An Investigation into the Relationships Between Globalisation, Firm Structure, Productivity and Knowledge using UK Firm-level Data

by

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Abstract

This thesis is a micro-econometric investigation into the relationship between globalisation, productivity, knowledge and firm structure. It is composed of three main investigations using large panel datasets of UK firms. The datasets are created by combining the ARD, BERD, BSD. The AFDI is used to identify multinational status and FAME provides additional financial statistics. The first investigation aims to identify if differences exist between multinational and non-multinational firms in terms of productivity and knowledge and also if complementarities exist between internal and external knowledge. The data is analysed using a Cobb-Douglas production function including knowledge interaction terms with system GMM. The findings show that multinational firms are more productive than non-multinational firms and the main source of this arises from differences in the returns to capital. The study shows little evidence to support complementarities between internal and external knowledge. Secondly, it aims to understand the motivations behind firm restructuring events and if these motivations differ between foreign and UK-owned firms. This investigation uses a multinomial logit model to identify average characteristics of firms engaging in each type of event. The findings imply that managerial, synergistic and refocusing motivations for restructuring are present. Foreign firms may be motivated to engage in joining events by innovation synergies. The third aim is to determine the impact of firm restructuring events on productivity and innovation activity. The propensity score method is applied to obtain matched samples to estimate the treatment effect on the treated. The results show that restructuring events lead to an increase in productivity, but the findings for innovation activity are less conclusive.

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This work was based on data from the ARD, AFDI, BERD and BSD, produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data are Crown Copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the data in this work does not imply the endorsement of ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

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1 Introduction

1.1 Motivation and Aims

This thesis investigates the relationships between globalisation, firm structure, productivity and knowledge. Globalisation refers to increasing interconnections between countries across the world. Rising integration in recent decades has arisen from technological advances and enhanced liberalisation of trade policy. Technological advances in communication and transportation have lowered the costs of organisation and distribution and therefore improved the economic viability of international trade. Reductions in import tariffs, quotas and other government imposed barriers have been promoted by international institutions[1] to encourage free trade and enhance international competition. Firms have the incentive to engage in international trade to exploit comparative advantage, overcome limitations of domestic demand and to increase geographical diversification to reduce exposure to domestic shocks.

The Ricardian notion of trade gains from comparative advantage arise when countries have differing relative efficiencies of production over a range of products. In a two country example, the incentive to trade exists if the opportunity cost of producing a good is lower in one country than the other. Lower marginal costs can occur due to the quantity and quality of factors of production, the level of technology and investment in research and development (R&D). This facilitates the transmission of knowledge and dissemination of innovation. Knowledge plays a crucial role in productivity improvements, which are essential for economic growth and prosperity.

A relationship between firm restructuring and knowledge also exists. Joining events such as mergers and acquisitions may be motivated by the aim of gaining knowledge from target firms, creating synergies or applying knowledge to the target firms. This knowledge may take the form of technical knowledge on products or processes, managerial capabilities or localised knowledge on geographical markets. Differences in these attributes may

[1]These include the International Monetary Fund (IMF) and the World Trade Organization (WTO), formerly known as the General Agreement on Tariffs and Trade (GATT).

be particularly distinct for foreign firms.

Incentives for separating events such as breakups and divestments may arise if firm structure is large and complex. Excessive growth or over-diversification may result in a lack of communication and dissemination of knowledge within the organisation. This may have a negative impact on productivity. Refocusing or streamlining may be motivated by the desire to remove less productive parts of the organisation, free up funds to invest in improving existing knowledge flows or perform innovation activity.

This thesis aims to identify differences between domestic and globalised UK-based firms in terms of productivity, innovation activity and firm restructuring. There are three strands of investigation. The first seeks to establish if differences in productivity and knowledge exist between multinational and non-multinational firms and if complementarities exist between internal and external knowledge sources. The second attempts to identify the motivations behind firm restructuring events and establish if differences exist between foreign and UK owned firms in terms of these motivations. The third assesses the impact of restructuring events on productivity and innovation activity and also attempts to distinguish between outcomes for Foreign and UK owned firms.

Each of these micro-econometric investigations provide a contribution to the literature using a unique combination of firm-level datasets from the Secure Data Service (SDS). These datasets include the Annual Inquiry into Foreign Direct Investment (AFDI), Annual Respondents Database (ARD), Business Enterprise Research and Development (BERD) and the Business Structure Database (BSD).[2] This allows the research questions to be addressed using large detailed panel datasets. The majority of previous UK studies in this literature have used cross-sectional or small panels of data from the Community Innovation Survey (CIS). This provides mostly qualitative firm-level data on innovation activity and knowledge sources for a sample of firms. Although it also includes some self-reported quantitative data on internal and external R&D expenditure, this data is not utilised by the majority of papers that use the CIS. The CIS is also limited by the

[2] Data from Bureau Van Dijk's Financial Analysis Made Easy (FAME) is also combined with the SDS datasets in chapter 4. This provides details of firm-level financial characteristics.

fact that it only covers a relatively small number of firms during the 1997-2005 period and few of the firms in the sample perform innovation. The sample is performed in waves therefore annual CIS data is not available and the rate of attrition is high between waves, so this presents difficulties in tracking firms over time. BERD contrasts this by providing annual quantitative data on R&D expenditure for the population of R&D performing firms in the UK. The ARD provides data on firm characteristics for a stratified sample of firms and the AFDI indicates multinational status. Firm restructuring events can be identified from the BSD using some careful coding, as this dataset covers the population of all UK firms.

1.2 Thesis Structure

This thesis makes three substantive contributions to the literature. The first contribution is made in chapter 2. It aims to understand if differences exist between multinational and non-multinational firms in terms of productivity and knowledge. It also seeks to establish if complementarities exist between internal and external knowledge sources. This chapter contains an overview of the relevant literature, description of the ARD, BERD and AFDI datasets and empirical analysis relating to these research questions. The empirical analysis uses a Cobb-Douglas production function with output as the dependent variable and inputs as the explanatory variables. The inputs include capital stock, labour and a set of knowledge variables. The knowledge variables are stock of internal R&D expenditure, stock of expenditure on R&D transfers from UK sources and stock of expenditure on R&D transfers from foreign sources. Interaction terms are used to investigate differences by multinational status and identify complementarities between different knowledge sources.

The subsequent chapters develop upon the productivity, knowledge and globalisation themes introduced in chapter 2 with the additional theme of firm restructuring. Chapter 3 provides a review of the theoretical and empirical literature surrounding the motivation for restructuring events and post-event outcomes. Motivations and outcomes are highly interrelated, therefore it is appropriate that they are discussed together.

Chapter 4 describes the identification of firm restructuring from the BSD using enterprise and enterprise group reference codes and the merging of the datasets used in the analysis. Restructuring events include joining events (acquirer, acquired and merger), separating events (divestor, divested and break-up) and other more complex events. This restructuring event variable is used to answer the research questions posed in chapters 4 and 5. The remainder of chapter 4 investigates the motivations behind firm restructuring events using a multinomial logit model. This identifies the average characteristics of firms engaging in each type of event and allows inferences to be drawn about the underlying motivations. The findings from this chapter are used to inform the following chapter. Chapter 5 looks at post-event outcomes in terms of productivity and innovation activity. The propensity score method is applied to obtain matched samples to estimate the average treatment effect on the treated. This approach controls for selection bias by obtaining a matched sample with similar characteristics to the treated firms to create an estimated counterfactual. The findings of the thesis and conclusions are summarised in chapter 6.

2 Productivity, Knowledge and Globalisation

2.1 Introduction

Over the last few decades the pace of globalisation has increased leading to a sharp rise in the number of multinational firms. Several studies have found that subsidiaries of multinational firms tend to outperform their wholly domestic counterparts. If this is the case, what is the source of this apparent advantage? There is currently a high level of active investigation aiming to understand the correlation between global engagement and productivity. Many speculate that differences in the ability to understand and apply knowledge plays a crucial role in this relationship.

Firms can invest in knowledge creation by performing in-house R&D. Cohen and Levinthal (1989) and Griffith and Van Reenen (2003) suggest that R&D investment has two aspects. The first aspect being the direct impact on output and the second being the addition to absorptive capacity; a firm's ability to utilise and absorb information. This depends on previous experience in innovative activity or skills embedded within human capital. Firms that have a higher level of innovative familiarity are more able to exploit information flows from external sources to their own advantage. Multinational subsidiaries may benefit from a broader range of knowledge spillovers than purely domestic firms. These spillovers could arise from existing knowledge stocks within their enterprise group or exposure to foreign markets.

The aim of this chapter is to address the following questions: do differences in productivity and knowledge exist between multinationals and non-multinationals? Are there complementarities between internal and external sources of knowledge? These are interesting questions to address in our increasingly globalised world.

A production function approach is applied to analyse the relationship between productivity, multinational status and various forms of knowledge. These forms include the firm's own knowledge stock, knowledge transfers from external sources and non-market knowledge spillovers from firms within the local area or industry sector. A specific contribution to the literature is made by investigating the role for knowledge spillovers and distinguishing between types of labour. Labour is divided into skilled R&D labour and other labour to observe differential effects between the two types of labour in the workforce. This is then analysed by multinational status.

This investigation also adds to this very active research area by using a unique combination of highly detailed datasets. The data used for the analysis is taken from the ARD, BERD and AFDI and covers the period 1998-2005 and includes 8057 firms. The ARD provides a census on all large enterprises and a stratified sample of firms with less than 100 employees. It includes data on value added and capital expenditure. Data from the AFDI is used to identify multinational status and the foreign ownership code from the ARD is used to distinguish between UK and foreign multinationals. BERD provides data for all known innovating firms and includes data on R&D expenditure and employees. The use of quantitative innovation data distinguishes this analysis from other UK studies in this area which mostly use qualitative survey data taken from the CIS. An additional benefit of BERD is that data is collected annually. This allows the creation of a panel. The CIS is performed less regularly and questions are often inconsistent across waves.

This study investigates a number of methodological approaches to estimate the production function coefficients. Initially OLS is employed including time and industry dummies. This provides a benchmark set of results which are likely to be biased. Secondly, the regression is weighted by the inverse sampling probability in order to generate estimates that are consistent for the population of innovating firms despite a non-random sample. Thirdly, fixed effects is used which has the benefit of controlling for unobserved heterogeneity. However a drawback to this method is that the multinational coefficient relies on changes between status. Those that maintain constant status over the period must be omitted. The fourth method used is two-stage least squares with industry averages as instruments as an alternative way of treating endogeneity arising from simultaneity. Industry averages should control for industry wide shocks to the firm-level variables. The final and preferred method for treating endogeneity in this study is system GMM.

Key findings are consistent with the literature and suggest that multinationals are more productive than domestic firms. This is partly attributed to differences in returns to capital, whereas no significant differences exist in terms of returns to R&D investment between multinationals and non-multinationals. No significant evidence is found to support the notion of absorptive capacity.

2.2 Literature Review

2.2.1 Introduction

This section is divided into three parts and highlights the approaches taken and important findings in the literature. Firstly a brief overview of the Productivity-Knowledge-Globalisation literature is provided, where the key concepts and theoretical background are explained. The second part outlines and considers a variety of knowledge measures used in the literature. Thirdly, a detailed analysis of the approaches taken to model productivity and knowledge is covered. Specific attention is paid to methodology and functional form for a selection of key and relevant papers. A summary of the empirical studies described in this section are provided in table (2.1).

2.2.2 Overview of the Literature

Knowledge and Productivity

The increasingly popular term, absorptive capacity, has been incorporated into various studies involving innovation and knowledge transfers. The idea was introduced by Arrow (1969) and described as the second face of R&D in a seminal paper by Cohen and Levinthal (1989). Within a firm, R&D has a primary role of creating new knowledge and a secondary role of improving a firm's ability to absorb and utilise knowledge spillovers. By undertaking R&D, firms gain familiarity with specialist concepts. This leaves them better placed to understand and apply information derived from external sources. Therefore a firm's absorptive capacity depends on the level of R&D it has previously undertaken. In their model, absorptive capacity is not directly observable so they test for the influence of absorptive capacity on the technological opportunity variables, which include sources of external knowledge such as universities, research institutes, suppliers or customers.

Lokshin et al. (2008) state that absorptive capacity is the intangible attribute derived from internal R&D activity that assists in the assimilation of external knowledge. They test for complementarities between internal and external R&D using a firm-level panel of annual data from the Netherlands and find that a positive impact of external R&D is only found when sufficient internal R&D has been undertaken. This finding supports the idea of absorptive capacity.

Other papers, such as Leiponen (2005) and Kneller and Stevens (2006), choose to broaden the definition of absorptive capacity by going beyond the second face of R&D and including a role for human capital. These studies argue that absorptive capacity, defined as a firm's ability to absorb spillovers, depends on previous R&D activity and also the skill sets of employees.

Global Engagement and Productivity

Since the early work of Caves (1974), the theory of the multinational enterprise has been dominated by the notion of intangible assets. Entry into foreign markets is costly and domestic firms have the advantage of possessing local knowledge. Only firms with superior intangible assets can successfully become multinational and compete with domestic firms. These intangible assets usually take the form of management expertise and superior technological capabilities and are likely to lead to higher observed productivity for multinational firms. If costs surpass benefits for multinationals they may be less productive, but costs associated with entry are only expected to be a temporary impairment to performance.

Early empirical studies conform to the general consensus that a positive relationship exists between productivity and global engagement. Some of these studies use naive methodology that does not fully control for industry and firm characteristics. More recent work has used more robust methodology. Results are mixed but the majority find a positive relationship. Harris and Robinson (2003) estimates a production function using the Generalised Method of Moments (GMM) approach to test for TFP differences between foreign and domestically owned plants. The data is taken from the ARD and covers 20 UK manufacturing industries. The sample is weighted to ensure representation of the UK manufacturing population. The findings show foreign owned plants generally perform better than domestic owned plants. Conyon et al. (2002) suggest that foreign firms may select the most productive firms as acquisition targets. Their findings for the UK show that on average acquisition by foreign owners improves labour productivity of an acquired firm.

Knowledge and Globalisation

There is a large literature relating to spillovers that emanate from multinational firms and lead to improvements in productivity of domestic/local firms. Blake et al. (2009) study the effects of foreign direct investment on local firms within Chinese manufacturing. They suggest various channels through which productivity spillovers may be transfered from multinationals to local firms including labour mobility between firms, vertical linkages via the supply-chain between supplier and customer, horizontal linkages with competing firms and state-owned organisations and by encouraging the local firms to engage in exporting activity by displaying exporting possibilities which local firms can mimic. This suggests that the knowledge spillovers take various forms.

Driffield and Love (2003) suggest a role for the reverse of these spillovers, where the multinational firm benefits from the absorption of knowledge spillovers emanating from the host country. The choice of FDI location may therefore depend on proximity to technology leaders, such as universities or competing firms. It is expected that evidence of reverse spillovers will be stronger in industries which have placed more emphasis on R&D investment and therefore may generate more spillovers for foreign firms to draw upon. They identify two types of foreign investors in host country, these are those which seek to adapt technology to suit the host country market and those that seek to absorb spillovers.

Harris and Li (2009) use UK data from the CIS 3 and ARD to explore the relationships between exporting, R&D and absorptive capacity. They use a probit model, where R&D and exports are binary variables,with their preferred method being a Heckman sample selection model which acknowledges the self-selection aspect of exporting.[3] They find that R&D and absorptive capacity plays a role in overcoming barriers to entering international markets and also establishment size, in terms of number of employees, is also found to be important.

Crespi et al. (2008) use UK panel data to test the learning-by-exporting hypothesis. There is a causality issue with the study of exporting and productivity as firms with higher productivity are more likely to export. The point of difference with this study is that it attempts to measure learning rather than looking directly at the relationship between productivity and exporting. The latter approach may distort the discernable relationship between learning and exporting as correlations are likely to exist between exporting and other unmeasured variables. In order to establish if learning has occurred, they use responses from CIS 2 and CIS 3 which identify if a firm has used clients or customers as a source of knowledge for innovation. Using a production function approach with a balanced panel of 787 firms, they then test if exporting firms are more likely to learn from customers than entirely domestic firms. They find that firms that have previously exported are more likely to learn from their clients than from alternative sources and for those that have previously learned from clients, there is a greater likelihood that they will have higher productivity.

[3] Melitz (2003) finds that more productive firms chose to become exporters, whereas less productive firms tend to remain as domestic suppliers.

2.2.3 Measuring Knowledge

The dictionary defines knowledge as expertise and skills acquired through experience or education, the theoretical or practical understanding of a subject or what is known in a particular field. In this instance the aim is to measure the level of knowledge that a firm possesses. This can be created through R&D, embodied in skilled human capital and through absorbing information flows from external sources.

Knowledge is a difficult concept to measure as it is not directly quantifiable. Various approaches have been taken; broadly speaking these measures are based on inputs into the innovation process, innovation outputs or innovation survey responses.

Inputs include variables such as R&D expenditure and number of research employees. Outputs include data on patents. These observable variables are not perfect indications of the level of knowledge possessed by a firm. Not all innovations are patented therefore some innovation activity will be overlooked in patent statistics. Furthermore, each patent is assumed to generate a homogenous level of impact. Drawbacks to R&D expenditure arise due to differences in set up costs and efficiency across projects.

Measuring Internal Knowledge

Knowledge within the firm is built up over a period of time. Following Griliches (1979), current state of knowledge is assumed to be a function of current and previous R&D undertaken R, which interacts with a lag polynomial to weight the contribution of R&D in reference to time t. This ties in with Schumpeter's idea of creative destruction by recognising that knowledge is a path dependent process which becomes obsolete over time; as new knowledge is created, old ideas become outdated.

$$K_{it} = R_{it} + (1-\delta)R_{it-1} + (1-\delta)^2 R_{it-2} + \ldots + (1-\delta)^n R_{it-n} \tag{2.1}$$

This perpetual inventory method for creating a knowledge stock variable has been used in a vast array of studies with various measures of R including patents, R&D expenditure and R&D employees.

Measuring Absorptive Capacity

Absorptive capacity is an intangible concept and therefore presents measurement difficulties. This section outlines the approaches taken. A number of theoretical and empirical papers define absorptive capacity as the level of R&D, or stock of R&D, including Griffith and Van Reenen (2003), Grünfeld (2006), Leahy and Neary (2007). Other proxies which capture this aspect include the existence of an R&D lab (Veugelers (1997)) and engagement in continuous R&D activity (Becker and Peters (2000)).

Guellec and Van Pottelsberghe de la Potterie (2004) suggest that absorptive capacity is derived from stock of R&D and education, training and learning by doing, although the human capital element is omitted from their model. They use lagged R&D stock as a measure of absorptive capacity. Leiponen (2005) uses share of employees with a technical or science degree and share with a post-graduate degree to model the human capital aspect of absorptive capacity at the firm level. Whereas Kneller and Stevens (2006) use average years of schooling in the population and stock of R&D using the perpetual inventory method as a proxy in their macro level study.

Schmidt (2010) argues that a firm's absorptive capacity is composed of three factors. These are previous R&D activity, skills and knowledge of employees and internal knowledge flows within the firm. These dimensions act as complements because some competency in each attribute is required in order to identify, assimilate and exploit external knowledge to commercial ends. He argues that output measures can proxy absorptive capacity.

Harris and Li (2009) use a merged CIS and ARD dataset. They define absorptive capacity as the ability to exploit knowledge that is embodied in intangible assets and use a principle components analysis[4] of 36 CIS variables to define five distinct variables which capture different aspects of absorptive capacity. These include networking with

[4]This is a orthogonal transformation which converts a large number of potentially correlated variables into a smaller number of uncorrelated variables

external bodies at the national level, implementing new organisational structures and human resource management strategies, building up partnerships with other enterprises or institutions at the international level and acquiring and absorbing codified knowledge from research partners. This technique may present problems with interpretation as the meaning of the correlated variables may be poorly defined.

Hussinger (2012) investigates the role of absorptive capacity in post-merger innovation by empirically testing if the absorptive capacity of the acquiring firm has a positive impact on patent productivity. They use two measures of absorptive capacity, stock of external co-authors which captures the ability to acquire, assimilate and exploit external knowledge and stock of non-patent references (i.e. citations of scientific articles) which proxies the ability to decode complex information. The degree of technological diversification in the firm's patent portfolio is taken into account. The variable is close to 1 for a highly diversified portfolio and equals zero for firms which patent only within one class. The results show that firms with higher levels of absorptive capacity require "less post-acquisition measures" to achieve the same levels of productivity as other post-acquisition firms.

Measuring External Knowledge

If a firm has adequate levels of absorptive capacity, they can utilise incoming knowledge spillovers from external sources, therefore the size of the relevant external knowledge pool available to a firm will affect its level of knowledge. Spillovers occur due to imperfect appropriability as a result of failure in the methods of innovation protection. The majority of spillover proxies in the literature are calculated as the weighted sum of other firm's knowledge stock, where the knowledge stocks have been weighted in various different ways, such as industrial proximity, geographical proximity and size.

$$K_{it}^{S} = \sum_{j \neq i} \omega_{it} K_{jt}^{R} \tag{2.2}$$

Jaffe (1986) proposes that a firms' technological position can be identified according to the distribution of patents across technology-based patent classes. A position vector F is created for each firm which contains the proportion of total patents in each class. The weighting is calculated using the uncentred correlation of vectors F_i and F_j, thus measuring the technological proximity of firm i to another firm j.

$$\omega_{ij} = \frac{F_i F_j'}{\sqrt{F_i F_j F_{ij}}} \tag{2.3}$$

The weighting ω_{ij} can take any value between 0 and 1, where 0 would occur if firms i and j have no common research areas and 1 would indicate that firms i and j have identical F vectors. This method generates a logical spillover weighting as it places a greater weighting on spillovers emanating from firms that innovate in closely related technological fields. A disadvantage of using patent data is that some innovations may go unrecorded and therefore the measure may not represent the true weighting.

