column (2) reports our classification of high and low growth regimes. We define low growth regimes as fiscal years consisting with at least two consecutive quarters of declining growth. We define high growth regimes as periods with less than two consecutive quarters of declining low growth. Column (1) reports mean MDR which is the sum of short-term and long-term borrowing over the market value of equity plus the sum of short-term and long-term borrowing. Column (2) and (3) report net debt and equity issues where net debt is the first difference of total borrowing over total assets and net equity issue is calculated as cash proceeds from share issues less cash outflows from stock redemption's over total assets (Strebulaev and Yang, 2013). Column (6) and (9) report active debt and equity which is the proportion of non-zero values in the numerator, of which debt and equity increases (column (7) and (10)) and decreases (column (8) and (11)) denote the proportion of positive and negative values in the numerator, respectively. * indicates significance at the 10% level,** indicates significance at the 5% level and *** indicates significance at the 1% level. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table 3.5: Univariate Tests by Firm-Group by Year

Panel A: Mean Statistics Comparison	Full Sample Sample (1)	Group Affiliated (2)	Private (3)	Difference Test (2) vs (3) (4)
1. Market Debt Ratio (MDR)	0.423	0.440	0.408	0.032***
2. Profitability	0.088	0.094	0.084	0.010***
3. Market-to-Book	1.086	1.136	1.044	0.093***
4. Non-Debt Tax Shields	0.030	0.030	0.030	0.001***
5. Size	7.543	8.322	6.899	1.423***
6. Asset Tangibility	0.323	0.339	0.309	0.030***
7. R&D Expenditure Indicator	0.175	0.254	0.109	0.145***
8. Industry Medium MDR	0.411	0.435	0.391	0.044***
9. Absolute Financing Deficit	0.076	0.069	0.082	-0.014***
10. Sales Growth	0.087	0.083	0.089	-0.006
11. Dividend Payout Indicator	0.535	0.620	0.464	0.156***
12. Export Intensity	0.187	0.171	0.200	-0.030***
13. Import Intensity	0.476	0.519	0.440	0.079***

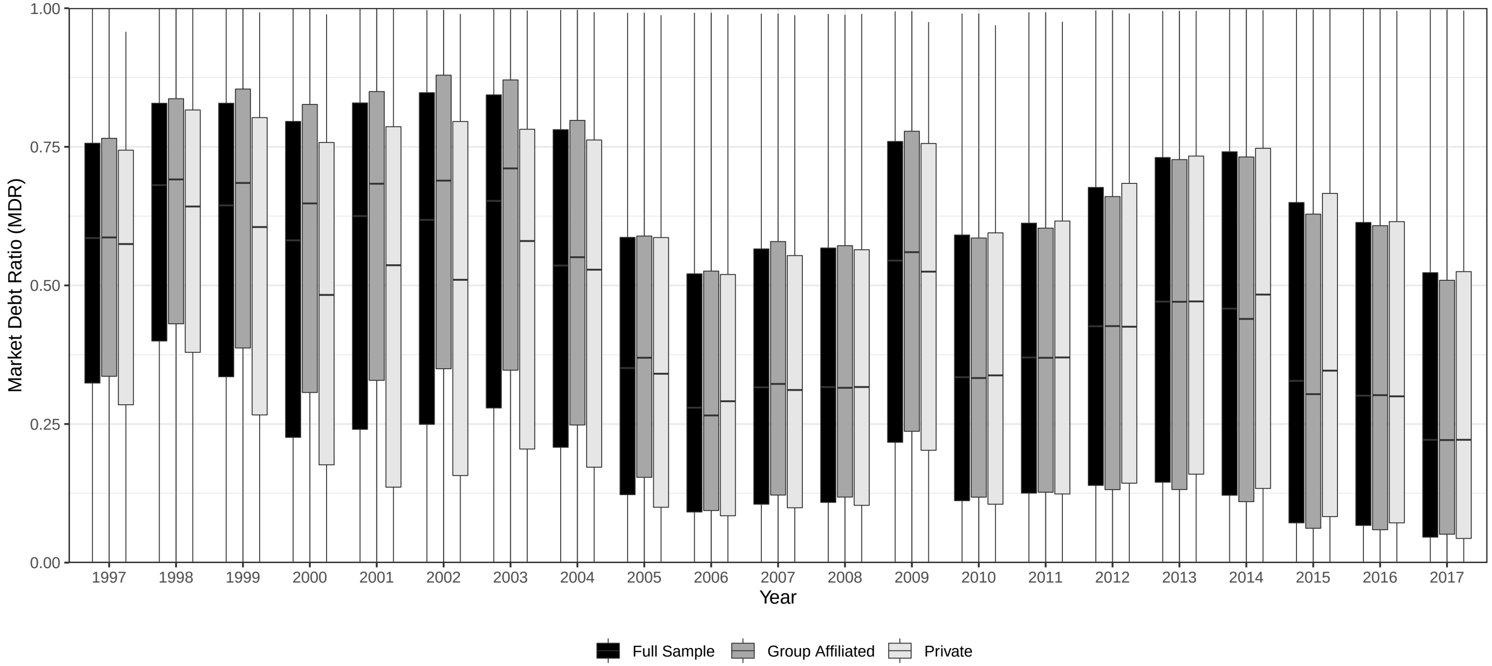
Panel B: Distribution of MDR from 1997-2017

Year	GDP Growth (1)	Performance Regime (2)	Full Sample (3)	Group Affiliated (4)	Private (5)	Difference Test (4) vs (5) (6)
1997	4.72	Low	0.530	0.540	0.516	0.024
1998	4.83	Low	0.596	0.611	0.574	0.037*
1999	6.06	High	0.571	0.603	0.533	0.070***
2000	7.58	High	0.516	0.566	0.466	0.100***
2001	2.05	Low	0.538	0.585	0.479	0.107***
2002	6.42	Low	0.545	0.596	0.480	0.116***
2003	3.55	Low	0.560	0.601	0.507	0.094***
2004	8.81	High	0.497	0.516	0.478	0.038**
2005	8.46	High	0.372	0.387	0.360	0.027*
2006	9.59	High	0.327	0.326	0.328	-0.003
2007	9.24	High	0.349	0.358	0.342	0.016
2008	8.30	Low	0.352	0.358	0.347	0.010
2009	0.19	Low	0.491	0.505	0.481	0.024
2010	13.08	High	0.364	0.366	0.363	0.003
2011	9.51	High	0.383	0.385	0.382	0.003
2012	4.22	Low	0.422	0.419	0.424	-0.006
2013	5.74	Low	0.453	0.448	0.457	-0.008
2014	6.36	High	0.447	0.433	0.457	-0.023
2015	7.37	High	0.382	0.370	0.390	-0.020
2016	8.61	High	0.362	0.360	0.364	-0.004
2017	5.82	Low	0.310	0.311	0.308	0.003

Source: Prowess - Author's own calculation.

Notes: Panel A reports the mean statistics for all main text variables for our full sample (1) and the sub-groups of group affiliated firms (2) and private listed firms (3). Column (4) reports the difference in mean values between column (2) and (3), where the corresponding asterisk represent the p-value associated with the t-test for differences in means. Panel B reports reports yearly MDR statistics respective to our high and low growth regime classification. Column (1) reports yearly GDP growth for the fiscal year ending the 31st March. Column (2) reports our classification of high and low growth regimes. We define low growth regimes as fiscal years consisting with at least two consecutive quarters of declining growth. We define high growth regimes as periods with less than two consecutive quarters of declining low growth. Column (3), (4) and (5) report the by yearly mean of MDR for our full sample, group affiliated and private listed firms respectively. Column (6) reports the difference in mean values between column (4) and (5), where the corresponding asterisk represent the p-value associated with the t-test for differences in means. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. All variable names, definitions and sources can be found in appendix Table A.3.1.

Figure 3.1: Distribution of the Market Debt Ratio from 1997-2017



Source: Prowess - Author's own calculation.

3.5 Empirical Results

In this Section we discuss our main empirical findings. In Section 3.5.1 we estimate the traditional dynamic partial adjustment model in order to illustrate the importance of estimator choice. In Section 3.5.2 we extend our the baseline specification to account for firm-specific adjustment costs and in Section 3.5.3 we document our main results of how firm-specific adjustment costs vary over the macroeconomic cycle.

3.5.1 Baseline Specification and Estimator Choice

As illustrated in Chapter 2, incorrect estimation of dynamic panel data models can give rise to inaccurate estimates of the autoregressive coefficient and thus, spurious conclusions about the true SOA. Accordingly, prior to our main analysis, in this section we examine the economic implications of estimator choice. In Table 3.6 we report the estimates of the traditional dynamic partial adjustment model via the OLS, the FE and the DPF estimator. The first column of each respective estimator includes the most robust determinants of the MDR (Frank and Goyal 2009; Öztekin 2015) while the final column includes our full set of controls. Starting with column (1) and (3), as expected, the OLS and FE estimators provide contrasting estimates of the autoregressive coefficient, and subsequently the implied SOA. In terms of model fit, we find controlling for unobserved firm-specific factors to have little impact on the coefficient of determination - largely due to the existence of the autoregressive parameter - nevertheless, we find both the unobserved firm- and year-specific fixed-effects to be jointly significant at the 1% significance level and their inclusions to be preferable with respect to the AIC and the BIC.

The empirical estimates in column (1) and (3) are widely consistent with the simulations in Chapter 2 and while one can confidently suggest that such estimates of the autoregressive coefficient's are invalid, they are not completely redundant. Given the OLS (FE) estimator consistently overestimates (underestimates) the autoregressive coefficient, one can conjecture that the true unbiased SOA lies between 15.30% and 36.80%[11]. In column (5) we report the autoregressive coefficient of the DPF estimator to lie between such goal posts, thus, based our findings in Chapter 2 as well as the work of Dang et al. (2015) and Elsas and Florysiak (2015), we conjecture the DPF estimator more accurately estimates the true SOA. Again, similar to FE estimates, we find controlling for both firm- and year-fixed effects to be jointly significant at the

[11] In the parlance of econometric literature this would imply the unbiased estimate of the autoregressive coefficient is highly persistent. As illustrated in Chapter 2, the consistency of estimators are most hampered by highly persistent data, thus, the choice of estimation procedure is of even greater importance

1% level, we also further evidence - via a simple likelihood ratio test - the superiority of the DPF estimator over a traditional pooled tobit estimator. Thus, in light of the aforementioned arguments, column (9) can be considered our fully specified baseline estimate of the traditional dynamic partial adjustment model. In turn, the unconditional SOA for the average Indian listed firm to be 26.90% with a corresponding half-life of 2.21 years[12] which is widely consistent with the DPF estimates of other studies reported in Table A.3.1.

In terms of explanatory variables, all variables report predicted signs and consistent magnitudes. Specifically, profitability is negative suggesting that firms with higher profit use less leverage due to their preference towards internal funds, in line with the pecking order (Myers and Majluf, 1984) and dynamic trade-off theory (Leary and Roberts, 2005). Equally, growth opportunities display a negative sign suggesting high growth firms use less leverage to mitigate agency problems Jensen (1986), while the substitution channel of non-debt tax shields is as expected, negative. Both firm size and asset tangibility also report a positive prediction of the MDR, suggesting that larger, more tangible firms, have low bankruptcy, agency, and transaction cost, hence a stronger incentive to utilize debt. We find our dividend payout indicator to be negative and statistically significant adhering to substitution effect of adjacent internal governance mechanisms. Finally, only import intensity significantly determines firms target leverage with exports showing limited statistical significance's across all estimates.

In Table 3.7 we compare the performance of the DPF estimator to the alternative estimators trialed in Chapter 2. We find the FD- and SYS-GMM estimators to fall within the desired range, as both estimators pass the required validity diagnostic tests of 2nd-order autocorrelation and the Hansen overidentification test. Comparatively speaking, the AS-GMM estimator performs poorly in both tests and as a result provides an implausible SOA estimate of 11.80% exceeding the thresholds set by the OLS and FE estimators. Naturally, one cannot expect to alleviate the correlation between the lagged dependent variable and the residual with poorly identified instruments. However, while the FD- and SYS-GMM estimators perform well in this regard, their similarity in estimates to the FE estimator is concerning. We find the LD4 and QML estimators to similarly provide unconvincing estimates of the autoregessive coefficient while the LSDVC estimator most closely match's the estimates of the DPF estimator in line with Elsas and Florysiak (2015).

[12] An order one autoregessive model specification has an exponentially declining response function to shocks. Therefore, half-life is the time the process needs to close the gap between the actual debt ratio and the target by 50% and is calculated as $log(0.5)/log(1-\lambda)$.

Overall, it is clear that while the SOA remains consistent across an array of controls and misspecification tests, the choice of estimator can have economically sizeable effects on the implied SOA, thus, reiterating the sentiment of Chapter 2 and the paramount importance of accurate estimation of the autoregessive coefficient. We conjecture that the DPF estimator most accurately estimates the SOA for our sample of Indian listed firms and thus will be employed throughout the remainder of the chapter.

Table 3.6: Capital Structure Adjustment Misspecification Tests

	OLS		FE		DPF	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MDR}_{i,t-1}$	0.847***	0.840***	0.632***	0.616***	0.746***	0.731***
	(0.003)	(0.003)	(0.007)	(0.007)	(0.005)	(0.005)
$\text{Profitability}_{i,t}$	-0.404***	-0.360***	-0.514***	-0.449***	-0.499***	-0.451***
	(0.010)	(0.012)	(0.017)	(0.017)	(0.013)	(0.017)
$\text{Market-to-Book}_{i,t}$	-0.011***	-0.011***	-0.016***	-0.016***	-0.017***	-0.016***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$\text{Non-Debt Tax Shields}_{i,t}$	-0.243***	-0.245***	-0.194**	-0.180**	-0.279***	-0.259***
	(0.046)	(0.046)	(0.090)	(0.091)	(0.080)	(0.079)
$\text{Size}_{i,t}$	0.010***	0.011***	0.040***	0.042***	0.037***	0.039***
	(0.000)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
$\text{Asset Tangibility}_{i,t}$	0.019***	0.020***	0.037***	0.035***	0.032***	0.031***
	(0.005)	(0.005)	(0.011)	(0.011)	(0.008)	(0.010)
$\text{R\&D Expenditure Indicator}_{i,t}$	-0.017***	-0.016***	-0.010***	-0.008**	-0.005*	-0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\text{Industry Medium MDR}_{i,t}$	0.056***	0.058***	0.169***	0.167***	0.182***	0.176***
	(0.006)	(0.007)	(0.018)	(0.017)	(0.012)	(0.014)
$\text{Absolute Financing Deficit}_{i,t}$		-0.028*		-0.037**		-0.041***
		(0.015)		(0.016)		(0.003)
$\text{Sales Growth}_{i,t}$		-0.012***		-0.014***		-0.013***
		(0.002)		(0.002)		(0.016)
$\text{Dividend Payout Indicator}_{i,t}$		-0.016***		-0.036***		-0.024***
		(0.002)		(0.003)		(0.002)
$\text{Export Intensity}_{i,t}$		0.007**		-0.009		-0.004
		(0.003)		(0.008)		(0.006)
$\text{Import Intensity}_{i,t}$		0.002		-0.009**		-0.010***
		(0.002)		(0.004)		(0.004)
$\text{MDR}_{i,0}$					0.072***	0.071***
					(0.005)	(0.004)
Firm Fixed-Effects	No	No	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
$\text{SOA}(1-\hat{\lambda})$	15.30%	16.00%	36.80%	38.40%	25.40%	26.90%
AIC	-25,925.82	-26,189.40	-42,432.70	-42,913.83	30,569.54	-31,194.87
BIC	-25,705.93	-25,937.30	-42,212.82	-42,661.46	-30,235.70	-30,828.93
Wald-1	268.90	279.80	151.00	159.86	3504.58	3667.56
Wald-2	-	-	-	-	497.74	494.96
Wald-3	-	-	2.782	2.755	-	-
LR-test	-	-	-	-	737.65	738.76
Adjusted R^2	0.848	0.852	0.870	0.873	-	-
Firms	2,650	2,650	2,650	2,650	2,650	2,650
Observations	25,968	25,968	25,968	25,968	25,968	25,968

Source: Prowess - Author's own calculation.
Notes: This table reports our estimates of the dynamic partial adjustment model in equation (3.3). OLS and FE refer to the pooled OLS and within transformation estimators while the DPF estimator is the dynamic panel fractional variable estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015). Bootstrapped standard errors are reported in parentheses where we set the repetition rate R=250. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. Wald-3 reports the test statistic for a Wald test of the joint signicance of the firm fixed-effects, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table 3.7: The Impact of Estimator Choice on Adjustment Speeds

	Core Estimators			Alternative Estimators					
	OLS	FE	DPF	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MDR_{i,t-1}$	0.840***	0.616***	0.731***	0.647***	0.879***	0.687***	0.819***	0.713***	0.677***
	(0.003)	(0.007)	(0.005)	(0.037)	(0.031)	(0.023)	(0.008)	(0.008)	(0.007)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOA $(1-\hat{\lambda})$	16.00%	38.40%	26.90%	35.30%	12.10%	31.30%	18.10%	28.70%	32.30%
m_1 test (p-value)	-	-	-	0.000	0.000	0.000	-	-	-
m_2 test (p-value)	-	-	-	0.100	0.016	0.173	-	-	-
Hansen J test (p-value)	-	-	-	0.126	0.052	0.123	-	-	-
Firms	2,650	2,650	2,650	2,650	2,735	2,650	-	2,650	1,642
Observations	25,968	25,968	25,968	21,193	26,539	25,128	12,816	25,128	15,034

Source: Prowess - Author's own calculation.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005), QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002) and finally the DPF estimator is the dynamic panel fractional variable estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015). All variable names, definitions and sources can be found in appendix Table A.3.1. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

3.5.2 Capital Structure Adjustment and Firm-specific Adjustment Costs

In this section we introduce the first extension of the traditional dynamic partial adjustment model. Specifically, we extend the traditional specification via a quartile dummy variable approach to embody our three measures of adjustment cost heterogeneity, namely, absolute financing imbalance, the market-to-book ratio and profitability. The importance of this section is twofold. First, it allows us to examine the comparability of the three firm specific measures relative to the existing literature and second; this section establishes the effects of such adjustment cost asymmetries under the assumption of homogeneous macroeconomic effects.

In Table 3.8 we report the results for absolute financing imbalance. Our results show how the degree of financial imbalance impacts the speed at which firms can adjust towards their target MDR. For our full sample estimates (column (1)), the reference category (Q1) reports a SOA of 25.70% $(1 - 0.743)$ with a corresponding half life of 2.33 years. Comparatively, firms in fourth quartile adjust both statistically and economically faster with a SOA of 29.10% $(1 - (0.790 - 0.108))$ and a half life of 2.01 years. Our findings are consistent with our earlier prediction and the work of Faulkender et al. (2012), that suggests firms with high financial imbalance adjust quicker due to the size of adjustment required and the greater benefits received from re-optimization.

To inspect the robustness of our findings, and, in part, extend our results further, we examine the within heterogeneity of our sample by splitting it into two sub-samples, that is, one sample of group-affiliated firms and one of private-listed firms[13]. In column (2) and (3), we find the reference category for private listed firms adjust, on average, roughly six percentage points faster than their group affiliated counterparts, however, the increments across firm groups remain similar. Subsequently, the autonomous difference between the base categories suggests there is structural difference between the two groups adjustment speeds with group affiliated firms' facing fewer incentives to adjust towards target MDR. That is, given the very nature of business groups and their ability to channel financial funds internally, on top of their wider reputational advantages, one can infer that private firms face greater incentives to adjust towards their optimal capital structure as failing to do so may prove costly in future market dealings, an incentive less pertinent for group-affiliated firms. Indeed, such findings prove consistent with the recent work of

[13]Note: For the sake of simplicity, we opt for a sub-sample approach over a dummy variable interaction approach. While a conditional specification would allow for the direct inspection of the statistical significance between both groups, we advocate - given the already high level of parameterisation within the current and indeed later model specifications - for a sub-sampling approach to avoid over-parameterisation and multicollinearity concerns.

Yamada (2019), who finds Japanese private listed firms, on average, adjust towards their capital structure target significantly quicker than their group-affiliated (keiretsu) counterparts.

Table 3.9 reports the rate of adjustment conditional on the quartile rankings of the market-to-book ratio. We document a positive linear relationship between the SOA and the market-to-book ratio quartile groups, with firms in Q4 adjusting their capital structure significantly and economically faster than their counterparts at 39.00%, consistent with Elsas and Florysiak (2011) and Dang et al. (2012). Such adjustment asymmetries support our earlier prediction and summary statistics in that, high growth firms adjust faster due to their frequent visits to capital markets, which in turn provides them with more opportunities to find an appropriate mix of debt and equity and at a lower cost. Furthermore, consistent with the market timing hypothesis, high market-to-book value firms issue equity more frequently in order to take advantage of high share prices and lower costs of equity. Sub-group analysis in column (2) and (3) shows our findings are robust across both firm-groups, however, it seems that private listed firms more aggressively adjust their capital structure with an implied SOA of 43.00% compared to their slower group affiliated counterparts of 33.70%. Accordingly, one can posit that group-affiliated firms face fewer incentives to adjust their capital structure and are possibly less willing to defuse ownership through equity issues.

Table 3.10 reports the effect of our final measure of firm-specific adjustment costs; profitability. We find firms with the highest profit and greatest financial flexibility adjust statistically and economically faster than their more constrained counterparts, closing the gap between actual and target leverage by 35.80% per annum. While the difference in adjustment speeds are similar to that of firms with the highest market-to-book values, the costs and incentives of adjustment are indeed different. Our results support the prediction that firms with higher profit levels benefit more from financial flexibility and are therefore more able to increase and/or decrease debt at lower costs. In reference to Table 3.3, while these firms still issue equity, the difference between equity issues across firms groups is small. In comparison, most profitable firms buy-back the most amount of equity and more frequently decrease debt levels relative to any other quartile group. Our empirical findings remain affirmed and economically comparable across both sub-samples suggesting group-affiliated and private listed firms face similar adjustment costs across profitability levels.

All in all, we show, consistent with the existing literature, that differences in firm-specific adjustment costs impact the SOA, with the cross-sectional heterogeneity in absolute financing deficit, the market-to-book ratio and profitability all displaying a positive association with the

SOA. Subsequently, our evidence in this case bares a clear criticism of the early homogeneous partial adjustment models employed in the literature (e.g., Flannery and Rangan 2006, Antoniou et al. 2008 and Huang and Ritter 2009). In the next section, we develop our analysis further by examine the importance of opposing adjustment costs over the course of the business cycle.

Table 3.8: Capital Structure Adjustment Conditional on Absolute Financing Imbalance

	Full Sample	Group Affiliated	Private
	(1)	(2)	(3)
$\text{MDR}_{i,t-1}$	0.743***	0.776***	0.717***
	(0.008)	(0.009)	(0.009)
$\text{MDR}_{i,t-1}$*AFD_{Q2}	-0.005	-0.003	-0.006
	(0.004)	(0.004)	(0.005)
$\text{MDR}_{i,t-1}$*AFD_{Q3}	-0.008**	-0.013**	-0.002
	(0.004)	(0.006)	(0.006)
$\text{MDR}_{i,t-1}$*AFD_{Q4}	-0.034***	-0.036***	-0.030***
	(0.007)	(0.009)	(0.010)
$\text{Profitability}_{i,t}$	-0.450***	-0.441***	-0.457***
	(0.013)	(0.020)	(0.019)
$\text{Market-to-Book}_{i,t}$	-0.016***	-0.012***	-0.020***
	(0.001)	(0.002)	(0.002)
$\text{Non-Debt Tax Shields}_{i,t}$	-0.255***	-0.256**	-0.286***
	(0.096)	(0.099)	(0.099)
$\text{Size}_{i,t}$	0.038***	0.040***	0.038***
	(0.002)	(0.002)	(0.003)
$\text{Asset Tangibility}_{i,t}$	0.032***	0.009	0.054***
	(0.012)	(0.012)	(0.011)
$\text{R\&D Expenditure Indicator}_{i,t}$	-0.005	-0.001	-0.010**
	(0.003)	(0.003)	(0.004)
$\text{Industry Medium MDR}_{i,t}$	0.175***	0.178***	0.155***
	(0.014)	(0.019)	(0.020)
$\text{Absolute Financing Deficit}_{i,t}$	0.019	0.022	0.014
	(0.023)	(0.032)	(0.030)
$\text{Sales Growth}_{i,t}$	-0.013***	-0.018***	-0.011***
	(0.002)	(0.004)	(0.003)
$\text{Dividend Payout Indicator}_{i,t}$	-0.023***	-0.021***	-0.024***
	(0.002)	(0.004)	(0.003)
$\text{Export Intensity}_{i,t}$	-0.004	0.000	-0.007
	(0.007)	(0.012)	(0.008)
$\text{Import Intensity}_{i,t}$	-0.010***	-0.006	-0.015***
	(0.004)	(0.005)	(0.005)
$\text{MDR}_{i,0}$	0.071***	0.056***	0.087***
	(0.007)	(0.006)	(0.008)
Firm Fixed-effect	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes
$\text{SOA}_1(1-\hat{\lambda})$	25.70%	22.40%	28.30%
$\text{SOA}_4(1-(\hat{\lambda}+\hat{\varphi_4}))$	29.10%	26.00%	31.30%
AIC	-31,433.91	-16,896.55	-14,853.57
BIC	-31,043.16	-16,541.83	-14,493.47
Wald-1	3,657.54	2,288.99	1,583.97
Wald-2	493.15	286.25	225.59
LR-Test	728.64	207.13	469.30
Firms	2,650	1,069	1,581
Observations	25,968	12,134	13,834

Source: Prowess - Author's own calculation.
Notes: This table reports the DPF estimates for equation (3.4) where AFD_j denotes the quartile group allocated to firms conditional on their level of absolute financing deficit . SOA_1 reports the SOA for quartile group one where SOA_4 reports the conditional SOA for quartile group four. Bootstrapped standard errors are reported in parentheses where we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table 3.9: Capital Structure Adjustment Conditional on The Market-to-book ratio

	Full Sample (1)	Group Affiliated (2)	Private (3)
$\text{MDR}_{i,t-1}$	0.758***	0.782***	0.734***
	(0.007)	(0.010)	(0.010)
$\text{MDR}_{i,t-1}$*MB_{Q2}	-0.001	-0.001	0.009
	(0.004)	(0.005)	(0.008)
$\text{MDR}_{i,t-1}$*MB_{Q3}	-0.057***	-0.056***	-0.049***
	(0.005)	(0.005)	(0.007)
$\text{MDR}_{i,t-1}$*MB_{Q4}	-0.148***	-0.119***	-0.164***
	(0.008)	(0.009)	(0.011)
$\text{Profitability}_{i,t}$	-0.460***	-0.451***	-0.470***
	(0.014)	(0.019)	(0.023)
$\text{Market-to-Book}_{i,t}$	-0.009***	-0.006***	-0.012***
	(0.001)	(0.001)	(0.001)
Non-Debt Tax $\text{Shields}_{i,t}$	-0.180**	-0.192	-0.207**
	(0.080)	(0.126)	(0.097)
$\text{Size}_{i,t}$	0.037***	0.038***	0.036***
	(0.002)	(0.003)	(0.003)
Asset $\text{Tangibility}_{i,t}$	0.043***	0.018	0.066***
	(0.010)	(0.012)	(0.016)
R&D Expenditure $\text{Indicator}_{i,t}$	-0.005*	-0.002	-0.010*
	(0.003)	(0.003)	(0.006)
Industry Medium $\text{MDR}_{i,t}$	0.168***	0.173***	0.147***
	(0.011)	(0.018)	(0.021)
Absolute Financing $\text{Deficit}_{i,t}$	-0.031*	-0.045*	-0.020
	(0.019)	(0.023)	(0.019)
Sales $\text{Growth}_{i,t}$	-0.013***	-0.018***	-0.010***
	(0.003)	(0.004)	(0.003)
Dividend Payout $\text{Indicator}_{i,t}$	-0.022***	-0.022***	-0.021***
	(0.002)	(0.003)	(0.003)
Export $\text{Intensity}_{i,t}$	-0.006	-0.004	-0.009
	(0.007)	(0.009)	(0.009)
Import $\text{Intensity}_{i,t}$	-0.010**	-0.006	-0.014***
	(0.004)	(0.005)	(0.005)
$\text{MDR}_{i,0}$	0.077***	0.064***	0.092***
	(0.007)	(0.006)	(0.007)
Firm Fixed-effect	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes
$\text{SOA}_1(1-\hat{\lambda})$	24.20%	21.80%	26.60%
$\text{SOA}_4(1-(\hat{\lambda}+\hat{\varphi_4}))$	39.00%	33.70%	43.00%
AIC	-32,331.78	-17,273.12	-15,387.32
BIC	-31,941.02	-16,918.4	-15,027.21
Wald-1	4,010.29	2,463.15	1,767.16
Wald-2	539.34	303.90	260.82
LR-Test	935.76	265.91	621.74
Firms	2,650	1,069	1,581
Observations	25,968	12,134	13,834

Source: Prowess - Author's own calculation.

Notes: This table reports the DPF estimates for equation (3.4) where MB_j denotes the quartile group allocated to firms conditional on their level of the market-to-book ratio . SOA_1 reports the SOA for quartile group one where SOA_4 reports the conditional SOA for quartile group four. Bootstrapped standard errors are reported in parentheses where we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix TableA.3.1.

3.5.3 Capital Structure Adjustment Over The Business Cycle

In this section we present our main empirical findings. We begin by investigating the direct effect of the business cycle on the SOA. In order to evaluate the impact of the business cycle directly, we first report the estimates from a restricted version of equation (3.5), whereby we assume homogeneous adjustment costs between firms, yet, heterogeneous adjustment costs over the business cycle. In Table 3.11 we uncover that the typical Indian firm adjusts both statistically and economically faster in periods of high economic growth (29.80%) compared to periods of low economic growth (22.69%), supporting the pro-cyclical view that more prosperous macroeconomic conditions help to alleviate the market frictions associated with adjustment costs. Furthermore, the net difference across regimes is close to twice the 4% difference reported by Cook and Tang (2010) in US, thus, we posit that the relief of adjustment costs induced by macroeconomic performance is greater in India as market frictions and imperfections are more prominent. In line with Halling et al. (2016), we also observe some notable differences in the determinants of MDR, specifically, we document large changes in coefficient values in the substitution channels of non-debt tax shields and the dividend payout indicator, where the former suggests firms are more likely to prefer alternative tax shields in low growth periods to avoid increasing bankruptcy risk.

In Table 3.12-3.14 we report both the direct and asymmetric effects the business cycle via our three measures of firm-specific adjustment costs over high and low growth regimes. Furthermore, we illustrate the implied SOA in Figure 3.2-3.4. Starting with Table 3.12 and absolute financing deficit, generally speaking we find the direct effect (i.e. the difference between reference groups across regimes) to remain consistent with the previous estimates, however, we find limited evidence of asymmetric adjustment across firm-groups over both regimes. Our result show only firms in the highest quartile adjust faster relative to those in the lowest quartile in high growth periods. Furthermore, in low growth periods we find private-listed firms display no statistical sensitivity to their levels of financial imbalance across firm groups, implying homogeneous adjustment costs given the firms financial imbalance.

In contrast, we report both a direct and indirect effect of the business cycle across market-to-book quartile groups. In Table 3.13 we find the direct effect of the business cycle to be consistent with our earlier estimates, with the average firm in our reference group adjusting 5.40% faster in high growth regimes. However, we also document an increasing, or put differently, greater asymmetric response across quartile groups over high and low growth periods. That is, firms in

Table 3.10: Capital Structure Adjustment Conditional on Profitability

	Full Sample	Group Affiliated	Private
	(1)	(2)	(3)
$MDR_{i,t-1}$	0.770***	0.804***	0.745***
	(0.005)	(0.008)	(0.010)
$MDR_{i,t-1}*P_{Q2}$	-0.015***	-0.015***	-0.012*
	(0.004)	(0.005)	(0.007)
$MDR_{i,t-1}*P_{Q3}$	-0.056***	-0.063***	-0.052***
	(0.004)	(0.006)	(0.008)
$MDR_{i,t-1}*P_{Q4}$	-0.128***	-0.121***	-0.135***
	(0.006)	(0.009)	(0.010)
Profitability$_{i,t}$	-0.286***	-0.263***	-0.305***
	(0.017)	(0.023)	(0.022)
Market-to-Book$_{i,t}$	-0.018***	-0.014***	-0.022***
	(0.001)	(0.002)	(0.002)
Non-Debt Tax Shields$_{i,t}$	-0.195***	-0.183	-0.231**
	(0.076)	(0.111)	(0.101)
Size$_{i,t}$	0.035***	0.035***	0.034***
	(0.002)	(0.003)	(0.003)
Asset Tangibility$_{i,t}$	0.033***	0.008	0.057***
	(0.009)	(0.011)	(0.016)
R&D Expenditure Indicator$_{i,t}$	-0.005	-0.002	-0.011**
	(0.003)	(0.004)	(0.005)
Industry Medium MDR$_{i,t}$	0.172***	0.173***	0.155***
	(0.011)	(0.018)	(0.020)
Absolute Financing Deficit$_{i,t}$	-0.025*	-0.038*	-0.015
	(0.015)	(0.022)	(0.022)
Sales Growth$_{i,t}$	-0.013***	-0.017***	-0.010***
	(0.003)	(0.004)	(0.004)
Dividend Payout Indicator$_{i,t}$	-0.018***	-0.016***	-0.018***
	(0.003)	(0.004)	(0.004)
Export Intensity$_{i,t}$	-0.003	-0.002	-0.004
	(0.007)	(0.010)	(0.009)
Import Intensity$_{i,t}$	-0.010***	-0.005	-0.015***
	(0.004)	(0.006)	(0.005)
$MDR_{i,0}$	0.073***	0.058***	0.090***
	(0.004)	(0.006)	(0.008)
Firm Fixed-effect	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes
$SOA_1(1-\hat{\lambda})$	23.00%	19.60%	25.50%
$SOA_4(1-(\hat{\lambda}+\hat{\varphi_4}))$	35.80%	31.70%	39.00%
AIC	-32,151.77	-17,207.48	-15,267.95
BIC	-31,761.01	-16,852.76	-14,907.85
Wald-1	3,558.77	2,256.92	1,514.60
Wald-2	477.93	268.99	235.02
LR-Test	870.35	247.86	570.59
Firms	2,650	1,069	1,581
Observations	25,968	12,134	13,834

Source: Prowess - Author's own calculation.