Kaiser (2002) attempts to imitate Jaffe (1986), but replaces patent data with a selection of variables from the Mannheim Innovation Panel. The assumption here is that the chosen variables reflect technical proximity between firms, these include the proportions of high, medium and low skilled employees, expenditure on training, labour cost per employee, investment and 5 'hampering innovation' variables. A criticism of this method is that if the firms are matched on these characteristics, it does not necessarily imply that the knowledge a firm may spillover would be useful to the other firm as it does not include information about common industry or research areas.

Ornaghi (2006) suggests that simply using the sum of knowledge stocks within a firm's industrial classification implies that all firms within the same industrial classification are equally able to absorb and utilise information. Under the assumption that the size of firm i relative to firm j determines firm i's ability to absorb spillovers from firm j, he groups firms into 6 size classifications and creates 11 spillover variables depending on relative size. Variables exist for -5, -4, -3,-2,-1, 0, 1, 2, 3, 4, 5, and 6 of these categories will be missing for each firm. Missing values are replaced with zero before normalising with respect to the mean. This seems an odd approach to take as the underlying assumption does not appear to be particularly robust. The data is taken from a Spanish Survey of Business Strategy and may have arisen due to constraints of available data.

2.2.4 Modelling Productivity and Knowledge

The production function has featured heavily in the productivity literature and has given rise to much debate about its specification. In generalised form, the production function depicts output Y as a function of inputs into the production function X.

$$Y = f(X) \tag{2.4}$$

The vector of inputs X include labour and capital, but other inputs such as materials, energy, human capital and knowledge have been included in some specifications. There is some debate as to whether it is justifiable to enter knowledge or human capital into the production function as an input or as a factor influencing technological change. The Cobb-Douglas production function assumes that inputs can be traded off against each other, as firms can chose to be more labour intensive or capital intensive.

The seminal work by Griliches (1979) discusses modelling the relationship between innovation and productivity and highlights the associated measurement problems. He specifies the production function as $Y = F(X, K, u)$ where Y is a measure of output, X is a vector of conventional inputs into the production process such as labour L and capital C, K represents the level of technical knowledge at the current time as defined by a knowledge production function. Griliches (1979) suggests that the current state of knowledge K is a function of current and previous R&D undertaken.[5] This recognises that knowledge is a path dependent process, but knowledge becomes obsolete over time. He chooses to measure this using R&D expenditure rather than an R&D output measure.

[5]This interacts with a lag polynomial to weight the contribution of R&D in reference to time t as discussed earlier.

The model assumes separability of L and C from K and states that functional form is not of crucial importance unless there is particular interest in the interaction between K and another input or reason to suspect that a complementarity exists. For simplicity, the production function is specified in Cobb-Douglas form and assuming that all firms are technically efficient.

$$Y = DC^{\alpha}L^{\beta}K^{\gamma}exp(\lambda t + u) \tag{2.5}$$

where D is a constant, exp is the inverse of natural log, and α, β, γ and λ are parameters. Although it is acknowledged that knowledge is a different type of input than labour and capital, they all enter the equation in the same way. This approach is adopted in subsequent papers such as Hall and Mairesse (1995).

Hu et al. (2005) investigate the role of R&D and technology transfer on productivity using data from China. The data is taken from an annual survey of large and medium size enterprises and the panel covers around 10,000 manufacturing firms during a five-year period. A Cobb-Douglas functional form is assumed for the production function.

$$Y_{it} = A_{it}C_{it}^{\alpha}L_{it}^{\beta} \tag{2.6}$$

Y represents value added output, A is the total factor productivity parameter, C and L denote capital and labour respectively and α and β are their respective output elasticities. In this model the firm's knowledge production function is incorporated into A_{it}, which characterises the behaviour of productivity.

$$A_{it} = exp(f(K_{it}^{F}, K_{it}^{D}, K_{it}^{R}) + rt + \sum_{j}\gamma_j I_j + \sum_{h}\delta_h W_h + \sum_{s}\lambda_s T_s \tag{2.7}$$

The knowledge production function comprises of K_{it}^{R} the stock of firm's own R&D, K_{it}^{F} the stock of foreign technology transfer and K_{it}^{D} the stock of domestic technology. The technology transfer variables are representative of knowledge spillovers from sources external to the firm. Stocks are calculated using the perpetual inventory method to account for path dependency and depreciation of knowledge[6]. Industry dummies I_j, ownership dummies[7] W_h and time dummies T_s are also included. *exp* is the inverse of the natural logarithm. A_{it} is substituted back into equation (2.6) to provide the single estimating equation below, where lowercase letters indicate the natural logs of the variables.

$$y_{it} = \alpha_0 + \alpha_1 c_{it} + \alpha_2 l_{it} + \sum_R \beta_R k_{it}^R + \sum_R \sum_F \beta_{RF} k_{it}^R k_{it}^F + \sum_F \beta_F k_{it}^F +$$
$$\sum_F \sum_D \beta_{FD} k_{it}^F k_{it}^D + \sum_D \beta_D k_{it}^D + \sum_D \sum_R \beta_{DR} k_{it}^D k_{it}^R + \sum_j \gamma_j I_j + \sum_h \delta_h W_h + \sum_s \lambda_s T_s + \epsilon_{it} \tag{2.8}$$

Their model is estimated using OLS and IV methods as the explanatory variables are likely to be correlated with the error term, ϵ. They use all explanatory variables averaged at the four-digit industry level and ownership structure, year and industry dummies as instruments. They find positive and significant effects of in-house R&D and negative and significant effects of knowledge transfers from domestic sources. The interaction terms between K_{it}^R and the two technology transfer variables capture some of the effects of absorptive capacity and are found to be positive and significant in most of their results, furthermore when these interactions appear in the model, the coefficients on the K_{it}^D K_{it}^F terms are negative.[8] Hu et al. (2005) suggest that this indicates that technology transfer is more productive for a firm with a higher level of absorptive capacity. By entering the knowledge production function into A_{it}, this model is assuming that the knowledge variables can only influence output through shifting the production frontier as technical change is hicks neutral and therefore does not directly interact with labour and capital to adjust the shape of the production frontier. The Cobb-Douglas specification of the

[6] It is conventional in the literature to use a discount rate of 0.15 to calculate R&D stock. This rate is used by Parisi et al. (2006) and Hu et al. (2005) amongst others.

[7] The ownership dummies control for state owned, privately owned, collectively owned, limited liability, jointly operated, stock-incorporated, foreign-invested and Kong-Taiwan-Macao-invested enterprises.

[8] Also, K_{it}^F reduces in significance compared to the results from the interaction omitted model.

model assumes that all firms are technically efficient, suggesting that they do not have the potential to increase output through improvements in technical efficiency without an increase in inputs. Hu et al. (2005) can be criticised as they do not attempt to investigate the human capital aspect of absorptive capacity, but this may be due to the limitations of the data. Furthermore, they do not investigate the impact of knowledge spillovers from external sources.

Parisi et al. (2006) use data taken from two waves of an Italian Manufacturing firms survey, 'Indagine sulle Imprese Manifatturiere' to study the effect of process and product innovations on productivity. Each wave contains around 5000 firms, but by merging the two waves, removing outliers and firms with missing observations they obtain a balanced panel covering 465 manufacturing firms. This results in large amounts of unused data and a relatively small sample which is less representative of the general population as there are a higher proportion of large firms within the sample than in the population. They argue that the use of a data panel is necessary to overcome endogeneity problems arising from correlations between the explanatory variables and the error term. The production function is specified in Cobb-Douglas form, where Y_{it} is gross output, M_{it} represents inputs of materials and services measured using a Tornqvist index[9], K_{it} is a measure of fixed capital stock calculated using the perpetual inventory method, L_{it} represents labour, measured by the number of non-R&D employees, A_{it} is technical progress, λ and η denote firm i and time t specific shocks respectively and ϵ is a random error term.

$$Y_t = A_{it} M_{it}^{\theta} K_{it}^{\beta} L_{it}^{\alpha} e^{\lambda_i + \epsilon_{it} + \eta_t} \tag{2.9}$$

Equation (2.9) can be written in log-linear form.

$$lnY_{it} = lnA_{it} + \theta lnM_{it} + \beta lnK_{it-1} + \alpha lnL_{it-1} + \lambda_i + \epsilon_{it} + \eta_t \tag{2.10}$$

Technical progress lnA_{it} is modelled as a function of a series of innovation dummies

[9] M_{it} is required because the dependent variable is gross output rather than value added output.

D_{it} that indicate if firm i has introduced a product innovation, process innovation or either during each of the two time periods.[10]

$$\Delta lnA_{it} = \phi + \psi D_{it} \tag{2.11}$$

Equation (2.12) is created by imposing the assumption of constant returns to scale on equation (2.10), then differencing between the two waves of data in order to remove time invariant industry specific effects, and substituting in equation (2.11).

$$\Delta_3 ln(\frac{Y_{it}}{L_{it-1}}) = \phi + \psi D_{it} + \theta \Delta_3 ln(\frac{M_{it}}{L_{it-1}}) + \beta \Delta_3 ln(\frac{K_{it-1}}{L_{it-1}}) + \Delta_3 \epsilon_{it} + \Delta_3 \eta_t \tag{2.12}$$

This specification imposes the assumption of constant returns to scale by setting $\theta + \beta + \alpha = 1$, [11] which places a restriction on the model[12]. They assume that ΔlnA_{it} can be substituted into the difference equation despite the fact that it does not span the same time period as Δ_3[13]. Innovation enters into the production function via equation (2.11), which acts to shift the production function and does not interact directly with the inputs, in a similar way to equation (2.7) in the Hu et al. (2005) model. Findings show that process innovation provides a greater impact on productivity than product innovation. Equation (2.11) is far more simplistic as it only includes dummy variables to indicate the introduction of innovations within the firm, rather than the measures of internal and external knowledge stock as used by Hu et al. (2005). The analysis is also limited by the fact that the impact of knowledge transfers and knowledge spillovers are not investigated.

Crespi et al. (2008) use ARD and CIS data and focus on total factor productivity (TFP) growth as the dependent variable. Their paper aims to address four questions.

[10] The first wave covers the period 1992-1994 and the second covers 1995-1997.
[11] $\alpha = 1 - \theta - \beta$ is then substituted into (2.10) and rearranged given that $ln(Y/L) = lnY - lnL$.
[12] Although they test this assumption and find it cannot be rejected for their data.
[13] Δ covers the period during each wave, whereas Δ_3 refers to the change between the waves of data.

These include: which knowledge flows are the source of TFP growth? what is the impact of these flows on TFP growth? Can these knowledge flows be considered to be spillovers? How do these results which use direct measures of knowledge flows compare with the results in other papers which use indirect measures? The data taken from the CIS involves responses to the question "Please indicate the sources of knowledge used in your technological innovation activities and their importance". They suggest that the raw survey response data cannot be directly compared over a cross-section of firms due to the heterogeneity in the way that each firm perceives the importance of knowledge sources. In an attempt to remove firm biases from the CIS survey responses, they use the difference from the mean level of importance. Levels of importance[14] are given values 0 to 3 respectively and the mean is calculated across 17 different information sources. If the deviation from the mean is positive the variable is given a value of 1 and if it is negative or equal to zero the variable takes the value of 0, thus creating a binary variable for each of the information sources.

$$I(L^j)_{ij} = 1 \text{ if } (L^j_{it} - \overline{L^j_{it}}) > 0 \tag{2.13}$$

L^j_{it} is the level of importance of source j and $\overline{L^j_{it}}$ is the mean level of importance across all sources.[15] The drawback to this method is that it hides a lot of the information given in the survey. Firms which report all sources to have the same level of importance will be given a value of zero and those which are low importance may be given a value of one if other sources are classed as not used. The same value of 1 would be used for highly important if at least one source was considered less important. Therefore cross-sectional comparisons are still not valid, although they include the mean level of importance as a control in their model. The use of this method is potentially advantageous over using dummies for each source and level of importance as collinearity problems may occur. Particularly if there is a high tendency for firms to rank each source with the same level

[14] These are 'not used', 'low', 'medium' and 'high'.

[15] This method is also used in Crespi et al. (2008) in their analysis of learning by exporting.

of importance across the five categories investigated.

They test the data in various ways. Firstly, they use a knowledge production function approach to test the validity of their knowledge variables. They use patents as the dependent variable and include competitors, suppliers, clients, enterprise group and universities as the information sources. The number of patents takes a non negative integer value, therefore it is considered to be count data. They appropriately use negative binomial estimation and also allow for random effects. The majority of the explanatory variables are not significant, with the exception of universities as an information source. This variable is highly significant, suggesting that firms that regard information from universities to have above average importance to their innovation activities are more likely to be involved in development of frontier technology and patent their innovations. Whereas collaborations with other sources may yield less patentable innovations.

The main analysis in the paper is based on a Cobb-Douglas production function model, from which the total factor productivity model is derived.

$$\Delta lnY_{it} = \alpha^K \Delta lnx_{it}^K + \alpha^M \Delta lnx_{it}^M + \alpha^L \Delta lnx_{it}^L + \gamma_1 R_{it-1} + \Sigma\gamma_2 I(L_i^j)_{it-1} + \gamma_3 \overline{L}_{it-1} + \lambda + \varepsilon_{it} \tag{2.14}$$

x_{it}^K, x_{it}^M and x_{it}^L represent inputs of capital, materials and labour, R_{it-1} is the ratio of R&D employees to total employees, $I(L)$ is the knowledge variables discussed earlier and $\overline{L}$ is the mean response. A disadvantage of using the TFP model is that the α coefficients must stay the same. The model can be criticised as it does not include a direct measure of absorptive capacity to account for the knowledge stock built up over time within the firm which assists in the effective utilisation of knowledge flows.[16] Although R_{it-1} may capture the human capital aspect of absorptive capacity.

Results are presented for an OLS and random effects estimation of the Cobb-Douglas model, where input variables, competitors, suppliers and enterprise group are found to have a significant effect on output growth, ΔlnY_{it} , R_{it-1} is found to be significant at the

[16] This limitation is also noted in the conclusion.

10% level in the random effects estimation whereas university and clients as information sources are not significantly different from zero in either estimation. These results are compared with the estimations from the TFP specification, where coefficients remain at similar magnitudes but fewer significant variables are observed. The initial sample used consists only of UK owned firms. They present further results on various subsections of the sample as robustness checks on both the Cobb-Douglas and TFP forms. Subsections include firms that do not perform R&D, firms which do perform R&D, firms that patent and firms that do not patent. They then test for significance of additional variables using the UK-owned firm sample, such as the share of foreign employees within the 2-digit sector, which is found to be significant at the 10% level, a competition measure representing the lag of change in market share, a product innovation dummy and log number of patents, which are not significant. The sample is then expanded to include foreign owned firms, and the model is estimated including a multinational dummy, which is also found to be significant and only has a negligible effect on the size of the coefficients.

In order to relate their work with other literature they perform probit regressions using the binary knowledge variables as dependent variables, where 1 indicates a positive deviation from the mean of the 'importance of information source'. They focus on competitors and suppliers as knowledge sources. Explanatory variables include R&D expenditure to turnover ratio at the 3-digit industry level, the price cost margin at the 3-digit industry level, the TFP gap with the 90th percentile 4-digit firm and the ratio of employment in foreign multinational enterprises to employment in all multinational enterprises at the 3-digit industry level. This captures the share of the industry inhabited by foreign multinationals. They suggest that MNEs are more likely to locate in fast advancing industries where firms are likely to experience rapid growth.

Findings show R&D expenditure to turnover ratio and the MNE share of employees are positive and significant when competitor as information source is the dependent variable. Whereas price-cost is the only significant variable when supplier is the source of information. In their discussion they mention the importance of location but do not investigate using the CIS data on location of collaborating partner.

Criscuolo et al. (2010) focus on estimating a 'knowledge production function' using data from the UK CIS 2 and 3 merged with data from the Annual Inquiry into Foreign Direct Investment (AFDI) and Annual Respondents Database (ARD). They suggest that the findings that globally engaged firms have higher productivity in comparison to their domestic counterparts can be explained in terms of knowledge differences and specify a 'knowledge production function' where new knowledge depends on investment in creating new innovation and absorptive capacity.

$$\Delta K_i = f(H_i, K'_{ii}, K'_i) \tag{2.15}$$

where ΔK is the change in knowledge stock, K'_{ii} and K'_i are flows of knowledge to firm i from internal and external sources respectively and H is investment in human capital which expands absorptive capacity. Data on knowledge flows is taken from the CIS and identifies universities, government, suppliers and customers, competitors, commercial and from within the firm as sources. Human capital is measured as the number of full-time equivalent employees engaged in R&D activities[17] A variety of measures are used as the dependent variable including novel sales which is the value of sales created by new and improved products, number of patents applied for and binary variables indicating patent applications and involvement in innovation activities. Their information source variables differ in construction to those used in Crespi et al. (2008). They create dummies for each source and level of importance and check for robustness using variables that indicate whether the information source was used (1) or not (0), disregarding the level of importance placed on the source as they deem this to be not comparable across firms. These methods create results which are more intuitively interpretable than Crespi et al. (2008), where 1 indicates a positive deviation from the mean.

The descriptive statistics show that on average, firms which are part of a multina-

[17]The model is also run using alternative measures of H which include proportion of scientists and engagement in intermural R&D.

tional group find knowledge from within their enterprise group, and external sources, more important than domestic multi plant firms, with multinational affiliates finding within group information more important than multinational parents. For the patent and innovation binary variables probit models in various forms are used. They control for 2 digit industry, region, firm age, size by number of employees, structural change, established firm, merger and sale/closure of part of enterprise, but they highlight the fact that endogeneity arising from unobserved firm effects could cause positive or negative bias, therefore they experiment with instrumental variables on the human capital variable using Amemiya Generalised Least Squares (AGLS). They also attempt to overcome endogeneity by using a panel consisting of 2 waves of the CIS, but they note that attrition between the samples may partly be a consequence of firm deaths, thus resulting in selection bias. They estimate probits on a pooled crossection including a wave dummy, fixed effects conditional logits are used on a subsample of firms which switch innovation status[18] and also OLS is employed with fixed and random effects. Although OLS is not considered appropriate for binary dependent variable model as it imposes a linear probability, they argue that it presents similar marginal effects to the probit and allows for the computation of elasticities.[19]

A Tobit model is used when novel sales is the dependent variable. Again, endogeneity is addressed by using instrumental variables and by using a panel. The negative binomial model is used when number of patents is the dependent variable as the number of patents takes a positive integer value. The majority of their results show that multinational firms generate more innovation outputs and use more internal and external knowledge flows. But when the conditional logit and negative binomial are employed with fixed effects on the 2 wave panel, only internal information is found to be significant.

They follow this by using a decomposition method suggested by Mohnen et al. (2006) to identify the extent of the difference between innovation outputs of multinationals

[18]They suggest that this subsection consists of 128 firms in section 4.2.1, but in section 5 they indicate that there are 247 firm, which becomes 494 when observed twice.

[19]The OLS estimates are not displayed in the paper.

and domestic firms that is explained by the explanatory variables. They suggest that the majority of the adjusted differential is explained by knowledge inputs therefore suggesting that globally engaged firms rely upon a greater use of knowledge inputs to create more knowledge outputs. The models used in this paper do not directly link innovation with productivity, but they suggest that it could be a source of productivity differences.

This overview of the literature shows that productivity is mostly evaluated using a production function with a Cobb-Douglas functional form. This is generally accepted as a reasonable simplifying assumption. The econometric methodological approach should seek to remove endogeneity arising from simultaneity of input and output decisions. Unobserved time-consistent firm effects can be accounted for when panel data is used. The majority of studies have used qualitative innovation measures. UK studies have mainly used data from the CIS, which has the disadvantage of providing relatively few observations in the earlier waves of the survey, it is not performed annually and the sample varies across waves. Panels of this data tend to be small and heavily biased towards large firms, whereas cross-sectional analysis is likely to suffer from endogeneity bias. Although the CIS survey asks a large number of detailed questions, these questions are not always consistent across waves. These problems cause limitations for the current UK literature in this area.

Innovation data from BERD appears to be underutilised in the literature. The BERD dataset provides annual measures of R&D expenditure for the population of R&D performing firms, allowing for the creation of a large panel. This data is very similar to the Chinese data used in Hu et al. (2005). This paper does not attempt to investigate the human capital aspect of absorptive capacity. R&D employees are likely to play an important role in the absorption of knowledge from external sources and therefore this relationship should be investigated further.

Knowledge spillovers emanating from external sources are also overlooked in the Hu et al. (2005) analysis. Findings by Crespi et al. (2008) and Criscuolo et al. (2010) using the UK CIS have shown external sources of information, such as competitors, to be important in knowledge production and productivity growth. This presents further areas for investigation with BERD data using a measure of external knowledge spillovers similar to those suggested by Jaffe (1986) or Ornaghi (2006). It would also be interesting to investigate differences in the effect of these variables for multinational and non-multinationals firms by merging the ARD and AFDI with the BERD dataset.