Notes: This table reports the DPF estimates for equation (3.4) where P_j denotes the quartile group allocated to firms conditional on their level of profitability. SOA_1 reports the SOA for quartile group one where SOA_4 reports the conditional SOA for quartile group four. Bootstrapped standard errors are reported in parentheses where we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

the highest quartile group adjust nearly 1.5 times faster in high growth periods relative to low growth periods, this can be most clearly observed in Figure 3.3. One possible explanation for the asymmetric difference in adjustment speeds is high market-to-book value firms could be more willing to engage in external markets in high periods of macroeconomic performance in order to pursue investment opportunities. Furthermore, such firms may experience greater missvalaution in high growth periods thus resulting in lower equity issue costs and greater incentives to adjust their capital structure mix.

Interesting, the asymmetric impact of macroeconomic performance is even more pronounced for profitability, however, the direct effect on almost vanishes. In Table 3.13 column (1), we find difference between high and low regimes for our reference group (Q1) to be both statistically (at the 10% level) and economically indifferent, with reported speeds of 23.90% and 22.60%, respectively. Unreported mean statistics infer over both regimes the average firm in Q1 is making a loss, therefore, irrespective of the wider macroeconomic conditions, it appears firms adjust at similar rates when they are financially unprofitable. Comparatively, the opposite effect occurs for highly profitable firms. Firms with the highest profit levels adjustment both statistically and economically faster in high growth periods, with an asymmetric response in adjustment and net difference of roughly 14% between regimes. Accordingly, it is likely that such firm use excess earnings to retire debt and buy-buy equity in high growth periods, however, pose less desire to do so in low growth periods, and subsequently direct other earnings to other operational areas or use excess funds as precautionary cash holdings.

Overall, this section illustrates that time-variation in macroeconomic performance to be an important factor in the adjustment process with high growth periods corresponding to faster adjustment speeds, consistent with Cook and Tang (2010) and Dang et al. (2014). Our results in this section demonstrate, however, that the impact of macroeconomic performance can vary across firm-groups facing alternative cost threshold as firms with high market-to-book and profit levels display the highest adjustment speeds in high growth regimes, while the adjustment speeds of firms in financial decline are largely unaffected by external macroeconomic performance.

Table 3.11: Capital Structure Adjustment over the Business cycle

	Full Sample		Group-Affiliated		Private	
	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
$\mathrm{MDR}_{i,t-1}$	0.702***	0.771***	0.736***	0.798***	0.679***	0.753***
	(0.008)	(0.008)	(0.009)	(0.011)	(0.010)	(0.012)
$\mathrm{Profitability}_{i,t}$	-0.446***	-0.459***	-0.432***	-0.450***	-0.456***	-0.468***
	(0.015)	(0.022)	(0.024)	(0.028)	(0.026)	(0.024)
$\mathrm{Market\text{-}to\text{-}Book}_{i,t}$	-0.017***	-0.018***	-0.013***	-0.013***	-0.021***	-0.022***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Non-Debt Tax $\mathrm{Shields}_{i,t}$	-0.212***	-0.326***	-0.148	-0.432***	-0.283**	-0.303**
	(0.074)	(0.076)	(0.128)	(0.147)	(0.114)	(0.151)
$\mathrm{Size}_{i,t}$	0.039***	0.039***	0.040***	0.039***	0.037***	0.041***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Asset $\mathrm{Tangibility}_{i,t}$	0.039***	0.021**	0.024*	-0.011	0.053***	0.055***
	(0.010)	(0.010)	(0.013)	(0.018)	(0.015)	(0.016)
R&D Expenditure $\mathrm{Indicator}_{i,t}$	-0.017***	-0.006	-0.021***	-0.010	-0.015***	-0.003
	(0.003)	(0.005)	(0.005)	(0.007)	(0.004)	(0.006)
Industry Medium $\mathrm{MDR}_{i,t}$	0.168***	0.150***	0.165***	0.162***	0.150***	0.122***
	(0.019)	(0.018)	(0.019)	(0.019)	(0.025)	(0.021)
Absolute Financing $\mathrm{Deficit}_{i,t}$	-0.005	-0.004	0.001	-0.004	-0.014**	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
Sales $\mathrm{Growth}_{i,t}$	-0.019	-0.074**	-0.030	-0.087**	-0.012	-0.062*
	(0.018)	(0.029)	(0.028)	(0.037)	(0.025)	(0.032)
Dividend Payout $\mathrm{Indicator}_{i,t}$	-0.031***	-0.013***	-0.030***	-0.011**	-0.030***	-0.014**
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)
Export $\mathrm{Intensity}_{i,t}$	0.002	-0.012*	0.005	-0.004	-0.000	-0.019*
	(0.005)	(0.007)	(0.010)	(0.013)	(0.010)	(0.010)
Import $\mathrm{Intensity}_{i,t}$	-0.005	-0.019***	-0.002	-0.013**	-0.009*	-0.025***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
$\mathrm{MDR}_{i,0}$	0.067***	0.085***	0.051***	0.070***	0.082***	0.102***
	(0.007)	(0.007)	(0.005)	(0.011)	(0.010)	(0.010)
Firm Fixed-Effects	Yes		Yes		Yes	
Year Fixed-Effects	Yes		Yes		Yes	
$\mathrm{SOA}(1-\hat{\lambda})$	29.80%	22.90%	26.40%	20.20%	32.10%	24.70%
AIC	-31,272.05		-16780.47		-14794.04	
BIC	-30,816.66		-16366.94		-14374.59	
Wald-1	2,869.57		1817.46		1,244.53	
Wald-2	491.32		280.25		225.53	
LR-Test	748.20		218.35		473.96	
Firms	2,735		1,110		1,625	
Observations	27,681		13,102		14,579	

Source: Prowess - Author's own calculation.
Notes: This table reports the DPF estimates for a restricted specification of equation (3.5). Sub-columns labeled High and Low detail the coefficients and standard errors for both high and low regimes of GDP growth, of which by year classifications are detailed in Table 3.4. Bootstrapped standard errors are reported in parentheses where we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table 3.12: Capital Structure Adjustment over the Business Cycle Conditional on Absolute Financing Deficit

	Full Sample		Group Affiliated		Private	
	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
$\text{MDR}_{i,t-1}$	0.713***	0.785***	0.745***	0.815***	0.691***	0.760***
	(0.007)	(0.008)	(0.010)	(0.011)	(0.012)	(0.013)
$\text{MDR}_{i,t-1}$*AFD_{Q2}	-0.003	-0.009**	-0.000	-0.008	-0.005	-0.008
	(0.004)	(0.005)	(0.006)	(0.007)	(0.006)	(0.009)
$\text{MDR}_{i,t-1}$*AFD_{Q3}	-0.006	-0.013**	-0.007	-0.024***	-0.003	0.001
	(0.005)	(0.007)	(0.008)	(0.007)	(0.008)	(0.012)
$\text{MDR}_{i,t-1}$*AFD_{Q4}	-0.037***	-0.032***	-0.034***	-0.039***	-0.038***	-0.015
	(0.007)	(0.010)	(0.010)	(0.014)	(0.013)	(0.016)
$\text{Profitability}_{i,t}$	-0.445***	-0.457***	-0.433***	-0.449***	-0.455***	-0.466***
	(0.016)	(0.022)	(0.026)	(0.032)	(0.024)	(0.031)
$\text{Market-to-Book}_{i,t}$	-0.018***	-0.018***	-0.013***	-0.014***	-0.021***	-0.022***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$\text{Non-Debt Tax Shields}_{i,t}$	-0.207**	-0.321***	-0.142	-0.425***	-0.273**	-0.302**
	(0.086)	(0.099)	(0.120)	(0.150)	(0.121)	(0.140)
$\text{Size}_{i,t}$	0.038***	0.039***	0.040***	0.039***	0.037***	0.040***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\text{Asset Tangibility}_{i,t}$	0.040***	0.022*	0.026*	-0.008	0.052***	0.055***
	(0.011)	(0.011)	(0.015)	(0.019)	(0.012)	(0.016)
$\text{R\&D Expenditure}_{i,t}$	-0.005	-0.004	0.001	-0.004	-0.014**	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)
$\text{Industry Medium MDR}_{i,t}$	0.167***	0.149***	0.165***	0.162***	0.150***	0.121***
	(0.017)	(0.016)	(0.022)	(0.020)	(0.019)	(0.019)
$\text{Absolute Financing Deficit}_{i,t}$	0.047**	-0.022	0.045	-0.005	0.050	-0.044
	(0.023)	(0.037)	(0.033)	(0.056)	(0.041)	(0.059)
$\text{Sales Growth}_{i,t}$	-0.017***	-0.006	-0.021***	-0.011	-0.015***	-0.003
	(0.002)	(0.005)	(0.005)	(0.007)	(0.004)	(0.005)
$\text{Dividend Payout}_{i,t}$	-0.031***	-0.013***	-0.030***	-0.011**	-0.029***	-0.013**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
$\text{Export Intensity}_{i,t}$	0.002	-0.012	0.006	-0.005	-0.001	-0.019*
	(0.008)	(0.008)	(0.011)	(0.011)	(0.009)	(0.010)
$\text{Import Intensity}_{i,t}$	-0.005	-0.019***	-0.002	-0.013*	-0.009	-0.025***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)
$\text{MDR}_{i,0}$	0.066***	0.085***	0.051***	0.070***	0.082***	0.102***
	(0.005)	(0.007)	(0.008)	(0.009)	(0.009)	(0.010)
Firm Fixed-Effects	Yes		Yes		Yes	
Year Fixed-Effects	Yes		Yes		Yes	
$\text{SOA}_1(1-\hat{\lambda})$	28.70%	21.50%	25.50%	18.50%	30.90%	24.00%
$\text{SOA}_4(1-(\hat{\lambda}+\hat{\varphi}_4))$	32.40%	24.70%	28.90%	22.40%	34.70%	25.50%
AIC	-31,419.73		-16867.54		-14849.36	
BIC	-30,915.54		-16409.69		-14384.97	
Wald-1	2,877.46		1819.46		1248.20	
Wald-2	481.87		277.22		219.50	
LR-Test	728.82		216.02		457.97	
Firms	2735		1110		1625	
Observations	27681		13102		14579	

Source: Prowess - Author's own calculation.
Notes: This table reports the DPF estimates for equation (3.5) where AFD_j represent the quartile groups classification conditional on absolute financing deficit. Sub-columns labeled High and Low detail the coefficients and standard errors for both high and low regimes of GDP growth, of which by year classifications are detailed in Table 3.4. SOA_1 reports the SOA for quantile group one where SOA_4 reports the conditional SOA for quantile group four for each respective regime. Bootstrapped standard errors are reported in parentheses were we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table 3.13: Capital Structure Adjustment over the Business Cycle Conditional on The Market-to-book ratio

	Full Sample		Group Affiliated		Private	
	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
$\text{MDR}_{i,t-1}$	0.735***	0.789***	0.760***	0.810***	0.712***	0.770***
	(0.008)	(0.010)	(0.010)	(0.013)	(0.011)	(0.014)
$\text{MDR}_{i,t-1}*\text{MB}_{Q2}$	-0.002	-0.000	-0.002	0.000	0.009	0.012
	(0.005)	(0.006)	(0.006)	(0.008)	(0.007)	(0.010)
$\text{MDR}_{i,t-1}*\text{MB}_{Q3}$	-0.075***	-0.027***	-0.076***	-0.026***	-0.062***	-0.024**
	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)	(0.011)
$\text{MDR}_{i,t-1}*\text{MB}_{Q4}$	-0.171***	-0.113***	-0.139***	-0.093***	-0.190***	-0.124***
	(0.009)	(0.008)	(0.013)	(0.011)	(0.012)	(0.015)
$\text{Profitability}_{i,t}$	-0.453***	-0.466***	-0.441***	-0.455***	-0.466***	-0.478***
	(0.018)	(0.022)	(0.025)	(0.031)	(0.025)	(0.034)
$\text{Market-to-Book}_{i,t}$	-0.009***	-0.013***	-0.007***	-0.009***	-0.011***	-0.016***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
$\text{Non-Debt Tax Shields}_{i,t}$	-0.110	-0.274**	-0.064	-0.363***	-0.171	-0.259*
	(0.083)	(0.111)	(0.133)	(0.137)	(0.112)	(0.152)
$\text{Size}_{i,t}$	0.036***	0.037***	0.038***	0.038***	0.034***	0.038***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\text{Asset Tangibility}_{i,t}$	0.052***	0.030***	0.036***	-0.003	0.067***	0.066***
	(0.010)	(0.010)	(0.011)	(0.017)	(0.013)	(0.017)
$\text{R\&D Expenditure}_{i,t}$	-0.005**	-0.004	-0.000	-0.005	-0.013**	-0.003
	(0.003)	(0.004)	(0.005)	(0.004)	(0.006)	(0.007)
$\text{Industry Medium MDR}_{i,t}$	0.158***	0.139***	0.159***	0.153***	0.140***	0.111***
	(0.018)	(0.016)	(0.018)	(0.020)	(0.023)	(0.023)
$\text{Absolute Financing Deficit}_{i,t}$	-0.004	-0.071***	-0.016	-0.082*	0.004	-0.057
	(0.018)	(0.027)	(0.025)	(0.042)	(0.022)	(0.042)
$\text{Sales Growth}_{i,t}$	-0.018***	-0.005	-0.022***	-0.010	-0.014***	-0.003
	(0.003)	(0.004)	(0.005)	(0.007)	(0.004)	(0.006)
$\text{Dividend Payout}_{i,t}$	-0.029***	-0.013***	-0.030***	-0.012**	-0.026***	-0.012**
	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.005)
$\text{Export Intensity}_{i,t}$	-0.002	-0.014*	0.000	-0.008	-0.004	-0.020**
	(0.008)	(0.008)	(0.012)	(0.014)	(0.008)	(0.009)
$\text{Import Intensity}_{i,t}$	-0.006	-0.017***	-0.003	-0.012**	-0.009*	-0.024***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)
$\text{MDR}_{i,0}$	0.073***	0.089***	0.059***	0.077***	0.086***	0.105***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.011)
Firm Fixed-Effects	Yes		Yes		Yes	
Year Fixed-Effects	Yes		Yes		Yes	
$\text{SOA}_1(1-\hat{\lambda})$	26.50%	21.10%	24.00%	19.00%	28.80%	23.00%
$\text{SOA}_4(1-(\hat{\lambda}+\hat{\varphi}_4))$	43.60%	32.40%	37.90%	28.30%	47.80%	35.40%
AIC	-32,364.20		-17,275.58		-15,392.49	
BIC	-31,860.02		-16,817.73		-14,928.1	
Wald-1	3110.36		1924.35		1377.50	
Wald-2	526.60		295.95		252.95	
LR-Test	941.47		281.03		602.74	
Firms	2,735		1,110		1,625	
Observations	27,681		13,102		14,579	

Source: Prowess - Author's own calculation.

Notes: This table reports the DPF estimates for equation (3.5) where MB_j represent the quartile groups classification conditional on the market-to-book ratio. Sub-columns labeled High and Low detail the coefficients and standard errors for both high and low regimes of GDP growth, of which by year classifications are detailed in Table 3.4. SOA_1 reports the SOA for quantile group one where SOA_4 reports the conditional SOA for quantile group four for each respective regime. Bootstrapped standard errors are reported in parentheses were we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table 3.14: Capital Structure Adjustment over the Business Cycle Conditional on Profitability

	Full Sample		Group Affiliated		Private	
	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
$\text{MDR}_{i,t-1}$	0.761***	0.774***	0.795***	0.807***	0.737***	0.750***
	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.016)
$\text{MDR}_{i,t-1}*\text{P}_{Q2}$	-0.031***	0.016***	-0.029***	0.010	-0.029***	0.024**
	(0.006)	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)
$\text{MDR}_{i,t-1}*\text{P}_{Q3}$	-0.086***	-0.001	-0.093***	-0.011	-0.080***	0.005
	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.011)
$\text{MDR}_{i,t-1}*\text{P}_{Q4}$	-0.175***	-0.046***	-0.162***	-0.049***	-0.184***	-0.042**
	(0.010)	(0.010)	(0.011)	(0.014)	(0.013)	(0.019)
$\text{Profitability}_{i,t}$	-0.222***	-0.398***	-0.196***	-0.372***	-0.244***	-0.425***
	(0.020)	(0.025)	(0.028)	(0.033)	(0.025)	(0.041)
$\text{Market-to-Book}_{i,t}$	-0.020***	-0.019***	-0.016***	-0.014***	-0.024***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
$\text{Non-Debt Tax Shields}_{i,t}$	-0.138*	-0.290***	-0.060	-0.381***	-0.216*	-0.278*
	(0.075)	(0.103)	(0.142)	(0.144)	(0.119)	(0.144)
$\text{Size}_{i,t}$	0.034***	0.036***	0.035***	0.035***	0.032***	0.038***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\text{Asset Tangibility}_{i,t}$	0.041***	0.023**	0.024	-0.011	0.056***	0.056***
	(0.010)	(0.011)	(0.016)	(0.014)	(0.015)	(0.018)
$\text{R\&D Expenditure}_{i,t}$	-0.004	-0.005	0.001	-0.005	-0.013***	-0.003
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
$\text{Industry Medium MDR}_{i,t}$	0.162***	0.147***	0.155***	0.157***	0.152***	0.124***
	(0.015)	(0.013)	(0.020)	(0.021)	(0.021)	(0.020)
$\text{Absolute Financing Deficit}_{i,t}$	-0.001	-0.066**	-0.012	-0.082**	0.007	-0.052
	(0.019)	(0.027)	(0.027)	(0.038)	(0.020)	(0.043)
$\text{Sales Growth}_{i,t}$	-0.015***	-0.008**	-0.018***	-0.012*	-0.012***	-0.005
	(0.003)	(0.003)	(0.005)	(0.007)	(0.003)	(0.006)
$\text{Dividend Payout}_{i,t}$	-0.022***	-0.012***	-0.022***	-0.010*	-0.021***	-0.012**
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
$\text{Export Intensity}_{i,t}$	0.001	-0.012	0.002	-0.006	0.001	-0.017
	(0.007)	(0.007)	(0.010)	(0.013)	(0.010)	(0.011)
$\text{Import Intensity}_{i,t}$	-0.006	-0.018***	-0.002	-0.012**	-0.010*	-0.025***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
$\text{MDR}_{i,0}$	0.070***	0.085***	0.054***	0.069***	0.086***	0.103***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)
Firm Fixed-Effects	Yes		Yes		Yes	
Year Fixed-Effects	Yes		Yes		Yes	
$\text{SOA}_1(1-\hat{\lambda})$	23.90%	22.60%	20.50%	19.30%	26.30%	25.00%
$\text{SOA}_4(1-(\hat{\lambda}+\hat{\varphi}_4))$	41.40%	27.20%	36.70%	24.20%	44.70%	29.20%
AIC	-32,212.17		-17,233.04		-15,285.99	
BIC	-31,707.98		-16,775.20		-14,821.6	
Wald-1	2,807.81		1,804.11		1,198.12	
Wald-2	463.50		259.74		226.41	
LR-Test	876.89		261.71		559.12	
Firms	2,735		1,110		1,625	
Observations	27,681		13,102		14,579	

Source: Prowess - Author's own calculation.

Notes: This table reports the DPF estimates for equation (3.5) where P_j represent the quartile groups classification conditional on profitability. Sub-columns labeled High and Low detail the coefficients and standard errors for both high and low regimes of GDP growth, of which by year classifications are detailed in Table 3.4. SOA_1 reports the SOA for quantile group one where SOA_4 reports the conditional SOA for quantile group four for each respective regime. Bootstrapped standard errors are reported in parentheses were we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Figure 3.2: Business Cycle Adjustment Speeds Across Quartile Groups: Absolute Financial Deficit

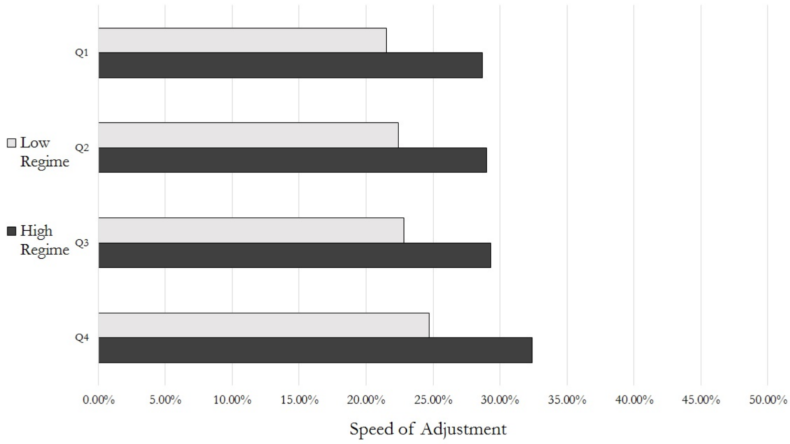


Figure 3.3: Business Cycle Adjustment Speeds Across Quartile Groups: Market-to-book

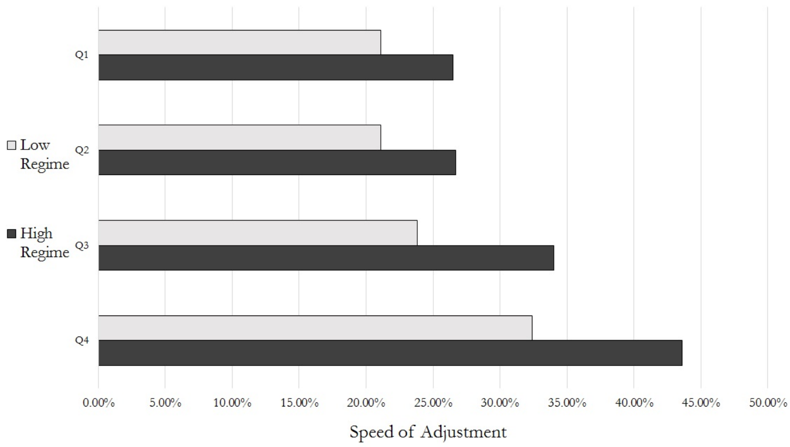
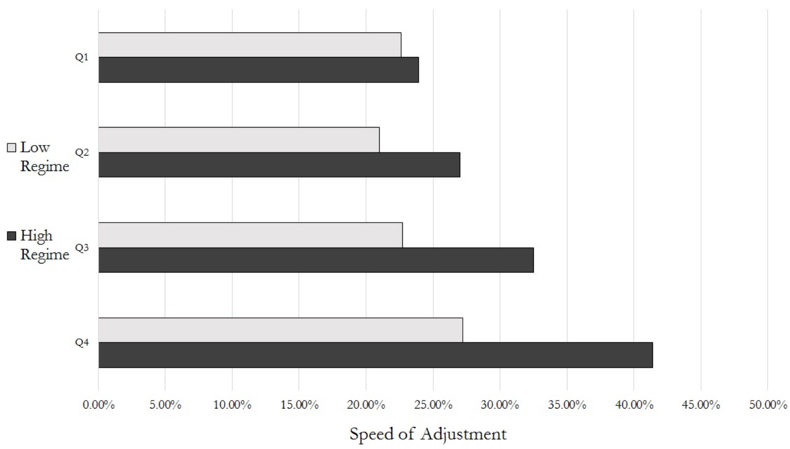


Figure 3.4: Business Cycle Adjustment Speeds Across Quartile Groups: Profitability



Source: Prowess - Author's own calculation.

3.6 Robustness Analysis

To illustrate the empirical stoutness of our findings provide additional three tests. To avoid overkill, the analysis presented in this section mainly focuses on our full sample estimates over the business cycle, however, the unreported results for group affiliated and private listed firms are widely consistent with the forthcoming discussion.

For the first robustness test we draw from chapter 2 where we documented that the degree of cross-sectional heterogeneity and the level panel unbalancedness can have a sizable impact on the bias of the autoregressive coefficient and therefore the implied SOA. To ensure our estimates are not affected by such factors, we explicitly examine the SOA for surviving firms. Following Lemmon et al. (2008), we classify survivor firms as firms that exist in the sample dataset for a minimum of 20 years, therefore, we remove all firms with less than 20 years of observations. Thus, by there very definition surviving firms in our sub-sample are less unbalanced than our original full sample. Equally, surviving firms are naturally older and generally display less variance across explanatory variables and can be considered a more homogeneous sub-sample of firms. In Table A.3.6 we report the results from our sub-sample estimates are, on average, consistent with our main findings. We find the direct effect of the business cycle to be slightly more pronounced for survivors, and in terms of firm-specific variables, we note that survivors with high market-to-book values in high growth periods adjust economically faster at a considerable 54.10%.

For the second robustness test we examine the consistency of our firm-specific measures of adjustment cost heterogeneity, by using three similar yet alternative proxies. Specifically, for our measure of absolute financing deficit, Faulkender et al. (2012) suggests the use of industry median investment in order to alleviate endogeniety concerns, however, given our quartile classification approach is by its definition exogenous, we propose an alternative absolute financing deficit measure based on the deductions of the firms actual investment, thus, providing a more concise estimate of a firms financial imbalance. For the market-to-book ratio we propose sale revenue growth, a common alternative proxy of investment opportunities (e.g. D'Espallier and Guariglia 2015), and for our measure of profitability we use return on capital employed. In Table A.3.7 we find our alternative measures of absolute financing deficit and return on capital employed to report similar levels of significance and adjustment speeds. However, while the sale growth reports a similar pattern of adjustment as the market-to-book ratio, the divergence across adjustment speeds between firm groups is notably less, suggesting that firms capital structure adjustment is more responsive to market valuations than book based measures of growth.

For the third and final robustness test, we examine the potential misspecification of our quartile dummy variable approach. Specifically, to account for potential within industry decision making and within industry reference groups, we re-define the quartile groups by year and industry, thus, accounting for potential within industry differences across our three measures of adjustment heterogeneity. In Appendix Table A.3.8 we illustrate that the results presented in this chapter are robust to alternative definitions of quartile rankings. Furthermore, in unreported results, we test the sternness of our results across alternative quantiles, namely, quintiles and deciles, and find the results are qualitatively the same.

3.7 Concluding Remarks

The dynamic trade-off theory of capital structure advances that firms facing opposing adjustment costs should in turn follow different paths towards their optimal target leverage. In this chapter we employ a novel empirical model specification to test this prediction by investigating both firm-specific asymmetric adjustment costs over the course of the business cycle. In terms of empirical approach, we emphasize the importance of robust econometric techniques throughout this paper by examining a range of econometric estimation procedures. To this end, we claim that the results presented in this chapter by the DPF estimator best approximate the true SOA due its propensity to alleviate fractional bias and estimate the autoregressive coefficient most accurately.

Our results document several forms of asymmetric adjustment with firms with greater financial imbalance, higher market-to-book ratios and higher profit levels all adjusting faster than their counterpart, consistent with the exiting literature. More importantly however, the efforts of this chapter extend the recent work of Cook and Tang (2010), Dang et al. (2014) and Drobetz et al. (2015) by providing complementary evidence on the pro-cyclical nature of firms capital structure adjustment speeds from an a new emerging market context. We find the effect of macroeconomic performance on Indian listed firms adjustment speeds is close to twice the 4% difference reported by Cook and Tang (2010) in the US, therefore, illustrating the greater importance of macroeconomic performance in a developing market context.

All in all, this study has contributed to academic efforts that seek to pin down the factors that govern the capital structure adjustment process, thus, addressing our the second research objective of this thesis. In terms of policy recommendations, despite India's financial sector development in recent years, policy makers may endeavour to introduce greater counter-cyclical buffers to alleviate the extenuated market frictions brought about in economic downturns. Accordingly, future research may look to examine how different macroeconomic shocks - both real and financial - in emerging economies effect capital market frictions and in turn the capital structure adjustment process.

3.8 Appendix

Table A.3.1: Variable Definitions and Sources

Data Reference	Definition	Source
Market Debt Ratio (MDR)	Total borrowing over the market value of equity plus total borrowing	Prowess
Profitability	Net earnings over Total Assets	Prowess
Market-to-Book	Market value of equity plus total borrowing over Total Assets	Prowess
Non-Debt Tax Shields	Total depreciation over total assets	Prowess
Size	The natural logarithm of total assets	Prowess
Asset Tangibility	Fixed assets over total assets	Prowess
R&D Expenditure	A binary variable equaling one if the firm invested in R&D otherwise zero	Prowess
Industry Medium	Industry medium leverage ratio based on 2 digit NIC Industry Classifications	Prowess
Absolute Financing Imbalance	The absolute value of operating income before depreciation	Prowess
	less income taxes, less interest expense, less mean industry investment	
Sales Growth	The percentage increase in total sales revenue over total assets	Prowess
Dividend Payout	A Binary variable equaling one if the firm paid dividends otherwise zero	Prowess
Export Intensity	Sales revenue generated by foreign sales over total sales revenue	Prowess
Import Intensity	Foreign raw materials over total materials	Prowess
Net Debt Issue	The first difference of total debt over total assets	Prowess
Net Equity Issue	Value of equity issues less the value buy-backs over total assets	Prowess
Active Debt	The percentage of non-zero values in the numerator of Net Debt Issue	Prowess
Debt Increase	The percentage of positive values in the numerator of Net Debt Issue	Prowess
Debt Decrease	The percentage of negative values in the numerator of Net Debt Issue	Prowess
Active Equity	The percentage of non-zero values in the numerator of Net Equity Issue	Prowess
Equity Increase	The percentage of positive values in the numerator of Net Equity Issue	Prowess
Equity Decrease	The percentage of negative values in the numerator of Net Equity Issue	Prowess
GDP Growth	The reported GDP growth of India	OECD
High Growth Dummy	The binary classification for high economic performance in India	OECD
Low Growth Dummy	The binary classification for Low economic performance in India	OECD

Table A.3.2: Unconditional Capital Structure Adjustment Speeds

Author(s)	Year of Publication	Country	Model Specification	Sample Coverage	Average T	Debt Type	SOA (%)
Ozkan	2001	UK	1	1984-1996	10.59	Book	$22^{(1)}, 41^{(3)}$
De Miguel and Pindado	2001	Spain	1	1990-1997	7.64	Market	$79^{(3)}$
Flannery and Rangan	2006	USA	1	1965-2001	8.60	Market	$38^{(2)}$
Kayhan and Titman	2007	USA	2	1960–2003	9.96	Market	$19^{(4)}$
Byoun	2008	USA	2	1972-2002	-	Market	$22^{(1)}$
Lemmon et al.	2008	USA	2	1965-2003	-	Book	$17^{(1)}, 39^{(2)}, 22^{(4)}$
Brav	2009	UK	2	1993-2002	-	Book	$23^{(2)}$
Chang and Dasgupta	2009	USA	1	1971-2004	-	Book	$38^{(2)}$
Huang and Ritter	2009	USA	1	1963-2001	-	Market	$21^{(5)}$
Cook and Tang	2010	USA	1	1977-2006	-	Market	$32^{(2)}$
Elsas and Florysiak	2011	USA	1	1965–2009	10.38	Market	$39^{(2)}, 26^{(7)}$
Guney et al.	2011	China	1	1994-2006	-	Book	$35^{(4)}$
Dang et al.	2012	UK	1	1996–2003	6.28	Market	$60^{(3)}$
Aybar-Arias et al.	2012	Spain	1	1995-2005	7.6	Market	$44^{(4)}$
Öztekin and Flannery	2012	USA	1	1991–2006	8.00	Market	$39^{(4)}, 37^{(6)}$
Öztekin and Flannery	2012	India	1	1991–2006	7.00	Market	$30^{(4)}, 31^{(6)}$
Öztekin and Flannery	2012	UK	1	1991–2006	8.00	Market	$25^{(4)}, 28^{(6)}$
Ebrahim et al.	2014	Malaysia	1	1988-2009	8.39	Book	$28^{(4)}$
Faulkender et al.	2012	USA	2	1965–2006	-	Market	$22^{(1)}$
Dang et al.	2014	USA	1	2002–2012	8.33	Book	$29^{(3)}$
Dang et al.	2015	USA	1	1967–2006	15.00	Book	$15^{(1)}, 40^{(2)}, 16^{(3)}, 18^{(4)}, 7^{(5)}, 26^{(6)}, 27^{(7)}$
Elsas and Florysiak	2015	USA	1	1965–2009	10.38	Market	$15^{(1)}, 39^{(2)}, 26^{(4)}, 27^{(6)}, 26^{(7)}$

Notes: Table 4.1 presents the estimated speed of adjustment for each paper listed, sorted by date. Author(s) lists the name of the author(s). Year or publication is the citation year of publication. Sample coverage is the country of which the firms of interest reside. Model specification lists if the author(s) employed a one or two-step approach. Estimation period lists the data sample coverage. Average T consists of either the average firm years provided by the author or a calculation of total firm-year observations divided by the number of firms. Debt type lists the dependent variable of interest, SOA(%) reports the estimated speed of adjustment given the type of estimator where (1) denotes the OLS estimator, (2) the FE estimator, (3) the FD-GMM estimator of Arellano and Bond (1991), (4) the system-GMM estimator of Blundell and Bond (1998), (5) the LD4 estimator of Huang and Ritter (2009), (6) the LSDVC estimator of Kiviet (1995) and finally (7) denotes the DPF estimator of Elsas and Florysiak (2011) and Elsas and Florysiak (2015).

Table A.3.3: Panel Structure By Firm

	Full Sample		Group Affiliated		Private	
No. of obs. per firm	No. of obs.	Percentage (%)	No. of obs.	Percentage (%)	No. of obs.	Percentage (%)
1997	675	2.23	393	2.87	282	1.70
1998	758	2.50	446	3.25	312	1.88
1999	951	3.14	516	3.76	435	2.62
2000	1,002	3.31	506	3.69	496	2.99
2001	807	2.66	449	3.27	358	2.16
2002	858	2.83	485	3.54	373	2.25
2003	846	2.79	481	3.51	365	2.20
2004	1,207	3.98	618	4.51	589	3.55
2005	1,482	4.89	676	4.93	806	4.85
2006	1,622	5.35	716	5.22	906	5.46
2007	1,719	5.67	726	5.30	993	5.98
2008	1,789	5.90	751	5.48	1,038	6.25
2009	1,728	5.70	731	5.33	997	6.01
2010	1,919	6.33	790	5.76	1,129	6.80
2011	1,929	6.36	794	5.79	1,135	6.84
2012	1,906	6.29	792	5.78	1,114	6.71
2013	1,848	6.10	763	5.56	1,085	6.54
2014	1,799	5.93	767	5.59	1,032	6.22
2015	1,871	6.17	776	5.66	1,095	6.60
2016	1,808	5.96	766	5.59	1,042	6.28
2017	1,789	5.90	769	5.61	1,020	6.14
Total	30,313	100.00	13,711	100.00	16,602	100.00

Table A.3.4: Panel Structure By Year

	Full Sample		Group Affiliated		Private	
Year	No. of obs.	Percentage (%)	No. of obs.	Percentage (%)	No. of obs.	Percentage (%)
3	405	1.34	117	0.85	288	1.73
4	500	1.65	188	1.37	312	1.88
5	630	2.08	225	1.64	405	2.44
6	960	3.17	318	2.32	642	3.87
7	1,218	4.02	392	2.86	826	4.98
8	1,240	4.09	424	3.09	816	4.92
9	1,503	4.96	387	2.82	1,116	6.72
10	1,860	6.14	470	3.43	1,390	8.37
11	2,145	7.08	759	5.54	1,386	8.35
12	1,968	6.49	756	5.51	1,212	7.30
13	1,846	6.09	624	4.55	1,222	7.36
14	1,652	5.45	672	4.90	980	5.90
15	1,890	6.23	825	6.02	1,065	6.41
16	1,824	6.02	816	5.95	1,008	6.07
17	2,397	7.91	1,275	9.30	1,122	6.76
18	1,638	5.40	1,026	7.48	612	3.69
19	2,223	7.33	1,292	9.42	931	5.61
20	1,600	5.28	940	6.86	660	3.98
21	2,814	9.28	2,205	16.08	609	3.67
Total	30,313	100.00	13,711	100.00	16,602	100.00

Table A.3.5: Panel Unit Root Tests: Fisher-type Augmented Dickey-Fuller (ADF) & Phillips-Perron (PP)

	Augmented Dickey-Fuller		Phillips-Perron	
	Drift	Drift and Trend	Drift	Drift and Trend
MDR	-16.651***	-12.322***	-27.062***	-17.104***
Profitability	-21.743***	-17.868***	-36.682***	-30.792***
Market-to-Book	-17.712***	-5.826***	-32.141***	-22.940***
Non-Debt Tax Shields	-15.223***	-13.475***	-24.198***	-20.531***
Size	-17.841***	-15.756***	-9.340***	-10.124***
Asset Tangibility	-12.169***	-10.347***	-19.712***	-18.003***
Industry Medium	-2.703***	-0.455	-19.503***	-16.905***
Absolute Financing Imbalance	-47.135***	-31.264***	-95.255***	-78.682***
Sales Growth	-45.336***	-39.325***	-91.809***	-80.859***
Export Intensity	-17.671***	-13.670***	-25.912***	-20.693***
Import Intensity	-22.523***	-14.632***	-31.313***	-19.927***

Source: Prowess - Author's own calculation.

Notes: The table reports augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) fisher-type panel unit root tests on all continuous variables. All ADF and PP tests include one lag, while each stylised test has been reported with the inclusion of a drift and a drift with time trend. Each test is examined under the null hypothesis that all panels contain unit roots with the alternative hypothesis that at least one panel is stationary. Reported test statistics are based on inverse normal test (Z).*, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table A.3.6: Robustness Analysis: Sample Survivors

	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
$\mathrm{MDR}_{i,t-1}$	0.689***	0.798***	0.726***	0.793***	0.770***	0.810***
	(0.016)	(0.018)	(0.015)	(0.017)	(0.018)	(0.020)
$\mathrm{MDR}_{i,t-1}$*AFD_{Q2}	0.006	-0.006				
	(0.012)	(0.014)				
$\mathrm{MDR}_{i,t-1}$*AFD_{Q3}	0.005	-0.007				
	(0.013)	(0.015)				
$\mathrm{MDR}_{i,t-1}$*AFD_{Q4}	-0.064***	-0.015				
	(0.017)	(0.020)				
$\mathrm{MDR}_{i,t-1}$*MB_{Q2}			-0.010	0.018		
			(0.012)	(0.014)		
$\mathrm{MDR}_{i,t-1}$*MB_{Q3}			-0.107***	-0.018		
			(0.013)	(0.014)		
$\mathrm{MDR}_{i,t-1}$*MB_{Q4}			-0.267***	-0.080***		
			(0.018)	(0.021)		
$\mathrm{MDR}_{i,t-1}$*P_{Q2}					-0.041***	0.000
					(0.014)	(0.016)
$\mathrm{MDR}_{i,t-1}$*P_{Q3}					-0.108***	-0.011
					(0.015)	(0.017)
$\mathrm{MDR}_{i,t-1}$*P_{Q4}					-0.179***	-0.053**
					(0.018)	(0.022)
Firm Controls	Yes		Yes		Yes	
Firm Fixed-Effects	Yes		Yes		Yes	
Year Fixed-Effects	Yes		Yes		Yes	
$\mathrm{SOA}_1(1-\hat{\lambda})$	31.10%	20.20%	27.40%	20.70%	23.00%	19.00%
$\mathrm{SOA}_4(1-(\hat{\lambda}+\hat{\varphi}_4))$	37.50%	21.70%	54.10%	28.70%	40.90%	24.30%
AIC	-5243.22		-5457.44		-5090.21	
BIC	-4948.93		-5163.15		-5384.49	
Wald-1	709.74		726.02		681.81	
Wald-2	158.35		152.46		161.66	
LR-Test	58.61		83.88		70.07	
Firms	214		214		214	
Observations	4,160		4,160		4,160	

Source: Prowess - Author's own calculation.

Notes: This table reports the DPF estimates for equation (3.5) where AFD_j, MB_j and P_j represent the quartile groups classification conditional on absolute financial deficit, the market-to-book ratio and profitability, respectively. Sub-columns labeled High and Low detail the coefficients and standard errors for both high and low regimes of GDP growth, of which by year classifications are detailed in Table 3.4. SOA_1 reports the SOA for quantile group one where SOA_4 reports the conditional SOA for quantile group four for each respective regime. Bootstrapped standard errors are reported in parentheses were we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table A.3.7: Robust Analysis: Alternative Measures

	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
$\text{MDR}_{i,t-1}$	0.716***	0.779***	0.738***	0.783***	0.761***	0.794***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.002)	(0.007)
$\text{MDR}_{i,t-1}$*AAFD_{Q2}	0.006	-0.005				
	(0.005)	(0.006)				
$\text{MDR}_{i,t-1}$*AAFD_{Q3}	-0.014***	-0.021***				
	(0.005)	(0.007)				
$\text{MDR}_{i,t-1}$*AAFD_{Q4}	-0.038***	-0.048***				
	(0.007)	(0.009)				
$\text{MDR}_{i,t-1}$*SG_{Q2}			-0.019***	-0.018***		
			(0.005)	(0.007)		
$\text{MDR}_{i,t-1}$*SG_{Q3}			-0.044***	-0.034***		
			(0.006)	(0.007)		
$\text{MDR}_{i,t-1}$*SG_{Q4}			-0.067***	-0.040***		
			(0.006)	(0.008)		
$\text{MDR}_{i,t-1}$*ROCE_{Q2}					-0.067***	-0.023***
					(0.017)	(0.017)
$\text{MDR}_{i,t-1}$*ROCE_{Q3}					-0.112***	-0.042***
					(0.018)	(0.018)
$\text{MDR}_{i,t-1}$*ROCE_{Q4}					-0.273***	-0.131***
					(0.023)	(0.025)
Firm Controls	Yes		Yes		Yes	
Firm Fixed-Effects	Yes		Yes		Yes	
Year Fixed-Effects	Yes		Yes		Yes	
$\text{SOA}_1(1-\hat{\lambda})$	28.40%	22.10%	26.20%	21.70%	23.90%	20.60%
$\text{SOA}_4(1-(\hat{\lambda}+\hat{\varphi}_4))$	32.20%	26.90%	32.90%	25.70%	47.90%	33.70%
AIC	-31,415.51		-31,438.02		-32,005.25	
BIC	-31,024.76		-31,047.27		-31,414.50	
Wald-1	3,663.48		3,625.38		3,357.44	
Wald-2	495.88		495.82		481.22	
LR-Test	725.24		748.58		847.09	
Firms	2,735		2,735		27,35	
Observations	27,681		27,681		27,681	

Source: Prowess - Author's own calculation.

Notes: This table reports the DPF estimates for equation (3.5) where $AAFD_j$, SG_j and $ROCE_j$ represent the quartile groups classification conditional on an alternative measure of absolute financial deficit, sales growth and return on capital employed, respectively. We define industries as via NIC industry classifications. Sub-columns labeled High and Low detail the coefficients and standard errors for both high and low regimes of GDP growth, of which by year classifications are detailed in Table 3.4. SOA_1 reports the SOA for quantile group one where SOA_4 reports the conditional SOA for quantile group four for each respective regime. Bootstrapped standard errors are reported in parentheses were we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Table A.3.8: Robustness Analysis: Industry-year Quartile Groups

	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
$\text{MDR}_{i,t-1}$	0.716***	0.779***	0.733***	0.772***	0.763***	0.773***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
$\text{MDR}_{i,t-1}\text{*AFD}_{Q2}$	0.006	-0.006				
	(0.005)	(0.006)				
$\text{MDR}_{i,t-1}\text{*AFD}_{Q3}$	-0.013**	-0.022***				
	(0.005)	(0.007)				
$\text{MDR}_{i,t-1}\text{*AFD}_{Q4}$	-0.038***	-0.048***				
	(0.007)	(0.008)				
$\text{MDR}_{i,t-1}\text{*MB}_{Q2}$			0.002	0.011*		
			(0.005)	(0.006)		
$\text{MDR}_{i,t-1}\text{*MB}_{Q3}$			-0.055***	-0.018***		
			(0.005)	(0.007)		
$\text{MDR}_{i,t-1}\text{*MB}_{Q4}$			-0.156***	-0.108***		
			(0.007)	(0.008)		
$\text{MDR}_{i,t-1}\text{*P}_{Q2}$					-0.033***	0.003
					(0.005)	(0.006)
$\text{MDR}_{i,t-1}\text{*P}_{Q3}$					-0.088***	-0.017**
					(0.006)	(0.007)
$\text{MDR}_{i,t-1}\text{*P}_{Q4}$					-0.155***	-0.061***
					(0.008)	(0.009)
Firm Controls	Yes		Yes		Yes	
Firm Fixed-Effects	Yes		Yes		Yes	
Year Fixed-Effects	Yes		Yes		Yes	
$\text{SOA}_1(1-\hat{\lambda})$	28.40%	22.10%	26.70%	22.80%	23.70%	22.70%
$\text{SOA}_4(1-(\hat{\lambda}+\hat{\varphi_4}))$	32.20%	26.90%	42.30%	33.60%	39.20%	28.80%
AIC	-31407.51		-32216.51		-32105.25	
BIC	-31016.76		-31825.76		-31714.50	
Wald-1	3661.61		3937.40		3557.44	
Wald-2	496.24		530.06		490.22	
LR-Test	725.93		917.32		867.09	
Firms	2,735		2,735		2,735	
Observations	27,681		27,681		27,681	

Source: Prowess - Author's own calculation.

Notes: This table reports the DPF estimates for equation (3.5) where AFD_j, MB_j and P_j represent the industry-quartile group classification conditional on absolute financial deficit, the market-to-book ratio and profitability, respectively. We define industries as via NIC industry classifications. Sub-columns labeled High and Low detail the coefficients and standard errors for both high and low regimes of GDP growth, of which by year classifications are detailed in Table 3.4. SOA_1 reports the SOA for quantile group one where SOA_4 reports the conditional SOA for quantile group four for each respective regime. Bootstrapped standard errors are reported in parentheses were we set the repetition rate R=250. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. AIC and BIC report the Akaike information criterion and Bayesian information criterion, respectively. Wald-1 reports the test statistic for a Wald test of the joint signicance of the year fixed-effects, asymptotically distributed as χ^2 under the null of no relation. Wald-2 reports the test statistic for a Wald test of the joint signicance of the all firm-averages, asymptotically distributed as χ^2 under the null of no relation. LR-test reports the test statistic for a likelihood-ratio test comparing a pooled-tobit model to the DPF estimator including correlated random effects. All variable names, definitions and sources can be found in appendix Table A.3.1.

Chapter 4

Dividend Decisions, Peer Effects and Geographical Proximity: Evidence from India

Abstract: *The dividend payout decisions of firms have long been considered independent from the decisions of their peers. However, recent research has shown that the corporate policies of firms, including corporate payout policy, are in fact largely interdependent on the policies of their industry counterparts. In this chapter, we extend this line of enquiry by examining if the propensity of peer influence on corporate dividend decisions is conditional on said peers geographical location. Using a large unbalanced panel of 3,670 firms over the period of 1995-2017, we show that the decisions to increase and decrease dividends are more influenced by the decisions of their geographically closer industry counterparts, an effect we attribute to imperfect information and possible pressure from local investor clienteles and/or local market competition.*

4.1 Introduction

The decisions of individual economic agents are often influenced by the decisions of their peers. This notion of social interaction and peer influence has long been established in many areas of economics, such as: behavioural, labour and urban economics (e.g., Duesenberry et al. 1949, Scharfstein et al. 1990, Abel 1990, Sacerdote 2001, Glaeser et al. 2003, Zimmerman 2003, Angrist and Lang 2004, Angrist and Pischke 2008, Maurer and Meier 2008, Moretti 2011, Helmers and Patnam 2014 and Blume et al. 2015). In recent years, peer effects have also received substantial attention from the corporate finance literature. Traditionally, the dividend payout decisions of firms have been assumed to be independent from the actions and/or characteristics of their peers. However, the recent work of Adhikari and Agrawal (2018) and Grennan (2019) have shown that peer behaviour is more important for determining corporate payout policy than many well established firm-specific determinants, such as profitability and firm size. Similar interdependencies have also been documented for firms' capital structure (e.g., Leary and Roberts 2014 and Im 2019), corporate social responsibility policy (e.g., **?**), precautionary cash holdings (e.g., Hoberg et al. 2014 and Chen et al. 2019) and investment decisions (e.g., Patnam 2011 and Foucault and Fresard 2014).

One of the major empirical challenges of peer effect analysis is the identification and categorisation of economic agents reference groups (Maurer and Meier, 2008). In practice, reference groups approximate the peer group structure of economic agents as the true identity of said peer groups are often unobserved by the researcher. For example, in the context of peer effects and educational performance, the identification of each student's friendship (peer) group, is, in most cases, latent. Accordingly, in order to examine the effects of peer behaviour on exam performance, some broader approximations must be made regarding the peer group structures of students, e.g. peer groups based on classroom allocation.

What makes reference group categorisation even more challenging is the fact that peer influence is often nonlinear and can manifest itself through multiple channels (Sacerdote 2011; Duflo et al. 2011). In addition, the size and topological structure of individual peer groups also often differ for each individual economic agent. With regards to our previous example, a student's friendship (peer) group may consist of a *best friend* which is likely to be more influential than a mere associate. Furthermore, the *most popular* student, by it's very definition, is going to have a larger friendship (peer) group than the average student. Ultimately, failing to account for such intricacies can result in the misspecification of peer measures, which can give rise to spurious economic inferences about the true nature of peer effects (Angrist 2014; Feld and Zölitz 2017).

In the corporate finance literature, researchers have adopted a number of different reference groups proxies. Most commonly, researchers have used industry classifications (e.g., Leary and Roberts 2014 and Adhikari and Agrawal 2018) and/or text-based product similarity groups (e.g., Grennan 2019 and **?**) to construct peer reference groups assuming transitivity, i.e. all firms within the same industry are interconnected and considered peers of equal influence. Consequently, many of the aforementioned studies fail to account for the potential nonlinearity of peer effects that are likely to be prominent in the corporate finance setting, and more specifically, for dividend payout decisions. For instance, transitive reference groups ignore market imperfections such as imperfect and incomplete information, where less easily observed industry peers - e.g. peers located further away - may be less influential than their closer, more easily observed industry counterparts who are more likely to adopt competitive corporate policies. Furthermore, the assumption of transitivity neglects the possibility that information asymmetries related to geographical location may effect the size and topological structure of individual firms peer reference groups. The purpose of this chapter is to overcome such limitations.

In this chapter we investigate if firms decisions to increase or decrease dividend payments are influenced by the actions and/or characteristics of their industry peers. In particular, using intransitive proximity based reference groups, we examine if geographically closer industry peers bear greater influence on firms dividend decisions than the broader industry average peer effect.

Prior to our study, the geographical distance to alternative economic agents and institutions have been found to play an import role in determining corporate payout policy (e.g., John et al. 2011). In its broadest sense, the existing finance literature has shown geographical distance eases the transfer of soft information, reduces information asymmetries and lowers potential agency problems (Petersen and Rajan 2002; Liberti and Petersen 2018). As a result of such factors, both individual (Ivković and Weisbenner, 2005) and institutional (Coval and Moskowitz, 1999) investors often display a preference bias towards firms with nearby headquarters. Subsequently, such favouritism towards nearby firms has been found to result in equity market segmentation and increased competition between firms for local dividend clienteles (Becker et al., 2011), where more remotely located firms often pay higher dividends to compensate for greater information asymmetries (John et al., 2011). Based on these premises, in this chapter, we conjecture that geographically closer industry peers are more likely to influence the dividend decisions of firms due to more complete information and/or greater rivalry for local dividend clienteles, local market share, resources and revenue.

The existing studies of peer effects on corporate policies have predominantly documented the presence of peer influence in developed economies, e.g. the US, where issues of asymmetric information and agency problems are marginal due to well-functioning capital, labour and product markets and strong legal systems. In contrast, issues of incomplete information and agency problems are particularly severe in emerging economies (Allen et al., 2005). Emerging economies such as India, are typically characterised by low levels of information dispersion, illiquid capital markets and high levels of corruption (Khanna and Palepu 1997; La Porta et al. 2000; Khanna and Palepu 2000). However, since India's financial liberalisation, numerous initiatives have been taken by the stock exchange board of India to improve market liquidity and governance practice, whereby minority shareholder protection in India is now comparable to that of developed economies (World Bank, 2018). Accordingly, it is the juxtaposition of low information dispersion yet improved market and governance conditions that make India an ideal laboratory for our empirical study.

Using a large unbalanced panel of 3,670 Indian listed firms this chapter investigates the dividend decisions of Indian firms over the period of 1995-2017. To test our empirical hypothesis, we use the distance between firms headquarters to create four sets of geographically weighted peer proximity measures. Specifically, based on the radial distances of 250 miles, 500 miles, 750 miles and 1000 miles, we calculate, for each distance band, the average peer dividend decision and the average of all peer-specific characteristics. We then estimate, individually, each set of peer proximity measures on the decisions to increase or decrease dividends.

While the concept of peer influence is indeed intuitively palpable, empirically, the correct estimation of peer effects is challenging due to a specific form of endogeneity, known as the reflection problem (Manski, 1993). In its simplest sense, if the dividend decisions of firms are influenced by their industry counterparts, then firm i's dividend decision is a function of firm k's and vice versa. Thus, a clear simultaneity issue exists. To address this inherent endogeneity problem, this chapter employs the instrumental variable approach devised by Leary and Roberts (2014) which has also been adopted by the likes of Adhikari and Agrawal (2018), Grennan (2019) and Chen et al. (2019). Using stock market data we calculate two measures, namely, peer idiosyncratic equity shock and peer idiosyncratic equity risk, which we use as instruments in our identification strategy. In Section 4.3.2, we outline our approach in detail and discuss the relevance and validity of such measures at length. However, in short, our instrumental variable approach uses peer idiosyncrasies to isolate peer dividend changes and then we test how the effected peers' change in dividend payout influences the unaffected firms' dividend decision.

Prior to our main discussion, we establish the presence of peer effects under the existing assumption of transitive peer reference groups. We find, using the overall industry peer averages, that both dividend increases and dividend decreases are influenced by peer dividend decisions. These findings both support and conflict with the contemporaneous findings of Grennan (2019) who only documents industry peers to effect the decision to increase dividends and not decrease. Similar to Leary and Roberts (2014), Adhikari and Agrawal (2018) and Grennan (2019), we find the estimated marginal effect of peer influence - for both dividend increases and dividend decreases - to be larger than many previously identified dividend determinants. Moreover, the effect of peer influence on dividend decisions proves to be asymmetric - consistent with the survey evidence of Brav et al. (2005) - with peer behaviour having a more pronounced effect on dividend decreases.

With the existence of dividend peer effects confirmed, we address to our main empirical inquiry. Our results show that the geographical location of peers matter for both dividend increases and dividend decreases. Using our proximity based peer measures, we find that intransitive reference groups based on closer industry peers, e.g. 250 miles, display significantly greater influence on dividend decisions than wider based peer averages. The negative relationship between geographical distance indicates that peer influence on corporate dividend decisions is indeed nonlinear, where firms are more susceptible to the dividend decisions of their geographically closer industry counterparts. These finding are in line with the idea of corporate isomorphism and support our conjecture that firms respond to the decisions of their closer industry peers due to more complete information, more pressure from local investor clienteles and/or local competition. Accordingly, our findings lend partial support to the recent work of Adhikari and Agrawal (2018) and Grennan (2019) who suggest that firms mimic the dividend policies of their rivals in order to maintain their competitive parity.

To further consolidate our understanding of peer proximity effects, we examine the potential alternative channels of peer influence and the temporal permanence of our results with respect to the recent financial crisis. We find that the decision to increase dividends is made independently from peer firms decision to decrease dividends. In contrast, firms are statically less likely to decrease dividends if their closer industry counterparts increase their payout. Thus, indicating an upward stickiness of dividend payout decisions brought on via peer behaviour. With respect to the temporal stability of our initial results, we find peer effects related to dividend increases are largely consistent over time, yet, the role of peer influence on dividend decreases is most statistical and economically significant during/after the recent financial crisis when economic uncertainty was most pronounced.

To buttress our empirical results we conduct several robustness tests. First, similar to Leary and Roberts (2014) and Grennan (2019) we address the latent common factors attributable to our use of industry-based reference groups. We administer a placebo test based on randomly assigned peer groups and find insignificant peer effects for our randomised reference groups. In addition, we examine the validity of our results to various standard error structures, potential omitted factors and extended radius measures. We illustrate that our findings are not a product of specific variance assumptions nor are they driven by omitted variable bias or arbitrary distance measures. Overall, our results remain empirically stout.

The contributions made in this chapter are threefold. First, we contribute to the work on peer effects in corporate finance (e.g., Leary and Roberts 2014, Foucault and Fresard 2014, Kaustia and Rantala 2015, Adhikari and Agrawal 2018 and Grennan 2019) by proposing a new reference group structure based on peer geographical proximity. Accordingly, we propose a alternative measure that relaxes the strict assumption of within industry transitivity adopted by many previous studies and allows for the non-linearity of peer effects. Our second contribution is to the dividend literature regarding geographical distance (e.g., John et al. 2011) as we provide, to the best of our knowledge, the first evidence that the dividend decisions of firms are influenced by the dividend decisions of their local industry peers. Finally, we contribute to both the peer effects and dividend literature by providing the first empirically robust evidence of dividend decisions and peer effects in India, an alternative institutional setting to the existing peer effects literature on dividends. Accordingly, as a result of our alternative institutional setting, we prove peer effect manifestations are not strictly subject to developed institutional contexts, i.e. the US, nor does the existence of peer influence only display itself in the specific dividend decisions reported by Adhikari and Agrawal (2018) and Grennan (2019).

The remainder of the chapter is structured as follows. Section 4.2 provides a brief review of relevant literature and states our empirical hypothesis. Section 4.3 introduces the data used in our study. Section 4.3.2 discusses our empirical approach, including model specification, peer proximity measures and instrument construction. Section 4.4 provides summary statistics and Section 4.5 reports our empirical results. Finally, Section 4.5 documents our robustness analysis and Section 4.6 concludes the chapter.

4.2 Related Literature and Hypothesis Development

Since the original propositions of Modigliani and Miller (1958) and Miller et al. (1961) the corporate payout policies of firms have received substantial attention in the corporate finance literature. Theoretical research promoting the relevance of payout policies have been supported by a plethora of anecdotal and empirical evidence (e.g., Michaely et al. 1995, Fama and French 2001, Grullon et al. 2002, Short et al. 2002, Allen and Michaely 2003, Brav et al. 2005, DeAngelo et al. 2006 and Leary and Michaely 2011). However, until recently, the dividend payouts of firms have largely been analysed independently from the behaviour of their peers, or, at best, within industry interdependencies have only been investigated indirectly via industry averages, industry fixed-effects or competition related analysis (e.g., Hoberg et al. 2014 and Grullon et al. 2019).

In its broadest sense, Lieberman and Asaba (2006) propose two possible theories of why firms may decide to imitate the actions of their peers: i) the information-based theory, which suggests that firms may imitate those who are perceived to have superior information and ii) the rivalry-based theory, which posits firms may keep pace with their peers in order maintain their competitive parity. The recent empirical evidence on peer effects within the corporate finance literature shows, in line with the information-based theory, that important corporate decisions relating to capital structure (e.g., Leary and Roberts 2014) corporate investment (e.g., Foucault and Fresard 2014) and stock dilution (e.g., Kaustia and Knüpfer 2012) are all influenced by the behaviours of their larger, better informed and more experienced peers.

In contrast, the dividend payout policies of firms have been shown to be driven by more competitive tendencies. Specifically, using a large sample of US firms from 1965-2010 Adhikari and Agrawal (2018) find that the decision to initiate dividends, the amount of dividends paid and stock repurchases are all influenced by their industry peers, yet, firms place more importance on the actions of their peers that are similar in age and size. Parallel to this, Grennan (2019) shows that market leaders often utilise peer influence to their competitive advantage by forcing financially vulnerable firms to increase dividends in order to limit their free cash flow and future growth.

To explain such competitive tendencies, a number of arguments exist relating to competition for market share, resources and revenue. For example, firms in the same industry are often privy to similar investment opportunities, use similar inputs and compete in the same labour markets. Therefore, drawing from the theoretical work of Benoit (1984) and Bolton and Scharfstein (1990), financially vulnerable dividend paying firms may decrease or even omit dividends to match the potential expansive or predatory behaviour of their cash rich industry counterparts, similar to the empirical evidence provided by Grennan (2019). In the presence of imperfect and incomplete information, firms are more likely to observe and indeed react to the behaviour of their nearby peers rather than their more distance industry counterparts as they compete for market share and resources.

Another possible motive for peer imitation relates to dividends propinquity with equity markets and investors. The initial purpose of dividends was to make equity look like debt, thus, allowing investors an easier means of calculating share value and a more accessible form of stock comparison (Frankfurter and Wood, 1997). The concept that dividends can be used as a yardstick measure of valuation remains, to this day, prominent amongst individual (Graham and Kumar, 2006) and institutional investors (Ben-David, 2010). Given that dividends reflect a means of value, advocates of the signalling theory often argue that changes in dividend payout can transmit significant information to investors about a firms future prospects. Empirically, it has been shown that markets react positively to dividend initiations and dividend increases, while negatively to dividend omissions and dividend decreases (e.g., Bhattacharya 1980, Miller and Rock 1985, John and Williams 1985 and Michaely et al. 1995). Subsequently, considering that investor generally adopt the same or similar dividend yields to price firms within the same industry, if firms wish to compete in equity markets for investors, then their hands are effectively tied as they are forced to imitate the dividend decisions of their industry counterparts. This notion has been supported by the anecdotal work of Brav et al. (2005, p. 523) which concludes that "With respect to payout policy, the rules of the game include [...] do not deviate far from the competitors".

In addition to investors favoring specific payout decisions, empirical evidence has provided strong and consistent evidence that both individual and institutional investors exhibit a sizeable preference bias towards firms in closer geographical proximity. Coval and Moskowitz (1999) use US mutual fund data from 1995 and examine the distance from mutual funds headquarters to the headquarters of firms held in their respective portfolios. They find, on average, that mutual funds held companies that were 10% closer to the funds headquarters than the average of all listed firms. Moreover, individual investors, of whom have significantly less resources and are arguably more constrained by information asymmetries, display an even larger bias towards local companies relative to mutual funds. Ivković and Weisbenner (2005) examine the investments of 30,000 households in the US over 1991-1996 and find the average household invests 31% of its portfolio in local stocks located within 250 miles.

There exists a number of potential explanations for the such preference bias and favouritism towards nearby firms. First, geographical proximity has been shown, across a number of areas in finance, to ease the transfer of soft information, reduce information asymmetries and lower potential agency problems (Petersen and Rajan 2002, Berger et al. 2005, Uysal et al. 2008 and Liberti and Petersen 2018). Second, investors tend to have more/better information about closer firms and the surrounding economy than their more distance alternatives. Finally, behavioural finance theorist posit that investor bias towards nearby firms is driven by local sentiment, heuristics and/or familiarity bias (Tversky and Kahneman 1973; Huberman 2001). All in all, such favouritism towards nearby firms often results in investors holding a disproportionate number of local shares, thus, creating an informal segmentation of domestic equity markets (Pirinsky and Wang 2011).

In relation to the above literature, such equity market segmentation and investor favouritism has lead to the corporate policies of firms catering towards the demands of local investor clienteles.

Specifically, Becker et al. (2011) show that firms located in close proximity to a large number of senior investors are more likely to pay higher dividends to match the demands of seniors who favour cash dividends over alternative means of payment. Moreover, John et al. (2011) finds that firms located in more rural, less populated areas, often pay higher dividends to account for increased information asymmetries and monitoring costs. Thus, to rephrase our prior proposition, if firms wish to compete in equity markets, however, said equity markets are, to a degree, segmented; then to compete for local dividend clienteles firms must imitate the dividend decisions of their industry peers, yet, more so, the dividend decisions of their industry counterparts that closer in geographical proximity.

On this basis, given the existence of imperfect and incomplete information and that firms compete for more localised divided clienteles, we expect that the dividend decisions of firms are more likely to be influenced by the payout policies of their closer industry peers than the wider industry peer average. Consequently, we hypothesise that peer reference groups based on smaller geographical proximity's are likely to display a greater level of peer influence on firms' dividend decisions. It is this conjecture that we aim investigate empirically.

4.3 Data and Research Design

In this section we introduce the data used in our forthcoming empirical analysis. Section 4.3.1 details the data and our cleaning rules and Section 4.3.2 outlines the empirical methodology used to investigate the dividend decisions of Indian firms. For the sake clarity, we divide Section 4.3.2 into three segments. In Section 4.3.2.1, we detail the baseline model specification used to investigate whether dividend increases or dividend decreases are effected by the decisions of their industry peers, where peers groups are defined by the conventional transitive industry reference groups. In Section 4.3.2.2, we introduce our alternative peer measures based on geographical proximity that allow for intransitive reference groups within industries. Finally, in Section 4.3.2.3, we detail and construct our instrumental variables of peer idiosyncratic equity shock and peer idiosyncratic equity risk and discuss their relevance and validity.

4.3.1 Data

In order to analyse the dividend decisions of Indian listed firms we draw from a number of data sources. The primary data used in this chapter is obtained from Prowess, a database service maintained by the Centre for Monitoring the Indian Economy (CMIE). Prowess provides daily stock price data for BSE listed firms alongside annual accountancy data in a standardised format. To construct our instrumental variables of peer idiosyncratic equity shock and peer idiosyncratic equity risk we supplemented the market data available in Prowess with BSE Index data from the Royal Bank of India and US 10 year bond data from the Federal Reserve Bank of St. Louis. Furthermore, to calculate the distance based peer measures we obtained latitude and longitude coordinates from Geonames which we then match to each firm's headquarter address via pincodes.

After the construction of our two instrumental variables we applied a number of standard data restrictions to obtain final annual dataset. Following Leary and Roberts (2014), Adhikari and Agrawal (2018) and Grennan (2019) we excluded all firms operating in financial (NIC64-NIC66) and utility sectors (NIC35-NIC39) since these industries are largely subject to alternative accounting standards. Next, we removed all observations that have missing data and removed all industry-year observations that had less then three observations, where industries are defined by the two-digit NIC classification. Thus, at a minimum, each firm has at least two industry peers in any given year. Finally, we winsorized all continuous explanatory variables at the 1st and 99th percentiles to mitigate the effect of outliers and eradicate any potential errors in the data.

Our final sample coverage is from 1995-2017 and consists of 3,670 firms with a total of 28,961 firm-year observations, approximating an average panel length of 7.89 years per firm. The average industry-year observation consists of 71 firms with the largest industry consisting of 203 firms. Detailed summary statistics for our dataset are reported in Section 4.4 and all variable names, definitions and data sources can be found in Appendix Table A.4.1. Finally, information regarding the structure of our unbalanced panel and the distribution of firm–year observations can be found in Appendix Table A.4.2 and Appendix Table A.4.3, respectively.