Table 2.1: Literature Overview 1

Author	Methodology	Data	Key Variables	Results
Becker and Peters (2000)	Heckman two-step model and variables created using factor analysis	Mannheim Innovation Panel 1990-1992, around 1200 observations of innovative firms,	Dependent: log R&D intensity and patent dummy, Explanatory: factor scores for importance of external sources for internal innovation, R&D lab dummy, regularity of R&D dummy, interactions between R&D dummies and external source variables, Controls: appropriability, size, high-tech and low-tech dummies, diversification and foreign sales	Co-operation with universities, in-house R&D lab and regular R&D activity have a significant positive effect on R&D intensity and patents. Positive significant interaction terms indicate absorptive capacity.
Blake et al. (2009)	OLS	Asia Market Intelligence Database, 998 Chinese manufacturing firms in 2000	Dependent: TFP, Explanatory: share of employees with experience of working for foreign-owned firms, share of foreign-owned firms in the industry, export concentration, linkages with foreign-owned suppliers and buyers and interactions of these variables with in-house R&D expenditure and average training per worker to identify absorptive capacity.	Exports, share of foreign-owned firms in the industry and labour transfers from foreign-owned firms are found to be important sources of spillover. No evidence of absorptive capacity.
Cohen and Levinthal (1989)	OLS, GLS, Tobit	Yale Survey on Industrial R&D, sample 1: 1719 obs all firms, sample 2: 1302 obs R&D performing firms	Dependent: R&D intensity, Explanatory: importance of external knowledge on a seven-point scale from suppliers, customers, government research labs and universities, appropriability, relevance of 11 basic and applied science fields, new plant, time	The importance of external knowledge sources and appropriability have a positive impact on R&D intensity

Table 2.1 (continued): Literature Overview 1

Author	Methodology	Data	Key Variables	Results
Crespi et al. (2008)	OLS, RE, negative binomial	Annual Respondents Database (ARD) and Community Innovation Survey (CIS) 1994-1996 wave and 1998-2000 wave	Dependent: change in log output, change in log TFP, number of patents, Explanatory: log R&D expenditure, log R&D employees, change in log capital, change in log input materials, change in log labour, dummy variables indicating above average importance of external sources of knowledge, where external sources include competitors, suppliers, clients, enterprise group, university	The relationship between TFP growth and above average information flows is significant for competitors, suppliers and within enterprise group
Criscuolo et al. (2010)	Probit, Tobit, Instrumental Variables and Fixed Effects	UK firm-level data from CIS waves 2 and 3, ARD and ADFI	Dependent: innovate dummy, patent protect indicator, novel sales and patents Explanatory: export dummy, multinational parent dummy, multinational affiliate dummy, R&D employees, sources of external information including competitors, university, government, internal sources of knowledge	Globally engaged firms produce more innovation outputs and use more innovation inputs from internal and external sources. The majority of output differences between globally engaged and domestic firms is due to differences in inputs.
Driffield and Love (2003)	2SLS with deviations from group means as instruments and difference GMM	UK manufacturing sectors at 3-digit industry level 1984-92 from ONS	Dependent: Log value added output Explanatory: Foreign capital stock, foreign employment of operatives, foreign employment of non-operatives, domestic capital investment, regional concentration measure	Domestically created technology spills over to foreign multinationals in R&D intensive industries. Spillovers are affected by regional concentration of industry activity.
Griffith and Van Reenen (2003)	Fixed effects and instrumental variables	Industry level data from 14 manufacturing industries across 12 OECD countries	Dependent: change in TFP Explanatory: R&D to value added ratio, country distance from Frontier in terms of TFP, the interaction of these terms and control variables including human measures.	Evidence supports the existence of R&D-induced innovation technology transfer and R&D based absorptive capacity.

Table 2.1 (continued): Literature Overview 1

Author	Methodology	Data	Key Variables	Results
Guellec et al. (2004)	Error Correction Model (ECM)	Industry-level data for 16 countries from OECD National Accounts Database and Main Science and Technology Indicators 1980-1998	Dependent: long term productivity Explanatory: Business R&D stock, foreign R&D stock, public sector R&D stock including lagged terms and interactions of R&D stock variables and employment rate	R&D is a significant determinant of economic growth and performance of business R&D increases the impact of public sector and foreign R&D
Hall and Mairesse (1995)	OLS, Fixed Effects, First Differences and Longer-Differences	351 French manufacturing firms 1980-1987	Dependent: log output to labour ratio Explanatory: log capital to labour ratio, log knowledge capital to labour ratio, log labour	Performance of R&D over past periods should be taken into account in R&D stock variables, but results are not sensitive to the depreciation rate used. It is important to account for double counting in capital and labour in R&D stock estimates.
Harris and Li (2009)	Heckman 2-Stage Selection Model	UK firm-level data from CIS wave 3 and ARD	Stage 1 dependent: Export dummy Stage 2 dependent: log export intensity Explanatory: R&D dummy, firm size dummies, external knowledge source dummies, log capital to labour ratio, log labour productivity, market concentration, industry agglomeration, industry dummies	R&D increases the probability of exporting but does not increase export intensity of exporting firms. Access to knowledge from external sources also reduces barriers to exporting.
Harris and Robinson (2003)	System GMM	UK Plant-level manufacturing data 1974-1995 from the ARD	Dependent: log gross output Explanatory: log of intermediate inputs, log employees, log plant and machinery capital stock, plant age, foreign-ownership dummies for EU, US, Old Commonwealth, SE Asia and other, time dummies and interactions between foreign ownership and time	Evidence suggests that foreign-owned firms are more productive than domestic-owned firms.

Table 2.1 (continued): Literature Overview 1

Author	**Methodology**	**Data**	**Key Variables**	**Results**
Hu et al. (2005)	OLS and instrumental variables where 5-digit industry averages are used as instruments	Firm-level data from China's National Bureau of Statistics 1995-1999	Dependent: log value added output Explanatory: log labour, log capital, log in-house R&D stock, log stock of domestic external R&D transfers, log stock of foreign external R&D transfers and interactions between R&D variables	In-house R&D has a positive impact on productivity and evidence to support absorptive capacity is found.
Hussinger (2012)	Heckman 2-Stage Selection Model	Inventor-level data taken from the European Patent Office (EPO) and the M&A Database from Bureau Van Dijk	Stage 1 dependent: Inventor remains with firm post-acquisition dummy Stage 2 dependent: log post-acquisition patents Explanatory: log pre-acquisition patents, log pre-acquisition patents squared, time since last patent, private patents, pre-acquisition citation rate, small and large group of inventors in target firm dummies, acquirer patent stock and other firm characteristics	Post-acquisition productivity of inventors increases for target firms with higher levels of absorptive capacity.
Kaiser (2002)	Heckman 2-Stage Selection Model	German Service sector firm-level data from the Mannheim Innovation Panel	Stage 1 dependent: co-operation dummy Stage 2 dependent: log innovation intensity and log innovation expenditure Explanatory: log spillovers from horizontal and vertical sources, dummies to indicate number of important information sources, dummies to indicate scientific and private information sources, dummies indicating increase or decrease in sales, diversification measure, log employees, log employees squared, industry dummies, eastern Germany dummy, export dummy and foreign competition dummy	Co-operative research stimulates in-house research expenditure.

Table 2.1 (continued): Literature Overview 1

Author	Methodology	Data	Key Variables	Results
Kneller and Stevens (2006)	Stochastic Frontier Analysis (SFA)	Industry-level data across 12 OECD countries 1973-1991	Stage 1 dependent: log output Stage 1 explanatory: log labour, log capital (translog functional form) log stock of R&D expenditure, log of average years of schooling at country-level Stage 2 dependent: Estimated efficiencies Stage 2 explanatory: log stock of R&D expenditure, log of average years of schooling and country dummies	Inefficiency in production is largely due to differences in the level of human capital, whereas stock of R&D expenditure is less important.
Leiponen (2005)	Fixed Effects and System GMM	159 Manufacturing firms from the Finnish Innovation Survey, Annual National Business and R&D Survey, Register for Domestic Patent Applications and the Employment Register 1990-1996	Dependent: profit Explanatory: product and process innovation dummies, collaboration dummies, R&D intensity, number of patents, share of employees with an engineering or science degree, higher share of skilled employees than industry average dummy, share of post-graduate degree employees, number of employees, capital intensity, market share, industry and time dummies	Complementarities exist between R&D performing human capital and innovation activity.
Lokshin et al. (2008)	System GMM	304 Dutch Manufacturing firms from the Netherlands' Census of Manufacturers and Annual R&D Surveys 1996-2001	Dependent: log productivity Explanatory demand: lag dependent variable, log growth in labour, log growth in investment, industry dummies, internal R&D intensity, external R&D intensity and interactions between the R&D intensity variables.	Complementaries exist between internal and external R&D.

Table 2.1 (continued): Literature Overview 1

Author	Methodology	Data	Key Variables	Results
Ornaghi (2006)	Difference GMM	Spanish Manufacturing firms from the ESSE Business Strategy Survey 1990-1999	Dependent demand: log output Explanatory demand: log R&D stock, log knowledge spillovers, log labour, log capital, log material inputs Dependent supply: log sales Explanatory supply: log price, log advertising expenditure, log stock of R&D expenditure and log spillovers	Innovation Spillovers positively affect the productivity growth of firms.
Parisi et al. (2006)	First Differences and instrumental variables	465 Italian Manufacturing firms from the 1995 and 1998 waves of the MCC Survey	Dependent: log output to labour ratio Explanatory: product and process innovation dummies, log material to labour ratio, log capital to labour ratio	Process innovation has a positive impact on productivity.
Schmidt (2010)	Probit and Multinomial Probit	German firms from the Mannheim Innovation Panel 2003 wave	Dependent: Absorptive capacity dummy or categorical variable Explanatory: R&D intensity, R&D intensity squared, continuous R&D dummy, share of employees with higher education, number of employees, number of employees squared, collaboration dummies, industry dummies and eastern Germany dummy	R&D intensity has no significant impact on the absorption of external knowledge.
Veugelers (1997)	OLS and probit	Flemish R&D performing firms	Dependent: log internal R&D, co-operation dummy Explanatory: log firm size measured by sales, multinational dummy, diversification dummy, industry dummies, log R&D subsidies from Government, log external R&D, R&D department dummy, (co-operation dummy)	R&D co-operation and external R&D have a positive impact on in-house R&D for firms with a specific R&D department.

2.3 Data and Methodology

2.3.1 The Model

The model used in this chapter is based upon a generalised production function for firm i. Value added output Y_i is the dependent variable. Capital C_i and labour L_i represent the inputs into production, and A_i represents the firm's current state of knowledge. By using value added output as opposed to gross output, it is not necessary to include materials as inputs into the production function.

$$Y_i = f(C_i, L_i, A_i) \tag{2.16}$$

A firm's current level of knowledge can be influenced by a number of factors including the firm's previous R&D effort, market-based R&D transfers and spillovers from other firms within the industry. Therefore A_i is determined by the stock of knowledge K^R, knowledge transfers K^T , the knowledge spillovers pool K^S, a vector of multinational dummies M and diversified D firms are included as explanatory variables. Multinationals may have generated knowledge stocks outside of the UK and can potentially transfer this knowledge to UK subsidiaries through the direct transfer of information or transfer of workers between units of enterprise groups. Furthermore, multinational enterprises may have more exposure to spillovers than domestic firms due participation in foreign markets.

$$A_i = f(K^R, K^T, K^S M, D) \tag{2.17}$$

Knowledge can be considered different to the other determinants of Y_i because it does not directly act as an input into the production process; it influences the way the inputs, such as labour and capital, are used. Following Griliches (1969), the labour input can be separated out into highly skilled labour, L_i^H, and less skilled labour, L_i^L, where highly skilled labour is measured as the number of employees with a degree level qualification. Separating these labour variables seems to be a logical step as these different types of workers may affect output differently. By taking A_i outside of the production function $f(\cdot)$ knowledge does not directly interact with labour or capital, therefore A_i acts to shift the position of the production frontier and the inputs are assumed to be Hicks neutral as the impact of technology influences labour and capital in the same way.

$$Y_i = A_i f(C_i, L_i^H, L_i^L) \tag{2.18}$$

This model can be specified more specifically by assuming a Cobb-Douglas functional form for simplicity. The Cobb-Douglas production function assumes that all firms are technically efficient, therefore significant coefficients on the dummy variables will indicate a shift in the production function.

$$Y_i = A_i L_i^{H\alpha} L_i^{L\beta} C_i^{\gamma} e^{u_i} \tag{2.19}$$

$$lnY_i = lnA_i + \alpha lnL_i^H + \theta lnL_i^L + \gamma lnC_i \tag{2.20}$$

The knowledge production function can be specified as follows.

$$lnA_i = \beta_0 + \beta_1 lnK_i^R + \beta_2 lnK_i^T + \beta_3 lnK_i^S + \beta_4 lnK_i^R lnK_i^T + \beta_5 lnK_i^R lnK_i^S + \beta_6 M + \beta_7 D \tag{2.21}$$

The interaction terms model complementarities between knowledge variables. A positive and significant coefficient on these interaction terms indicates the existence of absorptive capacity; firms with greater own knowledge stock can better absorb knowledge transfer or spillovers to improve productivity than those with lower knowledge stocks. The role of labour can also be explored by including interactions between highly skilled labour and knowledge transfers or spillovers.

Substituting equation (2.21) into equation (2.20) yields the estimating equation.

$$lnY_i = \beta_0 + \beta_1 lnK_i^R + \beta_2 lnK_i^T + \beta_3 lnK_i^S + \beta_4 lnK_i^R lnK_i^T + \beta_5 lnK_i^R lnK_i^S + \beta_6 M + \beta_7 D$$
$$+ \alpha lnL_i^H + \theta lnL_i^L + \gamma lnC_i + X_i + \epsilon_i \quad (2.22)$$

The model can test whether multinational and diversified firms have higher productivity levels than domestic and none diversified firms based on the dummy variable coefficients. Furthermore, it can test whether differences in absorptive capacity help explain productivity differences.

2.3.2 Estimation Methodology

Bias in OLS

The problem of endogeneity arises when the error term is correlated with the explanatory variables. This can be a result of measurement error, ommited variable bias and reverse causality. The presence of endogeneity can lead to seriously biased estimates. This will be discussed in more detail in the following subsections.

Fixed Effects

The problem of omitted variable bias can be addressed by using a fixed effects model on panel data. This method removes time-consistent unobserved heterogeneity at the firm-level. Consider the following equation, where y_{it} is the dependent variable, x_{it} is a vector of explanatory variables, α_i is a fixed effect for firm i that remains constant over time t and ϵ_{it} is the error term.

$$y_{it} = \beta x_{it} + \alpha_i + \epsilon_{it} \quad (2.23)$$

Averaging this equation over time t for each firm i yeilds the following.

$$\bar{y_{it}} = \beta\bar{x_{it}} + \alpha_i + \bar{\epsilon_{it}} \tag{2.24}$$

Then subtracting equation (2.24) from equation (2.23) provides equation (2.26), where α_i cancelled out.

$$y_{it} - \bar{y_{it}} = \beta(x_{it} - \bar{x_{it}}) + (\epsilon_{it} - \bar{\epsilon_{it}}) \tag{2.25}$$

$$\hat{y_{it}} = \beta\hat{x_{it}} + \hat{\epsilon_{it}} \tag{2.26}$$

$\hat{y_{it}}$ is known as the 'within' or time-demeaned transformation on y and similarly for $\hat{x_{it}}$ and $\hat{\epsilon_{it}}$. Therefore the significance of the coefficients relies upon within firm changes over time. If x_{it} remains close to its average, $\bar{x_{it}}$, due to a lack of variation over time, the coefficient on $\hat{x_{it}}$ will not be significantly different from zero.

The sample used in this study has little within-firm variation over time due to the persistent nature of production inputs. This implies that coefficients on the fixed effects model will be closer to zero than coefficients on pooled models. The pooled models capture within and between firm effects, but are also subject to omitted variable bias. Although the fixed effects estimator removes some of the endogeneity arising from omitted variable bias, it may increase problems if time-inconsistent measurement errors are present.

Instrumental Variables

An underlying assumption of the OLS model is that the error term is unrelated to the explanatory variables, $E(\epsilon|x) = 0$. This assumption is required to ensure that estimated coefficients are consistent. Instrumental variables can be used to provide consistent estimates when explanatory variables are correlated with the error term, assuming that the instruments z are correlated with the endogenous regressors and uncorrelated with the error term $E(\epsilon|z) = 0$.

Consider a simple model where y is the dependent variable, x is an explanatory variable and β represent the estimated coefficients.

$$y = \beta_0 + \beta_1 x + \epsilon \tag{2.27}$$

OLS estimates remain consistent if there is no association between x and ϵ, but estimates become biased if a correlation exists between x and ϵ. Simultaneity is likely to be present in the context of a production function. The level of output is determined by the inputs, but inputs levels may be chosen to produce a desired level of output, therefore causality runs in both directions. A shock to the output will lead to an adjustment in inputs during a given period and vice versa. Measurement error may also exacerbate the endogeneity problem.[20] Error terms can be plotted against the dependent variable and explanatory variables to test for the presence of endogeneity. Post-estimation tests which compare OLS and IV models can also be applied to test for endogeneity, such as the Durbin-Wu-Hausman test.

Suitable instruments z comply with the conditions $Cov(z, x) \neq 0$ and $Cov(z, u) = 0$. The first condition is testable and states that z is correlated with the endogenous explanatory variables x. The second condition is untestable and states that z is uncorrelated with the error. There are various methods of testing the validity of the first condition. Instruments can be regressed on the endogenous explanatory variables to obtain t-statistics, R^2 and the Shea partial R^2 statistics (Shea, 1997). Post-estimation tests for instrument validity should also be performed if the model is over-identified.

Hu et al. (2005) suggest that four digit industry averages of each input variable can be used as suitable instruments in a production function with knowledge stock variables. These instruments aim to capture industry conditions. Shocks to the industry may result in simultaneous adjustments in outputs and inputs by firms, therefore should be correlated with firm inputs but independent of firm specific characteristics captured in the error. Measurement error shocks may also be captured by these instruments.

[20]Panel methods can be applied to remove time-consistent endogeneity arising from omitted variable bias.

The two-stage least squares (2SLS) method can be used to obtain parameter estimates. The first stage regresses the instruments on the endogenous variables to obtain estimated fitted values of the endogenous variables. The fitted values are purged of the correlation with the error term because the instruments are uncorrelated with the error. The second stage estimates the structural equation using the fitted values for the endogenous variables. This removes endogeneity from the structural equation.

The generalised method of moments (GMM) is a method of deriving parameter estimates from moment conditions. OLS and IV estimators can be viewed as special cases of GMM. This estimation technique can be applied to provide more efficient estimates when heteroscedasticity is present in the 2SLS model.

Difference and System GMM

Arellano and Bond (1991) present a method of GMM estimation that takes first differences to remove unobserved firm-specific heterogeneity and uses lagged level instruments to correct for simultaneity. The Arellano-Bond GMM difference method suffers from weak instrument bias when the level variables are highly persistent overtime. This problem is present in production data because firm outputs and inputs remain relatively stable overtime. This results in a weak correlation between the lagged instruments and first-differences. Blundell and Bond (1998) proposed the system GMM estimator to overcome this problem. The system GMM estimator instruments level variables with differences to remove fixed effects from the instruments. This will result in less biased estimates, assuming the instruments are uncorrelated with the errors.

The one-step method equates to 2SLS with GMM using the appropriate instruments. The two-step procedure is efficient and robust regardless of heteroscedasticity or autocorrelation. This method uses an estimated weighting matrix based on the residuals from the one-step model, but generates downward biased standard errors. Windmeijer (2005) provides a finite-sample correction for the two-step covariance matrix, thus rendering the two-step estimates preferable to one-step cluster-robust estimates.

The Sargan test and Hansen test can be used to test for the joint validity of the identifying restrictions when the model is over-identified.[21] This tests the validity of instruments. The Sargan test is inconsistent if heteroscedasticity is present in the sample, therefore the Hansen test is considered to be more reliable.

2.3.3 Data Sources and Variables

This study focusses on the UK by using micro-level data from the Office of National Statistics (ONS). The datasets used include the Annual Respondents database (ARD), Annual Inquiry into Foreign Direct Investment (AFDI) and Business Expenditure on Research and Development (BERD). These can be matched using the Inter-Departmental Business Register (IDBR) reference numbers.

The Annual Respondents Database (ARD)

The ARD is a database which contains firm's responses to the Annual Business Inquiry (ABI) across eight industries from 1997-2007.[22] The survey covers all large firms with more than 250 employees and a stratified sample of small and medium firms. It provides a variety of different variables including employment, turnover, sales, purchases, stocks, capital expenditure and investment, foreign ownership and Standard Industrial Classification (SIC) code. Value added output Y, plant and machinery capital stock C and total number of employees for L can be derived from this data, where the capital stock variable is calculated using the perpetual inventory method.

Data in the ARD is recorded at reporting unit level. This generally corresponds with plant level for multi-plant firms and firm level for single plant firms. SIC codes identify the main industry of activity at reporting unit level. Therefore diversified firms can be identified as those with multiple UK plants with different industry codes as their main industry of activity. This method may also capture single product firms that operate in

[21] Over-identification occurs when there are more instruments than endogenous independent variables.
[22] The data included only production and construction industries between 1994 and 1997 and prior to 1994, only production

multiple industries. For instance, some of these firms may produce different components of the same product; a car is composed of metal, plastic and electronic parts made in separate plants. From this data it cannot be clearly distinguished why or how firms are operating in different industries. Furthermore, it cannot be established if one single plant produces various products because one main SIC code is recorded for each plant.

In the ARD capital is divided into plant and machinery, buildings and vehicles. As the sample does not cover the entire population of small firms, some missing values exist in the data, therefore it is necessary to impute some values in order to perform the calculations.

Business Expenditure on Research and Development(BERD)

BERD is an annual survey that is available from 1994-2008 and aims to cover the population of UK R&D performing firms. These firms are identified from a variety of different sources including the Annual Business Inquiry, the UK Innovation Survey, New R&D sector firms for Business Register, International Trade and Services (ITIS), Department for Business, Innovation and Skills (BIS) and HMRC R&D Tax Credit claimants. Data is provided on R&D expenditure, both internal to the firm and commissioned to external parties. It also gives the number of R&D employees categorised by scientists, engineers and technicians. Internal expenditure is broken down in various ways; by type of research expenditure- experimental, applied, basic, R&D salaries and R&D capital, by funding source, and by product group and purpose.

The number of observations ranges from 4846 in 1994 to approximately 14000 in 2008. The data is self-reported by firms via a postal survey and results are imputed by the ONS for non-responding and un-sampled innovating firms,[23] therefore attrition in the data only occurs as a result of company deaths or cessation of R&D activity. The data is provided at reporting unit level, but can be aggregated to enterprise level. Reporting units may differ between datasets, whereas enterprises remain consistent. Observations

[23] For example, in 2005 there were around 2971 actual respondents and 10923 imputed observations

can be merged with other datasets at the enterprise level using lookup table provided by Richard Harris.