4.3.2 Research Design

4.3.2.1 Baseline Model Specification

To examine the effects of industry peers on dividend payout decisions we follow the likes of Leary and Roberts (2014), Kaustia and Rantala (2015), Adhikari and Agrawal (2018) and Grennan (2019) and adopt the following baseline model specification:

$$y_{i,j,t} = \alpha + \varphi\bar{y}_{-i,j,t} + \psi'\bar{X}_{-i,j,t-1} + \beta'X_{i,j,t-1} + \zeta'Z_{i,j,t-1} + \eta_j + \eta_t + \upsilon_{i,j,t} \tag{4.1}$$

where the indices i, j and t correspond to firm, industry, and year, respectively. The dependent variable $y_{i,j,t}$ is binary and reflects firm i's decision to either increase or decrease their dividend payout in year t. Thus, $y_{i,j,t}$ takes the value of one if firm i increases (decreases) their dividend payout or else zero. By separating these two types of dividend adjustment we allow for statistical and economic asymmetries in determinants as advocated by the literature (e.g., Michaely et al. 1995 and Leary and Michaely 2011). The variable $\bar{y}_{-i,j,t}$ is fractional and denotes the average peer dividend decision, more specifically, it is the equally weighted average of all firms in industry j except firm i in year t, to avoid mechanical correlation, where industry j is set at the two-digit NIC classification level[1]. We follow Leary and Roberts (2014) and Adhikari and Agrawal (2018) and use the contemporaneous values of $\bar{y}_{-i,j,t}$, as firms in a competitive environment are more likely to imitate current peer dividend decisions. Subsequently, $\bar{y}_{-i,j,t}$ is considered endogenous and therefore calls for instrumental variables. Moreover, it should be noted that by construction, this measure of peer dividend decision assumes transitivity and equal peer influence for all industry peers in a given year.

The vectors $\bar{X}_{-i,j,t-1}$ and $X_{i,j,t-1}$ contain peer firm averages and firm-specific characteristics, where the former vector consists of contextual variables (Manski, 1993) through which firms may respond to changes in their peers characteristics and the latter vector consists of firm-specific determinants. Our choice of firm-specific determinants, and in turn, peer characteristics, are motivated by two central frictions known to effect dividend decisions, namely, information asymmetries and agency problems (Allen and Michaely 2003; DeAngelo et al. 2009; Connelly et al. 2011). Specifically, we include eight different variables: profitability, the market-to-book ratio, investment, leverage, firm size, tangibility and the firm-specific measures of idiosyncratic equity shock and idiosyncratic equity risk[2]. We lag all variables by one period to alleviate potential endogeneity concerns.

It is well documented that profitably has a first order effect on firms dividend payout policies (Lintner 1956; Fama and French 2001). Naturally, firms with excess income must decide to either retain earnings, re-invest or distribute dividends. Subsequently, the literature, almost conclusively, suggests that profitability has a positive association with dividend payouts (Allen and Michaely, 2003). Therefore, firms with low or even negative profitability are less likely to pay dividends and are less able to use dividends as a signaling mechanism (DeAngelo et al., 2006). Unlike profitability, the market-to-book ratio which controls for signalling effects and growth opportunities have been found to display mixed effects on dividends. Typically, in line with the

[1]Note: The likes of Leary and Roberts (2014), Adhikari and Agrawal (2018) and Grennan (2019) use three digit SIC in the US to classify industry peers. However, due to a smaller sample and our peer proximity measures this study adopts a broader level of industry classification.

[2]Note: All variable names, definitions and data sources can be found in Appendix Table A.4.1.

life-cycle theory, mature firms with low growth opportunities are more likely to pay dividends (Grullon et al., 2002). However, such effects are largely conditional on the institutional setting, with international studies finding the opposite outside of anglosphere economies (e.g., Denis and Osobov 2008). With regards to other determinants, it is often argued that increasing investment reduces the degree of retained earnings available to signal with dividends (Guttman et al., 2010) while leverage, an adjacent internal governance mechanism, protects free cash flow against agency problems and is found to have a negative effect on dividend payout. Moreover, larger firms are often less affected by information asymmetries, while more tangible firms are generally more transparent than their intangible counterparts. Finally, firms with greater idiosyncratic risk and more frequent shocks require greater earning reserves and subsequently are less likely to pay dividends (Hoberg and Prabhala, 2009).

To control for the degree of competition within industries the vector $Z_{i,j,t-1}$ includes three variables, namely, a measure of industry competition (Herfindahl-Hirschman Index), the logarithm of the number of firms per industry and a firm-specific measure, which is the logarithm of the average distance from firm i to the remainder of it's industry peers in industry j, which reflects firm $i's$ degree of by yearly geographical centrality. In addition to the endogenous, contextual, firm- and industry-specific determinants, we include industry, η_j, and year, η_t, fixed effects to account for unobserved effects and common correlated factors that may influence or indeed cause coinciding dividend decisions. Finally, $\upsilon_{i,j,t}$ denotes the firm-specific error term and is assumed to be correlated within the firm and heteroskedastic. Subsequently, all reported standard errors are robust to heteroskedasticity and are clustered at the firm level to allow for within dependence (Petersen, 2009)[3].

4.3.2.2 Geographical Peer Proximity Measures

The main limitation of the empirical approach outlined in the previous section is that both the endogenous, $\bar{y}_{-i,j,t}$, and contextual effect, $\bar{x}_{-i,j,t}$, measures are based on simple leave-out means with equal weights for all industry peers. Consequently, the economic implications of said measures is that the relationships between firms, in a given industry, are assumed to be both transitive and homogeneous irrespective of their geographical location. Thus, such measures imply each firm has perfect information and operates within perfect (unsegmented) equity markets. The principal aim of this chapter is to address these issues as we investigate how the dividend decisions of firms are affected by their geographical closer industry counterparts.

[3]As a form of robustness test in Section 4.6, we examine the validity of our findings to alternative standard error assumptions. Our main findings remain unchanged.

In this study, we draw from the spatial econometrics literature, for example: Arbia and Baltagi (2008) and Bramoullé et al. (2009) and propose an alternative set of peer measures where peer reference groups are based on industry peers within set geographical distances. Specifically, we use the geographical distance between firm headquarters to calculate leave-out mean measures based on the proximity radiuses of 250 miles, 500 miles, 750 miles and 1000 miles. Before we discuss the favourable properties of the proposed peer proximity measures, we aid our discussion with a simple example consisting of three firms, namely: firm A, firm B and firm C, where we outline the steps used to construct our alternative peer measures. To begin, let us consider the n by 1 vector $\mathbf{y}$ which contains each firms decision to either increase dividends or not:

$$\mathbf{y} = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \tag{4.2}$$

here each row reflects the corresponding firms dividend decision. Based on the conventional leave-out mean peer measure, it is clear to see that 100% of firm A's peers increase their dividends, whereas only 50% of firm B's and firm C's peers increase their dividend payouts. To construct the proximity-based peer measure we first calculate the distance, in miles, between each firm-pair headquarters using the haversine formula:

$$Distance_{AB} = 2 \cdot R \cdot arcsin(min(1, \sqrt{z})) \tag{4.3}$$

$$z = (sin(\frac{Lat_A - Lat_B}{2}))^2 + cos(Lat_B) \cdot cos(Lat_A) \cdot (sin(\frac{Lon_A - Lon_B}{2}))^2 \tag{4.4}$$

where Lat and Lon denote the respective latitude and longitude coordinates for the headquarters of firm A and firm B and R is set to 3,963 miles to approximate the earths radius. For the sake of simplicity, let us assume that firm A is located directly north of firm B by 200 miles while firm C is located directly south of firm B also by 200 miles. Accordingly, the distance of each firm-pair can be displayed in an n by n distance matrix which we define as matrix $\mathbf{D}$:

$$\mathbf{D} = \begin{bmatrix} 0 & 200 & 400 \\ 200 & 0 & 200 \\ 400 & 200 & 0 \end{bmatrix} \tag{4.5}$$

here each row of the matrix $\mathbf{D}$ reports the distance between each corresponding firm-pair, for example, $\mathbf{D}(1,2)$ contains the distance between firm A and firm B while $\mathbf{D}(3,2)$ contains the distance between firm C and firm B. Next, based on a set proximity band, in this case 250 miles, one can then define the following binary n by n peer indicator matrix, $\mathbf{P}$, which we row standardise to obtain the spatial weight matrix $\mathbf{W}$:

$$\mathbf{P} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \Rightarrow \mathbf{W} = \begin{bmatrix} 0 & 1 & 0 \\ 0.5 & 0 & 0.5 \\ 0 & 1 & 0 \end{bmatrix} \tag{4.6}$$

as we can see the main diagonal element of $\mathbf{P}$ and $\mathbf{W}$ are equal to zero which prevents any firm from being defined as it's own peer. Furthermore, based on the proximity radius of 250 miles, firm A and firm C only have one corresponding industry peer while firm B has two industry peers, thus, inducing within industry intransitivity. Finally, by taking the product of matrix $\mathbf{W}$ and the vector $\mathbf{y}$, we obtain the peer proximity measure for the radius of 250 miles, which we define as $\mathbf{Wy}$:

$$\mathbf{Wy} = \begin{bmatrix} 0 & 1 & 0 \\ 0.5 & 0 & 0.5 \\ 0 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0.5 \\ 1 \end{bmatrix} \tag{4.7}$$

where the row of the n by 1 vector $\mathbf{Wy}$ contains the peer firm average dividend decision for each firm. In contrast to the simple leave-out mean approach, based on the peer proximity measures 100% of firm A's and firm C's peers increase their dividends while only 50% of firm B's peers increase their dividend payout.

In order to test our empirical research hypothesis, we use the above procedure and calculate peer proximity measures for our four proposed radial distances of 250 miles, 500 miles, 750 miles and 1000 miles. Specifically, for each industry-year observation, we calculate the geographically weighted peer averages for all endogenous and contextual effect variables and replace them in the baseline model discussed previously. In doing so, our peer proximity measures and new empirical specification yield a number of distinct qualities.

Most importantly, by construction, our empirical approach allows for firm-specific reference groups where said references groups are intransitive within industries. Thus, based on geographical proximity, peer reference groups are unique in size inducing a more acute measure of firms peer reference groups which are more likely to encapture the true nature of peer effects under imperfect information and segmented equity markets. Moreover, by calculating specific peer proximity measures for each year, we allow peers to both enter and exit the residing firms reference group. Finally, by using geographically weighted endogenous and contextual effect measures we are able to see how firms' decision to increase or decrease dividends are effected by both the actions and/or characteristics of their closer industry peers. All in all, it is based on these factors and our forthcoming empirical analysis where this chapter makes it most important contribution to the literature.

4.3.2.3 Identification Strategy

In order to identify the effect of industry peers on firms dividend payout decisions this study adopts an instrumental variable approach. While the notion of peer effects is relatively straightforward to contextualise, in practice, the identification of the true causal effect is notoriously challenging due to a specific form of endogeneity, known as the reflection problem (Manski, 1993). The primary difficulty arises from the presence of the endogenous effect, $\bar{y}_{-i,j,t}$, in equation (4.1). If the decisions of firms in industry j are truly influenced by one another, then firm $i's$ outcome is a function of firm $k's$ and vice versa. Thus, a clear simultaneity issue exists.

To address the inherent endogeneity problem, this study adopts a similar identification strategy to that of Leary and Roberts (2014), Adhikari and Agrawal (2018) and Grennan (2019). In particular, we use stock factor decomposition to abstract firm-specific idiosyncrasies, namely: idiosyncratic equity shock and idiosyncratic equity risk, and thereafter, we generate peer measures of idiosyncratic equity shock and idiosyncratic equity risk which are used as instrumental variables in our identification procedure. Stock factor decomposition is well established in the finance literature and has a number of auspicious empirical qualities. First, unlike some possible alternative instruments - for example, CEO deaths - stock market data is regularly available and provides sizeable time-series data for each firm. Furthermore, in line with the efficient market hypothesis, stock market prices reflect all firm related information, thus, encompassing all positive and negative shocks. Finally, stock market data, unlike firm-specific book values, are predominately exogenous and not as easily subject to value manipulation, therefore, proving empirically advantageous. In what follows, we illustrate the construction of our two instrumental variables and discuss their relevance and validity in relation to dividend decisions.

4.3.2.4 Instrument Construction

To construct our two instrumental variables we follow Leary and Roberts (2014) and adopt the following model specification:

$$R_{i,j,t_d} = \alpha_{i,j,t_d} + \beta^{M}_{i,j,t_d}(RM_{t_d} - RF_{t_d}) + \beta^{IND}_{i,j,t_d}(\bar{R}_{-i,j,t_d} - RF_{t_d}) + \zeta_{i,j,t_d} \tag{4.8}$$

where R_{i,j,t_d} denotes the daily return of firm i in industry j for day t_d. α_{i,j,t_d} is the firm-specific constant, RM_{t_d} is daily market return which we proxy by the BSE SENEX 50 index return[4]. RF_{t_d} is the risk free rate which we proxy by daily yield on US 10 year bonds. $\bar{R}_{-i,j,t_d}$ is an

[4]We use the BSE SENEX 50 index return over other indices due to it's time-series availability. For example, daily BSE 500 index data is only available from 01/02/1999. In unreported results we test the validity of our estimates to alternative index's and our results remain affirmed.

equally weighted portfolio of the average daily return for all firms in industry j except firm i on day t_d, again, set at the two-digit NIC classification level. Accordingly, β^{M}_{i,j,t_d} and β^{IND}_{i,j,t_d} are the structural parameters for the measures of market excess return ($RM_t - RF_{t_d}$) and industry excess return ($\bar{R}_{-i,j,t} - RF_{t_d}$).

We estimate equation (4.8) for each firm on a rolling annual basis using the historical return data. We require the minimum number of daily observations to be greater than 50 per year to ensure a suitable estimation sample. To ensure missing observations are correctly classified, and not a product of trading breaks, we augment our daily calendar to correspond to the dates of the daily market return, that is, observations are only classified as missing if daily stock observations are unavailable and market return data is present. Next, to obtain the expected and idiosyncratic return for a given company, for example, Tata Motors on the 1st April 2010, we first estimate equation (4.8) using daily returns from the 1st April 2009 to the 31st March 2010. Then, using the estimated coefficients from (4.8) and the daily factor returns for the 1st April 2010, we calculate both the expected and idiosyncratic daily returns, as shown below:

$$\text{Expected Return} \equiv \hat{R}_{i,j,t_d} = \hat{\alpha}_{i,j,t_d} + \hat{\beta}^{M}_{i,j,t_d}(RM_{t_d} - RF_{t_d}) + \hat{\beta}^{IND}_{i,j,t_d}(\bar{R}_{-i,j,t_d} - RF_{t_d}) \quad (4.9)$$

$$\text{Idiosyncratic Return} \equiv \hat{\zeta}_{i,j,t_d} = R_{i,j,t_d} - \hat{R}_{i,j,t_d} \quad (4.10)$$

where all coefficient values denoted with hats reflect the estimated parameters for a given stock regression and idiosyncratic return for a given stock is nothing more than actual return minus the expected return, or put differently, the residual. In order to generate the idiosyncratic return for Tata motors for the following day we update this process by moving the estimation window forward by one period. Therefore, it is clear, that this process generates coefficient values that are firm-specific and time-varying.

In Table 4.1 Panel A, we present the mean, median and standard deviation statistics for the estimated factor regression's. Overall, the estimated sample consists of a little less than 5.5 million daily observations where the average (median) number of days per rolling regression is 214 (234). Moreover, the average adjusted R^2 is 13.6% and the mean beta coefficient values sum to just below one ($0.209 + 0.711$=0.92). In Table 4.1 Panel B, we report the mean, median and standard deviation statistics for daily return, expected daily return and idiosyncratic daily return. The mean daily return is 10 basis points with a standard deviation of 0.047 while the average idiosyncratic return, as expected, equals zero.

Using the estimates of daily idiosyncratic return ($\hat{\zeta}_{i,j,t_d}$), we generate annual idiosyncratic equity shock ($IES_{i,j,t}$) and annual idiosyncratic equity risk ($IER_{i,j,t}$). For annual idiosyncratic equity shock we take a simple arithmetic mean of daily idiosyncratic return from the 1st of April to the 31st of March and for annual idiosyncratic equity risk we use the standard deviation of daily idiosyncratic return over the same time frame. Finally, using our two aggregated annual measures, $IES_{i,j,t}$ and $IER_{i,j,t}$, we calculate the overall industry peer instrumental variables of peer idiosyncratic equity shock ($I\bar{E}S_{-i,j,t}$) and peer idiosyncratic equity risk ($I\bar{E}R_{-i,j,t}$) by taking the average of idiosyncratic equity shock and idiosyncratic equity risk for firm $i's$ peers in industry j, excluding firm i, to avoid mechanical correlation and potential validity validations. We further calculate their spatial weighted equivalents based on the procedure outlined in Section 4.3.2.2. In each case, we propose the lag of both variables as valid and relevant instruments.

4.3.2.5 Instrument Relevance and Validity

In order to examine whether the dividend decisions of Indian listed firms are influenced by the decisions of their peers, this study adopts and instrumental variable approach whereby we instrument peer dividend decisions on our two proposed instruments of peer idiosyncratic equity shock and peer idiosyncratic equity risk. Subsequently, what lies at the heart of our success in this

Table 4.1: Stock Equity Regression Summary: Merged Sample Statistics

Panel A: Regression Statistics	Mean	Median	S.D.
$\hat{\alpha}_{i,t}$	0.001	0.000	0.004
$\hat{\beta}^{M}_{i,t}$	0.209	0.201	0.443
$\hat{\beta}^{IND}_{i,t}$	0.711	0.686	0.477
Adjusted R^2	0.136	0.106	0.123
Obs. Per Regression	214	234	41
Panel B: Return Statistics	**Mean**	**Median**	**S.D.**
Daily Return	0.001	0.000	0.047
Expected Daily Return	0.001	-0.005	0.016
Idiosyncratic Daily Return	0.000	-0.002	0.043
Total Observations	5,497,095	5,497,095	5,497,095

Source: Prowess - Author's own calculation.
Notes: The sample consists of all firms in the annual database between 1995 and 2017. The table reports summary statistics for our daily rolling stock equity factor regressions. Panel A presents the mean factor loading's, the adjusted R^2 and the observations per regression. Panel B reports the summary statistics for daily (realised) return, expected equity return and idiosyncratic equity return, where expected equity return is computed using the estimated factor loadings and realized factors and idiosyncratic equity return is computed as the difference between daily and expected equity return. All variable names, definitions and sources can be found in appendix Table A.4.1.

chapter is both the validity and relevance of such instruments. While in later sections we affirm these conditions through the use of appropriate statistical tests, understanding the theoretical motivation behind our choice of instrumental variables is of equal importance. In fact, we argue it is crucial for the reader to appreciate the economic properties of our instruments in order to accept the forthcoming inferences made by this chapter. Therefore, in this section we explain how the proposed instruments of peer idiosyncratic equity shock and peer idiosyncratic equity risk are both valid and relevant.

First, for an instrument to be valid it must satisfy the exclusion restriction, that is, the instrument(s) should not directly effect the dependent variable (Wooldridge, 2005). As previously detailed, the construction of our two instruments are derived from an augmented asset pricing model from rich and well established literature (e.g., Fama and French 1993, Carhart 1997 and Fama and French 2015). The augmented asset pricing model adopted in this study is well known for it's ability to decompose stock returns into both common (market) and firm-specific factors. Furthermore, our explicit inclusion of industry-specific returns alleviates industry-specific, or more precisely, peer-specific commonalities in the residual. Subsequently, the residuals obtained via our rolling window estimation procedure are purely firm-specific and free of any market or peer-specific manifestations (Adhikari and Agrawal, 2018). In addition, Leary and Roberts (2014) highlight that the residuals from the augmented model are both serially uncorrelated and serially cross-uncorrelated, therefore, firm-specific shocks do not predict future firm shocks nor do they predict contemporaneous peer shocks. As a result, the peer averages of idiosyncratic equity shock and idiosyncratic equity risk are not correlated with our firm-specific measures of equity shock or risk, and most importantly, do not predict firm-specific dividend decisions.

Second for an instrument to be relevant, it must meet the relevance condition, i.e. the instrument(s) must be correlated with the endogenous explanatory variable(s) (Wooldridge, 2005). Failure to satisfy the relevance condition can often result in weak instrumental variables which can give rise to spurious economic inferences (Stock and Yogo 2005; Andrews et al. 2019). With respect to our measures of peer idiosyncratic equity shock and equity risk we discuss relevance of said variables with respect to two potential concerns for the reader, that is, the relevance of said measures in relation to dividend payout policy and also the relevance of said market-based measures in the context of India. Starting with the former, there exists an extensive literature documenting the relationship between shocks, risk and dividend decisions (e.g., Grullon et al. 2002, Ang and Liu 2007 and Kanas 2013). Survey evidence as far back as Lintner (1956) can be suggested to identify the negative association between risk and dividends, with managers proving reluctant to increase dividends they may ultimately have to reverse. In the anecdotal study of Brav et al. (2005), such conservatism still proves profound 50 years later, with managers explicitly citing firm risk as an important factor when deciding their dividend payout policy. Moreover, the empirical evidence of Hoberg and Prabhala (2009) in the US shows firm risk contributes to approximately 40% of the disappearing dividend puzzle. Aside from firm-specific shocks and risk having a direct impact of dividend decisions, such idiosyncrasies also manifest themselves indirectly via the core determinants of dividend payout policies, for example, profitability. Benartzi et al. (1997) find firms increase (decrease) dividends if they have experienced positive (negative) earnings shocks in the current and prior period. Moreover, Adhikari and Agrawal (2018) illustrates that the same measures of idiosyncratic equity shock and idiosyncratic equity risk contain significant information about market expectations, with the combination of both measures predicting profitability up to three years in advance.

With regards to the second point of attention, that is, the relevance of such market-based measures in an emerging market context, as documented in Chapter 1 section 1.2, since India's economic liberalisation in the early 1990's, India's economy, and most importantly, capital markets, have gone under significant legislative and structure reforms. The introduction of SEBI and numerous reforms have improved minority shareholder protection and liability standards for investors making India's legislative standings comparable to a developed economy and, to date, is ranked the 10th largest stock exchange in terms of both market capitalisation and turnover (La Porta et al. 2000 and World Bank 2018). Whether or not stock markets of development and/or emerging economies, truly reflect all available information - inline with the strong perspective of the efficient market hypothesis - is naturally up for debate, however, after taking into account the structural breaks induced by India's early economic reforms the work of Chaudhuri and Wu (2003) shows India's markets display similar mean reverting tendencies consistent to that of the US (Fama and French, 1988). To further emphasise the relevance of our two proposed instruments, in later sections we examine the temporal permanence of our results through sub-samples, indeed we find the both instruments to display greater strength in the later samples, yet, in both cases we find the instrument's to pass all statistical relevance requirements.

Thus, given the above arguments, we affirm, in line with Adhikari and Agrawal (2018) and Grennan (2019), that both peer idiosyncratic equity shock and peer idiosyncratic equity risk theoretically satisfy the validity and relevance conditions required for our proposed instrumental variable approach.

4.4 Summary Statistics and Univariate Tests

Prior to our multivariate analysis we provide a brief overview the sample of Indian listed firms used in our analysis. Table 4.2 reports the summary statistics for our full sample of firms from 1995-2017. In particular, Panel A details firm-specific variables, Panel B reports peer firm averages based on the full set of industry peers and Panel C reports the statistics for our three additional industry-specific controls. At a general level, over the course of our sample 18,008 (63%) firm-year observations report positive dividend payouts with the average duration of continued payment being approximately 5.59 years while 3,623 firm-year observations consist of one-off payments. Put differently, once initiated, the average firm in our sample continues to pay some form of payout for 5.59 years[5]. Looking at Panel A in Table 4.2 we note that 36% of firm-observations in our sample consist of dividend increases while, as expected, the number of dividend decreases are far less at just below 17%. Further inspection indicates that dividend increases are relatively steady over the sample duration, however, the majority of dividend decreases occur in periods of macroeconomic downturn, with 25% of firms decreasing dividends in 2001, 28% in 2009 and 35% in 2017. Such behaviour could suggest that firms are more concerned about their financial flexibility than the demands of investors and/or shareholders in periods of macroeconomic decline and heightened economic uncertainty.

With respect to other core variables, the average firm-year observation generates a profit of around 5.6% and has positive investment expenditure and positive growth opportunities. In terms of industry structure, the average industry in our sample consists of 71 firms where the average degree of firm centrality is close to 548 miles. In contrast, the smallest degree of centrality within our sample is approximately 17 miles whereas the most remotely located firm is, on average, 1,334 miles away for their industry counterparts[6].

In order to better our understanding of the type of the firms that increase or decrease dividends, In Table 4.3 we detail firm, peer and industry mean characteristics for the firm-year observations in our sample that correspond with such dividend decisions. It is evident that the characteristics of firms' that increase dividends differ in many regards to those who decrease dividends. Most notably, Panel A illustrates that the firms who decide to increase dividends are, on average, statistically larger, generate more profit and are less risky. However, we also find that

[5]Note: In unreported results we test the validity of our findings specific to continued dividend payers, i.e. all firm-year observations that pay dividends for more that one period. We find that our main findings remain qualitatively the same.

[6]Note: In terms of context, India measures 1,997 miles from north to south and 1,882 from east to west. The distance of 1,334 is the equivalent distance between London (UK) and Kyiv (Ukraine) which is approximately 1,330 miles

said firms have, on average, greater investment opportunities and larger investment expenditure. Seemingly, on the face of things, such observations are at odds with the life cycle hypothesis which posits that larger firms tend to increase dividends when there no longer exists positive investment opportunities (Grullon et al., 2002). Yet, such firm characteristics are consistent with the empirical analysis of Khanna and Palepu (1997) and Khanna and Palepu (2000) who find that larger Indian firms, often with group affiliations, have greater investment opportunities than their smaller, standalone opposites. In Panel B, we show that the peer characteristics of dividend increasing firms also display similar statistical differences. In particular, firms that increase dividends tend to have more profitable peers and peers with greater growth opportunities.

In Table 4.4 we document the reference group structure statistics and the peer variable summary statistics for our proximity based peer measures. Specifically, Panel A reports peer group summary statistics, detailing the mean, the standard deviation, the minimum and the maximum number of peers within each reference group category. In Panel B, we document the peer variable averages for each reference group structure, and in Panel C we report the correlations between our peer proximity measures and the conventional transitive peer averages. Furthermore, to provide extra clarity to the reader, we illustrate the correlation scatter plots for the endogenous variables in Panel C, i.e. dividend increases and dividend decreases, in Figure 4.1 and Figure 4.2, respectively.

A number of deductions can be made from Table 4.4. First, as to be expected, in Panel A, as the proximity distance of peer reference groups increases, the size of the reference groups converge towards the full set of industry peers in the transitive peer average. In Panel C, the same relationship can be said to exist for our peer proximity measures as we find that the wider the proximity band the more correlated the proximity measures are with the overall industry peer average. Put differently, economically speaking, the smaller the proximity band, the stronger the assumption of intransitively between industry peers. In addition, as illustrated in Figure 4.1 and Figure 4.2, we find, due to smaller reference groups (degrees of freedom), the peer proximity measures based on narrower proximity bands display more coarse and less granular peer averages. Therefore, assuming the existence of peers effects, it can be expected that relative to the transitive peer average effect, our more intransitive reference group structures - i.e. peer groups based on narrower proximity bands - will be more likely to yield more opposing economic results. However, whether the impact of peer location will be statistically significant in effecting the dividend decisions of firms is yet to be documented, thus, the requirement of our multivariate analysis.

Table 4.2: Summary Statistics: Full Sample

Panel A: Firm Variables	Observations	Mean	S.D.	Min	Q1	Median	Q3	Max
Dividend Payout	28,382	0.010	0.014	0.000	0.000	0.006	0.015	0.095
Dividend Increase	28,382	0.359	0.480	0.000	0.000	0.000	1.000	1.000
Dividend Decrease	28,382	0.166	0.372	0.000	0.000	0.000	0.000	1.000
Profitability	28,382	0.055	0.053	-0.028	0.018	0.041	0.076	0.371
Market-to-Book	28,382	1.018	0.994	0.110	0.525	0.720	1.093	11.033
Investment	28,382	0.064	0.087	-0.165	0.010	0.035	0.086	0.641
Leverage	28,382	0.292	0.178	0.000	0.149	0.289	0.420	0.777
Size	28,382	7.302	1.747	3.635	6.000	7.163	8.455	12.906
Tangibility	28,382	0.322	0.185	0.001	0.178	0.310	0.452	0.824
Idiosyncratic Equity Shock	28,382	0.000	0.006	-0.076	-0.002	0.000	0.001	0.090
Idiosyncratic Equity Risk	28,382	0.043	0.026	0.009	0.029	0.037	0.048	0.294
Panel B: Peer Variables								
Dividend Payout	28,382	0.011	0.005	0.000	0.007	0.010	0.014	0.040
Dividend Increase	28,382	0.358	0.151	0.000	0.250	0.354	0.451	0.857
Dividend Decrease	28,382	0.165	0.114	0.000	0.082	0.136	0.233	0.625
Profitability	28,382	0.057	0.020	0.009	0.043	0.055	0.069	0.195
Market-to-Book	28,382	1.065	0.574	0.317	0.740	0.965	1.256	14.552
Investment	28,382	0.063	0.036	-0.338	0.043	0.060	0.081	0.222
Leverage	28,382	0.293	0.075	0.060	0.239	0.287	0.350	0.474
Size	28,382	7.302	0.841	5.237	6.686	7.264	7.875	10.149
Tangibility	28,382	0.323	0.103	0.054	0.265	0.330	0.389	0.676
Idiosyncratic Equity Shock	28,382	0.000	0.002	-0.047	-0.001	0.000	0.000	0.046
Idiosyncratic Equity Risk	28,382	0.044	0.015	0.015	0.033	0.037	0.053	0.242
Panel C: Industry Variables								
HH Index	28,382	0.126	0.125	0.025	0.054	0.082	0.146	0.919
Number of Firms	28,382	70.631	48.214	3.000	30.000	59.000	107.000	203.000
Average Distance	28,382	548.346	149.438	17.347	445.498	521.132	638.924	1334.249

Source: Prowess - Author's own calculation.
Notes: The sample consists of all firms from 1995 and 2017. The table reports the summary statistics for all main text variables. Dividend Payout is the ratio of total cash dividends over total assets. Dividend Increase is a binary variable that takes the value 1 if the firm increase dividends or else zero. Dividend Decrease is a binary variable that takes the value 1 if the firm Decrease dividends or else zero. Profitability is the ratio of operating income before depreciation over total assets. The market-to-book ratio is the market value of equity plus the sum of short-term and long term borrowing over the book value of total assets. Investment is the first difference of net fixed assets plus deprecation over total assets. Leverage is the sum of short and long term borrowing over total assets. Size is the natural logarithm of total assets. Asset Tangibility is the ratio of fixed assets to total assets. Idiosyncratic Equity Shock is the average daily idiosyncratic return over the year and Idiosyncratic Equity risk is the standard deviation of daily idiosyncratic return over the same period. All peer measures are calculated via a leave-out-mean where industries are defined at the two digit NIC classification. HH index denotes a Herfindahl-Hirschman index calculated as the sum of sales squared. Number of firms represent the number of firms per industry. Average Distance is calculated as the average distance to peer firm headquarters. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.3: Differences of Mean Tests

	Full Sample	Dividend Increase	Dividend Decrease	Difference Test (2) - (3)
	(1)	(2)	(3)	(4)
Panel A: Firm Variables				
Dividend Payout	0.010	0.020	0.008	0.012***
Dividend Increase	0.359	1.000	0.000	-
Dividend Decrease	0.166	0.000	1.000	-
Profitability	0.055	0.080	0.040	0.040***
Market-to-Book	1.018	1.280	0.924	0.356***
Investment	0.064	0.079	0.065	0.014***
Leverage	0.292	0.278	0.306	-0.028***
Size	7.302	7.822	7.672	0.150***
Tangibility	0.322	0.322	0.328	-0.006**
Idiosyncratic Equity Shock	0.000	0.000	0.000	0.000
Idiosyncratic Equity Risk	0.043	0.037	0.040	-0.003***
Panel B: Peer Variables				
Dividend Payout	0.011	0.012	0.010	0.002***
Dividend Increase	0.358	0.402	0.311	0.091***
Dividend Decrease	0.240	0.144	0.219	-0.075***
Profitability	0.057	0.061	0.054	0.007***
Market-to-Book	1.065	1.083	1.016	0.067***
Investment	0.063	0.068	0.063	0.005***
Leverage	0.293	0.296	0.295	0.001
Size	7.302	7.247	7.341	-0.094***
Tangibility	0.323	0.329	0.328	0.001
Idiosyncratic Equity Shock	0.000	0.000	0.000	0.000***
Idiosyncratic Equity Risk	0.044	0.044	0.045	-0.001**
Panel C: Industry Variables				
HH Index	0.126	0.125	0.126	0.001
Number of Firms	70.631	69.585	68.892	0.693
Average Distance	548.346	546.405	549.484	-3.079
Total Numbers	28,382	10,177	4,798	-

Source: Prowess - Author's own calculation.
Notes: The sample consists of all firms from 1995 and 2017. The table reports the difference between firms that increase dividends and firms that decrease dividends. Panel A reports firm-specific variables. Panel B reports peer-specific variables where peers are defined as all firms in industry j expect for firm i in year t. Panel C reports industry related variables. Column (4) reports the difference in means between column (2) and column (3) where the corresponding asterisk represents the p-value associated with the t-test for differences in means. * indicates significance at the 10% level,** indicates significance at the 5% level and *** indicates significance at the 1% level. All variable names, definitions and sources can be found in appendix Table A.4.1.

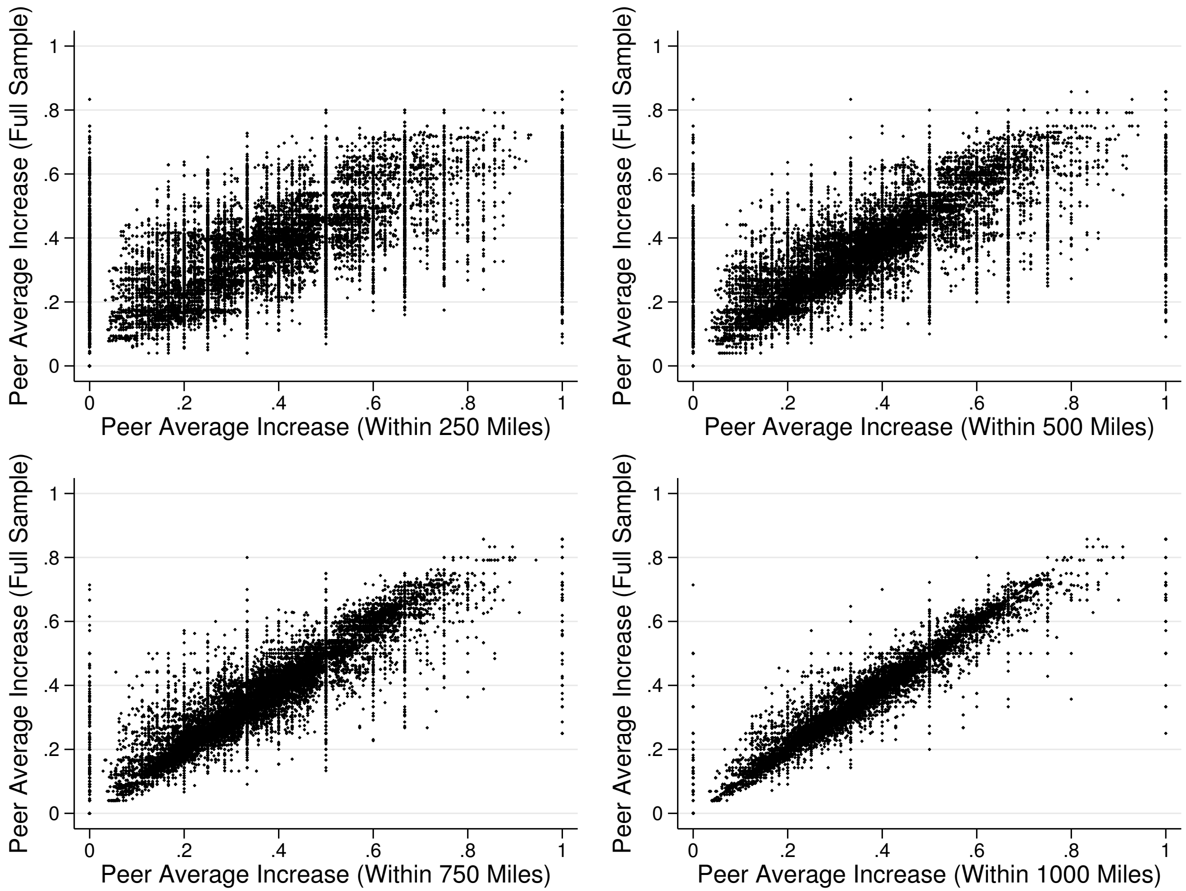
Table 4.4: Reference Group Structure and Peer Variables

	Proximity Radius 250 Miles (1)	Proximity Radius 500 Miles (2)	Proximity Radius 750 Miles (3)	Proximity Radius 1000 Miles (4)	Full Sample (5)
Panel A: Reference Group Statistics					
Mean Number of Peers	18.218	34.505	52.920	63.117	69.631
S.D. of Peers	19.299	32.010	41.520	45.521	48.214
Min Number of Peers	1	1	1	1	2
Max Number of Peers	118	165	195	202	202
Panel B: Peer Variable Means					
Dividend Increase	0.358	0.355	0.356	0.357	0.358
Dividend Decrease	0.163	0.164	0.164	0.165	0.165
Profitability	0.058	0.057	0.057	0.057	0.057
Market-to-Book	1.074	1.060	1.066	1.067	1.065
Investment	0.063	0.063	0.063	0.063	0.063
Leverage	0.292	0.294	0.292	0.292	0.293
Size	7.298	7.287	7.286	7.289	7.302
Tangibility	0.321	0.324	0.322	0.322	0.323
Idiosyncratic Equity Shock	0.000	0.000	0.000	0.000	0.000
Idiosyncratic Equity Risk	0.044	0.044	0.044	0.044	0.044
Panel B: Peer Variable Correlations					
Dividend Increase	0.646	0.794	0.925	0.973	1.000
Dividend Decrease	0.655	0.793	0.933	0.979	1.000
Profitability	0.639	0.789	0.921	0.974	1.000
Market-to-Book	0.746	0.868	0.955	0.987	1.000
Investment	0.701	0.842	0.951	0.986	1.000
Leverage	0.758	0.875	0.964	0.990	1.000
Size	0.832	0.918	0.975	0.993	1.000
Tangibility	0.844	0.920	0.978	0.993	1.000
Idiosyncratic Equity Shock	0.576	0.758	0.916	0.974	1.000
Idiosyncratic Equity Risk	0.841	0.927	0.979	0.995	1.000
No Peer Observations	1,041	324	74	29	0
Peer Observations	27,341	28,058	28,308	28,353	28,382

Source: Prowess - Author's own calculation.

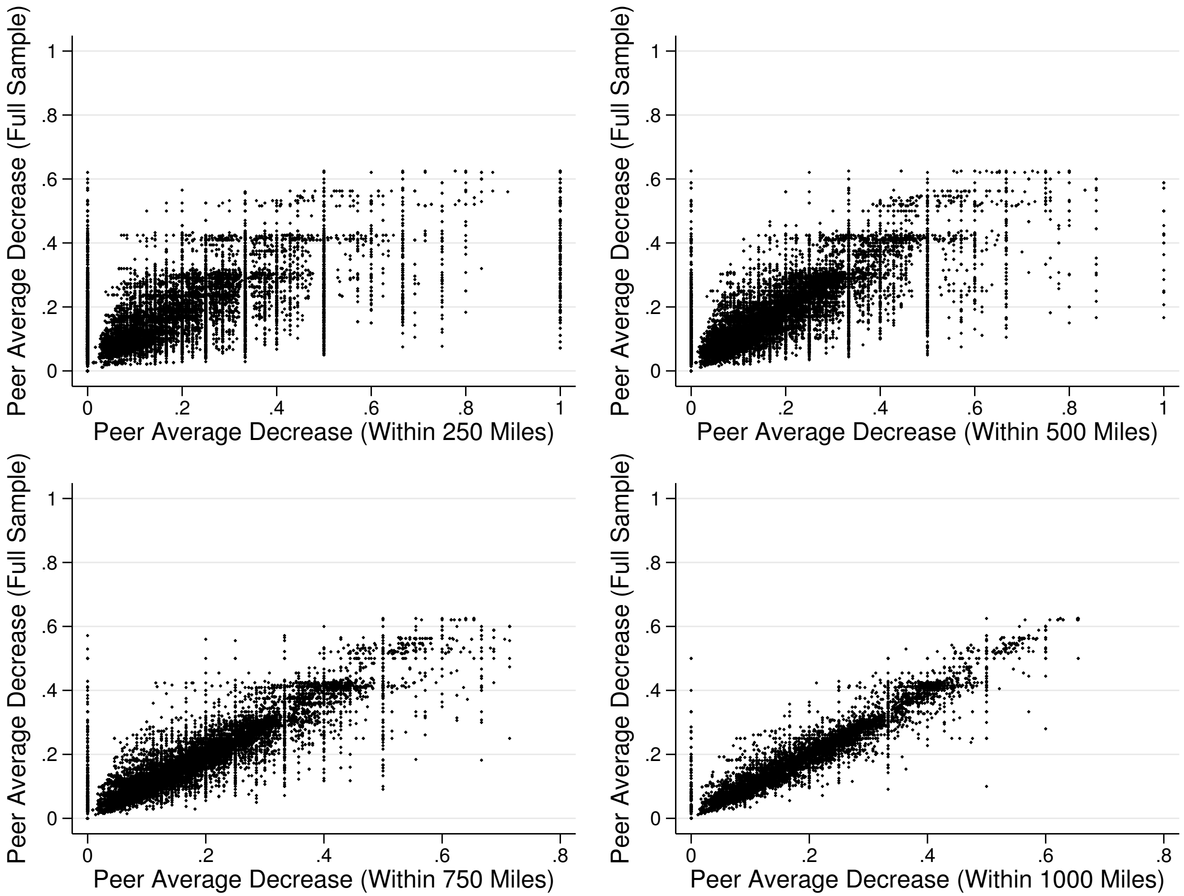
Notes: The sample consists of all firms from 1995 and 2017. The Table details statistics relating to our peer proximity reference groups (column (1) to (4)) and the overall industry average (column (5)). Panel A reports the mean, standard deviation, minimum and maximum number of peers in each reference group. Panel B reports peer variable averages. Panel C reports the correlation between the corresponding columns peer averages and the peer averages in column (5). All variable names, definitions and sources can be found in appendix Table A.4.1.

Figure 4.1: Proximity Scatter Plots: Peer Average Dividend Increase



Source: Prowess - Author's own calculation.

Figure 4.2: Proximity Scatter Plots: Peer Average Dividend Decrease



Source: Prowess - Author's own calculation.

4.5 Multivariate Analysis

In this section we report the results from our empirical analysis. Section 4.5.1 documents our baseline estimates where peer actions and characteristics are defined by transitive industry reference groups. In Section 4.5.2, we discuss our main empirical findings where we examine the importance of peer location via our intransitive peer proximity measures. In 4.5.3, we extend our empirical analysis by examining the impact of alternative economic channels of peer influence and the temporal permanence of our findings. All forthcoming tables report standardised coefficients to ease the interpretation of peer measures and all standard errors are clustered at the firm level to allow for within dependence (Petersen, 2009).

4.5.1 Baseline Results

As outlined in Section 4.3.2, in order to accommodate for the inherent endogeniety issues associated with peer effect analysis, this study adopts an instrumental variable approach similar to the likes of Leary and Roberts (2014), Adhikari and Agrawal (2018) and Grennan (2019). Therefore, for the sake empirical precision, in what follows we strictly report our two-stage least squares estimates. Nonetheless, ordinary least squares estimates for our baseline model specification along with a number of restricted model specifications can be found in Appendix Table A.4.4.

In Table 4.6 we report the first stage results from our two-stage least squares estimates. In column (1) we report the first stage results for the dividend payout ratio (the ratio of dividends over total assets) and in column (2) and column (3) we report the results for dividend increases and dividend decrease, respectively. We include the estimates of the dividend payout ratio in our baseline analysis for two reasons. First, the dividend payout ratio acts as empirical benchmark for our discussion of asymmetric responses in dividend determinants. Second, the ratio of dividends over total assets is arguably one of the most common measures of dividend payout, thus, its inclusion illustrates the robustness of our analysis to other prominent measures relating to corporate payout policy. In the interest of compactness, Table 4.5 details solely the coefficients and standard errors for firm and peer idiosyncratic equity shock and idiosyncratic equity risk, where the two peer measures are the respective instrumental variables for peer dividend payout, peer dividend increases and peer dividend decreases[7].

The first important takeaway is that across all estimates, peer firm measures prove statistically significant, while firm-specific measures do not. This observation is crucial as it illustrates

[7]Note: For completeness, the full set of estimated coefficients are reported in Appendix Table A.4.5.

the relevance of our instruments, with the firm-specific measures of idiosyncratic equity shock and idiosyncratic equity risk displaying no direct statistically significant effect on peer dividend payout or peer dividend decisions. In fact, we find no firm-specific characteristics to consistently display any statistical significance across all three estimates (see Appendix Table A.4.5). With regards to the peer measures, we document a positive (negative) relationship between peer idiosyncratic equity shock and peer dividend increases (decreases). Furthermore, consistent with Adhikari and Agrawal (2018) and Grennan (2019), we find peer idiosyncratic equity risk is positively (negatively) associated with peer dividend decreases (increases). Thus, a positive equity shock to peer firms, increases the probability that peers will increase dividends. Alternatively, an increase in peer risk is likely to result in peers decreasing their dividend payout.

To provide more formal statistical support for the relevance our instrumental variables, Table 4.5 reports three types of F-statistics. Specifically, following the suggestions of Andrews et al. (2019) we report the non-robust Cragg-Donald F-statistics (F^N), the Kleibergen and Paap (2006) robust F-statistics (F^R) and the Olea and Pflueger (2013) effective F-statistic (F^{Eff}), where the latter is considered the most effective statistic for detecting weak instruments in our over-identified non-homoskedastic case. Nonetheless, for peer dividend payout, peer dividend increase and peer dividend decrease we find all the corresponding F-statistic's to exceed the empirical requisite of 10, thus, sufficing the minimal bias threshold proposed by Stock and Yogo (2005).

In Table 4.6 we report the second stage results for dividend payout and both dividend decisions. Focusing on the latter, we find peer dividend increases and peer dividend decreases to be positive and statistically significant at the 5% and 1% level for dividend increases and dividend decreases, respectively. In each case, we fail to reject the null of the Hansen J test, thus confirming the statistical validity of our instruments. In terms of economic implications, the coefficients of the transitive peer measures in column (2) and (3) can be interpreted as follows: a one standard deviation increase in the fraction of peer firms increasing (decreasing) dividend payments increases the probability that a firm will increase (decrease) dividend payments by 14.7% (19.9%) on average, all else equal. In terms of reference, a one standard deviation increase in peer influence is equivalent to an additional 15.0% (11.4%) of peer firms in the industry increasing (decreasing) their dividend subject to an average of 35.7% (16.5%).

Given these empirical findings, three important statements can be made. First, both firms decision to increase and decrease dividends are influenced by the dividend decisions of their industry peers. Thus, such results provide a clear criticism of the extant literature that fails to acknowledged the interdependent nature of dividend decisions (e.g., DeAngelo and DeAngelo

1990, DeAngelo et al. 1992, Grullon et al. 2002, Baker and Wurgler 2004, Goergen et al. 2005 and Leary and Michaely 2011). Next, consistent with the work of Adhikari and Agrawal (2018) and Grennan (2019), the economic effect of peer dividend decisions is substantive comparative to other peer and firm-specific determinants. In fact, for both dividend increases and dividend decreases, peer dividend decisions prove to be the prevailing effect in the decision making process. Finally, the degree of peer influence is asymmetric with peer dividend decisions having a more pronounced effect on dividend deceases, thus, supporting our decision to not focus on dividend ratio's that implicitly assume homogeneous coefficients for dividend increases and dividend decreases.

With regards to peer firm averages, we find a number of peer characteristics to be statistically and economically significant for firms' dividend decisions. We find that peer characteristics do not displace firm-specific covariates and therefore both can be considered important for the decision making process (See Appendix Table A.4.4 for a number of restriction tests). Peer market-to-book valuations prove statistically significant for both dividend decisions consistent the signalling theory and the recent work of Foucault and Fresard (2014). Such findings would suggest that information on firms prospects are reflected in the market valuations of their industry counterparts, with peer market-to-book valuations displaying a negative (positive) relationship with dividend increases (decreases). In addition, we find firms are less likely to increase dividends if their peers are larger and have higher earnings.

With regards to dividend increases, we find the estimates of firm-specific determinants in column (2) to be largely consistent with the literature. As promoted by Lintner (1956), firm profitability proves to be a core driver of dividend increases after peer dividend decisions. Moreover, firms are more likely to increase dividends as they become larger, engage in less risk taking behaviour and hold lower levels of external debt. Interesting, we find that the previous years investment and market-to-book ratio positively influence dividend increases contrary to the life-cycle hypothesis. Such behaviour is consistent with our earlier summary statistics and lends itself more to the pecking order theory wherein said measures correlate to firms current profitability (Fama and French, 2002).

In many cases, the adjacent narrative holds true for dividend decreases. We find firms with lower market-book-ratios and higher debt are more likely to decrease dividends. However, it is, on the face of things, somewhat curious that the previous years profitability displays a positive effect on both dividend increases and dividend decreases. One possible explanation is that in order to decrease dividends firms must of in the previous year paid dividends resulting in a positive correlation. We address this potential misspecification in section 4.6 where we test the omission of present and future earnings similar to DeAngelo et al. (1992). In each case, our results regarding peer influence remain qualitatively unchanged.

All in all, the baseline results presented in this section illustrate the importance of peer dividend decisions. Our baseline results provide support to the recent work of Adhikari and Agrawal (2018) and Grennan (2019) and further bear a clear criticism of the extant literature that fails to account for the interdependent nature of dividend decisions. Our evidence shows that peers decisions based on transitive reference groups matter for the decisions of Indian listed firms. In the next section, we relax this assumption and examine the effects of peers based on intransitive references groups.

Table 4.5: Baseline Results: First Stage Estimates

	Peer Avg. Dividend Payout	Peer Avg. Dividend Increase	Peer Avg. Dividend Decrease
	(1)	(2)	(3)
Firm-specific Variables:			
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.002	0.001	-0.010
	(0.004)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.001	0.009	0.009
	(0.007)	(0.007)	(0.007)
Peer Firm Averages:			
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.047***	0.058***	-0.060***
	(0.007)	(0.007)	(0.008)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.113***	-0.035*	0.089***
	(0.017)	(0.018)	(0.019)
Additional Firm-specific Variables	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes
F-statistic^{N}	130.650	62.082	78.699
F-statistic^{R}	54.556	36.265	37.957
F-statistic^{Eff}	47.544	30.196	38.737
Firms	2,851	2,851	2,851
Observations	22,296	22,296	22,296

Source: Prowess - Author's own calculation.

Notes: This table presents the first stage estimates for our two-stage least squares (2SLS) estimation procedure. The sample consists of all firms between 1995 and 2017. The first stage results reported in this table correspond to the second stage estimates reported in Table 4.6. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation, where industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^{N} denotes the Cragg-Donald F-statistic, F-statistic^{R} denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.6: Baseline Results: Second Stage Estimates

	Dividend Payout	Dividend Increase	Dividend Decrease
	(1)	(2)	(3)
Instrumented Peer Avg. Div. Payout$_{i,j,t}$	0.004**		
	(0.002)		
Instrumented Peer Avg. Increase$_{i,j,t}$		0.147**	
		(0.067)	
Instrumented Peer Avg. Increase$_{i,j,t}$			0.199***
			(0.051)
Firm-specific Variables:			
Profitability$_{i,j,t-1}$	0.005***	0.047***	0.025***
	(0.000)	(0.005)	(0.003)
Market-to-Book$_{i,j,t-1}$	0.003***	0.034***	-0.024***
	(0.000)	(0.004)	(0.004)
Investment$_{i,j,t-1}$	-0.000**	0.016***	0.017***
	(0.000)	(0.004)	(0.003)
Leverage$_{i,j,t-1}$	-0.003***	-0.013***	0.008**
	(0.000)	(0.005)	(0.004)
Size$_{i,j,t-1}$	0.001***	0.106***	0.036***
	(0.000)	(0.005)	(0.004)
Tangibility$_{i,j,t-1}$	0.000	-0.001	-0.009**
	(0.000)	(0.005)	(0.004)
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.001***	0.016***	0.000
	(0.000)	(0.004)	(0.003)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.002***	-0.041***	-0.020***
	(0.000)	(0.006)	(0.004)
Peer Firm Averages:			
Profitability$_{i,j,t-1}$	-0.001**	-0.012**	-0.011**
	(0.000)	(0.006)	(0.004)
Market-to-Book$_{i,j,t-1}$	-0.001***	-0.015**	0.010**
	(0.000)	(0.006)	(0.005)
Investment$_{i,j,t-1}$	-0.000*	-0.008	-0.010
	(0.000)	(0.006)	(0.007)
Leverage$_{i,j,t-1}$	0.001***	0.015	0.006
	(0.000)	(0.009)	(0.010)
Size$_{i,j,t-1}$	-0.000	-0.048***	-0.025
	(0.000)	(0.013)	(0.018)
Tangibility$_{i,j,t-1}$	-0.000	-0.006	0.009
	(0.001)	(0.016)	(0.011)
Industry Controls	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes
Hansen J p-value	0.305	0.489	0.719
Firms	2,851	2,851	2,851
Observations	22,296	22,296	22,296

Source: Prowess - Author's own calculation.
Notes: This table presents the second stage estimates for our two-stage least squares (2SLS) estimation procedure. The sample consists of all firms between 1995 and 2017. The second stage results reported in this table correspond to the first stage estimates reported in Table 4.5. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation, where industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

4.5.2 Geographical Proximity Results

Table 4.7 and Table 4.8 detail the first stage peer proximity estimates for dividend increases and dividend decreases, respectively. First of all, it is important to clarify that the instrumental variables reported in Table 4.7 and Table 4.8 are based on the overall industry peer averages of idiosyncratic equity shock and idiosyncratic equity risk. Unreported results indicate that the spatially weighted values of peer idiosyncratic equity shock and peer idiosyncratic equity risk fail to suffice the appropriate instrument relevance tests for almost all proximity radiuses. Subsequently, for the sake of consistency and empirical proficiency, we use the overall averages of peer idiosyncratic equity shock and peer idiosyncratic equity risk in all forthcoming estimates unless stated otherwise.

We find the instruments of peer idiosyncratic equity shock and peer idiosyncratic equity risk enter the first stage estimates with expected signs and significance levels. Again, importantly, firm-specific measures of idiosyncratic equity shock and idiosyncratic equity risk do not determine peer dividend decisions. That is, we observe no statistically significant effect. For dividend decreases in Table 4.8, all peer proximity estimates based on intransitive reference groups report favourable F-statistics greater than 10. However, in Table 4.7, our instrumental variables in column (1) and column (2) marginally fall short of such threshold and therefore fail to suffice the rule of thumb (F-statistic $>$ 10) set by Stock and Yogo (2005). To install confidence in the reader, and to illustrate that our forthcoming results are not a manifestation of weak instrumental variables, we re-estimate our empirical specifications omitting industry-fixed effects to allow for greater explanatory power in our instrumental variables. In Appendix Table A.4.7 we demonstrate that our forthcoming second stage results are indeed consistent and not a manifestation of weak instrumental variables.

Table 4.9 and Table 4.10 report the second stages results for dividend increases and dividend decreases, respectively. For both dividend decisions we document a negative relationship between peer influence and our geographical proximity measures. Specifically, the dividend decisions of industry peers based on closer proximity bands bear greater influence than those based on broader peer averages. In terms of economic magnitude, we find the difference in peer influence between the reference group structures to be substantial. For example, a one standard deviation increase in the fraction of peer firms increasing (decreasing) dividend payments within 250 miles increases the probability that a firm will increase (decrease) dividend payments by 27.2% (25.6%) on average, all else equal. In contrast, a one standard deviation increase in the fraction of peer firms increasing (decreasing) dividend payments within 1000 miles only increases the probability that a firm will increase (decrease) dividend payments by 15.2% (19.7%).

Accordingly, the above findings confirm our empirical hypothesis and demonstrate, that, on average, the dividend decisions of Indian listed firms are influenced more by the dividend decisions of their closer industry peers. In relation to Section 4.2, a number of possible explanations coexist to explain such geographical interdependence. One credible explanation for why firms perceive the actions of their closer industry counterparts can be made in relation to imperfect information. In the presence of imperfect and incomplete information, the proportion of realised behaviour has a natural tendency to gravitate towards the actions of geographical closer industry peers. Put differently, the cost of acquiring information on local peers is, on average, considerably less than the cost corresponding to more distant industry counterparts. Subsequently, it is not surprising given India's institutional setting, that the dividend decisions of firms are most influenced by the actions of their closer peers of whom they likely hold more information on. Parallel to this, the dividend decisions of closer industry peers may also be of more financial pertinence to firms due to the existence local dividend clienteles. The presence of asymmetric information between investors and firms result in both individual (Ivković and Weisbenner, 2005) and institutional (Coval and Moskowitz, 1999) investors favouring the equity of local firms. Therefore, it is consistent to suggest that the pressure induced by local dividend clienteles may result in firms feeling forced to keep pace with the dividend decisions of their closer industry counterparts in order to protect their market value.

With regards to other peer determinants, for dividend increases in Table 4.9 we find the market-to-book ratio, investment and size of closer industry peers to bear a economically larger negative effect on dividend increases relative to the wider industry average measures. Accordingly, the similar negative relationship between peer effects and geographical proximity would imply firms not only take into account the dividend decisions of closer industry peers, but also their characteristics. In contrast, apart from peer profitability, we find peer characteristics seldom consistently influence firms decision to decrease dividends. Thus, one can infer that the characteristics of local peers are more important for dividend increase than dividend decreases.

All in all, the above findings contribute new evidence to the peer effects literature in corporate finance and importantly highlight the existence of non-linear peer effects via proximity based intransitive reference groups. Next, we dig deeper into the role of peer influence by exploring the inverse channels of peer effects and the temporal permanence of our findings relative to the recent financial crisis.

Table 4.7: Dividend Increase: First Stage Peer Proximity Results

	Peer Avg. Increase 250 Miles (1)	Peer Avg. Increase 500 Miles (2)	Peer Avg. Increase 750 Miles (3)	Peer Avg. Increase 1000 Miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.013	0.013	0.007	0.007
	(0.009)	(0.008)	(0.007)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.003	-0.002	0.003	0.008
	(0.007)	(0.007)	(0.007)	(0.007)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.029***	0.033***	0.047***	0.054***
	(0.009)	(0.008)	(0.007)	(0.007)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.031	0.006	0.025	-0.022
	(0.023)	(0.022)	(0.019)	(0.019)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^{N}	15.270	16.584	30.516	41.683
F-statistic^{R}	9.568	9.679	20.389	27.820
F-statistic^{Eff}	8.802	8.818	18.921	25.803
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270

Source: Prowess - Author's own calculation.
Notes: This table presents the first stage results for our two-stage least squares (2SLS) analysis of peer proximity effects on dividend increases. The sample consists of all firms between 1995 and 2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. The first stage results reported in this table correspond to the second stage estimates reported in Table 4.9. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^{N} denotes the Cragg-Donald F-statistic, F-statistic^{R} denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.8: Dividend Decrease: First Stage Peer Proximity Results

	Peer Avg. Decrease 250 Miles (1)	Peer Avg. Decrease 500 Miles (2)	Peer Avg. Decrease 750 Miles (3)	Peer Avg. Decrease 1000 Miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.014	-0.014	-0.009	-0.008
	(0.009)	(0.009)	(0.007)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.002	-0.002	0.004	0.009
	(0.009)	(0.008)	(0.007)	(0.007)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.032***	-0.039***	-0.057***	-0.060***
	(0.009)	(0.009)	(0.008)	(0.008)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.087***	0.076***	0.086***	0.094***
	(0.026)	(0.023)	(0.020)	(0.020)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^{N}	18.790	24.394	56.418	69.944
F-statistic^{R}	11.893	15.058	31.153	36.799
F-statistic^{Eff}	11.341	14.266	32.206	37.090
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270

Source: Prowess - Author's own calculation.

Notes: This table presents the first stage results for our two-stage least squares (2SLS) analysis of peer proximity effects on dividend decreases. The sample consists of all firms between 1995 and 2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. The first stage results reported in this table correspond to the second stage estimates reported in Table 4.10. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^{N} denotes the Cragg-Donald F-statistic, F-statistic^{R} denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.9: Dividend Increase: Second Stage Peer Proximity Results

	250 Miles (1)	500 Miles (2)	750 Miles (3)	1000 Miles (4)
WInstrumented Peer Avg. Increase$_{250mi.i,j,t}$	0.272*			
	(0.153)			
WInstrumented Peer Avg. Increase$_{500mi.i,j,t}$		0.243*		
		(0.136)		
WInstrumented Peer Avg. Increase$_{750mi.i,j,t}$			0.190**	
			(0.085)	
WInstrumented Peer Avg. Increase$_{1000mi.i,j,t}$				0.152**
				(0.075)
Firm-specific Variables:				
Profitability$_{i,j,t-1}$	0.044***	0.046***	0.046***	0.047***
	(0.005)	(0.005)	(0.005)	(0.005)
Market-to-Book$_{i,j,t-1}$	0.035***	0.036***	0.033***	0.034***
	(0.005)	(0.005)	(0.004)	(0.004)
Investment$_{i,j,t-1}$	0.014***	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Leverage$_{i,j,t-1}$	-0.011**	-0.010*	-0.012**	-0.013***
	(0.005)	(0.005)	(0.005)	(0.005)
Size$_{i,j,t-1}$	0.105***	0.106***	0.106***	0.106***
	(0.006)	(0.006)	(0.005)	(0.005)
Tangibility$_{i,j,t-1}$	-0.000	-0.004	-0.001	-0.001
	(0.006)	(0.007)	(0.006)	(0.005)
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.012***	0.014***	0.015***	0.016***
	(0.005)	(0.004)	(0.004)	(0.004)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.042***	-0.042***	-0.043***	-0.043***
	(0.006)	(0.006)	(0.006)	(0.006)
Peer Firm Averages:				
WProfitability$_{i,j,t-1}$	-0.025	-0.018	-0.013	-0.010
	(0.017)	(0.012)	(0.009)	(0.007)
WMarket-to-Book$_{i,j,t-1}$	-0.020*	-0.021**	-0.017**	-0.014**
	(0.011)	(0.009)	(0.006)	(0.006)
WInvestment$_{i,j,t-1}$	-0.008	-0.015***	-0.014**	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
WLeverage$_{i,j,t-1}$	0.022	0.015	0.015	0.017*
	(0.014)	(0.011)	(0.009)	(0.009)
WSize$_{i,j,t-1}$	-0.075*	-0.075**	-0.051***	-0.045***
	(0.044)	(0.035)	(0.019)	(0.012)
WTangibility$_{i,j,t-1}$	0.003	0.005	0.001	-0.000
	(0.008)	(0.012)	(0.013)	(0.015)
Industry Controls	Yes	Yes	Yes	Yes
Industry Fixed-effects	Yes	Yes	Yes	Yes
Year Fixed-effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.690	0.435	0.588	0.293
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270

Source: Prowess - Author's own calculation.
Notes: This table presents the second stage results for our two-stage least squares (2SLS) analysis of peer proximity effects on dividend increase. The sample consists of firms all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. All column numbers correspond to the first stage estimates in Table 4.7. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.10: Dividend Decrease: Second Stage Peer Proximity Results

	250 Miles (1)	500 Miles (2)	750 Miles (3)	1000 Miles (4)
WInstrumented Peer Avg. Decrease$_{250mi.i,j,t}$	0.256***			
	(0.094)			
WInstrumented Peer Avg. Decrease$_{500mi.i,j,t}$		0.252***		
		(0.080)		
WInstrumented Peer Avg. Decrease$_{750mi.i,j,t}$			0.207***	
			(0.055)	
WInstrumented Peer Avg. Decrease$_{1000mi.i,j,t}$				0.197***
				(0.052)
Firm-specific Variables:				
Profitability$_{i,j,t-1}$	0.027***	0.027***	0.025***	0.025***
	(0.004)	(0.004)	(0.004)	(0.003)
Market-to-Book$_{i,j,t-1}$	-0.025***	-0.023***	-0.025***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)
Investment$_{i,j,t-1}$	0.018***	0.016***	0.018***	0.018***
	(0.004)	(0.004)	(0.003)	(0.003)
Leverage$_{i,j,t-1}$	0.010**	0.010**	0.009**	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Size$_{i,j,t-1}$	0.034***	0.033***	0.034***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)
Tangibility$_{i,j,t-1}$	-0.010**	-0.010**	-0.010***	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.005	0.004	0.003	0.003
	(0.004)	(0.004)	(0.003)	(0.003)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.017***	-0.017***	-0.019***	-0.020***
	(0.005)	(0.004)	(0.004)	(0.004)
Peer Firm Averages:				
WProfitability$_{i,j,t-1}$	-0.012**	-0.017***	-0.012***	-0.012***
	(0.005)	(0.005)	(0.004)	(0.004)
WMarket-to-Book$_{i,j,t-1}$	0.009*	0.008*	0.006	0.009**
	(0.005)	(0.005)	(0.005)	(0.004)
WInvestment$_{i,j,t-1}$	-0.006	-0.007	-0.008	-0.012**
	(0.005)	(0.005)	(0.006)	(0.006)
WLeverage$_{i,j,t-1}$	-0.001	0.001	-0.000	-0.003
	(0.005)	(0.007)	(0.008)	(0.009)
WSize$_{i,j,t-1}$	-0.028*	-0.032*	-0.021	-0.019
	(0.016)	(0.018)	(0.017)	(0.017)
WTangibility$_{i,j,t-1}$	0.007	0.004	0.018**	0.019*
	(0.007)	(0.007)	(0.009)	(0.010)
Industry Controls	Yes	Yes	Yes	Yes
Industry Fixed-effects	Yes	Yes	Yes	Yes
Year Fixed-effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.919	0.860	0.542	0.503
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270

Source: Prowess - Author's own calculation.
Notes: This table presents the second stage results for our two-stage least squares (2SLS) analysis of peer proximity effects on dividend decreases. The sample consists of firms all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. The second stage results reported in this table relate to the first stage estimates reported in Table 4.8. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

4.5.3 Extended Peer Proximity Analysis

To deepen our understanding of peer effects, we extend our analysis by conducting two additional empirical exercises. First, we examine the potential alternative economic channels through which peer effects may manifest themselves. Specifically, we investigate the impact of the opposite peer dividend decision on firms decision to increase or decrease dividends. In line with the signalling theory, predatory firms may act opportunistically to peer dividend decreases by increasing their dividend payout in an attempt to indicate their financial strength to investors. Moreover, in the presence of agency conflicts, opportunistic managers may also persist in increasing dividends in order to signal their value in labour markets relative to other managers (Scharfstein et al., 1990). With regards to dividend decreases, firms and managers may also be reluctant to decrease dividends to avoid a potential negative market reaction if a significant proportion of their peers announce dividend increases.

In Table 4.11, we report the second stage results for peer dividend increases and peer dividend decreases on the opposing dividend decision[8]. Interesting, in Panel A we find peer dividend decreases bear next to no statistical effect on firms decision to increase dividends. However, in Panel B, we find, for all but one peer measure, that peer dividend increases yield a negative and statistically significant effect on dividend decreases, where, generally speaking, the dividend decision of closer industry peers carry the most economic importance. Thus, the bidirectional influence of peer dividend increases illustrates an upward pressure on dividends with firms being statistically more likely to increase and less likely to decrease dividends as their peers announce dividend increases.

As a second empirical test, we analyse the temporal permanence of our findings with respect to the recent financial crisis. Drawing from the theoretical work of Banerjee (1992) and Bikhchandani et al. (1992), in periods of economic uncertainty, information cascades and corporate herding is more likely to occur as firms personal information becomes more costly and more time consuming to obtain. In such cases, it is suggested that firms are likely put more weight on the tangible decisions of their industry peers rather than their personal, more opaque, information (Leary and Roberts, 2014). Accordingly, for our second empirical test we examine the temporal stability of finding over two sub-samples, one prior to the 2008 financial crisis and one during/post crisis when global and domestic economic uncertainty was amplified (see Figure 4.3).