The stock of knowledge K_i^R for each firm can be calculated using the perpetual inventory method with BERD data. The knowledge spillover variable K_i^S can be generated using a weighted sum of knowledge stocks for all other firm's within the BERD dataset covering all UK innovating firms.[24] These methods are consistent with a great deal of the literature discussed earlier. Due to the nature of the dataset, there is a strong possibility of measurement error in the knowledge variables as a proportion of the data is imputed.

The Annual Inquiry into Foreign Direct Investment (AFDI)

The AFDI is conducted at enterprise group level and comprises of an inward and outward FDI survey. The inward survey provides data on capital flows entering the UK from foreign subsidiaries/branches to their UK subsidiaries/branches. The outward survey deals with capital flows leaving the UK from UK subsidiaries/branches to foreign subsidiaries/branches. Repeated enterprise codes may appear due to foreign enterprises with more than one UK subsidiary in the inward survey and UK based enterprises with more than one foreign subsidiary in the outward survey. The ONS use a variety of resources including HM Customs and Revenue, Dunn and Bradstreet's 'Worldbase' system, and ONS inquiries on Acquisitions and Mergers to compile the register of firms and provide data on country of parent enterprise or foreign subsidiary. All MNEs which own large UK firms are asked to complete the survey and a stratified sample of MNEs owning small UK subsidiaries are also sent survey forms. Annual rotation of the chosen sample of small firms ensures different firms are chosen on consecutive years. By matching the enterprise group code with enterprise group code in the ARD, firms or reporting units can be identified as multinational if a match occurs.

[24] Innovating firms are defined as firms that "undertake creative work on a systematic basis in order to increase the stock of knowledge, including the knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications"(OECD Frascati Manual).

2.3.4 Creating Knowledge Variables

Knowledge Stock

In this study the variable used to measure a firm's own accumulation of knowledge $K^R_{i,t}$ is created using a perpetual inventory method based on previous and current intrafirm R&D expenditure. The data on intrafirm R&D expenditure is taken from BERD and includes basic, applied and experimental research. This excludes R&D salaries and R&D capital expenditure to avoid double counting. This expenditure data is deflated using industry deflators from the VICS in order to create real R&D expenditure and remain consistent with the deflators used in the creation of the capital stock variable and measure of output. This assumes that inflation on R&D expenditure is the same as industry average inflation which appears to be a reasonable assumption. The perpetual inventory is calculated as follows,

$$K^R_{i,t} = RD_{i,t} + (1 - \delta)K^R_{i,t-1} \tag{2.28}$$

where K^R_{it} represents firm i's own knowledge stock in year t, $RD_{i,t}$ is firm i's R&D expenditure in year t and $K^R_{i,t-1}$ is firm i's knowledge stock in the previous year which depreciates at a rate of δ. A depreciation rate of 15% ($\delta = 0.15$) is assumed following Hu et al. (2005) and Hall and Mairesse (1995), which according to Hu et al. (2005) is the convention in the literature. Knowledge stock is not accumulated prior to the firm's first investment in R&D therefore in this initial year $K^R_{i,t} = RD_{i,t}$. BERD data is available from 1994 onwards and therefore those units with R&D expenditure in and before 1994 take 1994 as the initial year of knowledge accumulation.

Although the sample used in the regression analysis covers the period 1998-2005, it is necessary to use as much of the R&D data as possible to create a more accurate portrayal of the firm's true knowledge stock. Unfortunately there is no data on birth year of the firm in BERD which could have been used to estimate knowledge accumulation prior to 1994 therefore the assumption must be made that all knowledge accumulated before

1994 is obsolete by 1998 and therefore would not affect productivity during the 1998-2005 sample. It is not necessary to impute values for missing observations as the ONS generates observations for the entire population of innovating firms, therefore any missing data should represent a year when a firm did not incur any R&D expenditures.[25]

Knowledge Transfer

The knowlege transfer variables represent the market transactions by firms to purchase knowledge from external sources. The BERD data distinguishes between external R&D expenditure on market based transfers of knowledge from UK sources and foreign sources. Therefore stock of knowledge transfer variables can be calculated using the same perpetual inventory method applied to the firm's own knowledge stock. The logic behind this is that as a firm purchases the R&D it absorbs the knowledge, thus adding to its overall stock of knowledge. Hu et al. (2005) use stock of knowledge transfer variables in their paper.

Knowledge Spillover

The knowledge spillover pool variable $K^S_{i,t}$ attempts to capture the external pool of knowledge relevant to firm i arising via spillovers from other firms j. The size of the knowledge pool firstly depends on the extent of the information leakage from firm j which may occur due to ineffectiveness of innovation protection methods or collaboration, and secondly depends on the mechanisms through which firm i receives the information from firm j, for instance, industry links or geographical location may be important factors in determining firm i's exposure to spillovers from firm j, and finally depends on the relevance of firm j's spillovers to firm i as firm i has no use for information completely unrelated to its product field. The ability of firm i to exploit these knowledge spillovers depends on its level of absorptive capacity, which is determined by previous R&D experience and skills of employees and therefore this can be tested using interaction terms between these

[25] There are few missing values within a run of observations.

variables.

In order to account for these relationships between firms a set of weightings are created for every firm i in relation to each other firm j. The knowledge spillover pool is therefore calculated as the weighted sum of the knowledge stocks of other firms,

$$K_{it}^{S} = \sum_{j \neq i} \omega_{ijt} K_{jt}^{R} \tag{2.29}$$

where K_{it}^{S} denotes the knowledge spillover pool, ω_{ijt} represents the weight given to firm j in relation to firm i and K_{jt}^{R} is the knowledge stock of firm j.

Unfortunately we have no information on the level of spillovers emanating from each firm, therefore assumptions must be made. BERD provides information on geographic region, industry code and product code. Weightings are generated based on geographical distance and industry sic codes. Distances between firm i and firm j are calculated using the eastings and northings derived from ONS anonymised postcodes as follows.

$$Distance = \sqrt{(\text{Firm } i_{Easting} - \text{Firm } j_{Easting})^2 + (\text{Firm } i_{Northing} - \text{Firm } j_{Northing})^2} \tag{2.30}$$

A weight of 1 is assigned for firms within a 50km radius of firm i, 0.5 for firms beyond 50km but within a 75km radius and 0.25 for firms beyond 75km but within a 100km radius. A weight of zero is given to firms which do not share a common 3-digit industry code with firm i. Various weightings were compared to check robustness of results.[26]

2.3.5 Creating a Capital Stock Variable

It is necessary to create a capital stock variable because information on capital stock is not provided via ONS survey data and a pre-calculated measure of capital stock is not provided within the SDS. The ARD provides data on capital expenditure during each year

[26] The initial plan was to compute a weighting following Jaffe (1986), but due to the sheer volume of observations the computations would take a very long time to run. Therefore this idea had to be abandoned in favour of a more simplistic method of computation. Although when comparing a small sample of weightings using the Jaffe method to weightings using the less complex method, the results appeared to provide little difference.

taken from the ABI survey, therefore a firm's capital stock can be estimated using the perpetual inventory method. This requires deflating capital expenditure and adjusting for depreciation before summing to give an estimate of capital stock.

As with the creation of any variable with a large and complex dataset, there are various issues to overcome. The ARD covers all large firms but provides a stratified sample of small and medium sized firms, therefore observations may not be included for these firms in each year of trading. It is reasonable to assume that firms continue to invest in capital during the years that they are absent from the survey, hence missing values may lead to underestimates of capital stock, therefore it is appropriate to impute observations for the missing years.

The first step in the creation of the capital stock variable is to adjust the capital expenditure for inflation. This is done using deflators from the Volume Index of Capital Services (VICS) calculated by the ONS which are split by asset, industrial sector and year. The ARD data is given in files which are separated by year and sector and therefore the deflated data must be appended across years and sectors to provide a panel. At this stage the panel includes only data by firm in the year that they responded to the ABI survey.

The second step is to update this panel to include observations for all firms which responded to the ABI survey by year and missing observations for those firms that did not respond to the survey in a given year but responded in another year. Those firms that never took part in the survey cannot be included as there is no information to base imputations on. To do this, a panel is created from a register of firms that includes all firms regardless of participation in the ABI survey and includes a variable which indicates if a firm participated in a given year. Those firms that never take part are dropped from the register panel. The panel of survey responses is then merged with the register panel, thus creating the appropriate framework to generate the necessary imputed values.[27]

The third step involves the imputation of missing values based on number of em-

[27] For further details see Gilhooly, R. 'Technical Guide: Estimating Capital Stock'

ployees. This is done by firstly imputing missing number of employee values using linear interpolations by firms and a localised average for missing values in the first year of firm's existence. Investment per employee is then calculated for the years that the investment data is available in order to create an average investment per employee estimate for each firm. The missing capital expenditure values are then replaced with the interpolated number of employees multiplied by the average investment per employee to provide an estimate of capital investment during the missing year.

The next step is to employ the perpetual inventory method (PIM) to generate estimates of capital stock for each firm by year. The perpetual inventory is calculated as follows,

$$C_{i,t} = I_{i,t} + (1 - \delta)C_{i,t-1} \tag{2.31}$$

where C_{it} represents capital stock in year t, $I_{i,t}$ is capital expenditure by firm i in year t and $C_{i,t-1}$ is firm i's capital stock in the previous year which depreciates at a rate of δ. A depreciation rate of 0.06 is assumed in this study, but robustness checks indicate that the findings are not sensitive to this assumption. Descriptive statistics indicate that the variable contains negative series therefore further action is taken to reduce the number of negative series. It seems reasonable to assume that these series are likely to be incorrect due to under estimates in investment which may occur due to a missing year coinciding with a large "lump" investment.

2.3.6 Merging ARD and BERD

Observations are recorded at reporting unit level in the ARD and BERD. Reporting units are not a meaningful level of aggregation therefore it is more appropriate to undertake the study at enterprise level. Although identical reporting units references may appear in the ARD and BERD, they may not necessarily refer to the same part of the firm. The ARD contains enterprise references for each reporting unit, therefore data for reporting units can be aggregated to enterprise level. This operation is not so straight forward in BERD because enterprise reference codes are not available within the dataset. A look-up table for obtaining the corresponding enterprise reference codes for each reporting unit was compiled by Richard Harris. This was created by using the IDBR and identifying missing enterprise references using postcodes and firm characteristics. This look-up table was used to obtain corresponding enterprise references for each reporting unit. This allowed BERD data to be aggregated to enterprise level and matched with the ARD by enterprise reference code. Table (2.2) indicates the number of enterprise level observations in the ARD and BERD and the number of matched and unmatched observations.

Table 2.2: ARD and BERD Merge

Year	Total		Not Matched		Matched
	BERD	ARD	From ARD	From BERD	Keep
1997	1118	48495	47700	323	795
1998	8484	51231	48552	5805	2679
1999	7852	52556	50212	5508	2344
2000	8,591	52324	49683	5950	2,641
2001	8,640	56878	54460	6222	2,418
2002	10781	53472	50268	7577	3,204
2003	9770	52849	50371	7292	2,478
2004	11812	52411	49372	8773	3,039
2005	12470	51158	48103	9415	3,055
Total	79518	471374	448721	56865	22653

Around 75% of BERD observations could not be matched to the ARD. Over 95% of BERD enterprise references can be matched against the BSD, which acts as a register of all enterprises within the population. This rules out problems with matching reference codes as a potential cause of this and confirms that this is due to the overlap of the ARD and BERD dataset.

2.3.7 Creating a Multinational Dummy

Merging the AFDI and ARD facilitates the identification of multinational firms. Any firm that is recorded to have an inward or outward flow of FDI is considered to be a multinational. All enterprises recorded within the AFDI are multinational therefore any match between the ARD and AFDI indicates a multinational firm.

On the face of things matching the AFDI and ARD may appear relatively straight forward, but there are a number of complications that add complexity to the task. The first complication is that ARD data is given at reporting unit level, whereas the AFDI data is given at enterprise group level. A second issue with the datasets is the lack of direct comparability between the reference numbers. A third complication is that the AFDI and the ARD do not include the entire population in their sample; not all small firms are included each year.

The first issue is relatively simple to resolve. In the IBDR there are various ways that units can be classified. Units can be classified by reporting unit or according to the EU Regulation on Statistical Units (EEC 696/93) as an enterprise, enterprise group, local unit or kind of activity unit (KAU). An enterprise is the smallest combination of legal units that organises and allocates its current resources and produces goods or services. An enterprise may carry out these activities at one or more locations or may be a sole legal unit. An enterprise group is an association of enterprises bound together by financial or legal ties. In some cases an enterprise group may consist of a single enterprise if the enterprise has no associations. A local unit refers to a specific geographic site (e.g. workshop, office, etc) which undertakes economic activity contributing to the enterprise. An enterprise may have various local units or consist of only one. Kind of activity unit refers to the operational subdivisions of an enterprise. The reporting unit is generally equivalent to the enterprise but in some cases can be defined at a less aggregated level based on kind of activity units.

In both the inwards and outwards AFDI each enterprise group code may not be unique. FDI flows are recorded by country therefore multiple observations per enterprise group many be observed if FDI flows from or to more than one country. In order to match with the ARD, the AFDI data must be restructured to show one observation per enterprise group. Table 2.3 shows the number of enterprise group observations in the restructured AFDI.

Table 2.3: Number of enterprise group observations in the AFDI Data

	AFDI out	**AFDI in**
1997	953	2077
1998	2353	6150
1999	2921	7662
2000	3201	8614
2001	3266	14045
2002	3041	13751
2003	2626	13141
2004	12642	13123
2005	13188	13439
Total	44191	92002

The ARD data provides a enterprise group reference code for each reporting unit observation. A one to many match will identify the reporting units which belong to a multinational enterprise group, as there are repeated enterprise group references in the ARD and unique enterprise group references in the restructured version of the AFDI. The second issue arises from the inconsistencies that exist between the enterprise groups reference codes in the ARD and the AFDI. Each enterprise group should have a 10 digit reference code stored as a string variable in stata, yet some reference codes are stored as numeric variables without lead zeros resulting in less than 10 digits and some of the codes in the AFDI have a leading number ranging from 1 to 6 which results in an 11 digit code. These inconsistencies are addressed by converting all reference codes to string variables with 10 digits by removing the lead numbers in the AFDI, see Criscuolo and Martin (2007), or adding lead zeros for those with less than 10 digits.[28]

Observations in the ARD with missing enterprise group codes have their enterprise group code replaced with their enterprise reference code. If this is also missing, the enterprise group reference code is replaced with their reporting unit code. This is a legitimate replacement as many observations have enterprise group reference codes which

[28]Firms with missing enterprise group reference codes in the AFDI must be dropped as there is no other form of reference code which allows of the data to be matched.

are consistent with their enterprise reference and also reporting unit reference. This improves the number of matches between the two datasets although there are still some AFDI enterprise group codes which do not match up with the ARD. This may be due to the fact that the ARD does not include all firms, a stratified sample of medium and small firms is taken, therefore the small firms included in the AFDI sample may not correspond to those included in the ARD or could be as a result of further differences between the enterprise group reference codes. For the purposes of this analysis the unmatched data from the AFDI is dropped as it is cannot be used without the corresponding ARD data.

Table 2.4: ARD-AFDI matches

	AFDI out			**AFDI in**		
Year	Unmatched	Matched	Total	Unmatched	Matched	Total
1997	48462	33	48495	48433	62	48495
1998	49115	2116	51231	50107	1124	51231
1999	50066	2490	52556	51506	1050	52556
2000	50088	2240	52328	51324	1004	52328
2001	54368	2485	56853	54698	2155	56853
2002	51300	2141	53441	51542	1899	53441
2003	50848	1970	52818	50654	2164	52818
2004	50862	1560	52422	51082	1340	52422
2005	49640	1515	51155	49881	1274	51155
Total	454749	16550	471299	465632	13453	471299

"unmatched" indicates the number of unmatched observations from the ARD and "total" indicates the total number of observations in the ARD.

In summary, after adjusting enterprise group references codes to yield the optimum number of matches, the dataset used for this analysis is derived by matching the ARD with the outward and inward AFDI. Unmatched observations from the AFDI are dropped but all observations from the ARD are kept regardless of their match status. Therefore this is the best sample that can be obtained given the constraints of the data. A multinational dummy is created where observations with a match with inwards AFDI or outwards AFDI are indicated with 1 and observations with no recorded flows of FDI, in or out, are indicated with 0.

Inaccuracies in correctly identifying multinational status may arise for small enterprises because when a small multinational enterprise is omitted from an AFDI survey there will be no match with the ARD and hence a zero value will be entered in the multinational dummy. An updated dummy is created where missing data is imputed based on multinational status in previous and succeeding years i.e. a zero is replaced with 1 if there are 1s in $n-1$ and $n+1$ and this affects around 100 observations.

2.3.8 Creating a Foreign Ownership Dummy

The BSD is a snapshot of the IDBR at a specific point in time and contains two variables for country of ownership; imm_foc is immediate country of ownership and ult_foc is ultimate country of ownership. Country of ownership data is taken from the Dun and Bradstreet (D&B) Worldbase and updated on the IDBR, where ownership is defined as the owners with the largest ownership share and majority voting power or least 10% of ordinary shares. Firms may potentially have multiple owners across different countries but the country with the largest ownership share is recorded. Ultimate ownership refers to the highest level of ownership at enterprise group level, whereas immediate ownership may to refer the owner of a unit within an enterprise group such as an enterprise or reporting unit.

The source of the ARD foreign ownership code is not explicitly stated in the ARD userguide but it seem sensible to assume that it is either taken directly from D&B or the IDBR. Comparisons between ARD and BSD show that this code is consistent with ult_foc. A few missing ownership codes in the ARD are replaced with codes from the BSD to maximise the number of non-missing codes.

For the purposes of this analysis it would be useful to distinguish UK-owned and foreign-owned firms. Foreign ownership codes do not remain consistent over years. According to the "ARD User Guide 2002", the UK is marked as 783 or 801. But a more recent list of codes obtained from the IDBR team suggests that UK-owned enterprises may also be coded as 826, 830 or 833. Missing codes are imputed if the codes in the previous and following year indicate ownership of the firm by the same country. This allows a foreign ownership dummy to be created where UK-owned firms are recorded as 0 and non-UK ownership codes are recorded as 1. The foreign ownership dummy can be interacted with the multinational dummy to identify non-multinationals, UK multinationals and foreign multinationals.

Table 2.5: List of Variables

Variable	**Description**
$logY$	log of gross value added
$logC$	log of capital stock
$logL$	log of the number of employees
$logL^H$	log of the number of R&D employees with Science and Technology degrees
$logL^L$	log of the number of other employees, where $L^L = L - L^H$
$logK^R$	log of in-house R&D stock
$logK^S$	log of knowledge spillovers
$logK^T$	log of knowledge transfer stock
$logK^T_F$	log of knowledge transfer stock from foreign sources
$logK^T_{UK}$	log of knowledge transfer stock from UK sources
$logK^R.logK^T$	log interaction between in-house R&D stock and knowledge transfer stock
$logK^R.logK^S$	log interaction between in-house R&D stock and knowledge spillovers
$logK^R.logK^T_{UK}$	log interaction between in-house R&D stock and knowledge transfer stock from UK sources
$logK^R.logK^T_F$	log interaction between in-house R&D stock and knowledge transfer stock from foreign sources
$logK^R.logL^H$	log interaction between in-house R&D stock and the number of R&D employees (with Science and Technology degrees)
$logK^T.logL^H$	log interaction between knowledge transfer stock and the number of R&D employees (with Science and Technology degrees)
Multinational	Dummy variable where 1 indicates multinational status and 0 indicates non-multinational status
UK Multinational	Dummy variable where 1 indicates UK-owned multinational and 0 indicates otherwise
Foreign Multinational	Dummy variable where 1 indicates Foreign-owned multinational and 0 indicates otherwise
$Hi - Tech^{industry}$	Dummy variable where 1 indicates activity in a high-technology industry
$Hi - Tech^{firm}$	Dummy variable where 1 indicates a high-technology firm

2.4 Descriptive Statistics

The sample used in the analysis is created by matching data from the ARD, AFDI and BERD. Therefore the size of the sample is dependent on the number of matches between the ARD and BERD. The number of matches with the AFDI does not affect sample size because these matches are used to indicate multinational status and the unmatched observations are given non-multinational status and remain within the sample. This is likely to generate a sample which has a slightly higher proportion of medium to large firms than the general population of UK firms because these firms are more likely to be common to BERD and ARD datasets. Table 2.6 shows the number of observations in each size-band for the ARD, BERD and ARD-BERD datasets for the period 1998-2005.

Table 2.6: Number of Observations by Size-band in Each Dataset 1998-2005

Number of Employees	**ARD**	**BERD**	**ARD-BERD Sample**	**GMM Sample**
0-20	269592	67061	854	204
21-50	69677	20879	2024	750
51-100	43789	15261	2583	1306
101-150	22904	8013	2612	1561
151-500	46722	16696	7463	4949
501-1000	13844	3676	2986	2210
1001-2500	8076	1921	1314	1008
2501-5000	2616	563	424	311
5001-10000	1155	192	189	142
10001+	709	289	219	170
Total	479084	134551	20668	12611

The ARD-BERD sample has 20668 observations covering the period 1998 to 2005. The observations from 1997 were dropped from the sample due to the poor merge rate with the AFDI in this year, resulting in few identified multinationals. A further 1190 observations were dropped due to missing variables. Columns 2-4 of table 2.7 indicate that the number of observations in each year fluctuates as firms move in and out of the sample. This sample is used to create OLS, Fixed Effects and 2SLS estimates. System GMM uses lagged first

Table 2.7: Number of Observations by Year and Multinational Status

	ARD-BERD Sample			GMM Sample		
Year	**Non-Mult**	**Mult**	**Total**	**Non-Mult**	**Mult**	**Total**
1998	673	1,688	2,361	-	-	-
1999	416	1,759	2,175	220	1,307	1,527
2000	532	1,998	2,530	195	1,316	1,511
2001	491	1,809	2,300	248	1,490	1,738
2002	800	2,262	3,062	257	1,524	1,781
2003	1,230	1,139	2,369	979	1,066	2,045
2004	1,956	980	2,936	1,145	756	1,901
2005	1,967	968	2,935	1,296	812	2,108
Total	8065	12603	20668	4340	8271	12611

differences as instruments, therefore the available sample size becomes smaller. Columns 5-7 indicate the number of observations by year for this smaller sample. This table also indicates the number of multinationals and non-multinationals in each year of the sample. This is largely due to the composition of the sample which includes only R&D performing firms and higher proportion of medium to large firms than the general population. These types of firms are more likely to be multinationals. When the entire BERD 1998-2005 dataset is divided into foreign and UK owned, over 50% of observations are foreign owned implying more than half of observations have multinational status. When the ARD is categorised into non-multinational, foreign owned and UK multinational, the majority of observations fall into the non-multinational category.

Tables 2.8 and 2.9 provide some average values with standard deviations. The mean statistics indicate that multinationals tend to be larger than non-multinationals. On average multinationals firms have higher output, capital stock, levels of knowledge stocks and more R&D employees and total employees. The capital to labour ratio and labour productivity also vary significantly across groups with particularly high values for foreign multinationals. Standard deviations are large suggesting a broad range of values exist

Table 2.8: ARD-BERD Sample Summary Statistics

Non-Multinational (N=8065)					
	mean	**s.d.**	**median**	**skewness**	**kurtosis**
Gross Value Added	16130.35	182721.80	2599.00	34.90	1451.38
Capital Stock	9839.48	220904.10	652.05	75.88	6312.61
No. Employees	425.66	5149.74	112.00	33.80	1232.79
No. R&D Employees	10.12	120.03	1.44	34.85	1382.03
Capital-Labour Ratio	94.52	4691.72	5.86	63.33	4025.46
Labour Productivity	109.27	3479.32	24.01	60.90	3903.01
In-house R&D Stock	3175.66	43212.69	240.00	38.21	1668.91
Knowledge Spillover	174.57	2509.82	0.00	28.22	942.49
Knowledge Transfers	296.77	4153.99	9.87	28.10	929.95
Knowledge Transfers UK	206.38	3135.61	7.25	31.66	1182.16
Knowledge Transfers F	90.39	1549.54	1.38	35.02	1439.73
UK Multinational (N=1112)					
	mean	**s.d.**	**median**	**skewness**	**kurtosis**
Gross Value Added	111083.80	636522.30	10460.00	10.81	138.02
Capital Stock	66638.76	717086.80	5144.83	21.72	496.80
No. Employees	1336.32	6245.61	330.00	11.72	160.32
No. R&D Employees	46.30	270.10	4.18	10.78	128.41
Capital-Labour Ratio	2827.86	76642.50	15.31	32.65	1079.82
Labour Productivity	5422.00	121718.80	33.99	30.78	988.10
In-house R&D Stock	22659.87	135425.50	1233.29	10.81	131.90
Knowledge Spillover	480.62	5650.25	0.00	16.57	292.65
Knowledge Transfers	3748.48	41732.76	38.72	22.92	602.42
Knowledge Transfers UK	1759.42	14507.10	27.41	16.04	324.10
Knowledge Transfers F	1989.06	28743.06	7.30	24.53	666.12
Foreign Multinational (N=11491)					
	mean	**s.d.**	**median**	**skewness**	**kurtosis**
Gross Value Added	48743.11	287000.90	8822.00	22.45	668.06
Capital Stock	38462.71	285546.30	4339.80	29.48	1189.14
No. Employees	1262.52	10002.90	310.00	38.06	2094.69
No. R&D Employees	29.29	142.97	3.44	11.46	167.10
Capital-Labour Ratio	890.51	34312.69	13.59	57.58	3525.27
Labour Productivity	1142.66	42008.86	28.79	66.05	5049.26
In-house R&D Stock	13976.96	84049.96	717.45	13.90	247.42
Knowledge Spillover	276.36	3949.84	0.00	28.62	1008.23
Knowledge Transfers	2220.64	25437.11	21.47	23.63	697.90
Knowledge Transfers UK	1309.72	12227.79	14.59	16.84	338.79
Knowledge Transfers F	910.92	15730.35	3.66	36.02	1579.09

Table 2.9: GMM Sample Summary Statistics

	mean	s.d.	median	skewness	kurtosis
Non-Multinational (N=4340)					
Gross Value Added	22536.94	230650.00	3860.13	29.18	993.92
Capital Stock	15731.56	299260.30	1464.01	56.61	3478.93
No. Employees	603.71	6455.76	156.00	27.22	801.51
No. R&D Employees	12.97	128.94	1.75	30.24	1055.19
Capital-Labour Ratio	165.58	6394.57	8.81	46.46	2166.17
Labour Productivity	157.55	4693.94	25.45	45.90	2186.69
In-house R&D Stock	5047.69	56865.50	460.18	30.13	1016.05
Knowledge Spillover	188.89	2745.04	0.00	28.81	958.00
Knowledge Transfers	455.09	5289.43	21.21	23.15	619.88
Knowledge Transfers UK	310.88	3886.45	15.53	26.35	817.06
Knowledge Transfers F	144.21	2051.62	3.17	27.49	863.70
UK Multinational (N=867)					
	mean	**s.d.**	**median**	**skewness**	**kurtosis**
Gross Value Added	127821.50	709139.20	12362.00	9.89	113.81
Capital Stock	79910.88	810280.90	6842.78	19.27	389.79
No. Employees	1495.98	6806.29	380.00	11.15	142.47
No. R&D Employees	50.75	285.59	4.36	10.44	119.77
Capital-Labour Ratio	3613.95	86793.27	17.41	28.82	841.50
Labour Productivity	6929.42	137828.00	34.31	27.17	770.05
In-house R&D Stock	26852.34	149183.80	1597.18	10.01	112.18
Knowledge Spillover	508.43	6017.82	0.00	16.29	278.27
Knowledge Transfers	4003.45	42889.88	50.63	24.25	654.33
Knowledge Transfers UK	1940.87	15013.01	35.78	16.23	333.44
Knowledge Transfers F	2062.57	29711.93	10.59	25.87	714.09
Foreign Multinational (N=7404)					
	mean	**s.d.**	**median**	**skewness**	**kurtosis**
Gross Value Added	54247.51	306613.50	10538.50	21.76	613.53
Capital Stock	46248.83	332668.60	5773.66	27.45	980.06
No. Employees	1447.51	11248.80	359.50	37.03	1915.17
No. R&D Employees	35.05	160.38	4.00	10.27	132.79
Capital-Labour Ratio	1235.52	42225.34	15.84	47.68	2381.55
Labour Productivity	1081.52	30498.61	29.66	48.69	2668.99
In-house R&D Stock	18976.16	100419.50	1096.89	11.88	179.48
Knowledge Spillover	293.68	3956.31	0.00	24.21	673.25
Knowledge Transfers	3066.25	30606.28	32.02	20.04	499.64
Knowledge Transfers UK	1815.32	14870.39	22.19	14.17	236.80
Knowledge Transfers F	1250.94	18676.30	6.02	31.17	1179.62

within each group.

Table 2.10: Number of Changes from Domestic to Multinational Status

	ARD-BERD Sample			**GMM Sample**		
Year	**No Change**	**Change**	**Total**	**No Change**	**Change**	**Total**
1998	2361	0	2361	-	-	-
1999	1989	186	2175	1341	186	1527
2000	2471	59	2530	1452	59	1511
2001	2222	78	2300	1660	78	1738
2002	2961	101	3062	1680	101	1781
2003	2328	41	2369	2004	41	2045
2004	2877	59	2936	1842	59	1901
2005	2838	97	2935	2011	97	2108
Total	20047	621	20668	11990	621	12611

Table 2.10 indicates the number of changes between multinational and non-multinational status in either direction. All changes in status are from domestic to multinational status. Changes become important when using fixed effects because variables that remain constant over time are swept out of the model. The table suggests that relatively few changes occur compared to the number of observations.

2.5 Estimation Results

In this section the estimation results are interpreted and discussed. Estimations were performed using OLS, Weighted Least Squares (WLS) , Fixed Effects (FE), two-stage least squares (2SLS) and System GMM. The OLS, WLS, 2SLS and system GMM models include year and industry dummies. Standard errors are clustered by enterprise unit in the OLS and FE models[29]. The GMM method is applied to 2SLS to provide efficient estimates in the presence of heteroscedasticty and two-step system GMM with Windmeijer (2005) standard errors is applied. The key findings are presented in this results section and robustness checks are found in the appendix. Results for the basic model using each methodology are initially displayed and subsequent tables provide two-step System GMM results. This is the preferred methodology. The subsequent results include interaction terms and allow for labour to be separated by R&D and non-R&D workers. Estimations are also performed and compared for sub-samples of the data by multinational status.

The progression in the methodology is described as follows. OLS simply provides a baseline specification as a point of reference to compare with other specifications. Estimates are likely to be biased because they do not account for endogeneity. WLS is used because the descriptive statistics suggest that the sample is biased towards medium sized firms. The regression is weighted by the inverse sampling probability in order to generate estimates that are consistent for the population of innovating firms despite a non-random sample.

Fixed effects is the most frequently used method of correcting for endogeneity arising from unobserved heterogeneity with panel data. A disadvantage of this method is that it assumes the unobserved firm specific characteristics remain constant over time and wipes out useful interfirm variation. This variation accounts for a large proportion of the total variation in this relatively short panel and time-consistent measurement error bias may be accentuated. Other papers in the literature have also found that the relationship between productivity and R&D stock is less robust in the time-series dimension than in

[29] The cluster option is not available when the the svy command is used for WLS.

cross-sectional data (Griliches (1984), Hu et al. (2005)).

The 2SLS instrumental variables approach offers an alternative approach to dealing with the endogeneity problem. Instruments should be correlated with the inputs but uncorrelated with the unobserved error term. Following Jaffe (1986) and Hu et al. (2005), four digit industry averages of input variables are used as instruments for the input variables. These instruments aim to capture industry conditions and are independent of firm specific characteristics. This controls for unobserved industry specific shocks and, unlike fixed effects, does not sweep away firm specific characteristics, such as intangible managerial capabilities. This model is exactly identified because each instrument is derived from an explanatory variable, therefore the number of instruments equates to the number of endogenous variables. Post-estimation test of instrument validity require over-identification of the model therefore cannot be performed in this instance. The Shea Partial R^2 tests the validity of instruments by confirming the correlation between instruments and endogenous variables. The null hypothesis cannot be rejected at the 10% level implying that the instruments are weak and estimated coefficients will be biased.

Two-stage System GMM is the preferred methodological approach. Lagged first differences provide suitable instruments according to the Hansen test, therefore endogeneity should be accounted for and estimates should be unbiased. The Windmeijer (2005) correction for standard errors provides reliable t-statistics. Less observations are available for this model because 2 years of consecutive data are required to create the first-differenced instruments.

The results reported in table 2.11 show the estimated coefficients and standard errors for the basic estimating equation with each methodological approach. The results remain fairly consistent regardless of the methodology used. The basic Cobb-Douglas estimating equation has no interaction terms and labour is represented by total employment. In all specifications capital and labour have significant positive effects on output. The size of the coefficients on labour and capital are larger in the OLS, WLS, and 2SLS models than in the FE, GMM models. The size of the coefficients in the system GMM model on capital and labour appear to be slightly low compared with other estimates using UK firm-level data from the ARD reported by Harris and Robinson (2003), but this could be due to the industry composition of the R&D performing firm sample. The size of the coefficients on capital and labour in the OLS and 2SLS models are smaller than the coefficients on the equivalent model in the Hu et al. (2005) paper, which may indicate that output is more sensitive to changes in labour and capital for Chinese firms than for UK firms. Firms' own stock of R&D (K^R) also has a positive and significant effect on output. The size of the coefficient is larger than the coefficient for in-house R&D stock in Hu et al. (2005), suggesting that UK firms see a greater increase in output than Chinese firms for a given increase in in-house R&D stock, other things held constant.

Knowledge transfers (K^T) have a significant negative impact on output. Knowledge transfers represent new knowledge bought through market transactions from external sources. This finding is consistent with Hu et al. (2005) and may represent difficulties in understanding and applying information from external sources. Further analysis reveals that the coefficients remain negative and significant when knowledge transfers are separated out into transfers from foreign sources and UK sources. When $LogK^T$ is interacted with foreign ownership, the coefficient on $LogK^T$ remains negative and the coefficient on the interaction is positive, although very small and not significant. This indicates that the negative effect is still present for foreign owned firms. These results imply that the source of the transfer and foreign ownership do not influence this effect, although a more detailed breakdown of transfer sources and foreign ownership by country may highlight differences between developed and developing countries. Additional findings show that the effect differs across industry sectors. Analysis by industry indicates that knowledge transfers have a positive impact in the 'service' sector and also in the 'transportation, utilities and telecommunication' sector. For these sectors, an increase in knowledge transfers leads to an increase in output.

The knowledge spillover pool variable using the postcode method (K^S) has a positive significant effect on output in the OLS, IV and WLS models, but it is not significant in the FE or system GMM models. This suggests that location relative to other firms may play a role, but changes over time in the knowledge spillover pool for a given firm do not have an impact on productivity. This implies some persistence in behaviour. Those firms that benefit from the spillover pool continue to benefit and those that don't benefit do not change this pattern.

Table 2.11: Base Specification

	OLS	**WLS**	**FE**	**2SLS**	**GMM**
	logY	*logY*	*logY*	*logY*	*logY*
logC	0.361***	0.382***	0.100***	0.427***	0.120***
	(0.018)	(0.026)	(0.020)	(0.034)	(0.044)
logL	0.382***	0.304***	0.092***	0.350***	0.139***
	(0.024)	(0.044)	(0.013)	(0.045)	(0.041)
$logK^R$	0.119***	0.164***	0.033***	0.088***	0.049**
	(0.014)	(0.026)	(0.011)	(0.025)	(0.026)
$logK^S$	0.027***	0.036***	0.0064	0.044***	0.016
	(0.004)	(0.009)	(0.005)	(0.008)	(0.011)
$logK^T$	- 0.016***	-0.021***	-0.0043	-0.011**	- 0.015**
	(0.002)	(0.004)	(0.003)	(0.005)	(0.007)
Multinational	0.116***	0.118**	0.026	0.089***	0.254***
	(0.024)	(0.051)	(0.046)	(0.030)	(0.022)
Diversification	0.254***	0.299***	0.033*	0.225***	0.399***
	(0.027)	(0.073)	(0.019)	(0.027)	(0.053)
Constant	4.170***	3.684***	7.209***	3.811***	6.057***
	(0.282)	(0.303)	(0.162)	(0.283)	(0.376)
Observations	20668	20668	20668	20668	12611

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

The coefficient on the diversification dummy is significant in all columns of table 2.11. The positive value of the coefficient indicates that firms that are part of a diversified enterprise are more productive. The multinational dummies are positive and significant in all except FE and 2SLS. As shown in table 4 of the descriptive statistics, there are relatively few changes between multinational status. Therefore a non-significant multinational coefficient is expected in the FE estimates.

Table 2.12 and subsequent tables provide results using the preferred system GMM approach. Column 1 repeats the results of the basic specification for comparison. Column

Table 2.12: Knowledge Interactions using System GMM

	(1)	(2)	(3)	(4)	(5)
	$logY$	$logY$	$logY$	$logY$	$logY$
$logC$	0.120***	0.141***	0.150**	0.170**	0.163**
	(0.044)	(0.050)	(0.053)	(0.064)	(0.058)
$logL$	0.139***	0.143***	0.161***	0.165***	0.162***
	(0.041)	(0.043)	(0.040)	(0.041)	(0.039)
$logK^R$	0.049**	0.045*	0.057***	0.059***	0.054**
	(0.024)	(0.024)	(0.022)	(0.022)	(0.022)
$logK^S$	0.0160	0.012	0.013	0.007**	0.013
	(0.011)	(0.011)	(0.011)	(0.003)	(0.011)
$logK^T$	-0.015**	-0.019**	-0.014***	-0.014***	-0.014***
	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
Multinational	0.254***		0.247***	0.219***	0.225***
	(0.022)		(0.036)	(0.051)	(0.041)
UK Multinational		0.112**			
		(0.033)			
Foreign Multinational		0.262***			
		(0.028)			
$logK^R.logK^T$			-0.000	-0.001	
			(0.001)	(0.001)	
$logK^R.logK^S$				0.000	
				(0.001)	
$logK^R.logK^T_{UK}$					-0.001
					(0.001)
$logK^R.logK^T_F$					0.001
					(0.001)
Diversification	0.399***	0.376***	0.357***	0.350***	0.355***
	(0.053)	(0.053)	(0.053)	(0.054)	(0.052)
Constant	6.057***	5.965***	5.732***	5.555***	5.664***
	(0.376)	(0.410)	(0.418)	(0.463)	(0.438)
Observations	12611	12611	12611	12611	12611

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

2 extends the basic model by including separate dummy variables for foreign multinational and UK multinational. The results show UK and foreign multinationals to be more productive than domestic firms with a positive and significant effects on output. Output is 12% higher for UK multinationals and 30% higher for foreign multinationals than non-multinational firms, other things held constant.[30] The coefficient on foreign multinationals is larger than UK multinationals, implying that subsidiaries owned by foreign multinationals are more productive that those owned by UK multinationals. This is relatively consistent with the findings in Criscuolo and Martin (2009) which show US multinationals to be 42% more productive and other multinationals to be 30% more productive than British non-multinational plants using ARD data.

Knowledge interaction terms are introduced in the subsequent columns. The specification presented in column 3 includes the log interaction between firm's own R&D stock and knowledge transfers ($LogK^R.logK^T$) column 4 includes an interaction between firm's own R&D stock and the knowledge spillover pool ($LogK^R.logK^S$) and column 5 includes interactions between firm's own R&D stock and knowledge transfers from UK sources ($LogK^R.logK^T_{UK}$) and from foreign sources ($LogK^R.logK^T_F$). The coefficients on these variables are not significant at the 5% level. This suggests that in-house R&D stocks do not impact a firm's ability to productively utilise knowledge transfers from external sources. The literature postulates that experience and knowhow created through engagement in in-house R&D provides a greater capacity for that firm to absorb and utilise other knowledge sources. Yet the lack of significance of the coefficient implies that a firm does not increase its absorptive capacity by increasing its in-house R&D expenditure. [31] Table 2.13 focuses on labour. Again, column 1 provides the basic specification for comparison. Column 2 expands the basic specification by splitting labour into R&D employees (L^H) and non-R&D employees (L^L), where R&D employees is defined as the number of skilled science and technology R&D workers. The coefficient on non-R&D employees is strongly

[30]The coefficients on the dummy variables are converted into percentages using $100.(exp(\beta) - 1)$.

[31]Results using alternative methodologies are provided in the appendix. OLS and WLS provide small positive significant coefficients on interactions, but these are likely to be biased as endogeneity is not suitably accounted for. FE results concur with the system GMM findings.

Table 2.13: Labour Interactions using System GMM

	(1)	**(2)**	**(3)**	**(4)**
	logY	*logY*	*logY*	*logY*
$logC$	0.120***	0.127**	0.185**	0.185**
	(0.044)	(0.050)	(0.075)	(0.075)
$logL$	0.139***			
	(0.041)			
$logL^H$		0.017*	0.008	0.004
		(0.009)	(0.023)	(0.024)
$logL^L$		0.097***	0.131***	0.136***
		(0.036)	(0.035)	(0.035)
$logK^R$	0.049***	0.054**	0.086***	0.062***
	(0.024)	(0.024)	(0.025)	(0.020)
$logK^S$	0.016	0.015	0.014	0.018
	(0.011)	(0.012)	(0.011)	(0.012)
$logK^T$	-0.015**	-0.019**	-0.026***	-0.015***
	(0.007)	(0.008)	(0.008)	(0.005)
Multinational	0.254***	0.273***	0.247***	0.265***
	(0.022)	(0.029)	(0.062)	(0.058)
$logK^R.logL^H$			0.002	0.002
			(0.004)	(0.004)
$logK^T.logL^H$				0.003
				(0.002)
Diversification	0.399***	0.403***	0.343***	0.338***
	(0.053)	(0.053)	(0.054)	(0.053)
Constant	6.057***	6.181***	5.501***	5.589***
	(0.376)	(0.388)	(0.483)	(0.470)
Observations	12611	12611	12611	12611

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

significant, where a 1% increase in the number of non-R&D employees increases output by 0.1%. The coefficient on R&D employees is much smaller and less significant. This implies that non-R&D workers have a larger impact on value added output in the short-run, but the impact of R&D employees is expected to increase over future periods. The returns arising from R&D labour may take time to impact productivity. In columns 3 and 4, R&D labour is interacted with in-house R&D and knowledge transfers. These interactions aim to capture absorptive capacity intrinsic to the labour force. The coefficients on these variables are not significant, again providing no support for the notion of absorptive capacity. This evidence is inconclusive because number of R&D workers is an imperfect measure as it represents quantity rather than quality of the workers.

Column 1 of Table 2.14 focuses on differences between non-multinationals and multinationals by interacting the multinational dummy with the explanatory variables of the basic specification. An F-test indicates that the dummy and interaction terms are jointly significant. The individual findings show no significant differences between multinationals and non-multinationals in terms of knowledge variables, but differences in labour and capital. There is a positive coefficient on the multinational-capital interaction and a negative coefficient on the multinational-labour interaction. This implies that multinational firms have a greater output elasticity of capital than non-multinationals. Multinationals may transfer existing technology from their overseas operations to UK subsidiaries, thus enhancing productivity.