[8]Note: We do not report the first stage estimates of peer dividend increase and peer dividend decrease as they are identical to the first stage estimates reported in Section 4.5.2 and Section 4.5.3.

In Table 4.12 and Table 4.13 we report the second stage results for dividend increases and dividend decreases, respectively[9]. We find peer dividend increases to be statistically significant across both periods, however, the dividend decisions of peers prove to be most influential during/post crisis. With regards to dividend decreases, we document more striking evidence between the two sub-samples. We find, prior to the financial crisis, the decision to decrease dividends was seldom influenced by the dividend decisions of firms industry counterparts. However, similar to dividend increases, peer decisions during/post crisis period prove statistically and economically significant across each of our peer measures - i.e. both transitive and intransitive - with the dividend decisions of closer industry peers, again, proving most influential. Therefore, the informational content embedded in peer dividend decisions may have provided a more reliable source of information for firms in periods of heightened economic uncertainty.

Overall, our extended empirical analysis of peer influence indicates that the dividend decisions of Indian firms are more complex than traditionally perceived. Evidently, peer dividend increases play a complex role in firms own dividend decisions and prove inflationary yielding upward pressure on dividends. Moreover, our evidence suggests that the role of peer influence may in fact have an embedded relationship with the current state of the domestic and even global economy. However, to more accurately validate this conjecture one requires a more in-depth empirical analysis, which, for now, we leave open for future research. In the next section we test the robust of our current contributions.

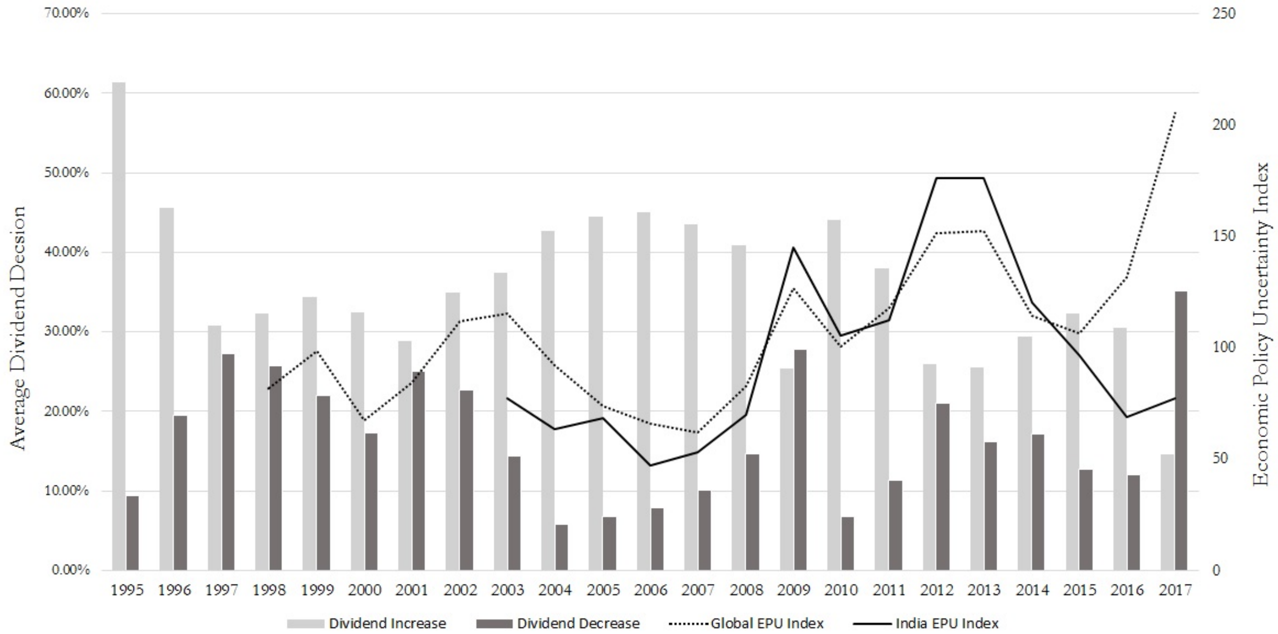
[9]Note: First stage estimates for dividend increases and dividend decreases can be found in Appendix Table A.4.8 and A.4.11, respectively.

Table 4.11: Alternative Economic Channels of Peer Effects

Panel A: Dividend Increases Results					
	Dividend Increase				
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)	Full Sample (5)
$\mathbf{W}$Instrumented Peer Avg. Decrease$_{250mi.i,j,t}$	-0.017				
	(0.088)				
$\mathbf{W}$Instrumented Peer Avg. Decrease$_{500mi.i,j,t}$		-0.068			
		(0.081)			
$\mathbf{W}$Instrumented Peer Avg. Decrease$_{750mi.i,j,t}$			-0.075		
			(0.059)		
$\mathbf{W}$Instrumented Peer Avg. Decrease$_{10000mi.i,j,t}$				-0.081	
				(0.056)	
Instrumented Peer Avg. Decrease$_{i,j,t}$					-0.099*
					(0.057)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.034	0.045	0.045	0.070	0.096
Firms	2,771	2,828	2,847	2,848	2,851
Observations	21,240	21,930	22,210	22,270	22,296
Panel B: Dividend Decreases Results					
	Dividend Decrease				
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)	Full Sample (5)
$\mathbf{W}$Instrumented Peer Avg. Increase$_{250mi.i,j,t}$	-0.130				
	(0.113)				
$\mathbf{W}$Instrumented Peer Avg. Increase$_{500mi.i,j,t}$		-0.255**			
		(0.115)			
$\mathbf{W}$Instrumented Peer Avg. Increase$_{750mi.i,j,t}$			-0.172**		
			(0.070)		
$\mathbf{W}$Instrumented Peer Avg. Increase$_{1000mi.i,j,t}$				-0.218***	
				(0.064)	
Instrumented Peer Avg. Increase$_{i,j,t}$					-0.213***
					(0.059)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.002	0.024	0.002	0.034	0.084
Firms	2,771	2,828	2,847	2,848	2,851
Observations	21,240	21,930	22,210	22,270	22,296

Source: Prowess - Author's own calculation.
Notes: This table presents the second stage two-stage least squares (2SLS) results for the inverse peer dividend decisions. Panel A reports the results for dividend increases and Panel B reports the results for dividend decreases. The sample of each panel consists of all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles and column (5) reports the results for transitive reference groups based on the full sample of industry peers. The second stage results reported in this table relate to the first stage estimates reported in Tables 4.5, 4.7 and 4.8. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Figure 4.3: Dividend Decisions and Economic Policy Uncertainty



Source: Author's own calculation.
Note: This Figure reports the average dividend decision for Indian listed firms from 1995-2017 and two time-series plots of global and domestic economic policy uncertainty. Dividend increases and dividend decreases reflect the percentage of each dividend decision in each year of our Prowess sample. Global and domestic index data for India is sourced from `https://www.policyuncertainty.com/` where Baker et al. (2016) economic policy uncertainty measures are freely available. India's economic policy uncertainty index is measured via text-based analysis of Indian newspapers. The Global index measure is the GDP weighted average of twenty countries economic policy uncertainty index.

Table 4.12: Stability of Peer Effects Over Time: Dividend Increase

Panel A: Dividend Increases Results: 1995-2007					
	Dividend Increase				
	250 miles	500 miles	750 miles	1000 miles	Full Sample
	(1)	(2)	(3)	(4)	(5)
WInstrumented Peer Avg. $\text{Increase}_{250mi.i,j,t}$	0.228**				
	(0.091)				
WInstrumented Peer Avg. $\text{Increase}_{500mi.i,j,t}$		0.231**			
		(0.093)			
WInstrumented Peer Avg. $\text{Increase}_{750mi.i,j,t}$			0.182***		
			(0.064)		
WInstrumented Peer Avg. $\text{Increase}_{1000mi.i,j,t}$				0.186**	
				(0.074)	
Instrumented Peer Avg. $\text{Increase}_{i,j,t}$					0.190**
					(0.077)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.854	0.924	0.776	0.567	0.424
Firms	2,015	2,063	2,082	2,084	2,086
Observations	9,322	9,688	9,843	9,862	9,871
Panel B: Dividend Increases Results: 2008-2017					
	Dividend Increase				
	250 miles	500 miles	750 miles	1000 miles	Full Sample
	(1)	(2)	(3)	(4)	(5)
WInstrumented Peer Avg. $\text{Increase}_{250mi.i,j,t}$	0.299***				
	(0.076)				
WInstrumented Peer Avg. $\text{Increase}_{500mi.i,j,t}$		0.266***			
		(0.074)			
WInstrumented Peer Avg. $\text{Increase}_{750mi.i,j,t}$			0.209***		
			(0.059)		
WInstrumented Peer Avg. $\text{Increase}_{1000mi.i,j,t}$				0.206***	
				(0.063)	
Instrumented Peer Avg. $\text{Increase}_{i,j,t}$					0.215***
					(0.074)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.909	0.876	0.743	0.765	0.791
Firms	2,126	2,167	2,179	2,181	2,184
Observations	11,918	12,242	12,367	12,408	12,425

Source: Prowess - Author's own calculation.
Notes: This table presents the second stage results for our two-stage least squares (2SLS) analysis of dividend increases over two sub-samples. Panel A details all firms from 1995-2007 and Panel B details all firms from 2008-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles and column (5) reports the results for transitive reference groups based on the full sample of industry peers. The second stage results reported in this table relate to the first stage estimates reported in Table A.4.7. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.13: Stability of Peer Effects Over Time: Dividend Decrease

Panel A: Dividend Decrease Results: 1995-2007					
	Dividend Decrease				
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)	Full Sample (5)
WInstrumented Peer Avg. Decrease$_{250mi.i,j,t}$	0.211				
	(0.133)				
WInstrumented Peer Avg. Decrease$_{500mi.i,j,t}$		0.112			
		(0.075)			
WInstrumented Peer Avg. Decrease$_{750mi.i,j,t}$			0.095*		
			(0.053)		
WInstrumented Peer Avg. Decrease$_{1000mi.i,j,t}$				0.085	
				(0.053)	
Instrumented Peer Avg. Decrease$_{i,j,t}$					0.098*
					(0.058)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.455	0.0793	0.0477	0.0303	0.0713
Firms	2015	2063	2082	2084	2086
Observations	9322	9688	9843	9862	9871

Panel B: Dividend Decrease Results: 2008-2017					
	Dividend Decrease				
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)	Full Sample (5)
WInstrumented Peer Avg. Decrease$_{250mi.i,j,t}$	0.234**				
	(0.094)				
WInstrumented Peer Avg. Decrease$_{500mi.i,j,t}$		0.167**			
		(0.070)			
WInstrumented Peer Avg. Decrease$_{750mi.i,j,t}$			0.125**		
			(0.055)		
WInstrumented Peer Avg. Decrease$_{1000mi.i,j,t}$				0.153**	
				(0.066)	
Instrumented Peer Avg. Decrease$_{i,j,t}$					0.134**
					(0.065)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.965	0.729	0.500	0.470	0.483
Firms	2,126	2,167	2,179	2181	2184
Observations	11,918	12,242	12,367	12,408	12,425

Source: Prowess - Author's own calculation.

Notes: This table presents the second stage results for our two-stage least squares (2SLS) analysis of dividend decrease over two sub-samples. Panel A details all firms from 1995-2007 and Panel B details all firms from 2008-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles and column (5) reports the results for transitive reference groups based on the full sample of industry peers. The second stage results reported in this table correspond to the first stage estimates reported in Table A.4.8. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

4.6 Robustness Analysis

In order to assess the empirical firmness of our findings we conduct a number of robustness tests for both our baseline and peer proximity results. For our first empirical examination we perform a placebo test similar to Leary and Roberts (2014) and Grennan (2019). We administer the placebo test to ensure that the evidence of peer influence documented in this study is not a by product of some unobservable common factor attributed to our use of industry defined reference groups. Subsequently, the test design is demised around the random allocation of industry groups, where, if some common latent factor is indeed present, misspecification of peers should not matter for the overall peer effect.

To deliver our placebo test, we issue, with equal probability, each firm-year observation a randomly generated number between 0 and 50, then, to match the number of industry classifications in our main sample, we reassign the random numbers into 50 random peer (industry) groups. We then recalculate the average peer dividend decision and peer idiosyncratic equity shock and risk for each random industry allocation. In Table 4.14 we report insignificant peer effects for both dividend increases and dividend decreases. Thus, the results support our earlier findings by suggesting that peer groups based on industry classifications are significant for peer effect analysis, and, more importantly, for firm dividend decisions.

For our next robustness test we examine the significance of our findings to alternative standard error assumptions. In recent years there has been a growing concern towards the use of correct, or put differently, incorrect standard errors in the corporate finance panel data literature (e.g., Hoechle 2007, Petersen 2009 and Thompson 2011), where incorrect assumptions regarding standard errors can lead to erroneous conclusions about the statistical significance of ones estimates. To address these concerns, we examine the validity of our findings - which so far have reported firm clustered standard errors - to different standard-error types. Specifically, we re-estimate our baseline results for dividend increases and dividend decreases using four alternative standard error structures, namely: homoscedastic, year clustered, white robust and firm-year clustered. In Table 4.15 and 4.16 we report the first and second stage results for dividend increases and dividend decreases and include the coefficient estimates and all five standard error types, where we re-report firm clustered standard errors for ease of comparison. Across both tables we find our main empirical findings of peer influence to be statistically robust to alternative standard error formulations. Furthermore, in almost all cases, peer averages and firm-specific covariates maintain their statistical significance with year clustering reporting the highest standard errors across both tables.

For our third robustness test we stress test the relationship between profitability and dividend decreases by examining the stability of our baseline results to earning dynamics by including present and future earnings. To recapitulate, in Section 4.5 we proposed that the lagged level of profitability possibly effects dividend decreases positively as the previous years earnings are associated to prior dividend increases. Accordingly, for our third test examine the validity of our results to the current years level of profitability as well as future profitability. In Table 4.12 we find that the level of current profit (column (1)) and future in profit (column (2)) both have a negative effect on dividend decreases consistent with the broader literature (e.g. Fama and French 2002, Grullon et al. 2002 and Leary and Michaely 2011). Thus, in line with our initial suggestion, it seems that Indian listed firms decide to decrease dividend based on current and future earnings, this lays parallel with the observation that the majority of dividend decreases in our sample directly occur in periods of economic downturn when firms earnings are significantly lower.

In our penultimate robustness exercise, we analyse the stability of our results to potential omitted factors. While our peer proximity estimates contain a variety of controls e.g. firm-, peer- and industry-specific variables along with industry- and year-fixed effects, one might suggest that said model specifications fail to account for potential unobserved state specific factors or the notion that firms smooth their dividends over time. Accordingly, to address the first potential endogeneity concern, in Table 4.18 we report the peer proximity estimates for dividend increases and dividend decreases with the addition of state-wise fixed-effects. As can be observed, our results remain qualitatively the same, and, therefore, we conclude our main empirical findings are not a by product of unobserved state-specific factors.

Second, to control for the notion of dividend smoothing, we calculate the consecutive number of periods that each firm, without break, has increased or decreased their dividend payout with respect to the current period. As originally documented by Lintner (1956), managers often smooth their dividends over time, whereby firms adjust towards their optimal payout ratio via a succession of smaller incremental increases or decreases. To account for the potential non-linear effects of such smoothing conditions, we also include the quadratic polynomial of each respective consecutive count variable. In Table 4.19 we report the peer proximity estimates for dividend increases and dividend decreases with the addition of our dividend smoothing controls. For both dividend increases and dividend decreases, we find both the level and square of our consecutive count variables to be significantly significant at the 1% level, with positive and negative signs, respectively. The results infer an inverse U-shape of between firms previous consecutive dividend decisions and their current payout decision, thus, supporting the notion of dividend smoothing. Nonetheless, after controlling for such omitted behaviour characteristics, we not that our main empirical results of peer related proximity effects are largely unchanged thus illustrating the stoutness of our main findings. Furthermore, in unreported results, we test a number of additional firm variables such as import intensity, export intensity and firm sales along with the combination of state fixed effects and dividend smoothing. Again, our main findings prove both statistically and economically robust.

As our final test, we illustrate that our peer proximity based results are not a product of arbitrary geographical distances. To do so, we increase each proximity radius by 50 miles and re-calculate the average peer proximity effect for all four distances for both dividend increases and decreases and re-estimate our empirical specification. In Table 4.17 we illustrate both the statistical and economic robustness of our findings, with all statistical and economic conclusions remaining qualitatively indifferent. Furthermore, in unreported results, we repeat this practice by decreasing our distance measure by 50 miles, again our results remain qualitatively unchanged.

Table 4.14: Placebo Test: Randomly Assigned Peers

Panel A: First Stage		
	Placebo Peer Avg. Dividend Increase (1)	Placebo Peer Avg. Dividend Decrease (2)
Firm-specific Variables:		
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.002	0.001
	(0.007)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.008	0.005
	(0.007)	(0.006)
Peer Firm Averages:		
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.000	0.002
	(0.006)	(0.007)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.012	0.015
	(0.014)	(0.013)
Peer Firm Averages	Yes	Yes
Firm-specific Variables	Yes	Yes
Industry controls	Yes	Yes
Year Fixed-effects	Yes	Yes
F-statistic^{N}	0.575	1.067
F-statistic^{R}	0.373	0.689
F-statistic^{Eff}	0.383	0.663
Panel B: Second Stage		
	Dividend Increase (1)	Dividend Decrease (2)
Instrumented Placebo Peer Avg. Increase$_{i,j,t}$	-0.909	
	(1.200)	
Instrumented Placebo Peer Avg. Decrease$_{i,j,t}$		0.575
		(0.676)
Peer Firm Averages	Yes	Yes
Firm Specific Factors	Yes	Yes
Placebo Industry Controls	Yes	Yes
Placebo Industry-fixed Effects	Yes	Yes
Year-fixed Effects	Yes	Yes
Firms	2,851	2,851
Observations	22,296	22,296

Source: Prowess - Author's own calculation.

Notes: This table presents the two-stage least squares (2SLS) results for randomly assigned industry groups. The sample consists of all firms from 1995-2017. Panel A reports the first stage results. Panel B reports the second stage results. Column (1) and (2) report the results for our placebo tests estimates for dividend increases and dividend decrease, respectively. Random peer group classification consists of 50 industry classifications. Each estimate includes all peer firm averages, firm-specific variables, industry controls and year fixed-effects. F-statistic^{N} denotes the Cragg-Donald F-statistic, F-statistic^{R} denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.15: Dividend Increase: Standard Error Robustness Analysis

	Coefficient	Homoscedastic	Firm Clustered	Year Clustered	White Robust	Firm-Year Clustered
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First Stage						
Firm-Specific Factors:						
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.016	(0.012)	(0.011)	(0.010)	(0.011)	(0.010)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.007	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Peer Firm Averages:						
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.058	(0.005)***	(0.007)***	(0.032)*	(0.007)***	(0.032)*
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.031	(0.012)**	(0.018)*	(0.072)	(0.017)*	(-0.073)
Panel B: Second Stage						
Instrumented Peer Avg. Increase$_{i,j,t}$	0.147	(0.065)**	(0.067)**	(0.033)***	(0.069)**	(0.028)***
Firm-specific Variables:						
Profitability$_{i,j,t-1}$	0.047	(0.004)***	(0.005)***	(0.007)***	(0.004)***	(0.007)***
Market-to-Book$_{i,j,t-1}$	0.034	(0.004)***	(0.004)***	(0.005)***	(0.004)***	(0.006)***
Investment$_{i,j,t-1}$	0.016	(0.004)***	(0.004)***	(0.005)***	(0.004)***	(0.005)***
Leverage$_{i,j,t-1}$	-0.013	(0.004)***	(0.005)***	(0.004)***	(0.004)***	(0.005)**
Size$_{i,j,t-1}$	0.106	(0.004)***	(0.005)***	(0.009)***	(0.004)***	(0.009)***
Tangibility$_{i,j,t-1}$	-0.001	(0.004)	(0.005)	(0.007)	(0.004)	(0.008)
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.016	(0.004)***	(0.004)***	(0.004)***	(0.004)***	(0.004)***
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.041	(0.004)***	(0.006)***	(0.009)***	(0.005)***	(0.009)***
Peer Firm Averages:						
Profitability$_{i,j,t-1}$	-0.012	(0.006)**	(0.006)**	(0.003)***	(0.006)**	(0.003)***
Market-to-Book$_{i,j,t-1}$	-0.015	(0.006)**	(0.006)**	(0.004)***	(0.006)**	(0.003)***
Investment$_{i,j,t-1}$	-0.008	(0.005)	(0.006)	(0.003)***	(0.006)	(0.003)***
Leverage$_{i,j,t-1}$	0.015	(0.008)*	(0.009)	(0.004)***	(0.008)*	(0.006)*
Size$_{i,j,t-1}$	-0.048	(0.011)***	(0.013)***	(0.007)***	(0.011)***	(0.009)***
Tangibility$_{i,j,t-1}$	-0.006	(0.015)	(0.016)	(0.009)	(0.015)	(0.010)

Source: Prowess - Author's own calculation.

Notes: This table presents the standard-error robustness analysis of our baseline dividend increase estimates. The sample consists of all firms in the annual database between 1995 and 2017. Panel A and Panel B report the first and second stage standard errors for the corresponding variables, respectively. Column (1) reports the associated variable coefficient. Column (2) reports Homoscedastic standard errors. Column (2) reports firm clustered standard errors. Column (3) reports year clustered standard errors. Column (4) reports huber-white robust standard errors. Column (5) reports firm-year robust standard errors, where firm-year standard errors are calculated using Thompson (2011)'s double clustered formula: V_{firm}+V_{year}-V_{white}. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.16: Dividend Decrease: Standard Error Robustness Analysis

	Coefficient (1)	Homoscedastic (2)	Firm Clustered (3)	Year Clustered (4)	White Robust (5)	Firm-Year Clustered (6)
Panel A: First Stage						
Firm-Specific Factors:						
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.010	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.009	(0.006)	(0.007)	(0.005)	(0.006)	(0.008)
Peer Firm Averages:						
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.060	(0.006)***	(0.008)***	(0.019)***	(0.008)***	(0.019)***
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.089	(0.014)***	(0.019)***	(0.062)	(0.019)***	(0.062)
Panel B: Second Stage						
Instrumented Peer Avg. Decrease$_{i,j,t}$	0.199	(0.047)***	(0.052)***	(0.036)***	(0.052)***	(0.036)***
Firm-specific Variables:						
Profitability$_{i,j,t-1}$	0.025	(0.003)***	(0.003)***	(0.005)***	(0.003)***	(0.005)***
Market-to-Book$_{i,j,t-1}$	-0.024	(0.003)***	(0.004)***	(0.007)***	(0.003)***	(0.007)***
Investment$_{i,j,t-1}$	0.017	(0.003)***	(0.003)***	(0.004)***	(0.003)***	(0.004)***
Leverage$_{i,j,t-1}$	0.008	(0.003)**	(0.004)**	(0.006)	(0.003)**	(0.006)
Size$_{i,j,t-1}$	0.036	(0.003)***	(0.004)***	(0.009)***	(0.003)***	(0.009)***
Tangibility$_{i,j,t-1}$	-0.009	(0.004)**	(0.004)**	(0.005)**	(0.003)***	(0.005)*
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.000	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.020	(0.004)***	(0.004)***	(0.006)***	(0.004)***	(0.006)***
Peer Firm Averages:						
Profitability$_{i,j,t-1}$	-0.011	(0.004)**	(0.004)**	(0.004)***	(0.004)**	(0.004)***
Market-to-Book$_{i,j,t-1}$	0.010	(0.004)***	(0.005)**	(0.003)***	(0.005)**	(0.003)***
Investment$_{i,j,t-1}$	-0.010	(0.006)*	(0.007)	(0.005)**	(0.006)	(0.005)*
Leverage$_{i,j,t-1}$	0.006	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
Size$_{i,j,t-1}$	-0.025	(0.016)	(0.018)	(0.012)**	(0.018)	(0.013)**
Tangibility$_{i,j,t-1}$	0.009	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)

Source: Prowess - Author's own calculation.
Notes: This table presents the standard-error robustness analysis of our baseline dividend decrease estimates.The sample consists of all firms in the annual database between 1995 and 2017. Panel A and Panel B report the first and second stage standard errors for the corresponding variables, respectively. Column (1) reports the associated variable coefficient. Column (2) reports Homoscedastic standard errors. Column (2) reports firm clustered standard errors. Column (3) reports year clustered standard errors. Column (4) reports huber-white robust standard errors. Column (5) reports firm-year robust standard errors, where firm-year standard errors are calculated using Thompson (2011)'s double clustered formula: V_{firm}+V_{year}-V_{white}. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.17: Dividend Decrease: Profitability Sensitivity Test

Panel A: First Stage				
	Peer Dividend Decrease			
	(1)	(2)	(3)	(4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.008	-0.007	-0.010	-0.008
	(0.006)	(0.006)	(0.007)	(0.007)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.003	0.006	0.005	0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.059***	-0.059***	-0.062***	-0.061***
	(0.008)	(0.008)	(0.009)	(0.009)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.104***	0.103***	0.069***	0.068***
	(0.019)	(0.019)	(0.021)	(0.021)
Peer Firm Averages	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes
Placebo Industry Controls	Yes	Yes	Yes	Yes
Placebo Industry-fixed Effects	Yes	Yes	Yes	Yes
Year-fixed Effects	Yes	Yes	Yes	Yes
F-statistic^N	70.989	69.198	55.704	54.038
F-statistic^R	35.570	34.750	28.380	27.66
F-statistic^{Eff}	36.304	35.344	29.174	28.315
Panel B: Second Stage				
	Dividend Decrease			
	(1)	(2)	(3)	(4)
Instrumented Peer Avg. Decrease$_{i,j,t}$	0.194***	0.168***	0.193***	0.167***
	(0.052)	(0.050)	(0.057)	(0.055)
Firm-specific Variables:				
Profitability$_{i,j,t+1}$			-0.020***	-0.026***
			(0.004)	(0.004)
Profitability$_{i,j,t}$	-0.070***	-0.128***	-0.056***	-0.108***
	(0.004)	(0.006)	(0.005)	(0.007)
Profitability$_{i,j,t-1}$		0.099***		0.096***
		(0.005)		(0.006)
Peer Firm Averages	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes
Placebo Industry Controls	Yes	Yes	Yes	Yes
Placebo Industry-fixed Effects	Yes	Yes	Yes	Yes
Year-fixed Effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.427	0.365	0.305	0.319
Firms	2,851	2,851	2,441	2,441
Observations	22,296	22,296	18052	18052

Source: Prowess - Author's own calculation.

Notes: This table presents the two stage least squares (2SLS) results our profitability sensitivity analysis on dividend decreases. The sample consists of all firms from 1995-2017. Panel A reports the first stage estimates and Panel B reports the second stage estimates. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^N denotes the Cragg-Donald F-statistic, F-statistic^R denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.18: Unobserved State Level Heterogeneity: Dividend Increase and Dividend Decrease

Panel A: Additional Control Results: Dividend Increase				
	Dividend Increase			
	250 Miles	500 Miles	750 Miles	1000 Miles
	(1)	(2)	(3)	(4)
WInstrumented Peer Avg. Increase$_{250mi.i,j,t}$	0.276*			
	(0.162)			
WInstrumented Peer Avg. Increase$_{500mi.i,j,t}$		0.233*		
		(0.134)		
WInstrumented Peer Avg. Increase$_{750mi.i,j,t}$			0.188**	
			(0.086)	
WInstrumented Peer Avg. Increase$_{1000mi.i,j,t}$				0.145**
				(0.073)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-fixed Effects	Yes	Yes	Yes	Yes
State-fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.552	0.348	0.513	0.249
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270

Panel B: Additional Control Results: Dividend Decrease				
	Dividend Decrease			
	250 Miles	500 Miles	750 Miles	1000 Miles
	(1)	(2)	(3)	(4)
WInstrumented Peer Avg. Decrease$_{250mi.i,j,t}$	0.264***			
	(0.098)			
WInstrumented Peer Avg. Decrease$_{550mi.i,j,t}$		0.253***		
		(0.081)		
WInstrumented Peer Avg. Decrease$_{750mi.i,j,t}$			0.204***	
			(0.056)	
WInstrumented Peer Avg. Decrease$_{1000mi.i,j,t}$				0.193***
				(0.051)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-fixed Effects	Yes	Yes	Yes	Yes
State-fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.998	0.813	0.517	0.478
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270

Source: Prowess - Author's own calculation.

Notes: This table presents the second stage two-stage least squares (2SLS) results for dividend increases and dividend decreases with the addition of state level fixed effects. Panel A reports the results for dividend increases. Panel B reports the results for dividend decrease. The sample of each panel consists of all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. The second stage results reported in this table relate to the first stage estimates reported in Table A.4.9. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.19: Dividend Smoothing Robustness: Dividend Increase and Dividend Decrease

Panel A: Additional Control Results: Dividend Increase				
	Dividend Increase			
	250 Miles (1)	500 Miles (2)	750 Miles (3)	1000 Miles (4)
WInstrumented Peer Avg. Increase$_{250mi.i,j,t}$	0.303*			
	(0.155)			
WInstrumented Peer Avg. Increase$_{500mi.i,j,t}$		0.259*		
		(0.134)		
WInstrumented Peer Avg. Increase$_{750mi.i,j,t}$			0.203**	
			(0.086)	
WInstrumented Peer Avg. Increase$_{1000mi.i,j,t}$				0.158**
				(0.075)
Consecutive Increase Count$_{i,j,t-1}$	0.084***	0.088***	0.089***	0.098***
	(0.007)	(0.007)	(0.007)	(0.007)
Consecutive Increase Count Squared$_{i,j,t-1}$	-0.049***	-0.052***	-0.052***	-0.052***
	(0.008)	(0.009)	(0.010)	(0.010)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.638	0.348	0.513	0.249
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270
Panel B: Additional Control Results: Dividend Decrease				
	Dividend Decrease			
	250 Miles (1)	500 Miles (2)	750 Miles (3)	1000 Miles (4)
WInstrumented Peer Avg. Decrease$_{250mi.i,j,t}$	0.255***			
	(0.094)			
WInstrumented Peer Avg. Decrease$_{550mi.i,j,t}$		0.252***		
		(0.079)		
WInstrumented Peer Avg. Decrease$_{750mi.i,j,t}$			0.206***	
			(0.055)	
WInstrumented Peer Avg. Decrease$_{1000mi.i,j,t}$				0.196***
				(0.051)
Consecutive Decrease Count$_{i,j,t-1}$	0.035***	0.031***	0.030***	0.030***
	(0.005)	(0.005)	(0.005)	(0.005)
Consecutive Decrease Count Squared$_{i,j,t-1}$	-0.019***	-0.016***	-0.016***	-0.016***
	(0.009)	(0.010)	(0.010)	(0.010)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.888	0.916	0.607	0.546
Firms	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270

Source: Prowess - Author's own calculation.
Notes: This table presents the second stage two-stage least squares (2SLS) results for dividend increases and dividend decreases with the addition of the number of previous continuous increases (decreases) and the square of this variable. Panel A reports the results for dividend increases. Panel B reports the results for dividend decrease. The sample of each panel consists of all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. The second stage results reported in this table relate to the first stage estimates reported in Table A.4.10. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table 4.20: Extended Radius Results: Dividend Increase and Dividend Decrease

Panel A: First Stage				
	Extended Radius Results: Dividend Increase			
	300 Miles (1)	550 Miles (2)	800 Miles (3)	1050 Miles (4)
WInstrumented Peer Avg. Increase$_{300mi.i,j,t}$	0.374*			
	(0.219)			
WInstrumented Peer Avg. Increase$_{550mi.i,j,t}$		0.234*		
		(0.120)		
WInstrumented Peer Avg. Increase$_{800mi.i,j,t}$			0.197**	
			(0.095)	
WInstrumented Peer Avg. Increase$_{1050mi.i,j,t}$				0.142*
				(0.073)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.915	0.374	0.506	0.237
Firms	2,794	2,833	2,847	2,849
Observations	21,474	21,990	22,232	22,288
Panel B: Second Stage				
	Extended Radius Results: Dividend Decrease			
	300 Miles (1)	550 Miles (2)	800 Miles (3)	1050 Miles (4)
WInstrumented Peer Avg. Decrease$_{300mi.i,j,t}$	0.282***			
	(0.105)			
WInstrumented Peer Avg. Decrease$_{550mi.i,j,t}$		0.278***		
		(0.089)		
WInstrumented Peer Avg. Decrease$_{800mi.i,j,t}$			0.223***	
			(0.062)	
WInstrumented Peer Avg. Decrease$_{1050mi.i,j,t}$				0.205***
				(0.055)
Additional Firm-Specific Variables	Yes	Yes	Yes	Yes
Additional Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Hansen J p-value	0.841	0.930	0.487	0.610
Firms	2,794	2,833	2,847	2,849
Observations	21,474	21,990	22,232	22,288

Source: Prowess - Author's own calculation.
Notes: This table presents the second stage two-stage least squares (2SLS) results for our extended radius analysis. Panel A reports the results for dividend increases. Panel B reports the results for dividend decrease. The sample of each panel consists of all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 300-1050 miles. The second stage results reported in this table relate to the first stage estimates reported in Table A.4.11. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

4.7 Concluding Remarks

The primary aim of this chapter was to investigate whether Indian listed firms dividend decisions are influenced by the decisions of their industry peers, and, if so, does the geographical location of peers matter. Our results conclude that this is indeed the case. We find the dividend decisions made by Indian firms are influenced by the decisions, and less so, the characteristics of their industry counterparts. We show that the decisions of geographically closer industry peers bear greater influence on the dividend payout decisions of Indian listed firms. We perform a number of additional robust tests and illustrate our empirical findings are not a product of latent common factors attributable to our use of industry-based reference groups. Moreover, we report our findings are not a product of specific variance clustering nor are they driven by omitted variable bias or arbitrary peer proximity distances.