It is important to acknowledge that projects and R&D size differ between and within industries and firms. Projects can focus on product or process innovation, they can have a specific aim or be purely experimental. The extent of experimental R&D is likely to be related to firm performance as firms are more likely to invest in this type of research when profits are high. Some industry sectors are considered to be more R&D intensive, such as the pharmaceutical and electronics industries, where projects are costly and continuous innovation plays an important part in competition. Differences in R&D also exist within industries, some firms are more R&D intensive than their industry counterparts. These firms are likely to be at the forefront of their industry, acting as technology leaders with state of the art innovations. Columns 2 and 3 of table 2.14 investigate differences between high technology and low technology firms. Two methods were used to identify high technology firms. Both methods are based on R&D intensity, defined as the ratio of R&D expenditure to output. Method 1 identified high technology firms as those operating in the top quintile of R&D intensive industries and Method 2 identified high technology firms as those within the top quartile of R&D intensive firms. The results show no significant differences between high and low technology firms within the sample, regardless of the high technology definition.[32]

[32] No significant differences were found when high technology was defined at the top decile either.

Table 2.14: Multinational and High-Technology Interactions using System GMM

	(1)	(2)	(3)
	$logY$	$logY$	$logY$
$logC$	0.187**	0.165**	0.137**
	(0.076)	(0.083)	(0.054)
$logL$	0.244***	0.156**	0.126**
	(0.044)	(0.073)	(0.093***)
$logK^R$	0.112***	0.081**	0.093***
	(0.025)	(0.037)	(0.031)
$logK^S$	0.018	0.011	0.027*
	(0.011)	(0.015)	(0.015)
$logK^T$	-0.027***	-0.031***	-0.031***
	(0.006)	(0.012)	(0.011)
Multinational	0.203***	0.299***	0.215***
	(0.040)	(0.014)	(0.024)
Diversification	0.342***	0.372***	0.355***
	(0.050)	(0.046)	(0.052)
Mult.$logC$	0.100***		
	(0.030)		
Mult.$logL$	-0.128***		
	(0.038)		
Mult.$logK^R$	-0.021		
	(0.022)		
Mult.$logK^S$	-0.011		
	(0.010)		
Mult.$logK^T$	-0.005		
	(0.005)		
$Hi-Tech^{Industry}$		0.766	
		(0.721)	
$Hi-Tech^{Firm}$			-0.880
			(0.904)
$Hi-Tech.logC$		-0.059	0.076
		(0.080)	(0.120)
$Hi-Tech.logL$		-0.025	0.034
		(0.083)	(0.078)
$Hi-Tech.logK^R$		-0.024	-0.034
		(0.041)	(0.054)
$Hi-Tech.logK^S$		0.010	-0.020
		(0.019)	(0.021)
$Hi-Tech.logK^T$		0.016	0.011
		(0.014)	(0.016)
Constant	4.847***	5.448***	5.978***
	(0.416)	(0.661)	(0.531)
Observations	12611	12611	12611

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

2.6 Conclusion

The aim of this chapter was firstly, to investigate differences between multinationals and non-multinationals in terms of productivity and knowledge and secondly, to investigate the existence of complementarities between internal and external source of knowledge. The findings provide an interesting insight into the relationships between knowledge, productivity and multinational status. One of the distinguishing characteristics of this study is the data sample obtained from a unique combination of datasets. The sample provides particularly detailed firm-level data with a large number of observations. This allows contributions to the literature to be made by investigating the role for knowledge spillovers, distinguishing between skilled R&D and non-R&D labour and examining the robustness of previous findings using alternative data samples.

The results show that multinational firms are more productive than non-multinationals. Furthermore, foreign-owned multinationals are more productive than domestic-owned multinationals. This finding seems logical because multinationals possess intangible advantages that allowed them to break into foreign markets.

The basic findings regarding the relationship between knowledge and productivity are supported by previous studies. The stock of in-house R&D expenditure has a positive impact on output, whereas knowledge transfers from external sources have a negative impact on output. These findings remain consistent regardless of multinational status, although the impact of knowledge transfers varies across industries. It would be useful to investigate differences in R&D behaviour across industry sectors in further research. Increases in the number of skilled R&D employees may create a small positive impact on productivity in the short-term, but returns to number of skilled R&D employees may be greater in the medium-long term.

There is little conclusive evidence to support the existence of absorptive capacity, which contrasts some previous studies. The findings suggest that an increase in the stock of in-house R&D expenditure or an increase in number of R&D workers does not improve a firm's ability to productively utilise knowledge from external sources, via transfers or spillovers. This result should be viewed with caution because R&D expenditure and number of R&D workers are imperfect measures of knowledge. They measure inputs into the R&D process and therefore do not perfectly represent the quality of knowledge created.

Differences in productivity between multinationals and non-multinationals are partly attributable to differences in the productivity of capital and labour. Multinational firms obtain higher returns to capital and lower returns to labour than their non-multinational counterparts. This implies that multinational firms have access to better machinery or utilise their equipment more effectively, suggesting evidence of technology transfer form other countries. The remainder of the productivity difference may be attributed to intangible knowledge that is not captured by the R&D expenditure based measure of knowledge stock. Intangible knowledge may include factors such as managerial skills, marketing and other forms of immeasurable know-how.

2.7 Appendix

Table 2.15: Robustness Checks

Description
Variable Creation
• Different small numbers were used to replace zero values for knowledge variables to prevent missing numbers being created when logged.
• Different weightings for knowledge spillover variable
• Different depreciation rates for knowledge stock variables
• Different definitions of domestic and multinational firms
• Share of R&D employees rather than number of R&D employees
Samples
• Zero values for knowledge variables dropped from sample
• Multinational sample
• Non-Multinational sample
• High-tech samples
Functional Form and Restrictions
• Translog
• Constant Returns to Scale

Various checks were performed to validate the robustness of the results. These include estimation using different methodological approaches, specifications and sub-samples and assumptions of variable creation as outlined in table (2.15). Tables (2.16) to (2.21) show results for different specifications and methodological approaches. Tables (2.22) to (2.24) show results for subsamples. The findings generally support the key conclusions presented in chapter 2, although some significant coefficients appear on the knowledge interaction terms in the OLS and WLS models. These results are considered to be invalid as they do not control for endogeneity.

Table 2.16: Base Specification with UK and Foreign Multinational Dummies

	OLS	**WLS**	**FE**	**2SLS**
	logY	*logY*	*logY*	*logY*
log C	0.362***	0.361***	0.0999***	0.382***
	(0.0183)	(0.0195)	(0.0199)	(0.0257)
log L	0.381***	0.381***	0.0919***	0.294***
	(0.0234)	(0.0269)	(0.0128)	(0.0433)
log K^R	0.120***	0.121***	0.0317***	0.162***
	(0.0144)	(0.0293)	(0.0117)	(0.0257)
log K^S	0.0278***	0.0647***	0.00469	0.0404***
	(0.00524)	(0.0112)	(0.00622)	(0.0122)
log K^T	-0.0160***	-0.0145***	-0.00443*	-0.0212***
	(0.00215)	(0.00542)	(0.00259)	(0.00433)
Diversification	0.250***	0.247***	0.0331*	0.264***
	(0.0274)	(0.0277)	(0.0194)	(0.0692)
Foreign Multinational	0.0965***	0.0940***	0.0138	0.115**
	(0.0230)	(0.0255)	(0.0396)	(0.0498)
UK Multinational	0.0883***	0.0838***	0.0273	0.0811***
	(0.0310)	(0.0316)	(0.0217)	(0.0308)
Constant	4.203***	4.191***	7.227***	3.767***
	(0.283)	(0.281)	(0.162)	(0.310)
Observations	20668	20668	20668	20668

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.17: Base Specification with Knowledge Interaction

	OLS	**WLS**	**FE**	**2SLS**
	logY	*logY*	*logY*	*logY*
$logC$	0.359***	0.374***	0.0999***	0.428***
	(0.0182)	(0.0250)	(0.0199)	(0.0342)
$logL$	0.378***	0.297***	0.0915***	0.349***
	(0.0234)	(0.0423)	(0.0129)	(0.0455)
$logK^R$	0.119***	0.165***	0.0331***	0.0879***
	(0.0138)	(0.0235)	(0.0113)	(0.0249)
$logK^S$	0.0262***	0.0354***	0.00638	0.0443***
	(0.00410)	(0.00896)	(0.00475)	(0.00849)
$logK^T$	-0.0442***	-0.0858***	-0.00505	-0.0271*
	(0.00764)	(0.0124)	(0.00642)	(0.0141)
$logK^R.logK^T$	0.00380***	0.00942***	0.000114	0.00240
	(0.00108)	(0.00170)	(0.00102)	(0.00236)
Multinational	0.124***	0.131***	0.0261	0.0893***
	(0.0246)	(0.0504)	(0.0463)	(0.0300)
Diversification	0.244***	0.262***	0.0330*	0.220***
	(0.0270)	(0.0658)	(0.0194)	(0.0276)
Constant	4.200***	3.719***	7.209***	3.826***
	(0.284)	(0.309)	(0.162)	(0.284)
Observations	20668	20668	20668	20668

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.18: Base Specification with Knowledge Interactions

	OLS	**WLS**	**FE**	**2SLS**
	logY	*logY*	*logY*	*logY*
$logC$	0.359***	0.374***	0.0998***	0.428***
	(0.0182)	(0.0250)	(0.0199)	(0.0342)
$logL$	0.378***	0.298***	0.0918***	0.349***
	(0.0234)	(0.0419)	(0.0129)	(0.0457)
$logK^R$	0.117***	0.161***	0.0322***	0.0854***
	(0.0142)	(0.0231)	(0.0115)	(0.0260)
$logK^S$	0.0166	0.0174	-0.00211	0.0311
	(0.0135)	(0.0336)	(0.0133)	(0.0261)
$logK^T$	-0.0438***	-0.0850***	-0.00486	-0.0261*
	(0.00756)	(0.0124)	(0.00642)	(0.0140)
$logK^R.logK^T$	0.00373***	0.00931***	0.0000866	0.00224
	(0.00107)	(0.00170)	(0.00102)	(0.00235)
$logK^R.logK^S$	0.00142	0.00287	0.00116	0.00211
	(0.00201)	(0.00459)	(0.00186)	(0.00410)
Multinational	0.124***	0.131***	0.0256	0.0893***
	(0.0247)	(0.0505)	(0.0464)	(0.0301)
Diversification	0.244***	0.262***	0.0332*	0.220***
	(0.0270)	(0.0657)	(0.0194)	(0.0276)
Constant	4.211***	3.737***	7.214***	3.839***
	(0.285)	(0.313)	(0.162)	(0.284)
Observations	20668	20668	20668	20668

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.19: Labour Specification

	OLS	**WLS**	**FE**	**2SLS**
	logY	*logY*	*logY*	*logY*
log C	0.361***	0.372***	0.0996***	0.421***
	(0.0180)	(0.0250)	(0.0198)	(0.0338)
log L^H	-0.0393***	-0.0792***	-0.00397	-0.0497***
	(0.00869)	(0.0174)	(0.00506)	(0.0145)
log L^L	0.374***	0.349***	0.0907***	0.360***
	(0.0189)	(0.0320)	(0.0124)	(0.0400)
log K^R	0.157***	0.203***	0.0363***	0.125***
	(0.0155)	(0.0247)	(0.0117)	(0.0261)
log K^S	0.0264***	0.0334***	0.00611	0.0445***
	(0.00404)	(0.00890)	(0.00476)	(0.00838)
log K^T	-0.0167***	-0.0224***	-0.00470*	-0.0117**
	(0.00208)	(0.00449)	(0.00264)	(0.00483)
Multinational	0.0999***	0.0917*	0.0217	0.0898***
	(0.0240)	(0.0484)	(0.0465)	(0.0296)
Diversification	0.261***	0.293***	0.0337*	0.240***
	(0.0276)	(0.0642)	(0.0195)	(0.0278)
Constant	4.078***	3.469***	7.209***	3.726***
	(0.282)	(0.295)	(0.161)	(0.284)
Observations	20668	20668	20668	20668

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.20: Labour Specification with Labour Interaction

	OLS	**WLS**	**FE**	**2SLS**
	logY	*logY*	*logY*	*logY*
logC	0.360***	0.372***	0.0991***	0.419***
	(0.0176)	(0.0245)	(0.0198)	(0.0333)
$logL^H$	-0.0814***	-0.132***	-0.0159	-0.108***
	(0.0244)	(0.0367)	(0.0146)	(0.0366)
$logL^L$	0.372***	0.341***	0.0888***	0.358***
	(0.0191)	(0.0318)	(0.0125)	(0.0404)
$logK^R$	0.153***	0.207***	0.0368***	0.124***
	(0.0163)	(0.0225)	(0.0111)	(0.0260)
$logK^S$	0.0261***	0.0334***	0.00615	0.0431***
	(0.00405)	(0.00893)	(0.00476)	(0.00844)
$logK^T$	-0.0166***	-0.0224***	-0.00481*	-0.0122**
	(0.00209)	(0.00450)	(0.00261)	(0.00494)
$logK^R.logL^H$	0.00535*	0.00653	0.00162	0.00816
	(0.00312)	(0.00424)	(0.00214)	(0.00521)
Multinational	0.109***	0.0937*	0.0196	0.0856***
	(0.0252)	(0.0482)	(0.0462)	(0.0295)
Diversification	0.254***	0.274***	0.0331*	0.223***
	(0.0267)	(0.0604)	(0.0195)	(0.0287)
Constant	4.107***	3.462***	7.220***	3.753***
	(0.286)	(0.298)	(0.161)	(0.291)
Observations	20668	20668	20668	20668

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.21: Labour Specification with Labour Interactions

	OLS	**WLS**	**FE**	**2SLS**
	logY	*logY*	*logY*	*logY*
$logC$	0.359***	0.372***	0.0988***	0.419***
	(0.0176)	(0.0247)	(0.0197)	(0.0331)
$logL^H$	-0.0672***	-0.126***	-0.0140	-0.101**
	(0.0259)	(0.0393)	(0.0145)	(0.0402)
$logL^L$	0.371***	0.340***	0.0891***	0.357***
	(0.0190)	(0.0314)	(0.0125)	(0.0406)
$logK^R$	0.156***	0.208***	0.0381***	0.125***
	(0.0164)	(0.0222)	(0.0111)	(0.0253)
$logK^S$	0.0258***	0.0333***	0.00605	0.0428***
	(0.00406)	(0.00893)	(0.00475)	(0.00847)
$logK^T$	-0.0225***	-0.0240***	-0.00604**	-0.0144**
	(0.00328)	(0.00607)	(0.00270)	(0.00700)
$logK^R.logL^H$	0.00319	0.00563	0.00126	0.00700
	(0.00331)	(0.00441)	(0.00207)	(0.00606)
$logK^T.logL^H$	0.00279**	0.00114	0.000653	0.00155
	(0.00111)	(0.00187)	(0.000736)	(0.00280)
Multinational	0.113***	0.0952**	0.0196	0.0867***
	(0.0252)	(0.0481)	(0.0461)	(0.0294)
Diversification	0.252***	0.274***	0.0333*	0.222***
	(0.0268)	(0.0607)	(0.0195)	(0.0286)
Constant	4.107***	3.460***	7.213***	3.754***
	(0.288)	(0.299)	(0.160)	(0.291)
Observations	20668	20668	20668	20668

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.22: High-Technology Subsamples using System GMM

	Industry 25%	**Industry 10%**	**Firm 25%**	**Firm 10%**
	logY	*logY*	*logY*	*logY*
log C	0.0880**	0.0951	0.207*	0.146
	(0.0436)	(0.0820)	(0.114)	(0.110)
log L	0.136***	0.250***	0.149***	0.124**
	(0.0473)	(0.0654)	(0.0505)	(0.0600)
log K^R	0.0741***	0.150***	0.0513	0.112
	(0.0267)	(0.0395)	(0.0415)	(0.0728)
log K^S	0.0284*	0.0384**	0.00759	0.00771
	(0.0145)	(0.0162)	(0.0157)	(0.0269)
log K^T	-0.0174**	-0.0138	-0.0201*	-0.0149
	(0.00876)	(0.0107)	(0.0121)	(0.0168)
Multinational	0.259***	0.217***	0.223***	0.202***
	(0.022)	(0.071)	(0.050)	(0.035)
Diversification	0.330***	0.220***	0.305***	0.355***
	(0.0571)	(0.0490)	(0.0738)	(0.110)
Constant	6.130***	5.089***	5.143***	5.062***
	(0.366)	(0.458)	(0.593)	(0.742)
Observations	8468	4201	5359	2293

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.23: Multinational Interactions using Hi-Tech Subsamples and System GMM

	Industry 25%	**Industry 10%**	**Firm 25%**	**Firm 10%**
	logY	*logY*	*logY*	*logY*
log C	0.127*	0.161	0.198**	0.114
	(0.0666)	(0.102)	(0.0934)	(0.0775)
log L	0.250***	0.311***	0.301***	0.375***
	(0.0513)	(0.0677)	(0.0672)	(0.0731)
log K^R	0.155***	0.227***	0.165***	0.251***
	(0.0257)	(0.0472)	(0.0452)	(0.0546)
log K^S	0.0260*	0.0305*	0.0135	0.0162
	(0.0140)	(0.0166)	(0.0166)	(0.0195)
log K^T	-0.0325***	-0.0226**	-0.0212**	-0.0148
	(0.00682)	(0.00930)	(0.00972)	(0.0115)
Multinational	0.211***	0.198***	0.210***	0.197***
	(0.017)	(0.051)	(0.041)	(0.021)
Diversification	0.290***	0.176***	0.224***	0.285***
	(0.0454)	(0.0455)	(0.0530)	(0.0822)
Mult.log C	0.146***	0.135**	0.256***	0.292***
	(0.0379)	(0.0527)	(0.0655)	(0.0754)
Mult.log L	-0.133***	-0.124*	-0.211***	-0.318***
	(0.0473)	(0.0677)	(0.0604)	(0.0793)
Mult.log K^R	-0.0686***	-0.0674*	-0.122**	-0.0828
	(0.0241)	(0.0400)	(0.0503)	(0.0682)
Mult.log K^S	-0.0000548	0.0310	-0.0132	0.0130
	(0.0134)	(0.0196)	(0.0174)	(0.0292)
Mult.log K^T	-0.00429	-0.00987	-0.00700	-0.00505
	(0.00623)	(0.0111)	(0.00980)	(0.0127)
Constant	4.937***	3.988***	3.887***	3.253***
	(0.340)	(0.381)	(0.310)	(0.411)
Observations	8468	4201	5359	2293

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2.24: Multinational Subsamples using System GMM

	All	**Multinational**	**Non-Multinational**
	logY	*logY*	*logY*
log C	0.120***	0.180**	0.0654
	(0.0438)	(0.0716)	(0.0458)
log L	0.139***	0.113***	0.353***
	(0.0406)	(0.0415)	(0.0713)
log K^R	0.0489**	0.0413	0.163***
	(0.0235)	(0.0253)	(0.0408)
log K^S	0.0160	0.0168	0.00419
	(0.0114)	(0.0126)	(0.0255)
log K^T	-0.0152**	-0.0161**	-0.0289**
	(0.00736)	(0.00790)	(0.0121)
Multinational	0.254***		
	(0.022)		
Diversification	0.399***	0.404***	0.135
	(0.0525)	(0.0610)	(0.0986)
Constant	6.057***	6.708***	4.830***
	(0.376)	(0.670)	(0.480)
Observations	12611	8271	4340

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

3 Literature Review

3.1 Introduction

In the subsequent chapters of this thesis the term 'event' refers to firm restructuring events, including acquisitions, mergers, change of ownership, divestments, break-ups and trade-sales. This review of the literature covers studies of acquisitions, mergers and divestment. There are a number of studies investigating merger and acquisition events, but fewer have investigated divestment. Previous studies have not investigated other events types due to data limitations.

Post-event outcomes are highly dependent on the underlying objectives of the firm's strategy, therefore it is important to discuss pre-event characteristics as drivers of post-event outcomes. Characteristics can give some indication of the type of firms undertaking these events and a sense of the underlying motives.

This section provides a summary of papers from the economics and management literature. Firstly, a theoretical background to this literature is provided, secondly, pre-merger and acquisition (M&A) characteristics are discussed, thirdly, post-M&A innovation outcomes, fourthly, productivity outcomes and foreign acquisition and finally, pre-divestment characteristics and post-divestment outcomes. A summary of the key findings in the literature concludes this section.

3.2 Distinguishing between Event Types

"Joining events" can be used as a term to broadly define a scenario where two or more firms join together. Manne (1965) observes the market for corporate control and identifies three mechanisms of gaining control of a target. These include proxy fights, direct purchase of shares and merger. A proxy fight describes a scenario where the acquirer attempts to convince shareholders of the target firm that the management should be replaced. This form of takeover is more common when the company shares are widely distributed, rather than when there are large holdings. This type of takeover may be seen as a compromise if the acquirer is unable to raise sufficient capital to buy control and reveals a willingness to share potential gains with other shareholders as payment for their vote. Shareholders are more likely to side with the acquirer if they are unsatisfied with the current management of the the target firm.

Another method of taking control of a target firm is via buy-outs with the direct purchase of shares. If the acquirer purchases a sufficient proportion of shares, they have the majority vote on governance proposals and therefore have control of the firm. Shares can be bought on the open market, via private negotiations with existing shareholders or by asking for tender offers. A tender offer is an offer from existing shareholders to sell shares to the acquirer at set price above the market value.

The merger differs from the previous mechanisms for gaining control in two major ways. Control is generally obtained through the exchange of shares rather than cash buy-outs and the merger is recommended by existing management. The 'Acquired' firm and the 'acquirer' are expected to have different characteristics because the 'acquirer' is in a dominant position, whereas the acquired target is vulnerable. Previous applied work has struggled to distinguish between the acquired firm and the acquiring firm, yet clearly we expect important differences between them. The merger event category consists of merger targets and merger acquirers, therefore there may be more variability within this category.

A 'change of ownership' indicates a situation where the firm becomes owned by a new majority shareholder enterprise group that has not existed previously in the UK. Therefore this event category also consists of firms that have been acquired by foreign enterprise groups that have not had any majority holdings in the UK before.

The term "separating events" can be used to jointly describe corporate actions where an enterprise splits itself into separate sections. These are known as divestments or demergers and can occur in various different ways. One mode of separation involves the creation of spin-off firms from the parent firm. The spin-off firm[33] takes assets, intellectual property, technology or products from the parent firm. Shareholders of the parent firm are reimbursed for this loss of assets with sufficient shares in the spin-off firm, therefore ownership of both spin-off and parent remains consistent at the time of divestment. The distribution of ownership changes as the shares are traded. In this type of separation there is no cash flow to the parent. The management team of the spin-off firm are often from the parent firm. Often market value will increase prior to a spin-off announcement (Krishnaswami and Subramaniam, 1999). This could be due to a expected increase in focus for both firms .

Another method of separation is via equity carve-outs. These events involve the creation of partial spin-offs or split-off IPOs. The new firm is launched on the stock market as a separate entity from the parent firm. Generally a proportion of the shares are retained for the existing shareholders of the parent firm and the remainder are offered to the public (Slovin et al., 1995). This mode of divestment creates cash flows for the parent firm. The 'divested', 'divestor' and 'breakup' events from the data can be defined in relation to this discussion. The 'divestor' belongs to the parent enterprise group and the 'divested' firm is the spin-off or partial spin-off from the enterprise group. The mode of divestment may or may not involve cash-flows for the parent firm because this cannot be distinguished from the data. A 'break-up' is an event that generates two or more separate firms and the parent enterprise group ceases to exist in the UK. The enterprise group could continue to exist elsewhere if it is multinational. The 'break-up' situation can occur in various different ways. Separation could be established by distributing ownership of shares for the new enterprise groups among existing shareholders or could represent two of more simultaneous divestments from a foreign parent, which may or may not generate cash for the parent group.

An asset sell-off, asset sale or trade-sale is another mode of divestment that generates cash funds for the parent. Shares from the divested firm are sold to an acquiring firm. The

[33] Also known as split-offs, spin-outs or starbursts.

parent may maintain part ownership of the firm of transfer ownership entirely (John and Ofek, 1995). From an industry perspective, this event combines separating and joining events. This type of situation is indicated by the 'tradesale' event in my data. This event category is assigned to the firm that undergoes a change in ownership from the divesting parent to the acquiring parent. This type of event is likely to generate cash flows for the divesting parent. Furthermore, the situation where a 'break-up' firm becomes owned by a foreign enterprise group is a trade-sale where the acquirer is likely to be an existing foreign enterprise group that has no previous majority ownership of firms within the UK.

Some demographic events can be defined as voluntary and others as involuntary. 'Takeover', 'divested' and 'tradesale' are generally assumed to be involuntary events, where the enterprise group has ultimate power over the decision and the target has no control. 'Acquirer' and 'divestor' appear to be voluntary events, although in some situations a firm may appear as an 'acquirer' or 'divestor' in the data but the decision is made at the enterprise group level. The decision maker in 'merger', 'break-up' or 'change of ownership' events cannot be distinguished.

In summary, this overview has outlined the differences between event types. It is preferable to disaggregate event types rather than consolidate them into fewer groups. This allows the data to identify similarities or differences between the types of firms engaging in each event type. The data used in this study benefits from the capacity to identify these detailed events. A drawback to the data is that it is impossible to distinguish between events that involve cash transfers and those that do not. The transfer of cash can influence motivations for divestment and takeover.

3.3 Theory

3.3.1 Economic Motivations for Joining Events

The application of the Cournot framework to the horizontal merger situation by Salant et al. (1983) assumes that a reduction in competition is the only motivation for firms to join together. When the assumption of constant costs and symmetric firms is imposed, joining firms may see a reduction in post-event joint profit, leaving profit maximising firms with no incentive to enter into a merger or acquisition. This self proclaimed "bizarre" result is known as the merger paradox. Subsequent papers relaxed the strong assumptions of this model to provide profit-based motivations for M&A. These extensions include the incorporation of non-symmetric firms, economies of scale, knowledge synergies and price-setting behaviour. Alternatively, managers may pursue goals other than profit maximisation. This section provides a discussion of these theories.

The seminal paper by Salant et al. (1983) applies the Cournot framework to the situation of horizontal mergers. The model assumes that an industry consists of n symmetric profit maximising firms. These firms face linear demand and constant marginal costs. Economies of scale are assumed away and the only motivation for merger is a decrease in market competition. The number of firms joining by merger is $m+1$. These firms are described as insiders, whereas the residual $n-m-1$ firms are the non-merging outsiders. The joint change in insider profits resulting from a merger is given by $g(n,m)$.

$$g(n,m) = \pi^{C}(n,m) - \pi^{NC}(n,m) \tag{3.1}$$

Where $\pi^{C}(n,m)$ represents post-merger insider joint profit and $\pi^{NC}(n,m)$ represents pre-merger insider joint profit. Given that firms are symmetric and there are $m+1$ insiders, $\pi^{NC}(n,m)$ can be defined as follows.

$$\pi^{NC}(n,m) = (m+1)\pi(n) \tag{3.2}$$

The merged insider firms combine to become one firm, therefore the post-merger industry consists of $n-m$ symmetric firms. Due to the additional assumption of constant marginal costs, the merged firm behaves identically to the remaining $n-m-1$ outsiders.

$$\pi^{C}(n,m) = \pi(n-m) \tag{3.3}$$

Assuming a linear demand function $P = \beta - \sum_{i=1}^{n} Q_i$. Profit is given by $\pi(n) = (P - \alpha)Q$, where α is constant marginal costs. Each firm aims to maximise profits by selecting the profit maximising output.

$$\max_{Q_j \geq 0} Q_j[\beta - Q_j - \sum_{i \neq j} Q_i - \alpha] \tag{3.4}$$

$$\beta - 2Q_j - \sum_{i \neq j} Q_i - \alpha = 0 \tag{3.5}$$

Output for each firm is identical in a symmetric Nash equilibrium, therefore $Q_i = Q_j = Q$.

$$\beta - 2Q - (n-1)Q - \alpha = 0 \tag{3.6}$$

$$Q = \frac{\beta - \alpha}{n+1} \tag{3.7}$$

The demand function and equilibrium output 3.7 can be substituted into the profit function to yeild equation 3.10.

$$\pi(n) = (P - \alpha)Q \tag{3.8}$$

$$\pi(n) = (\beta - nQ - \alpha)Q \tag{3.9}$$

$$\pi(n) = ([\beta - \alpha]/[n+1])^2 \tag{3.10}$$

The change in insider profits following the merger can now be expressed as follows.

$$g(n,m) = \left[\frac{\beta - \alpha}{n - m + 1}\right]^2 - (m+1)\left[\frac{\beta - \alpha}{n+1}\right]^2 \tag{3.11}$$

$$= (\beta - \alpha)^2 \left(\left[\frac{1}{n - m + 1}\right]^2 - (m+1)\left[\frac{1}{n+1}\right]^2 \right) \tag{3.12}$$

The profitability of the merger depends upon the number of insider firms in the coalition and the number of firms in the industry. A merger is profitable when $g(n,m) > 0$. This requires that $(n - m + 1)^{-2} > (m+1)(n+1)^{-2}$. Losses from merger are greater as the number of insider firms increases, but merger to monopoly is always profitable.

The logic that leads to a merger paradox situation is based on the idea that although industry profits and per firm profits increase following a decrease in industry concentration, the merged firms reduce output comparative to pre-merger joint output. Reduced industry output leads to an increase in price and the outsiders increase output accordingly. Industry output and profits are equivalent for each post-merger firm. This amount is less than the combined pre-merger profit for the insider firms. For insider firms there is no incentive for the merger to take place unless it results in monopoly. But a merger is beneficial for outsider firms within the industry because they will have increased post-merger profits.

There are several strong assumptions that generate this conclusion. Firstly, insider firms display a reduction in joint post-merger output and the assumption of constant marginal costs allows rival outsider firms to increase output to the same level as the merged firm as a response to a reduction in industry output. This result seems counterintuitive. Managers seek growth as a means of growing their empire, increasing remuneration and perks, etc. Economies of scale act as a motive for growth. Secondly, non-symmetric firms differences in size, state of technology can influence post-merger outcomes. These assumptions are relaxed in subsequent papers.

Perry and Porter (1985) argue that the combined productive capacity of the merged firm is greater than its component parts. They look at the incentive for two small firms to merge into one large firm. The model assumes that each firm is endowed with a share of industry capital stock and industry capital stock is fixed. This assumption rules out greenfield entry into the industry or investment on internal growth by existing firms. Merger is the only method of increasing capital stock. The industry is assumed to consist of n *large* oligopolists each with share of capital s and m *small* oligopolists each with a share of capital $s/2$. Total capital in the industry is assumed to sum to 1, therefore $sn + (s/2)m = 1$.

Each firm faces a cost function which depends on the share of capital owned by the firm and the amount of output produced. C is linearly homogeneous in output and capital, which rules out scale economies as a motive for merger. A proportionate increase in output and capital will lead to a proportionate increase in costs. This places focus on the incentives to merge relating to firm size and market conditions rather than efficiency improvements gained through economies of scale. Capital is assumed to be fixed therefore each firm faces an upwards sloping marginal cost curve with respect to output. The assumption of increasing marginal costs makes output expansion less attractive to outsiders.

Demand and marginal costs are assumed to be linear functions of output. The cost function for a firm with capital stock S is defined as follows, where g represents industry fixed costs.

$$C(x, S) = Sg + dx + (e/2S)x^2 \tag{3.13}$$

Differentiating costs with respect to output generates the marginal cost function, where d is the intercept.

$$C'(x, S) = d + (e/S)x \tag{3.14}$$

A change in S causes the marginal cost function to pivot about the intercept. Small firms with $s/2$ capital join together to create a merged firm with s capital, therefore the merged firm faces the same cost function as the large firms. The industry demand function is given as follows, where Z represents industry output.

$$P(Z) = a - bZ \tag{3.15}$$

e and b determine the slope of the marginal cost curve and demand function respectively.

V is total output supplied by the small firms and X is total output supplied by the large firms. Firm output depends on capital stock and a vector of variable inputs. Both types of firm have the same conjectural variation δ. The industry equilibrium is defined for small and large firms respectively as follows.

$$P(X+V)+(1+\delta)(V/m)P'(X+V)=C'((V/m),(s/2)) \tag{3.16}$$

$$P(X+V)+(1+\delta)(X/n)P'(X+V)=C'((X/n),s) \tag{3.17}$$

Using equations (3.14) and (3.15), the system can be solved to provide the output for the two types of firms as a function of n.

$$X(n)=\frac{(a-d)[b(1-\delta)+2e/s]n}{\Delta(n)} \tag{3.18}$$

$$V(n)=\frac{2(a-d)[b(1-\delta)+2e/s][1/s-n]}{\Delta(n)} \tag{3.19}$$

Where $\Delta(n)=[b(1+\delta)+e/s][b(1+\delta)+2(e+b)/s]-b^2(1+\delta)n$. The industry output is obtained by summing $X(n)$ and $V(n)$ to give

$$Z(n)=\frac{(a-d)[b(1-\delta)(2/s-n)+2e/s^2}{\Delta(n)} \tag{3.20}$$

Total output is a decreasing function of the number of large firms n, therefore output decreases as more small firms merge together to become large firms. This reduction in output is accompanied by a price rise. The output of the merged large firm is less than the combined output of the component small firms, therefore the incentive to merge requires that the increase in price is large enough to offset the decrease in output for the merged firm. This can be seen by comparing the pre-merger profits of a large firm, $\pi_L(n+1)$, with the post-merger combined profits of two small firms, $2\pi_S(n)$.

$$\pi_L(n+1)=P(Z(n+1))\left[\frac{X(n+1)}{n+1)}\right]-C\left[\frac{X(n+1)}{(n+1)},s\right] \tag{3.21}$$

$$\pi_S(n)=P(Z(n))\left[\frac{sV(n)}{2(1-sn)}\right]-C\left[\frac{sV(n)}{2(1-sn)},\frac{s}{2}\right] \tag{3.22}$$

Substituting in the equilibrium conditions and equilibrium output shows that

$$\pi_L(n+1) \geq 2\pi_S(n) \quad as \quad \Delta(n) \geq \bar{\Delta} \tag{3.23}$$

$$\pi_L(n+1) \leq 2\pi_S(n) \quad as \quad \Delta(n) \leq \bar{\Delta} \tag{3.24}$$

Where

$$\bar{\Delta} = \frac{(2b^2 q)}{2q - (q + e/s)(b(1+\delta) + q)^{\frac{1}{2}} q^{-\frac{1}{2}}} \tag{3.25}$$

and $q = b(1+\delta) + e/s$. Various scenarios arise from this result, where $\Delta(n)$ is a decreasing function of n. There is always an incentive to merge if $\max_n \Delta(n) = \Delta(0) < \bar{\Delta}$. There is never an incentive to merge if $\min_n \Delta(n) = \Delta((1/s) - 1) > \bar{\Delta}$. The incentive to merge requires that $e > 0$ in an industry with differing firm sizes, where e and s define the slope of the marginal cost function. The Salant et al. (1983) model equates to a special case of this model where $e = 0$ and firms are equal in size. Furthermore, the incentive to merge depends on the relationship between e and b, where b is the slope of the demand function. There is always an incentive to merge when $e > 3b$ and sometimes an incentive to merge when $e < 3b$ if n is small and s is sufficiently large.

Perry and Porter (1985) also provide a model depicting an industry that consists of n oligopolists and a competitive fringe of m small firms. The dominant oligopolists behave as a Stackelberg group with respect to the competitive fringe. The incentive to merge for the competitive fringe firms additionally depends upon the conjectural variation δ, where expectations of competitive responses act as a greater incentive for merger. These models overcome the merger paradox to suggest that the incentive to merge depends upon industry concentration and the relationship between supply and demand. They provide evidence that economies of scale are not a necessary condition for incentive for merger to exist.

Huck et al. (2001) depict a Stackelberg model that assumes the oligopolistic market consists of leaders and followers. Linear costs and homogeneous products are assumed.

They show that bilateral mergers between leaders and followers are always profitable, but mergers between two followers or two leaders rarely have incentive to merge. The merged firm produces the same output as the pre-merger leader and the follower essentially disappears. This results in a price increase that more than offsets the reduction in joint output. Both merging parties are better off but a reduction in total welfare is incurred. This outcome only holds if the leader is relatively larger and strategically stronger than the follower. This implies that the profitability of a merger depends on market structure, therefore the motivations to engage in merger will depend on a firm's relative position in the market.

Farrell and Shapiro (1990) investigate horizontal mergers from an efficiency perspective. The models by Salant et al. (1983) and Perry and Porter (1985) imply that merger is always associated with a reduction in output and increase in price. This reduces consumer surplus and therefore has welfare implications. Governments may intervene to prevent mergers that have a strong negative impact on consumer welfare, therefore some mergers may be prevented despite the existence of merger incentives for firms. Farrell and Shapiro (1990) suggest that opportunities for learning and economies of scale act as incentives for merger which enhance profit and may increase output and reduce price. Merged firms will not necessarily reduce their joint capacity.

Economies of scale lead to reduced average costs as production increases. Fixed costs are shared over more units and variable costs may be reduced due to improved efficiency of production. Sources of economies of scale include bulk buying inputs at lower cost, use of more efficient large scale machinery, increased specialisation through division of labour, lower cost finance and spreading R&D or marketing costs over greater output. Mergers are attractive when synergies can be created by combining complementary knowledge or capital. Learning can occur if one merging partner has superior expertise which can be applied to the other merging partner. Incentives to merge are greater when synergies exist because lower costs increase profitability and can potentially induce a positive effect on consumer welfare.

The Cournot and Stackelberg models assume that firms set output quantities, whereas the Bertrand model assumes firms set prices. Deneckere and Davidson (1985) suggests that the Bertrand model proves that mergers of any size can be beneficial as reaction functions in a price setting game are typically upward sloping. They suggest that the finding that mergers are undesirable arises from the focus on quantity as the strategic variable. Price setting ability implies non-homogeneous products, but this seems to be a realistic assumption.

Internal corporate structure is more complex than the Cournot, Bertrand and Stackelberg models acknowledge. Gordon (1961) notes that the rise in large corporations has lead to alternative aims other than profit maximisation. Berle and Means (1932) observe the separation of ownership and control in large corporations. They suggested that a conflict in interests may arise between the owners (principals) and the managers (agents). Although owners may desire profit maximisation, managers may have their own objectives. Baumol (1959) argues that managers aim to maximise sales, Marris (1964) believes that empire growth is the main objective, whereas Williamson (1963) suggests that pecuniary and non-pecuniary remuneration act as important motivations. These motivations are interrelated because the underlying incentives for managers to expand firm size and enhance sales growth are the rewards they receive in terms of prestige, perquisites and increased compensation.

These growth incentives are constrained by the desire to maintain job security in their managerial role. Baumol (1959) and Williamson (1963) suggest this constraint can be captured by minimum profit level. Profits must remain above this minimum level in order to keep shareholders content with dividend payments and ensure financial security of the firm. Marris (1964) prefers minimum firm valuation on the stock market as a constraint. The valuation reflects favourability with shareholders and vulnerability to takeover bids. Loss of shareholder favourability increases the risk of becoming a takeover target, which will lead to the displacement of management. Managers aim to maximise their objective function subject to this constraint, which reduces their ability to increase sales, stimulate growth or use retained profits to fund pecuniary and non-pecuniary remuneration. Jensen (1986) argues that high levels of leverage align the managerial and shareholder utility functions more closely, because failure is more harshly punished by threat of bankruptcy and managerial replacement becomes easier when debt levels are high. Managers may choose to invest free-cash-flow in expansion through merger in order to smooth dividend payments and prevent idle cash. This incentive occurs because fluctuating dividend payments imply fluctuating performance and shareholders find this unsettling.

The ratio of the market value to the replacement cost of capital is known as the Q value. The Q theory of investment suggests that a firm's investment rate should increase with its Q value. Jovanovic and Rousseau (2002) argue that investment can be internal or external, therefore a positive relationship should exist between a firm's Q and engagement in M&A activity. Their model treats M&A as used-capital market transactions. Firms are endowed with technology z and initial capital K. Output is a function of z and K.

$$output = zK \tag{3.26}$$

z is firm specific and follows the Markov process.[34] It captures all aspects of firm capabilities that influence efficiency, including managerial competence, use of technological know-how and innovations obtained through R&D. New capital can be purchased at a price of 1 per unit and disassembled at the cost of $1 - s$, where $s < 1$ is the salvage value. Firm capital can also be placed on the M&A market at a price of q per unit, where $q = s$ therefore $q < 1$.

X is the firm's investment in internal capital, Y is investment in acquisitions and δ is depreciation. Capital stock at $t + 1$ it therefore given by

$$K_{t+1} = (1 - \delta)K + X + Y \tag{3.27}$$

The firm faces the cost function $C(x, y)K$, where $x = X/K$ and $y = Y/K$ are the ratios

[34] $Pr[z_{t+1} \leq z' | z_t = z] = F(z', z)$

of investment to current capital. Synergies can be obtained if merging firms have differing levels of z. The model assumes that the higher level of z can be applied to all capital, therefore the merged firm can produce more efficiently than the sum of the pre-merged component firms. One unit of K can generate profit of $z - C(x,y) - x - qy$ and a market value of $Q(z)$

$$Q(z) = \max_{x \geq 0, y \geq 0} [z - C(x,y) - x - qy + (1 - \delta + x + y) Q^*(z)] \tag{3.28}$$

$Q^*(z)$ is the discounted present value of expected capital in $t+1$ given the current level of z. The firm can sell its capital at $t+1$ at q per unit.

$$Q^*(z) = \frac{1}{1+r} \int \max[q, Q(z')] dF(z', z) \tag{3.29}$$

The first order conditions for maximisation of equation (3.28) with respect to x and y are obtained to give equations (3.30) and(3.31), where z is correlated over time and Q^* is increasing in z.

$$c_x(x,y) = Q^*(z) - 1 \tag{3.30}$$

$$c_y(x,y) = Q^*(z) - q \tag{3.31}$$

A fixed cost of obtaining capital through acquisition ϕ is assumed.

$$C(x,y) = \begin{cases} c(x,y) + \phi & \text{if } y > 0 \\ c(x,0) & \text{if } y = 0 \end{cases}$$

Returns to scale remain constant as cost is defined per unit of capital. The gross investment in efficiency units can be defined as $i = x + y$. A firm making little investment will avoid the fixed cost ϕ by investing in new capital x, whereas a high investment firm will invest new capital and acquire capital from existing firms. The point of indifference between acquiring and not acquiring is defined as follows.

$$i + c(i, 0) = \phi + \min_{y}[(i - y) + qy + c(i - y, y)] \tag{3.32}$$

The value of i where this equation holds is i^*. Firms will aquire if i is higher than i^* and will not aquire if i is lower than i^*. The investment ratio i depends on the level of technology z, therefore a value z^* exists that generates i^*.

Firms also face the option of staying in business or not staying in business. A firm can exit the market by disassembling capital or being acquired. If the salvage or acquisition value $s = q$ is greater than the market value $Q(z)$, firms will exit the market. The point of indifference is obtained where z_e is the level of technology required for equation (3.33) to hold.

$$Q(z_e) = q \tag{3.33}$$

Firms with $z < z_e$ will be acquired or disassembled. A firm will invest in internal growth if $z^* \geq z \geq z_e$ and will invest internally and externally when $z > z^*$. This model essentially argues that market value depends on the level of technology that the firm possesses. The most efficient firms will in engage takeover activity and the least efficient firms will become targets or exit the market. This implies that productivity of the target firms should increase following a joining event. The advantage of this model is that it takes into account the costs of acquisition and the benefits derived from firm synergies, although it overlooks the competition element of merger activity. It provides a different perspective on the incentives to merge relating to technology and the market value for firms.