The empirical findings documented in this chapter contribute to the literature on peer effects in corporate finance in three ways (e.g., Leary and Roberts 2014, Foucault and Fresard 2014, Kaustia and Rantala 2015, Adhikari and Agrawal 2018 and Grennan 2019). First, this chapter employs a new reference group structure based intransitive reference groups defined by peers geographical location. Accordingly, our chapter provides the first empirical evidence of the relationship between peer dividend decisions and peer location. Finally, our analysis of Indian listed firms provides the first robust evidence of dividends and peer effects in a emerging market context and shows peer effect manifestations are not exclusive to the specific dividend decisions reported by Adhikari and Agrawal (2018) and Grennan (2019).

All in all, our analysis presents new and robust evidence that the dividend decisions of Indian listed firms are statistically and economically influenced by the decisions of their industry peers. As a result, this chapter provides a clear criticism of the existing empirical literature on corporate payout polices, which largely consider dividend decisions independent of their peers behaviour. In doing so, this chapter presents evidence into why the dividend decisions of firms often coincide with decisions of their industry counterparts. With regards to future research, we provide two recommendations. First, a deeper empirical analysis on the relevance of geographical proximity is required to further aid our understanding of why firms imitate one another and why some peers are more influential than others. Second, a broader international comparison of peer effects would help uncover the potential association between emerging market economies and peer influence touched upon in this chapter. Moreover, an international comparison would provide insight on the geographic importance of domestic and foreign peer behaviour.

4.8 Appendix

Table A.4.1: Variable Definitions and Sources

Data Reference	Definition	Source
Panel A: Daily Data		
Daily Return	The percentage change of daily close price	Prowess
Market Return	The percentage change of BSE Senex 50 daily close price	Royal Bank of India
Industry Return	The leave-out-mean of daily return	Prowess
Risk Free Return	The daily return on US 10 year bonds	Federal Reserve
Daily Expected Return	The predicted return for augmented asset pricing model	Prowess
Daily Idiosyncratic Return	The realised daily return less daily expected return	Prowess
Panel B: Firm Annual Data		
Dividend Payout	Total Cash Dividend (TCD) over Total Assets	Prowess
Dividend Increase	Takes the value 1 if the change in TCD is positive, or else zero	Prowess
Dividend Decrease	Takes the value 1 if the change in TCD is negative, or else zero	Prowess
Profitability	Net earnings over Total Assets	Prowess
Market-to-Book	Market Capitalisation plus Total Debt over Total Assets	Prowess
Investment	Change in net investment plus deprecation) over total assets	Prowess
Leverage	Short term debt plus long term debt over total assets	Prowess
Size	The natural logarithm of Total Assets	Prowess
Tangibility	Fixed assets over total assets	Prowess
Idiosyncratic Equity Shock	The annual average of daily idiosyncratic Return	Prowess
Idiosyncratic Equity Risk	The annual standard deviation of daily idiosyncratic return	Prowess
Panel C: Additional Annual Data		
Global EPU	Global economic policy uncertainty index	Policy Uncertainty
India EPU	India economic policy uncertainty index	Policy Uncertainty
Latitude and Longitude	Latitude and Longitude coordinates	GeoNames

Table A.4.2: Panel Structure By Firm

No. of obs. per firm	No. of obs.	Percentage (%)	Cumulative Percentage (%)
1	555	1.960	1.960
2	878	3.090	5.050
3	829	2.920	7.970
4	854	3.010	10.980
5	965	3.400	14.380
6	1125	3.960	18.340
7	1124	3.960	22.300
8	1064	3.750	26.050
9	1267	4.460	30.520
10	1619	5.700	36.220
11	1424	5.020	41.240
12	1235	4.350	45.590
13	1364	4.810	50.390
14	1449	5.110	55.500
15	1291	4.550	60.050
16	1328	4.680	64.730
17	1575	5.550	70.280
18	1349	4.750	75.030
19	1190	4.190	79.220
20	1117	3.940	83.160
21	1103	3.890	87.040
22	1216	4.280	91.330
23	2461	8.670	100.000
Total	28,382	100.000	100.000

Table A.4.3: Panel Structure By Year

No. of obs. per firm	No. of obs.	Percentage (%)	Cumulative Percentage (%)
1995	1333	4.600	4.600
1996	1680	5.800	10.400
1997	1376	4.750	15.150
1998	971	3.350	18.510
1999	749	2.590	21.090
2000	898	3.100	24.190
2001	810	2.800	26.990
2002	652	2.250	29.240
2003	765	2.640	31.880
2004	979	3.380	35.260
2005	1193	4.120	39.380
2006	1346	4.650	44.030
2007	1441	4.980	49.010
2008	1519	5.240	54.250
2009	1396	4.820	59.070
2010	1540	5.320	64.390
2011	1656	5.720	70.110
2012	1536	5.300	75.410
2013	1483	5.120	80.530
2014	1379	4.760	85.290
2015	1379	4.760	90.060
2016	1450	5.010	95.060
2017	1430	4.940	100.000
Total	28,382	100.000	100.000

Table A.4.4: Baseline Results: Restriction Tests

	Dividend Payout			Dividend Increase			Dividend Decrease		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Avg. Dependent Variable$_{i,j,t}$			0.001**			0.041***			0.038***
			(0.000)			(0.006)			(0.004)
Firm-specific Variables:									
Profitability$_{i,j,t-1}$	0.005***	0.005***	0.005***	0.046***	0.046***	0.047***	0.026***	0.026***	0.026***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Market-to-Book$_{i,j,t-1}$	0.003***	0.003***	0.003***	0.034***	0.035***	0.034***	-0.023***	-0.024***	-0.024***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Investment$_{i,j,t-1}$	-0.000***	-0.000**	-0.000**	0.016***	0.016***	0.016***	0.018***	0.018***	0.018***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Leverage$_{i,j,t-1}$	-0.003***	-0.003***	-0.003***	-0.012**	-0.012**	-0.012**	0.005	0.005	0.005
	(0.000)	(0.000)	(0.000)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Size$_{i,j,t-1}$	0.001***	0.001***	0.001***	0.104***	0.103***	0.104***	0.038***	0.039***	0.039***
	(0.000)	(0.000)	(0.000)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Tangibility$_{i,j,t-1}$	0.000**	0.000*	0.000**	0.001	0.001	0.000	-0.009**	-0.009**	-0.009**
	(0.000)	(0.000)	(0.000)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.001***	0.001***	0.001***	0.016***	0.016***	0.016***	-0.002	-0.002	-0.001
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.002***	-0.002***	-0.002***	-0.041***	-0.040***	-0.041***	-0.018***	-0.018***	-0.018***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Peer Firm Averages:									
Profitability$_{i,j,t-1}$		-0.000	-0.000		-0.004	-0.006		-0.002	-0.004
		(0.000)	(0.000)		(0.005)	(0.005)		(0.004)	(0.004)
Market-to-Book$_{i,j,t-1}$		-0.001***	-0.001***		-0.006	-0.009*		0.010**	0.010**
		(0.000)	(0.000)		(0.004)	(0.004)		(0.004)	(0.004)
Investment$_{i,j,t-1}$		-0.000***	-0.001***		-0.008	-0.008		0.005	0.002
		(0.000)	(0.000)		(0.006)	(0.006)		(0.005)	(0.005)
Leverage$_{i,j,t-1}$		0.001**	0.001*		0.013	0.014		-0.019***	-0.015**
		(0.000)	(0.000)		(0.009)	(0.009)		(0.007)	(0.007)
Size$_{i,j,t-1}$		-0.000	-0.000		-0.050***	-0.049***		0.028***	0.018*
		(0.000)	(0.000)		(0.012)	(0.012)		(0.010)	(0.011)
Tangibility$_{i,j,t-1}$		0.001**	0.001**		0.016	0.010		0.001	0.003
		(0.000)	(0.000)		(0.012)	(0.012)		(0.010)	(0.010)
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms	2,851	2,851	2,851	2,851	2,851	2,851	2,851	2,851	2,851
Observations	22,296	22,296	22,296	22,296	22,296	22,296	22,296	22,296	22,296

Source: Prowess - Author's own calculation.
Notes: This table presents the ordinary least squares (OLS) estimates for a number of model specifications. The sample consists of all firms from 1995-2017. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table A.4.5: Baseline Results: Detailed First Stage Estimates

	Peer Avg. Dividend Payout	Peer Avg. Dividend Increase	Peer Avg. Dividend Decrease
	(1)	(2)	(3)
Firm-specific Variables:			
Profitability$_{i,j,t-1}$	-0.003	-0.007	0.006
	(0.005)	(0.005)	(0.005)
Market-to-Book$_{i,j,t-1}$	-0.016***	0.003	-0.001
	(0.005)	(0.006)	(0.006)
Investment$_{i,j,t-1}$	-0.008*	0.001	0.002
	(0.004)	(0.005)	(0.006)
Leverage$_{i,j,t-1}$	0.003	0.006	-0.017***
	(0.005)	(0.005)	(0.005)
Size$_{i,j,t-1}$	-0.007	-0.025***	0.017***
	(0.005)	(0.005)	(0.005)
Tangibility$_{i,j,t-1}$	0.022***	0.010*	0.001
	(0.006)	(0.006)	(0.006)
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.002	0.001	-0.010
	(0.004)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.001	0.009	0.009
	(0.007)	(0.007)	(0.007)
Peer Firm Averages:			
Profitability$_{i,j,t-1}$	0.178***	0.053***	0.043***
	(0.009)	(0.008)	(0.008)
Market-to-Book$_{i,j,t-1}$	-0.014**	0.060***	0.006
	(0.006)	(0.006)	(0.006)
Investment$_{i,j,t-1}$	-0.072***	-0.009	0.089***
	(0.009)	(0.008)	(0.009)
Leverage$_{i,j,t-1}$	-0.209***	-0.008	-0.130***
	(0.016)	(0.017)	(0.019)
Size$_{i,j,t-1}$	-0.017	-0.034	0.303***
	(0.021)	(0.023)	(0.025)
Tangibility$_{i,j,t-1}$	0.265***	0.148***	-0.040*
	(0.026)	(0.021)	(0.024)
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.047***	0.058***	-0.060***
	(0.007)	(0.007)	(0.008)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.113***	-0.035*	0.089***
	(0.017)	(0.018)	(0.019)
Industry Controls	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes
F-statistic^{N}	130.650	62.082	78.699
F-statistic^{R}	54.556	36.265	37.957
F-statistic^{Eff}	47.544	30.196	38.737
Firms	2,851	2,851	2,851
Observations	22,296	22,296	22,296

Source: Prowess - Author's own calculation.
Notes: This table presents the detailed first stage results for our baseline two-stage least squares (2SLS) estimation procedure. The sample consists of all firms between 1995 and 2017. The first stage results reported in this table relate to the second stage results reported in Table 4.6. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation, where industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^{N} denotes the Cragg-Donald F-statistic, F-statistic^{R} denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table A.4.6: Peer Proximity Results: Restricted Second Stage Estimates

	Dividend Increase				Dividend Increase			
	250 Miles (1)	500 Miles (2)	750 Miles (3)	1000 Miles (4)	250 Miles (5)	500 Miles (6)	750 Miles (7)	1000 Miles (8)
WInstrumented Peer Avg. Decision$_{250mi.i,j,t}$	0.158***				0.301***			
	(0.056)				(0.091)			
WInstrumented Peer Avg. Decision$_{500mi.i,j,t}$		0.132***				0.269***		
		(0.039)				(0.069)		
WInstrumented Peer Avg. Decision$_{750mi.i,j,t}$			0.117***				0.222***	
			(0.036)				(0.052)	
WInstrumented Peer Avg. Decision$_{1000mi.i,j,t}$				0.111***				0.209***
				(0.030)				(0.050)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	No	No	No	No	No	No	No	No
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic^{N}	64.249	144.403	200.948	300.723	22.025	34.911	64.307	76.000
F-statistic^{R}	32.308	59.884	88.812	128.58	14.247	22.056	36.383	41.525
F-statistic^{Eff}	33.522	68.183	97.763	140.974	13.907	20.437	36.392	40.981
Hansen J p-value	0.585	0.432	0.515	0.502	0.655	0.546	0.151	0.176
Firms	2,771	2,828	2,847	2,848	2,771	2,828	2,847	2,848
Observations	21,240	21,930	22,210	22,270	21,240	21,930	22,210	22,270

Source: Prowess - Author's own calculation.

Notes: This table presents the second stage two-stage least squares (2SLS) results for dividend increases and dividend decreases with the omission of industry fixed-effects. The sample consists of all firms from 1995-2017. Column (1) - (4) report the results for dividend increase and the corresponding peer proximity's from 250-1000 miles. Column (5) - (8) report the results for dividend decrease and the corresponding peer proximity's from 250-1000 miles. First stage results are not reported for the sake of brevity. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^{N} denotes the Cragg-Donald F-statistic, F-statistic^{R} denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The wald test of strict exogeneity reports the Chi^2 statistic for the instrument regression on the corresponding residual. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table 4.1.

Table A.4.7: Stability of Peer Effects Over Time: Dividend Increase

Panel A: First Stage Dividend Increase Results: 1995-2007					
	Peer Dividend Increase				
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)	Full Sample (5)
Firm-specific Variables:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.016	0.007	0.001	-0.002	-0.006
	(0.010)	(0.009)	(0.007)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.006	0.008	0.012	0.017**	0.018**
	(0.009)	(0.007)	(0.008)	(0.007)	(0.008)
Peer Firm Averages:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.023**	0.024***	0.040***	0.042***	0.042***
	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.145***	0.135***	0.162***	0.120***	0.111***
	(0.030)	(0.029)	(0.024)	(0.023)	(0.023)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-statistic^N	23.401	27.434	65.690	58.492	59.421
F-statistic^R	13.752	15.510	37.870	30.259	30.980
F-statistic^{Eff}	15.208	16.585	39.620	31.991	32.643
Firms	2,015	2,063	2,082	2,084	2,086
Observations	9,322	9,688	9,843	9,862	9,871
Panel B: First Stage Dividend Increase Results: 2008-2017					
	Peer Dividend Increase				
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)	Full Sample (5)
Firm-specific Variables:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.014	0.020	0.012	0.017	0.020
	(0.016)	(0.014)	(0.014)	(0.013)	(0.013)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.036*	0.020	0.032	0.039*	0.043**
	(0.019)	(0.019)	(0.022)	(0.021)	(0.019)
Peer Firm Averages:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.048	0.044	0.038*	0.030	0.018
	(0.031)	(0.028)	(0.023)	(0.022)	(0.020)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.502***	0.504***	0.597***	0.560***	0.471***
	(0.080)	(0.085)	(0.072)	(0.071)	(0.068)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-statistic^N	36.056	45.101	82.237	83.554	61.406
F-statistic^R	20.846	18.249	34.436	31.416	23.908
F-statistic^{Eff}	23.091	23.379	45.553	42.630	32.831
Firms	2,126	2,167	2,179	2,181	2,184
Observations	11,918	12,242	12,367	12,408	12,425

Source: Prowess - Author's own calculation.

Notes: This table presents the first stage results for our two-stage least squares (2SLS) analysis of dividend increases over two sub-samples. Panel A details all firms from 1995-2007 and Panel B details all firms from 2008-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles and column (5) reports the results for transitive reference groups based on the full sample of industry peers. The second stage results reported in this table relate to the first stage estimates reported in Table 4.12. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^N denotes the Cragg-Donald F-statistic, F-statistic^R denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The wald test of strict exogeneity reports the Chi^2 statistic for the instrument regression on the corresponding residual. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table A.4.8: Stability of Peer Effects Over Time: Dividend Decrease

Panel A: First Stage Dividend Decrease Results: 1995-2007					
	Peer Dividend Decrease				
	250 miles	500 miles	750 miles	1000 miles	Full Sample
	(1)	(2)	(3)	(4)	(5)
Firm-specific Variables:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.010	-0.006	0.000	-0.003	-0.001
	(0.011)	(0.011)	(0.008)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.008	-0.011	-0.008	-0.002	-0.002
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
Peer Firm Averages:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.024**	-0.026***	-0.048***	-0.048***	-0.045***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.060*	-0.119***	-0.135***	-0.134***	-0.120***
	(0.035)	(0.029)	(0.027)	(0.027)	(0.026)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-statistic^N	7.243	21.826	54.226	58.055	52.428
F-statistic^R	4.629	12.292	29.173	28.724	25.378
F-statistic^{Eff}	4.364	12.712	27.811	28.129	24.415
Firms	2,015	2,063	2,082	2,084	2,086
Observations	9,322	9,688	9,843	9,862	9,871

Panel B: First Stage Dividend Decrease Results: 2008-2017					
	Peer Dividend Decrease				
	250 miles	500 miles	750 miles	1000 miles	Full Sample
	(1)	(2)	(3)	(4)	(5)
Firm-specific Variables:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.019	-0.028	-0.030**	-0.030**	-0.038***
	(0.018)	(0.018)	(0.015)	(0.014)	(0.014)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.041*	-0.053**	-0.031*	-0.023	-0.024
	(0.021)	(0.021)	(0.017)	(0.016)	(0.016)
Peer Firm Averages:					
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.091***	-0.112***	-0.089***	-0.065**	-0.054**
	(0.035)	(0.033)	(0.028)	(0.027)	(0.025)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.326***	-0.391***	-0.512***	-0.448***	-0.452***
	(0.078)	(0.077)	(0.065)	(0.058)	(0.057)
Firm-Specific Variables	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-statistic^N	15.577	27.129	49.817	42.331	42.529
F-statistic^R	11.611	18.787	41.055	32.817	34.812
F-statistic^{Eff}	11.765	18.349	36.307	31.032	33.256
Firms	2,126	2,167	2,179	2,181	2,184
Observations	11,918	12,242	12,367	12,408	12,425

Source: Prowess - Author's own calculation.

Notes: This table presents the first stage results for our two-stage least squares (2SLS) analysis of dividend decreases over two subsamples. Panel A details all firms from 1995-2007 and Panel B details all firms from 2008-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles and column (5) reports the results for transitive reference groups based on the full sample of industry peers. The second stage results reported in this table relate to the first stage estimates reported in Table 4.13. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^N denotes the Cragg-Donald F-statistic, F-statistic^R denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The wald test of strict exogeneity reports the Chi^2 statistic for the instrument regression on the corresponding residual. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table A.4.9: Unobserved State Level Heterogeneity: Dividend Increase and Dividend Decrease

Panel A: Extended Radius Results : Dividend Increase				
	Peer Dividend Increase			
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.008	0.007	0.003	0.003
	(0.008)	(0.007)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.003	0.003	0.007	0.008
	(0.009)	(0.008)	(0.008)	(0.007)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.028***	0.033***	0.047***	0.053***
	(0.009)	(0.008)	(0.007)	(0.007)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.024	0.003	0.023	-0.022
	(0.022)	(0.022)	(0.019)	(0.019)
Firm-Specific Variables	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
State-Fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^N	17.617	23.649	55.948	53.191
F-statistic^R	11.176	14.546	30.868	32.183
F-statistic^{Eff}	10.569	13.729	31.841	27.110
Firms	2,015	2,063	2,082	2,084
Observations	9,322	9,688	9,843	9,862
Panel B: Extended Radius Results : Dividend Decrease				
	Peer Dividend Increase			
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.009	-0.010	-0.003	-0.010
	(0.008)	(0.008)	(0.007)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.007	-0.000	0.004	0.008
	(0.010)	(0.009)	(0.008)	(0.008)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.031***	-0.038***	-0.057***	-0.060***
	(0.009)	(0.009)	(0.008)	(0.008)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.084***	0.075***	0.085***	0.094***
	(0.026)	(0.023)	(0.020)	(0.020)
Firm-Specific Variables	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
State-Fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^N	9.025	13.645	37.576	70.268
F-statistic^R	5.070	8.237	22.150	37.044
F-statistic^{Eff}	5.283	7.400	21.192	37.266
Firms	2,126	2,167	2,179	2,181
Observations	11,918	12,242	12,367	12,408

Source: Prowess - Author's own calculation.
Notes: This table presents the first stage two-stage least squares (2SLS) results for dividend increases and dividend decreases with the addition of state level fixed effects. Panel A reports the results for dividend increases. Panel B reports the results for dividend decrease. The sample consists of all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. The first stage results reported in this table correspond to the first stage estimates reported in Table 4.18. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^N denotes the Cragg-Donald F-statistic, F-statistic^R denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table A.4.10: Dividend Smoothing Robustness: Dividend Increase and Dividend Decrease

Panel A: Extended Radius Results : Dividend Increase				
	Peer Dividend Increase			
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.002	0.005	0.003	0.003
	(0.008)	(0.007)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.003	0.003	0.007	0.008
	(0.009)	(0.008)	(0.008)	(0.007)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.024***	0.033***	0.047***	0.053***
	(0.009)	(0.008)	(0.006)	(0.005)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.047	0.003	0.025	-0.022
	(0.022)	(0.022)	(0.014)	(0.012)
Firm-Specific Variables	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^{N}	10.021	13.490	37.600	53.565
F-statistic^{R}	5.621	8.056	22.146	32.626
F-statistic^{Eff}	6.545	7.063	21.326	27.410
Firms	2,015	2,063	2,082	2,084
Observations	9,322	9,688	9,843	9,862
Panel B: Extended Radius Results : Dividend Decrease				
	Peer Dividend Increase			
	250 miles (1)	500 miles (2)	750 miles (3)	1000 miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.002	-0.008	-0.002	-0.012
	(0.008)	(0.008)	(0.007)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.007	-0.004	0.003	0.008
	(0.010)	(0.009)	(0.008)	(0.008)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.032***	-0.038***	-0.057***	-0.060***
	(0.007)	(0.007)	(0.006)	(0.008)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.086***	0.076***	0.086***	0.094***
	(0.018)	(0.017)	(0.015)	(0.020)
Firm-Specific Variables	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^{N}	18.638	24.314	56.343	69.616
F-statistic^{R}	11.829	15.059	31.159	36.772
F-statistic^{Eff}	10.429	11.400	31.192	37.266
Firms	2,126	2,167	2,179	2,181
Observations	11,918	12,242	12,367	12,408

Source: Prowess - Author's own calculation.
Notes: This table presents the first stage two-stage least squares (2SLS) results for dividend increases and dividend decreases with the addition of state level fixed effects. Panel A reports the results for dividend increases. Panel B reports the results for dividend decrease. The sample consists of all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 250-1000 miles. The first stage results reported in this table correspond to the first stage estimates reported in Table 4.19. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^{N} denotes the Cragg-Donald F-statistic, F-statistic^{R} denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Table A.4.11: Extended Radius Results : First Stage Estimates

Panel A: Extended Radius Results : Dividend Increase				
	Peer Dividend Increase			
	300 miles (1)	550 miles (2)	800 miles (3)	1050 miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.007	0.008	0.002	0.002
	(0.008)	(0.008)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	-0.004	0.001	0.001	0.006
	(0.008)	(0.008)	(0.006)	(0.006)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	0.019**	0.036***	0.043***	0.054***
	(0.009)	(0.008)	(0.007)	(0.007)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.037	0.013	0.020	-0.029
	(0.024)	(0.021)	(0.019)	(0.020)
Firm-Specific Variables	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^N	6.325	17.123	30.752	54.459
F-statistic^R	3.440	10.405	16.993	32.459
F-statistic^{Eff}	3.434	9.484	16.127	26.567
Firms	2,794	2,833	2,847	2,849
Observations	21,474	21,990	22,232	22,288
Panel B: Extended Radius Results : Dividend Decrease				
	Peer Dividend Increase			
	300 miles (1)	550 miles (2)	800 miles (3)	1050 miles (4)
Firm-specific Variables:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.010	-0.008	-0.004	-0.008
	(0.008)	(0.008)	(0.006)	(0.006)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.002	0.000	0.004	0.008
	(0.008)	(0.008)	(0.006)	(0.006)
Peer Firm Averages:				
Idiosyncratic Equity Shock$_{i,j,t-1}$	-0.030***	-0.034***	-0.053***	-0.055***
	(0.009)	(0.010)	(0.008)	(0.008)
Idiosyncratic Equity Risk$_{i,j,t-1}$	0.081***	0.079***	0.080***	0.099***
	(0.026)	(0.023)	(0.022)	(0.020)
Firm-Specific Variables	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
F-statistic^N	16.904	22.017	48.079	62.183
F-statistic^R	10.059	12.353	25.068	31.623
F-statistic^{Eff}	9.833	11.751	25.745	25.745
Firms	2,794	2,833	2,847	2,849
Observations	21,474	21,990	22,232	22,288

Source: Prowess - Author's own calculation.
Notes: This table presents the first stage two-stage least squares (2SLS) results for our extended radius analysis. Panel A reports the results for dividend increases. Panel B reports the results for dividend decrease. The sample consists of all firms from 1995-2017. Column (1) - (4) report the results for the corresponding peer proximity's from 300-1050 miles. The first stage results reported in this table relate to the second stage estimates reported in Table 4.20. All coefficients have been scaled by the corresponding variable's standard deviation to ease interpretation. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the $i'th$ observation. Industries are defined by two-digit NIC level. Firm-Specific Factors denotes variables corresponding to firm $i's$ value. F-statistic^N denotes the Cragg-Donald F-statistic, F-statistic^R denotes the Kleibergen and Paap (2006) robust F-statistic and F-statistic^{Eff} denotes Olea and Pflueger (2013) effect F-statistic. The standard-errors are robust to heteroskedasticity and within firm dependence, and are shown in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. All variable names, definitions and sources can be found in appendix Table A.4.1.

Chapter 5

Concluding Remarks

The capital structure and corporate payout policies of firms have puzzled the minds of academics for the best part of half a century. In the pursuit of greater clarity, this thesis set out to address a coterie of existing ambiguities within the corporate finance literature by examining the financial policy dynamics of firms. Specifically, the body of this thesis has devoted its attention to three important areas of residing ambiguity and, in turn, addressed three fundamental research questions, namely: i) Why do many researchers provide conflicting evidence on the speeds in which firms adjust their financial policies?, ii) Which factors are dominant in determining the rate in which firms adjust their financial policies? and iii) Why do some of the most salient financial decisions made by firms often coincide with the decisions of their industry counterparts?

In the examination of these questions, this thesis has presented three independent essays that have collectively contributed substantial theoretical and empirical evidence to the understanding of financial policy dynamics. In order to conclude this thesis, we now provide a set of closing remarks together with the limitations of each chapter and potential avenues for future research.

In chapter 2 we utilised Monte Carlo simulations to furnish a systematic analysis of the dynamic panel estimators commonly employed in the empirical corporate finance literature. In doing so, the chapter presented a clear and comprehensive picture of the importance of estimator choice on the reported speed of financial policy adjustment, whereby, the chapter uncovered the auspicious statistical qualities of three estimators, namely, the QML, LSDVC and DPF estimators alongside the limitations of the traditional OLS and FE estimators as well as the popular FD- and SYS-GMM estimators. Accordingly, the contributions put forward by chapter 2 manifest themselves in the horse race to identify the most accurate econometric procedure for dynamic panel data models. From the analysis undertaken in chapter 2, two important recommendation can be made for future empirical research. First, future research regarding financial policy dynamics should strongly consider deviating from the industry standard GMM estimators by incorporating the more accurate QML, LSDVC and DPF estimators. Moreover, to build a more precise and consistent picture on the adjustment speeds of firms' financial policies, future research should not only contemplate such estimators as means of robustness test, but, should more forcefully place such methods at the centre of their empirical analysis. Second, despite the OLS and FE estimators proving consistently biased across all simulations, such qualities do not make them redundant from future empirical use. In fact, given the OLS and FE estimators ability to consistently overestimate and underestimate the autoregressive coefficient, such statistical methods should be maintained as a means of creating theoretical goal posts in which the true SOA should, on average, reside.

One potential limitation of our first essay is that our survey of dynamic panel estimators are drawn predominately from the corporate finance literature, thus, we neglect the potential benefits of alternative statistical methods employed in adjacent fields. For instance, the empirical finance literature has long leaned towards instrumental variable estimators to address the issues of unobserved cross-sectional heterogeneity in short dynamic panel data models. However, in sociology, the same problems have been dealt with using maximum likelihood estimation and structural equation modeling. Accordingly, in future research, we may look to compare the prominent estimators employed across adjacent bodies of literature, with the bootstrap-corrected fixed effect estimator of Everaert and Pozzi (2007) and the maximum likelihood approaches of Bai (2013) and Allison et al. (2017) being three estimators for future consideration.

Continuing in this vein, we may also look to enrich our understanding of dynamic panel estimators by considering alternative Monte Carlo experiments such as the impact of time-vary structure parameters. Generally speaking, our simulation design along with the wider literature explicitly assume time-invariant coefficients, yet, in practice, structural breaks and vast entrants and/or exits of cross-sectional units may indeed effect the stability of parameter coefficients over time. Therefore, going forward, we may wish to consider the time-varying nature of structural parameters with the measure of unobserved heterogeneity being a natural candidate to access the impact of growing unobserved firm divergence on estimator performance.

In chapter 3 we contributed to the literature by providing a comprehensive assessment of how Indian listed firms facing opposing adjustment costs transition towards their capital structure target over the course of the business cycle. Our analysis identified the pro-cyclical nature of adjustment speeds, with Indian listed firms proving sluggish in their capital structure management in periods of economic decline, especially those with limited financial flexibility and few growth opportunities. Subsequently, at a macroeconomic level, as India continues on its journey of economic development, policy makers should endeavour to address the counter-cyclical nature capital market frictions. Specifically, the provision of a more efficient and robust financial sector will help to alleviate the longevity of future macroeconomic shocks as firms will be more freely available to manage the composition of their capital structure, thus, avoiding periods of prolonged financial distress and allowing for the effective pursuit of growth promoting corporate operations.

In light of such suggestions, a potential drawback of the empirical approach adopted in this chapter is the opacity of our quartile dummy variable specification in the identification of distinct adjustment asymmetries over the course business cycle. Specifically, the a-priori style approach used in chapter 3 is partially confined in its ability to clearly identify potential adjustment cost threshold effects. Future research would thus benefit from the evaluation of capital structure dynamics via more sophisticated data driven approaches, such as the recent estimation procedure devised by Seo and Shin (2016) which allows for nonlinear asymmetric dynamics in a threshold panel data framework. The complexities of this estimation procedure have been recently made easily available to researchers thanks to the efforts Seo et al. (2019) and therefore; the incorporation of such methods and the identification of potential kink points would provide more explicit guidance to policy makers who are looking to tailor economic reforms to improve the most hindered and constrained firms within India's economy. Furthermore, future research in this regard would also favour from an international comparison of corporate leverage dynamics in order to compare and contrast the potential kink points of adjustment asymmetries in developed and emerging markets.

In the final empirical chapter of this thesis, chapter 4, we investigated the effects of industry peers on the dividend decisions of Indian listed firms. Our geographically influenced empirical approach provided, to the best of our knowledge, the first evidence of peer related proximity effects as we uncovered the importance of local industry peer dividend decisions on the dividend decisions made by Indian firms. Accordingly, the sizeable efforts of chapter 4 complement the contemporaneous studies of Adhikari and Agrawal (2018) and Grennan (2019) by making significant headway in the rapidly growing literature on peer effects within corporate finance.

While we made a substantial contribution in this regard, the research design adopted in chapter 4 can be readily improved in a number of ways. First, the use of more granular and dispersed firm level data would allow for the incorporation of alternative reference group structures based on exclusive rather than inclusive distance based reference groups. Alternatively, in future studies we may look to asymmetric inverse distance weights rather than our nearest neighbour style approach to accommodate for the sparsity of emerging market datasets. Moreover, in line with gravity model, future studies may also look to integrate such weighting styles with firm-specific characteristics - e.g. firm size - to construct peer group measures based on both geographical and economic characteristics. Indeed, the embodiment of such alternative measures would considerably improve our understanding of the relationship between firm location, peer proximity and industry related peer influence.

Aside from the development of more intricate reference group structures, better information on the activities of local economic agents - e.g., information on local household portfolios and/or regional analyst coverage - could be used to deepen our understanding of firms propensity to accommodate for local dividend clienteles. Furthermore, chapter 4 only provides preliminary insights into the informational content of peer dividend decisions over the course of the business cycle. Thus, a more thorough assessment of the such matters would significantly enrich the existing literature on peer effects within corporate finance. Equally, the examination of proximity related peer effects on alternative corporate policies also makes for an interesting avenue for future research.

All in all, this thesis has presented three independent essays on the financial policies of firms. Whilst significant progress has been made by this thesis to clarify the ambiguities of capital structure and corporate payout policy dynamics, a number of disparate issues and unanswered questions still prevail, which, going forward, we will duly endeavour to pursue.

References

Abel, A. B. (1990), 'Asset prices under habit formation and catching up with the', *The American Economic Review* **80**(2), 38.

Adhikari, B. K. and Agrawal, A. (2018), 'Peer influence on payout policies', *Journal of Corporate Finance* **48**(1), 615–637.

Aggarwal, R. and Kyaw, N. A. (2010), 'Capital structure, dividend policy, and multinationality: Theory versus empirical evidence', *International Review of Financial Analysis* **19**(2), 140–150.

Aguiar, M. and Gopinath, G. (2007), 'Emerging market business cycles: The cycle is the trend', *Journal of Political Economy* **115**(1), 69–102.

Ahn, S. C. and Schmidt, P. (1995), 'Efficient estimation of models for dynamic panel data', *Journal of Econometrics* **68**(1), 5–27.

Aivazian, V. A., Booth, L. and Cleary, S. (2006), 'Dividend smoothing and debt ratings', *Journal of Financial and Quantitative Analysis* **41**(2), 439–453.

Allen, F. and Michaely, R. (2003), Payout policy, *in* 'Handbook of the Economics of Finance', Vol. 1, Elsevier, pp. 337–429.

Allen, F., Qian, J. and Qian, M. (2005), 'Law, finance, and economic growth in China', *Journal of Financial Economics* **77**(1), 57–116.

Allison, P. D., Williams, R. and Moral-Benito, E. (2017), 'Maximum likelihood for cross-lagged panel models with fixed effects', *Socius* **3**, 1–17.

Alvarez, J. and Arellano, M. (2003), 'The time series and cross-section asymptotics of dynamic panel data estimators', *Econometrica* **71**(4), 1121–1159.

Anderson, T. W. and Hsiao, C. (1981), 'Estimation of dynamic models with error components', *Journal of the American Statistical Association* **76**(375), 598–606.

Andres, C., Betzer, A., Goergen, M. and Renneboog, L. (2009), 'Dividend policy of German firms: A panel data analysis of partial adjustment models', *Journal of Empirical Finance* **16**(2), 175–187.

Andrews, I., Stock, J. H. and Sun, L. (2019), 'Weak instruments in instrumental variables regression: Theory and practice', *Annual Review of Economics* **11**, 727–753.

Ang, A. and Liu, J. (2007), 'Risk, return, and dividends', *Journal of Financial Economics* **85**(1), 1–38.

Angrist, J. D. (2014), 'The perils of peer effects', *Labour Economics* **30**(1), 98–108.

Angrist, J. D. and Lang, K. (2004), 'Does school integration generate peer effects? Evidence from boston's metco program', *American Economic Review* **94**(5), 1613–1634.

Angrist, J. D. and Pischke, J.-S. (2008), *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

Antoniou, A., Guney, Y. and Paudyal, K. (2008), 'The determinants of capital structure: Capital market-oriented versus bank-oriented institutions', *Journal of Financial and Quantitative Analysis* **43**(1), 59–92.

Arbia, G. and Baltagi, B. H. (2008), *Spatial econometrics: Methods and applications*, Springer Science & Business Media.

Arellano, M. (1989), 'A note on the Anderson-Hsiao estimator for panel data', *Economics Letters* **31**(4), 337–341.

Arellano, M. and Bond, S. (1991), 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', *The Review of Economic Studies* **58**(2), 277–297.

Aybar-Arias, C., Casino-Martínez, A. and López-Gracia, J. (2012), 'On the adjustment speed of SMEs to their optimal capital structure', *Small Business Economics* **39**(4), 977–996.

Bai, J. (2013), 'Fixed-effects dynamic panel models, a factor analytical method', *Econometrica* **81**(1), 285–314.

Baker, M. and Wurgler, J. (2002), 'Market timing and capital structure', *The Journal of Finance* **57**(1), 1–32.

Baker, M. and Wurgler, J. (2004), 'A catering theory of dividends', *The Journal of Finance* **59**(3), 1125–1165.

Baker, S. R., Bloom, N. and Davis, S. J. (2016), 'Measuring economic policy uncertainty', *The Quarterly Journal of Economics* **131**(4), 1593–1636.

Balestra, P. and Nerlove, M. (1966), 'Pooling cross section and time series data in the estimation of a dynamic model: The demand for natural gas', *Econometrica* **34**(3), 585–612.

Baltagi, B. (2008), *Econometric analysis of panel data*, John Wiley & Sons.

Bandyopadhyay, A. and Barua, N. M. (2016), 'Factors determining capital structure and corporate performance in India: Studying the business cycle effects', *The Quarterly Review of Economics and Finance* **61**(1), 160–172.

Banerjee, A. V. (1992), 'A simple model of herd behavior', *The Quarterly Journal of Economics* **107**(3), 797–817.

Barclay, M. J. and Smith, C. W. (2005), 'The capital structure puzzle: The evidence revisited', *Journal of Applied Corporate Finance* **17**(1), 8–17.

Bates, T. W., Kahle, K. M. and Stulz, R. M. (2009), 'Why do US firms hold so much more cash than they used to?', *The Journal of Finance* **64**(5), 1985–2021.

Baum, C. F., Caglayan, M. and Rashid, A. (2017), 'Capital structure adjustments: Do macroeconomic and business risks matter?', *Empirical Economics* **53**(4), 1463–1502.

Becker, B., Ivković, Z. and Weisbenner, S. (2011), 'Local dividend clienteles', *The Journal of Finance* **66**(2), 655–683.

Ben-David, I. (2010), 'Dividend policy decisions', *Behavioral Finance* pp. 435–451.

Benartzi, S., Michaely, R. and Thaler, R. (1997), 'Do changes in dividends signal the future or the past?', *The Journal of Finance* **52**(3), 1007–1034.

Benoit, J.-P. (1984), 'Financially constrained entry in a game with incomplete information', *The RAND Journal of Economics* **15**(4), 490–499.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G. and Stein, J. C. (2005), 'Does function follow organizational form? Evidence from the lending practices of large and small banks', *Journal of Financial Economics* **76**(2), 237–269.

Bernanke, B. and Gertler, M. (1989), 'Agency costs, net worth, and business fluctuations', *The American Economic Review* **79**(1), 14–31.

Bhamra, H. S., Kuehn, L.-A. and Strebulaev, I. A. (2010), 'The aggregate dynamics of capital structure and macroeconomic risk', *The Review of Financial Studies* **23**(12), 4187–4241.

Bhattacharya, S. (1980), 'Nondissipative signaling structures and dividend policy', *The Quarterly Journal of Economics* **95**(1), 1–24.

Bhaumik, S. K., Das, P. K. and Kumbhakar, S. C. (2012), 'A stochastic frontier approach to modelling financial constraints in firms: An application to India', *Journal of Banking & Finance* **36**(5), 1311–1319.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992), 'A theory of fads, fashion, custom, and cultural change as informational cascades', *Journal of Political Economy* **100**(5), 992–1026.

Binder, M., Hsiao, C. and Pesaran, M. H. (2005), 'Estimation and inference in short panel vector autoregressions with unit roots and cointegration', *Econometric Theory* **21**(4), 795–837.

Blume, L. E., Brock, W. A., Durlauf, S. N. and Jayaraman, R. (2015), 'Linear social interactions models', *Journal of Political Economy* **123**(2), 444–496.

Blundell, R. and Bond, S. (1998), 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics* **87**(1), 115–143.

Bolton, P. and Scharfstein, D. S. (1990), 'A theory of predation based on agency problems in financial contracting', *The American Economic Review* **80**(1), 93–106.

Bond, S. and Meghir, C. (1994), 'Dynamic investment models and the firm's financial policy', *The Review of Economic Studies* **61**(2), 197–222.

Bradley, M., Jarrell, G. A. and Kim, E. H. (1984), 'On the existence of an optimal capital structure: Theory and evidence', *The Journal of Finance* **39**(3), 857–878.

Bramoullé, Y., Djebbari, H. and Fortin, B. (2009), 'Identification of peer effects through social networks', *Journal of Econometrics* **150**(1), 41–55.

Brav, A., Graham, J. R., Harvey, C. R. and Michaely, R. (2005), 'Payout policy in the 21st century', *Journal of Financial Economics* **77**(3), 483–527.

Brav, O. (2009), 'Access to capital, capital structure, and the funding of the firm', *The Journal of Finance* **64**(1), 263–308.

Brounen, D., De Jong, A. and Koedijk, K. (2006), 'Capital structure policies in Europe: Survey evidence', *Journal of Banking & Finance* **30**(5), 1409–1442.

Bruno, G. S. (2005), 'Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models', *Economics letters* **87**(3), 361–366.

Bun, M. J. and Kiviet, J. F. (2003), 'On the diminishing returns of higher-order terms in asymptotic expansions of bias', *Economics Letters* **79**(2), 145–152.

Bun, M. J. and Windmeijer, F. (2010), 'The weak instrument problem of the system-GMM estimator in dynamic panel data models', *The Econometrics Journal* **13**(1), 95–126.

Byoun, S. (2008), 'How and when do firms adjust their capital structures toward targets?', *The Journal of Finance* **63**(6), 3069–3096.

Carhart, M. M. (1997), 'On persistence in mutual fund performance', *The Journal of Finance* **52**(1), 57–82.

Chang, X. and Dasgupta, S. (2009), 'Target behavior and financing: How conclusive is the evidence?', *The Journal of Finance* **64**(4), 1767–1796.

Chang, Y.-K., Chou, R. K. and Huang, T.-H. (2014), 'Corporate governance and the dynamics of capital structure: New evidence', *Journal of Banking & Finance* **48**(1), 374–385.

Chaudhuri, K. and Wu, Y. (2003), 'Random walk versus breaking trend in stock prices: Evidence from emerging markets', *Journal of Banking & Finance* **27**(4), 575–592.

Chen, H. (2010), 'Macroeconomic conditions and the puzzles of credit spreads and capital structure', *The Journal of Finance* **65**(6), 2171–2212.

Chen, Y.-W., Chan, K. and Chang, Y. (2019), 'Peer effects on corporate cash holdings', *International Review of Economics & Finance* **61**(1), 213–227.

Connelly, B. L., Certo, S. T., Ireland, R. D. and Reutzel, C. R. (2011), 'Signaling theory: A review and assessment', *Journal of Management* **37**(1), 39–67.

Cook, D. O. and Tang, T. (2010), 'Macroeconomic conditions and capital structure adjustment speed', *Journal of Corporate Finance* **16**(1), 73–87.

Coval, J. D. and Moskowitz, T. J. (1999), 'Home bias at home: Local equity preference in domestic portfolios', *The Journal of Finance* **54**(6), 2045–2073.

Dang, V. A., Kim, M. and Shin, Y. (2012), 'Asymmetric capital structure adjustments: New evidence from dynamic panel threshold models', *Journal of Empirical Finance* **19**(4), 465–482.

Dang, V. A., Kim, M. and Shin, Y. (2014), 'Asymmetric adjustment toward optimal capital structure: Evidence from a crisis', *International Review of Financial Analysis* **33**(1), 226–242.

Dang, V. A., Kim, M. and Shin, Y. (2015), 'In search of robust methods for dynamic panel data models in empirical corporate finance', *Journal of Banking & Finance* **53**(1), 84–98.

De Miguel, A. and Pindado, J. (2001), 'Determinants of capital structure: New evidence from Spanish panel data', *Journal of Corporate Finance* **7**(1), 77–99.

DeAngelo, H. and DeAngelo, L. (1990), 'Dividend policy and financial distress: An empirical investigation of troubled NYSE firms', *The Journal of Finance* **45**(5), 1415–1431.

DeAngelo, H., DeAngelo, L. and Skinner, D. J. (1992), 'Dividends and losses', *The Journal of Finance* **47**(5), 1837–1863.

DeAngelo, H., DeAngelo, L., Skinner, D. J. et al. (2009), 'Corporate payout policy', *Foundations and Trends in Finance* **3**(2–3), 95–287.

DeAngelo, H., DeAngelo, L. and Stulz, R. M. (2006), 'Dividend policy and the earned/contributed capital mix: A test of the life-cycle theory', *Journal of Financial Economics* **81**(2), 227–254.

Denis, D. J. and Osobov, I. (2008), 'Why do firms pay dividends? International evidence on the determinants of dividend policy', *Journal of Financial Economics* **89**(1), 62–82.

D'Espallier, B. and Guariglia, A. (2015), 'Does the investment opportunities bias affect the investment–cash flow sensitivities of unlisted SMEs?', *The European Journal of Finance* **21**(1), 1–25.

Devos, E., Rahman, S. and Tsang, D. (2017), 'Debt covenants and the speed of capital structure adjustment', *Journal of Corporate Finance* **45**(1), 1–18.

Dharmapala, D. and Khanna, V. (2012), 'Corporate governance, enforcement, and firm value: Evidence from India', *The Journal of Law, Economics, & Organization* **29**(5), 1056–1084.

Doukas, J. A. and Pantzalis, C. (2003), 'Geographic diversification and agency costs of debt of multinational firms', *Journal of Corporate Finance* **9**(1), 59–92.

Drobetz, W., Schilling, D. C. and Schröder, H. (2015), 'Heterogeneity in the speed of capital structure adjustment across countries and over the business cycle', *European Financial Management* **21**(5), 936–973.

Drobetz, W. and Wanzenried, G. (2006), 'What determines the speed of adjustment to the target capital structure?', *Applied Financial Economics* **16**(13), 941–958.

Duesenberry, J. S. et al. (1949), 'Income, saving, and the theory of consumer behavior', *Harvard University Press* .

Duffie, D., Gârleanu, N. and Pedersen, L. H. (2007), 'Valuation in over-the-counter markets', *The Review of Financial Studies* **20**(6), 1865–1900.

Duflo, E., Dupas, P. and Kremer, M. (2011), 'Peer effects, teacher incentives, and the impact of tracking: Evidence from a randomized evaluation in Kenya', *American Economic Review* **101**(5), 1739–74.

Ebrahim, M. S., Girma, S., Shah, M. E. and Williams, J. (2014), 'Dynamic capital structure and political patronage: The case of Malaysia', *International Review of Financial Analysis* **31**, 117–128.

Elsas, R. and Florysiak, D. (2011), 'Heterogeneity in the speed of adjustment toward target leverage', *International Review of Finance* **11**(2), 181–211.

Elsas, R. and Florysiak, D. (2015), 'Dynamic capital structure adjustment and the impact of fractional dependent variables', *Journal of Financial and Quantitative Analysis* **50**(5), 1105–1133.

Everaert, G. and Pozzi, L. (2007), 'Bootstrap-based bias correction for dynamic panels', *Journal of Economic Dynamics and Control* **31**(4), 1160–1184.

Fama, E. F. and French, K. R. (1988), 'Permanent and temporary components of stock prices', *Journal of political Economy* **96**(2), 246–273.

Fama, E. F. and French, K. R. (1993), 'Common risk factors in the returns on stocks and bonds', *Journal of Financial Economics* **33**(1), 3–56.

Fama, E. F. and French, K. R. (2001), 'Disappearing dividends: Changing firm characteristics or lower propensity to pay?', *Journal of Financial Economics* **60**(1), 3–43.

Fama, E. F. and French, K. R. (2002), 'Testing trade-off and pecking order predictions about dividends and debt', *The Review of Financial Studies* **15**(1), 1–33.

Fama, E. F. and French, K. R. (2005), 'Financing decisions: Who issues stock?', *Journal of Financial Economics* **76**(3), 549–582.

Fama, E. F. and French, K. R. (2015), 'A five-factor asset pricing model', *Journal of Financial Economics* **116**(1), 1–22.

Faulkender, M., Flannery, M. J., Hankins, K. W. and Smith, J. M. (2012), 'Cash flows and leverage adjustments', *Journal of Financial Economics* **103**(3), 632–646.

Feld, J. and Zölitz, U. (2017), 'Understanding peer effects: On the nature, estimation, and channels of peer effects', *Journal of Labor Economics* **35**(2), 387–428.

Fischer, E. O., Heinkel, R. and Zechner, J. (1989), 'Dynamic capital structure choice: Theory and tests', *The Journal of Finance* **44**(1), 19–40.

Flannery, M. J. and Hankins, K. W. (2013), 'Estimating dynamic panel models in corporate finance', *Journal of Corporate Finance* **19**(1), 1–19.

Flannery, M. J. and Rangan, K. (2006), 'Partial adjustment toward target capital structures', *Journal of Financial Economics* **79**(3), 469–506.

Foucault, T. and Fresard, L. (2014), 'Learning from peers' stock prices and corporate investment', *Journal of Financial Economics* **111**(3), 554–577.

Frank, M. Z. and Goyal, V. K. (2009), 'Capital structure decisions: Which factors are reliably important?', *Financial Management* **38**(1), 1–37.

Frankfurter, G. M. and Wood, B. G. (1997), 'The evolution of corporate dividend policy', *Journal of Financial Education* **23**(1), 16–33.

Glaeser, E. L., Sacerdote, B. I. and Scheinkman, J. A. (2003), 'The social multiplier', *Journal of the European Economic Association* **1**(2-3), 345–353.

Goergen, M., Renneboog, L. and Da Silva, L. C. (2005), 'When do German firms change their dividends?', *Journal of Corporate Finance* **11**(1), 375–399.

Graham, J. R. and Harvey, C. R. (2001), 'The theory and practice of corporate finance: Evidence from the field', *Journal of Financial Economics* **60**(2-3), 187–243.

Graham, J. R. and Kumar, A. (2006), 'Do dividend clienteles exist? Evidence on dividend preferences of retail investors', *The Journal of Finance* **61**(3), 1305–1336.

Graham, J. R., Leary, M. T. and Roberts, M. R. (2015), 'A century of capital structure: The leveraging of corporate America', *Journal of Financial Economics* **118**(3), 658–683.

Grennan, J. (2019), 'Dividend payments as a response to peer influence', *Journal of Financial Economics* **131**(3), 549–570.

Griliches, Z. and Hausman, J. A. (1986), 'Errors in variables in panel data', *Journal of Econometrics* **31**(1), 93–118.

Grullon, G., Larkin, Y. and Michaely, R. (2019), 'Dividend policy and product market competition', *Available at SSRN 972221* .

Grullon, G., Michaely, R. and Swaminathan, B. (2002), 'Are dividend changes a sign of firm maturity?', *The Journal of Business* **75**(3), 387–424.

Guariglia, A. and Yang, J. (2016), 'A balancing act: Managing financial constraints and agency costs to minimize investment inefficiency in the chinese market', *Journal of Corporate Finance* **36**(1), 111–130.

Guney, Y., Li, L. and Fairchild, R. (2011), 'The relationship between product market competition and capital structure in Chinese listed firms', *International Review of Financial Analysis* **20**(1), 41–51.

Guttman, I., Kadan, O. and Kandel, E. (2010), 'Dividend stickiness and strategic pooling', *The Review of Financial Studies* **23**(12), 4455–4495.

Hackbarth, D., Miao, J. and Morellec, E. (2006), 'Capital structure, credit risk, and macroeconomic conditions', *Journal of Financial Economics* **82**(3), 519–550.

Hahn, J., Hausman, J. and Kuersteiner, G. (2007), 'Long difference instrumental variables estimation for dynamic panel models with fixed effects', *Journal of Econometrics* **140**(2), 574–617.

Halling, M., Yu, J. and Zechner, J. (2016), 'Leverage dynamics over the business cycle', *Journal of Financial Economics* **122**(1), 21–41.

Hayakawa, K. and Pesaran, M. H. (2015), 'Robust standard errors in transformed likelihood estimation of dynamic panel data models with cross-sectional heteroskedasticity', *Journal of econometrics* **188**(1), 111–134.

Helmers, C. and Patnam, M. (2014), 'Does the rotten child spoil his companion? Spatial peer effects among children in rural India', *Quantitative Economics* **5**(1), 67–121.

Hoberg, G., Phillips, G. and Prabhala, N. (2014), 'Product market threats, payouts, and financial flexibility', *The Journal of Finance* **69**(1), 293–324.

Hoberg, G. and Prabhala, N. R. (2009), 'Dividend policy, risk, and catering', *Review of Financial Studies* **22**(1), 79–116.

Hoechle, D. (2007), 'Robust standard errors for panel regressions with cross-sectional dependence', *The Stata Journal* **7**(3), 281–312.

Hsiao, C., Pesaran, M. H. and Tahmiscioglu, A. K. (2002), 'Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods', *Journal of Econometrics* **109**(1), 107–150.

Huang, R. and Ritter, J. R. (2009), 'Testing theories of capital structure and estimating the speed of adjustment', *Journal of Financial and Quantitative Analysis* **44**(2), 237–271.

Huberman, G. (2001), 'Familiarity breeds investment', *The Review of Financial Studies* **14**(3), 659–680.

Im, H. J. (2019), 'Asymmetric peer effects in capital structure dynamics', *Economics Letters* **176**, 17–22.

Ivković, Z. and Weisbenner, S. (2005), 'Local does as local is: Information content of the geography of individual investors' common stock investments', *The Journal of Finance* **60**(1), 267–306.

Jensen, M. C. (1986), 'Agency costs of free cash flow, corporate finance, and takeovers', *The American Economic Review* **76**(2), 323–329.

John, K., Knyazeva, A. and Knyazeva, D. (2011), 'Does geography matter? Firm location and corporate payout policy', *Journal of Financial Economics* **101**(3), 533–551.

John, K. and Williams, J. (1985), 'Dividends, dilution, and taxes: A signalling equilibrium', *The Journal of Finance* **40**(4), 1053–1070.

Judson, R. A. and Owen, A. L. (1999), 'Estimating dynamic panel data models: A guide for macroeconomists', *Economics letters* **65**(1), 9–15.

Kanas, A. (2013), 'Bank dividends, risk, and regulatory regimes', *Journal of Banking & Finance* **37**(1), 1–10.

Kaustia, M. and Knüpfer, S. (2012), 'Peer performance and stock market entry', *Journal of Financial Economics* **104**(2), 321–338.

Kaustia, M. and Rantala, V. (2015), 'Social learning and corporate peer effects', *Journal of Financial Economics* **117**(3), 653–669.

Kayhan, A. and Titman, S. (2007), 'Firms' histories and their capital structures', *Journal of Financial Economics* **83**(1), 1–32.

Khanna, T. and Palepu, K. (1997), 'Why focused strategies may be wrong for emerging markets', *Harvard Business Review* **75**(4), 41–48.

Khanna, T. and Palepu, K. (2000), 'Is group affiliation profitable in emerging markets? An analysis of diversified Indian business groups', *The Journal of Finance* **55**(2), 867–891.

Khanna, T. and Palepu, K. G. (2010), *Winning in emerging markets: A road map for strategy and execution*, Harvard Business Press.

Kisgen, D. J. (2006), 'Credit ratings and capital structure', *The Journal of Finance* **61**(3), 1035–1072.

Kiviet, J. F. (1995), 'On bias, inconsistency, and efficiency of various estimators in dynamic panel data models', *Journal of Econometrics* **68**(1), 53–78.

Kleibergen, F. and Paap, R. (2006), 'Generalized reduced rank tests using the singular value decomposition', *Journal of Econometrics* **133**(1), 97–126.

Korteweg, A. and Strebulaev, I. A. (2013), 'An empirical (s, s) model of dynamic capital structure', *Working Paper, Stanford University* .

Kripfganz, S. (2016), 'Quasi–maximum likelihood estimation of linear dynamic short-t panel-data models', *The Stata Journal* **16**(4), 1013–1038.

Kripfganz, S. and Schwarz, C. (2019), 'Estimation of linear dynamic panel data models with time-invariant regressors', *Journal of Applied Econometrics* **34**(4), 526–546.

Kruiniger, H. (2013), 'Quasi ml estimation of the panel ar (1) model with arbitrary initial conditions', *Journal of Econometrics* **173**(2), 175–188.

Kumar, P. (1988), 'Shareholder-manager conflict and the information content of dividends', *The Review of Financial Studies* **1**(2), 111–136.

La Porta, R., Lopez-de Silanes, F. and Shleifer, A. (2006), 'What works in securities laws?', *The Journal of Finance* **61**(1), 1–32.

La Porta, R., Lopez-de Silanes, F., Shleifer, A. and Vishny, R. W. (2000), 'Agency problems and dividend policies around the world', *The Journal of Finance* **55**(1), 1–33.

Leary, M. T. and Michaely, R. (2011), 'Determinants of dividend smoothing: Empirical evidence', *The Review of Financial Studies* **24**(10), 3197–3249.

Leary, M. T. and Roberts, M. R. (2005), 'Do firms rebalance their capital structures?', *The Journal of Finance* **60**(6), 2575–2619.

Leary, M. T. and Roberts, M. R. (2014), 'Do peer firms affect corporate financial policy?', *The Journal of Finance* **69**(1), 139–178.

Lemmon, M. L., Roberts, M. R. and Zender, J. F. (2008), 'Back to the beginning: persistence and the cross-section of corporate capital structure', *The Journal of Finance* **63**(4), 1575–1608.

Leszczensky, L. and Wolbring, T. (2018), 'How to deal with reverse causality using panel data? recommendations for researchers based on a simulation study', *Sociological Methods & Research* p. 0049124119882473.

Levine, R., Loayza, N. and Beck, T. (2000), 'Financial intermediation and growth: Causality and causes', *Journal of Monetary Economics* **46**(1), 31–77.

Liao, L.-K., Mukherjee, T. and Wang, W. (2015), 'Corporate governance and capital structure dynamics: An empirical study', *Journal of Financial Research* **38**(2), 169–192.

Liberti, J. M. and Petersen, M. A. (2018), 'Information: Hard and soft', *Review of Corporate Finance Studies* **8**(1), 1–41.

Lieberman, M. B. and Asaba, S. (2006), 'Why do firms imitate each other?', *Academy of management review* **31**(2), 366–385.

Lintner, J. (1956), 'Distribution of incomes of corporations among dividends, retained earnings, and taxes', *The American Economic Review* **46**(2), 97–113.

Loudermilk, M. S. (2007), 'Estimation of fractional dependent variables in dynamic panel data models with an application to firm dividend policy', *Journal of Business & Economic Statistics* **25**(4), 462–472.

Manski, C. F. (1993), 'Identification of endogenous social effects: The reflection problem', *The Review of Economic Studies* **60**(3), 531–542.

Maurer, J. and Meier, A. (2008), 'Smooth it like the 'Joneses'? Estimating peer-group effects in intertemporal consumption choice', *The Economic Journal* **118**(527), 454–476.

McLeod, A. I. and Hipel, K. W. (1978), 'Simulation procedures for box-jenkins models', *Water Resources Research* **14**(5), 969–975.

Michaely, R. and Roberts, M. R. (2011), 'Corporate dividend policies: Lessons from private firms', *The Review of Financial Studies* **25**(3), 711–746.

Michaely, R., Thaler, R. H. and Womack, K. L. (1995), 'Price reactions to dividend initiations and omissions: Overreaction or drift?', *The Journal of Finance* **50**(2), 573–608.

Miller, M. H., Modigliani, F. et al. (1961), 'Dividend policy, growth, and the valuation of shares', *The Journal of Business* **34**(4), 411–411.

Miller, M. H. and Rock, K. (1985), 'Dividend policy under asymmetric information', *The Journal of Finance* **40**(4), 1031–1051.

Modigliani, F. and Miller, M. H. (1958), 'The cost of capital, corporation finance and the theory of investment', *The American Economic Review* **48**(3), 261–297.

Modigliani, F. and Miller, M. H. (1963), 'Corporate income taxes and the cost of capital: A correction', *The American Economic Review* **53**(3), 433–443.

Mohan, R. and Kapur, M. (2015), 'Pressing the Indian growth accelerator: Policy imperatives', *IMF Working Paper* **53**(1), 15–53.

Moretti, E. (2011), 'Social learning and peer effects in consumption: Evidence from movie sales', *The Review of Economic Studies* **78**(1), 356–393.

Mundlak, Y. (1978), 'On the pooling of time series and cross section data', *Econometrica* **46**(1), 69–85.

Myers, S. C. and Majluf, N. S. (1984), 'Corporate financing and investment decisions when firms have information that investors do not have', *Journal of Financial Economics* **13**(2), 187–221.

Nerlove, M. (1967), 'Experimental evidence on the estimation of dynamic economic relations from a time series of cross sections', *The Economic Studies Quarterly* **18**(3), 42–74.

Nerlove, M. (1971), 'Further evidence on the estimation of dynamic economic relations from a time series of cross sections', *Econometrica* **39**(2), 359–382.

Nickell, S. (1981), 'Biases in dynamic models with fixed effects', *Econometrica: Journal of the Econometric Society* **49**(6), 1417–1426.

Olea, J. L. M. and Pflueger, C. (2013), 'A robust test for weak instruments', *Journal of Business & Economic Statistics* **31**(3), 358–369.

Ozkan, A. (2001), 'Determinants of capital structure and adjustment to long run target: Evidence from UK company panel data', *Journal of Business Finance & Accounting* **28**(1-2), 175–198.

Ozkan, A. and Ozkan, N. (2004), 'Corporate cash holdings: An empirical investigation of UK companies', *Journal of Banking & Finance* **28**(9), 2103–2134.

Öztekin, Ö. (2015), 'Capital structure decisions around the world: Which factors are reliably important?', *Journal of Financial and Quantitative Analysis* **50**(3), 301–323.

Öztekin, Ö. and Flannery, M. J. (2012), 'Institutional determinants of capital structure adjustment speeds', *Journal of Financial Economics* **103**(1), 88–112.

Pagan, A. (1984), 'Econometric issues in the analysis of regressions with generated regressors', *International Economic Review* **25**(1), 221–247.

Papke, L. E. and Wooldridge, J. M. (2008), 'Panel data methods for fractional response variables with an application to test pass rates', *Journal of econometrics* **145**(1-2), 121–133.

Patnam, M. (2011), Corporate networks and peer effects in firm policies, *in* 'Emerging Markets Finance Conference, Indira Gandhi Institute of Development Research'.

Petersen, M. A. (2009), 'Estimating standard errors in finance panel data sets: Comparing approaches', *The Review of Financial Studies* **22**(1), 435–480.

Petersen, M. A. and Rajan, R. G. (2002), 'Does distance still matter? The information revolution in small business lending', *The Journal of Finance* **57**(6), 2533–2570.

Phillips, R. F. (2015), 'On quasi maximum-likelihood estimation of dynamic panel data models', *Economics Letters* **137**, 91–94.

Phillips, R. F. (2017), 'Quasi maximum likelihood estimation of dynamic panel data models', *Communications in Statistics-Theory and Methods* **47**(16), 1–17.

Pindado, J., Requejo, I. and Torre, C. (2012), 'Do family firms use dividend policy as a governance mechanism? Evidence from the Euro zone', *Corporate Governance: An International Review* **20**(5), 413–431.

Pirinsky, C. A. and Wang, Q. (2011), 'Market segmentation and the cost of capital in a domestic market: Evidence from municipal bonds', *Financial Management* **40**(2), 455–481.

Rajan, R. G. and Zingales, L. (1995), 'What do we know about capital structure? Some evidence from international data', *The Journal of Finance* **50**(5), 1421–1460.

Rodrik, D. and Subramanian, A. (2005), 'From "Hindu growth" to productivity surge: The mystery of the Indian growth transition', *IMF Staff Papers* **52**(2), 193–228.

Roodman, D. (2009), 'A note on the theme of too many instruments', *Oxford Bulletin of Economics and Statistics* **71**(1), 135–158.

Sacerdote, B. (2001), 'Peer effects with random assignment: Results for Dartmouth roommates', *The Quarterly Journal of Economics* **116**(2), 681–704.

Sacerdote, B. (2011), Peer effects in education: How might they work, how big are they and how much do we know thus far?, *in* 'Handbook of the Economics of Education', Vol. 3, Elsevier, pp. 249–277.

Scharfstein, D. S., Stein, J. C. et al. (1990), 'Herd behavior and investment', *American Economic Review* **80**(3), 465–479.

Seo, M. H., Kim, S. and Kim, Y. (2019), 'Estimation of dynamic panel threshold model using stata', *Stata Journal* **19**(3), 685–697(13).

Seo, M. H. and Shin, Y. (2016), ‘Dynamic panels with threshold effect and endogeneity’, *Journal of Econometrics* **195**(2), 169–186.

Short, H., Keasey, K. and Duxbury, D. (2002), ‘Capital structure, management ownership and large external shareholders: A UK analysis’, *International Journal of the Economics of Business* **9**(3), 375–399.

Shyam-Sunder, L. and Myers, S. C. (1999), ‘Testing static tradeoff against pecking order models of capital structure1’, *Journal of Financial Economics* **51**(2), 219–244.

Stock, J. and Yogo, M. (2005), *Testing for Weak Instruments in Linear IV Regression*, Cambridge University Press, New York, pp. 80–108.

Strebulaev, I. A. (2007), ‘Do tests of capital structure theory mean what they say?’, *The Journal of Finance* **62**(4), 1747–1787.

Strebulaev, I. A. and Yang, B. (2013), ‘The mystery of zero-leverage firms’, *Journal of Financial Economics* **109**(1), 1–23.

Thompson, S. B. (2011), ‘Simple formulas for standard errors that cluster by both firm and time’, *Journal of Financial Economics* **99**(1), 1–10.

Titman, S. and Wessels, R. (1988), ‘The determinants of capital structure choice’, *The Journal of Finance* **43**(1), 1–19.

Tversky, A. and Kahneman, D. (1973), ‘Availability: A heuristic for judging frequency and probability’, *Cognitive psychology* **5**(2), 207–232.

Uysal, V. B., Kedia, S. and Panchapagesan, V. (2008), ‘Geography and acquirer returns’, *Journal of Financial Intermediation* **17**(2), 256–275.

Welch, I. (2004), ‘Capital structure and stock returns’, *Journal of Political Economy* **112**(1), 106–131.

Wintoki, M. B., Linck, J. S. and Netter, J. M. (2012), ‘Endogeneity and the dynamics of internal corporate governance’, *Journal of Financial Economics* **105**(3), 581–606.

Wojewodzki, M., Poon, W. P. and Shen, J. (2018), ‘The role of credit ratings on capital structure and its speed of adjustment: An international study’, *The European Journal of Finance* **24**(9), 735–760.

Wooldridge, J. M. (2005), 'Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models', *Review of Economics and Statistics* **87**(2), 385–390.

Wooldridge, J. M. (2010), *Econometric analysis of cross section and panel data*, MIT press.

World Bank (2018), 'India development update, March 2018'.
URL: *https://openknowledge.worldbank.org/handle/10986/29515*

Xu, J. (2012), 'Profitability and capital structure: Evidence from import penetration', *Journal of Financial Economics* **106**(2), 427–446.

Yamada, K. (2019), 'Inter-firm relationships and leverage adjustment', *Research in International Business and Finance* **50**, 381–391.

Zarnowitz, V. and Ozyildirim, A. (2006), 'Time series decomposition and measurement of business cycles, trends and growth cycles', *Journal of Monetary Economics* **53**(7), 1717–1739.

Zhou, Q., Faff, R. and Alpert, K. (2014), 'Bias correction in the estimation of dynamic panel models in corporate finance', *Journal of Corporate Finance* **25**(1), 494–513.

Zhou, Q., Tan, K. J. K., Faff, R. and Zhu, Y. (2016), 'Deviation from target capital structure, cost of equity and speed of adjustment', *Journal of Corporate Finance* **39**(1), 99–120.

Ziliak, J. P. (1997), 'Efficient estimation with panel data when instruments are predetermined: an empirical comparison of moment-condition estimators', *Journal of Business & Economic Statistics* **15**(4), 419–431.

Zimmerman, D. J. (2003), 'Peer effects in academic outcomes: Evidence from a natural experiment', *Review of Economics and Statistics* **85**(1), 9–23.