Guadalupe et al. (2012) argues that interrelationships exist between innovation and foreign acquisition. They suggest that two scenarios exist; takeover targets either have low productivity and acquirers transfer their technology to the targets or high productivity and acquirers absorb technology from the targets. Firms may increase output following a foreign takeover because their links with other countries are enhanced, thus increasing the size of the market available to them. Their model depicts a monopolistically competitive industry containing heterogeneous domestic firms, with constant elasticity of substitution and increasing returns to scale. Firm i has initial productivity φ_i, investment in productivity increasing innovation γ_i and marginal cost $\frac{1}{\gamma_i \varphi_i}$. Each firm produces one variety of the product and sets price at a constant markup over marginal cost. Firm i sets price at $\frac{1}{\rho \gamma_i \varphi_i}$ where ρ is a parameter in the constant elasticity of substitution utility function and $\sigma = \frac{1}{1-\rho} > 1$ determines the elasticity of substitution between the different varieties of the product and is constant across markets. A_i indicates the size of the markets available to firm i and profits are defined as follows, where $\chi = \left(\frac{1-\rho}{\rho}\right) \rho^{\sigma}$ and $\lambda_i = \gamma_i^{\sigma-1}$.

$$\pi_i = A_i \chi \lambda_i \varphi_i^{\sigma-1} \tag{3.34}$$

V_i, the value of firm i is given by profit π_i minus the cost of innovation $C_i(\lambda)$.

$$V_i(\lambda_i) = A_i \chi \lambda_i \varphi_i^{\sigma-1} - C_i(\lambda_i) \tag{3.35}$$

The cost of innovation is composed of a fixed and a variable component and defined as follows.

$$C_i(\lambda_i) = \alpha_i + b_i f(\lambda_i) \tag{3.36}$$

State of the art technology Φ_{max} acts as an upper bound to the level of technology achievable through innovation. Firm i aims to maximise its value by choosing the level of innovation λ_i^*. If the optimal innovation occurs at an interior solution, the firm innovates up until marginal benefit equals marginal cost.

$$A_i \chi \lambda_i \varphi_i^{\sigma-1} = b_i f'(\lambda^*) \tag{3.37}$$

Case 1 describes a situation where firms with a higher level of initial productivity φ_i, access to a larger market A_i or facing lower innovation costs b_i have a greater incentive to invest more in innovation, $\lambda_i^* = \lambda^*(\varphi_i, A_i, b_i)$. In case 2 acquisition creates an alternative method of increasing initial productivity. If firm i becomes an acquisition target, technology can be transfered from the parent firm at a fixed cost, where $b_i = 0$. Under these conditions it can be optimal for firm i to innovate to Φ_{max}.

Foreign acquisition is incorporated into the model in two ways. Firstly, foreign ownership provides access to larger markets. $A_F = A_D + A^*$, where A_D indicates the size of the domestic market, A^* indicates the additional markets accessed through foreign ownership and A_F indicates the size of the market available to a foreign-owned firm. Secondly, foreign ownership may result in lower costs of innovation, where $b_F \leq b_D$ and $\alpha_F \leq \alpha_D$. The optimum innovation levels are denoted as λ_i^{*F} for foreign owned firms and λ_i^{*D} for domestic owned firms. The incremental value of foreign acquisition of the firm is given as follows.

$$V_i^{*F} - V_i^{*D} = (A_F \lambda_i^{*F} - A_D \lambda_i^{*D}) \chi \varphi_i^{\theta-1} - (\alpha_F - \alpha_D) - (b_F f(\lambda_i^{*F}) - b_D f(\lambda_i^{*D}) \quad (3.38)$$

This expression is non-negative assuming that $A_F \geq A_D$, $b_F \leq b_D$ and $\alpha_F \leq \alpha_D$. When a foreign parent acquires firm i, a share $(1-\alpha)$ of the created value goes to the the domestic owner and the remaining share α goes to the foreign owner. The price that the foreign acquirer pays for firm i is given by R_i.

$$R_i = V_i^{*D} + (1-\alpha)(V_i^{*F} - V_i^{*D}) \quad (3.39)$$

Furthermore, a fixed cost of making an acquisition K is incurred by the acquirer, arising from acquisition search and transaction costs. A foreign firm has the incentive to make an acquisition when

$$V_i^{*F} - (V_i^{*D} + (1-\alpha)(V_i^{*F} - V_i^{*D}) - K \geq 0 \quad (3.40)$$

$$\alpha(V_i^{*F} - V_i^{*D}) \geq K \quad (3.41)$$

The first derivative of equation (3.38) with respect to $\varphi_i^{\theta-1}$ is obtained to understand the relationship between acquisition incentives and firm initial productivity.

$$\frac{d(V_i^{*F} - V_i^{*D})}{d\varphi_i^{\sigma-1}} = \chi(A_F \lambda_i^{*F} - A_D \lambda_i^{*D}) > 0 \qquad (3.42)$$

The relationship depends on the process by which λ_i^{*F} is defined. In case 1 λ_i^{*F} depends on initial productivity, size of the market and cost of innovation. This implies that the incentive for foreign firms to acquire increases with the initial productivity of the target domestic firm. A high level of initial productivity is more valuable under foreign control because foreign firms benefit from lower costs of innovation and access to larger markets. In case 2 the technology of the foreign parent Φ_{max} can be transfered to the domestic target. The value of the firm under foreign ownership becomes $V_i^{*F} = A_F \chi \Phi_{max}^{1-\sigma} - \alpha_F$ regardless of the initial productivity of the domestic target. This means that the lower the initial productivity of the target the greater the value created by foreign acquisition. In this scenario, foreign acquirers have an incentive to target low productivity firms.

The model shows that foreign acquirers will either target low productivity firms or high productivity firms. This depends upon the ability of the foreign firm to transfer technological knowledge to the targets. Productivity following foreign takeover is expected to increase in both cases, but by a greater extent if the target has low initial productivity. Investment in innovation may increase in case 1 following foreign acquisition due to increased market size, whereas technology transfer provides little scope for internal innovation therefore investment may decrease.

This section has identified various incentives for firms to join together. These can be broadly defined as strategic incentives, synergistic incentives and managerial incentives. Strategic incentives arise from industry conditions and depend upon the number of firms in the industry, the size of these firms, size of the market, conjectures about rival behaviour and elasticity of demand and supply. Synergistic incentives arise if the joining event is expected to create scale economies. This may occur through knowledge transfer, from a high technology firm to a firm with lower technological capacity, or by combining complementary capital. Fixed costs of R&D and marketing can be reduced to avoid replication. This implies that less productive firms and highly productive firms are likely to be chosen as joining partners. Managerial incentives arise when a misalignment of managerial and owner utility functions occurs. Managers may aim for empire growth to maximise prestige and remuneration.

Post-event behaviour will depend on the initial motivation for joining together. Mergers motivated by synergies are likely to see a rise in productivity relative to their pre-merger components. Strategy and managerial incentives may be less likely to increase productivity and the outcome will depend on the extent that synergies exist between the component firms. R&D expenditure is likely to be reduced when firms join together to avoid replication, but managers may choose to increase R&D investment in high technology firms. Foreign takeover provides improved access to international markets, lower innovation costs and potential for technology transfer. Productivity is expected to increase following foreign acquisition.

3.3.2 Economic Motivations for Separating Events

Separation events can be motivated by various different factors. They can be a strategic response to market conditions, an entry deterring strategy by an incumbent firm, a response to diseconomies of scale occurring through excessive growth and over-diversification or a shift of emphasis towards other areas as a response to changing demand conditions. This section discusses each of these incentives.

Baye et al. (1996) investigate the incentives for oligopolists to divide production of homogenous products among autonomous competing units. Their model focuses on the strategic motives for divisionalisation and therefore assumes that no cost advantages of separation exist. The notion of divisionalisation can be expanded to include franchising and divestment. Each firm is faced with identical marginal costs of production m regardless of the number of units and each unit has identical technology. The formation of competing units is costly, where the cost of adding another division is constant and equal for all firms. The model takes the form of a two stage game where each firm decides upon the number of divisions in the first stage and each division is an independent competing unit in the second stage. The inverse demand function for the industry is given as follows, where Q is industry output.

$$P = \alpha - Q \tag{3.43}$$

In stage one, firm i choses the number of divisions δ_i and output of the jth division of firm i is q_{ij}. The profit of the jth division of firm i is given by

$$\pi_{ij}(q, \delta) = (\theta - \sum_{k=1}^{n} \sum_{w=1}^{\delta_i} q_{kw}) q_{ij} \tag{3.44}$$

where $\theta = \alpha - m > 0$ and $\sum_{i=1}^{n} \delta_i$ denotes the number of competing divisions in stage two of the Cournot game. The profit of firm i is the sum of its divisions minus the cost of divisionalisation.

$$\pi_i(q, \delta) = \sum_{j=1}^{\delta_i} \pi_{ij}(q, \delta) - c\delta_i \tag{3.45}$$

The model is solved by backward induction. In stage two of the game each division j chooses its profit maximising output and assumes that firms face increasing fixed costs as the number of divisions increases, but no reduction in variable costs. Equation (3.44) is differentiated to obtain the first order condition for profit maximisation.

$$\frac{\partial \pi_{ij}}{\partial q_{ij}} = \theta - Q - q_{ij} = 0 \tag{3.46}$$

A symmetric Nash equilibrium output solution for each division can be obtained as follows.

$$q_{ij}(\delta) = \frac{\theta}{1 + \sum_{k=1}^{n} \delta_k} \tag{3.47}$$

This output is identical across the divisions of all firms, therefore industry output can be obtained by summing across the divisions.

$$Q(\delta) = \frac{\theta \sum_{k=1}^{n} \delta_k}{1 + \sum_{k=1}^{n} \delta_k} \tag{3.48}$$

Industry output and the output of each division depends upon the number of competing divisions and the size of the industry θ. As the number of divisions increases, industry output increases and price tends towards marginal cost. The profit of the parent firm can be derived by substituting equations (3.48) and (3.47) into (3.44).

$$\pi_i(\delta) = \sum_{j=1}^{\delta_i} \pi(q, \delta) = \delta_i \left[\frac{\theta}{1 + \sum_{k=1}^{n} \delta_k} \right]^2 - \delta_i c \tag{3.49}$$

Firm i chooses a number of divisions δ_i to maximise profits. Profit in each division j decreases as the number of divisions increases, but revenue of firm i increases with the number of divisions in firm i assuming that other firms hold their number of divisions constant. The rise in costs associated with an increased number of divisions acts as a disincentive for divisionalisation, but each firm has an incentive to divisionalise if the costs are sufficiently low. If other firms also divisionalise, industry output will further increase and profits are reduced. Less divisions are created when θ is low, which occurs when demand is low relative to marginal cost.

To expand this model to the divestiture case, a three stage game is considered. In stage one firm i chooses the number of divisions to be sold, in stage two these divisions are auctioned off and quantities are set in stage three. If the supply of purchasers is perfectly elastic, the sale price of the division equates to the Cournot profit. The results of the divestment game are equivalent to the divisionalisation game when the game is not repeated. The strategic incentive to divest in this model depends on the number of divisions in the industry, supply and demand conditions and the conjectured behaviour of rival firms. These findings parallel the results from the merger model depicted by Perry and Porter (1985).

Entry deterrence provides a further competitive strategy motivation for divestment. Schwartz and Thompson (1986) present a model where incumbent firms can create a division at lower cost than potential greenfield entrants to deter entry into the industry. Firms face the cost function,

$$C(Q_i, K_i) = F + wQ_i^2/K_i + rK_i \tag{3.50}$$

where F is the fixed entry cost, K_i is capital stock, X_i is output and input prices are given by w and r, where $c = 2\sqrt{wr}$. The fixed entry cost is only incurred once per firm and there is no cost of creating a division for an incumbent firm. Marginal cost is given by the partial derivative of the cost function with respect to output.

$$c = 2w\frac{Q_i}{K_i} \tag{3.51}$$

Demand is given by the following linear demand function.

$$P(Q) = \alpha - \sum_j Q_j \tag{3.52}$$

An entry threat will exist if the difference between demand and long-run average costs is sufficiently large, where $\alpha - c > 4\sqrt{F}$ is assumed to be a necessary condition for an entry threat. The industry is assumed to involve 2 firms. Firm 1 is an incumbent monopolist and firm 2 is the potential entrant. Firm 1 could set output at the 'limit price' output $\bar{Q}$ to deter entry by firm 2. This would reduce the potential profits of firm 2 to zero, where the residual demand price is $P(\bar{Q}+Q_2)$ and optimal output becomes $Q_2^*(\bar{Q}) = (\alpha - c - \bar{Q})/2$. Firm 2 has zero profits when $F = (P(\bar{Q} + Q_2^*(\bar{Q})) - c)Q_2^*(\bar{Q})$.

But the limit price output does not equate to the profit maximising monopoly output for firm 1. The profit maximising output with a single division of firm 1 occurs below $\hat{Q} = \alpha/2$, where $\hat{Q}$ denotes the output where marginal cost and marginal revenue equal zero. If firm 1 choses to produce monopoly output, firm 2 has an incentive to enter the market since the residual demand is greater than under the limit price conditions $P(\hat{Q} + Q_2) > (\bar{Q} + Q_2)$ and firm 2 will have above zero profit. Under these conditions the market equilbrium involves $m > 1$ firms with capital and output choices defined by vectors K^* and Q^*.

$$K^* = [K_1^*, K_2^*, ...K_m^*] \tag{3.53}$$

$$Q^* = [Q_1^*(K^*), Q_2^*(K^*), ...Q_m^*(K^*)] \tag{3.54}$$

The optimal strategy with no entry threat for firm 1 is to produce the profit maximising output. When faced with the threat of entry, divisionalisation becomes the best strategy. Firm 1 will set up m independent divisions to comply with vectors K^* and Q^*. In this scenario, firms 2,...m cannot profitably enter the industry. Firm 1 derives the sum of profits obtained by its divisions, therefore it is better off than if it had allowed entry. The profits from outputs $Q_2^*(K^*)$ to $Q_m^*(K^*)$ are attributed to the divisions of firm 1, rather than rival firms. This result also holds when a greater number of initial incumbents exist.

This incentive for divisionalisation depends on the ability of firm 1 to derive profits from its divisions. If divisional profits can be fully claimed by firm 1, the incentive to divisionalise exists. This practice may be seen as anti-competitive by the competition authorities and may be prevented through legislation. In the case of divestment, a firm sells ownership of the division to a new entrant. Divestment is preferable to allowing greenfield entry because firm 1 can derive benefit from the sale of the division. When divisions are purchased by firm 2...m the fixed cost of entry is paid to firm 1. Furthermore, firm 1 may maintain a proportion of shares in the sold division and therefore derive some of the profit.

In the resource-based view of strategic management Penrose (1955) argues that each firm is composed of a bundle of physical and human resources. Growth is limited by organisational factors within the firm and market factors outside of the firm. Increases in size lead to additional complexity of firm structure and scope of activity. Managerial capabilities are a limiting factor to growth. Research required to plan growth strategy diverts managerial resources away from organising existing business activity and the management team has a limited capacity to over see a large scale company as the efficiency of decision making is subject to diminishing returns. Large firms may choose to decentralise decisions, but this can create efficiency costs. Markides (1995) discusses the various arguments across the literature that support the notion of an optimum diversification level. Growth is limited by agency problems, such as lack of employee effort through shirking, misalignment of utility functions and distortion of objectives between employees and management. X-inefficiencies may occur as additional layers of hierarchy create further costs and processing limitations by central management also act as a constraint.

Over-diversification may occur for several reasons. Growth requires favourable demand conditions, therefore in situations of deficient demand it may be necessary to branch out into new markets (Penrose, 1955). Flexibility of resources is advantageous. Firms may decide to switch resources to another market, hence divestment may be necessary to pursue growth strategies. This interrelationship between different demographic events is considered in my study.

Jensen (1986) outlines a “free cash-flow theory” which provides a rationale for observed over-diversification. Free cash flow is defined as the remaining cash flow after all positive net present value projects have been funded. Managers may chose to smooth dividends over time by reinvesting profits rather than paying out dividends or pursue goals such as growth rather than shareholder value maximisation. In this situation, shareholders and managerial utility functions are not aligned. This may be a particular problem when free cash-flow is available. External finance is monitored by lenders, therefore riskier projects are less likely to be financed externally. In the past, the stock market has reacted positively to the announcement of diversifying acquisitions. This created an incentive for managers to invest in acquisition even if this was not the best action for them. Divergences in manager and shareholder expectations may also result in over-diversification if the manager over-estimates their own ability to transfer skills and assets to another industry or area, therefore enters a new market over-optimistically. Changes in market circumstances can change a once optimally diversified firm into an over diversified firm. This may occur due to reduced benefits of diversification eroded away through market deregulation and increased competition and increased costs of diversification rising through economic uncertainty, currency fluctuations, etc.

Kaul (2012) suggests that divestment can be seen as a firm strategy with reactive or proactive motives. The reactive perspective views divestment as a response to poor performance, over diversification or high levels of bureaucracy in order to improve the performance of the firm. This form of divestment is motivated by internal characteristics of the firm and its performance. As firms grow in size and become more diversified, the costs of associated with monitoring and information processing increase. This can create greater managerial burden and have a negative impact of firm performance if growth is excessive. Divestment is a method of reducing agency problems, increasing the concentration of corporate scope and discarding failed acquisitions to improve firm performance. This suggests that a firm is likely to have poor performance prior to divestment and may lack focus on innovation. Furthermore, this also implies that divesting firms may be more likely to be geographically or product market diversified prior to divestment. Following divestment, innovation may improve due to increased managerial focus and reduced bureaucracy costs which will free up resources to invest in R&D. The extent of the impact of divestment on innovation may depend on whether divestments are involved in core activities. Innovation may increase if non-core activities are divested as focus will increase on core activities, whereas an increase in innovation is less likely if core activities are divested.

In contrast, the proactive view suggests that divestments may be motivated by a desire to free up resources in order to pursue alternative opportunities or develop new capabilities as a response to changing market conditions or the emergence of new markets. This form of divestment is motivated by conditions external to the firm, rather than a response to under performance. Therefore this view implies that divestment is likely to have a positive effect on innovation and would also expect stronger pre-divestment performance than the reactive motivation. Although the initial motivations differ in contrasting view points, both scenarios benefit from freeing up resources and creating organisational slack to enable managerial focus to concentrate on innovation. Divestment may result in temporary disruptions to organisation, therefore short-run reductions in innovation may be incurred. The proactive motivation may be associated with acquisition prior to or following divestment as a wider restructuring strategy in response to changing external conditions. Innovation may increase following divestment of core or non-core activities with this motivation.

In summary, the theoretical literature suggests that events are driven by various factors. Managers may aim to maximise the value of the firm by seeking growth or R&D policies to improve productivity in existing processes or for product development. The appropriate strategy depends on market conditions, such as demand, concentration and the firm's position relative to competitiors and also financial conditions, including leverage, liquidity and market valuation. Competition laws prevent firms dominating markets. Firm growth may be limited by these conditions and by co-ordination costs and inefficiencies associated with large scale organisations.

The relevance of the strategic motivations depends upon the extent that the parent firm can derive profits from the divested unit. In my data the change of ownership occurs when the majority owner changes, therefore the parent firm could potentially maintain a proportion of shares in the divested firm or generate profit from the sale of shares.

3.4 Empirical Studies

3.4.1 Motivations for Mergers and Acquisitions (M&A)

Empirical studies on mergers and acquisitions began to emerge during the 1960s and 1970s due to improvements in available data. The early literature used linear probablilty models (Kuehn, 1969) or discriminant analysis techniques (Singh (1975), Stevens (1973)) to assess characteristics of acquired and acquiring firms. An overview of these early studies is provided by Harris et al. (1982). Findings suggest that financial characteristics play an important role in merger motivation, but these motivations may change over time. These estimation techniques were superseded by probit and logit models used by Harris et al. (1982), Dietrich and Sorensen (1984) and Palepu (1986) amongst others.[35]

Hannan and Rhoades (1987) develop the methodology used in the literature further by applying a multinomial logit model. They focus on the likelihood of bank acquisition by studying the relationship between bank and market characteristics and the incidence of acquisition. The aim is to provide a greater understanding of the motivations behind mergers and acquisitions specific to the banking industry. These motivations are unlikely to be identified in studies that use data covering all industries because motivations may differ. The banking industry has distinct differences from manufacturing, therefore it is logical to assess this industry separately and seems reasonable to assume that managers in the banking industry may be driven by similar motives.

The data used in this study covers banks in the US state of Texas during the period 1971 to 1982. Texas is a merger active state and is representative of other US states with similar competition laws. Limiting to one US state prevents the need to control for the legislation differences across the country. The data allows for a distinction to be made between geographically horizontal acquisitions and market extension acquisitions. They define horizontal acquisitions as those acquisitions where the acquirer comes from within the same geographical market and market extension acquisitions where the acquirer comes

[35] Although a number of papers in the management literature continued to use discriminant analysis methods.

from outside the geographical market. The sample consists of previously existing, separately owned banks, therefore excluding newly established firms, non-operating banks, firms that were not bank holding companies or commercial banks, foreign firms without previous US operations or acquisitions that account for less than 25% of a company.

The estimated model takes the form of a multinomial logit to account for the fact that the coefficients on the explanatory variables are likely to differ in strength and magnitude depending on the type of acquisition. Their multinomial logit allows for three outcome categories. These mutually exclusive categories are no acquisition, within market (horizontal) acquisition and outside market (market extension) acquisition. My study can be considered as an extension of this, where the multinomial logit allows for nine outcome categories. Their model is defined as follows.

$$P_t^{A\ in}/P_t^{no\ A} = exp(X_t'\beta^{A\ in}) \tag{3.55}$$

$$P_t^{A\ out}/P_t^{no\ A} = exp(X_t'\beta^{A\ out}) \tag{3.56}$$

$$X_t' = f(ROR_t, MS_t, CA_t, LA_t, BG_t, MG_t, CR_3, Assets_t, RU_t, T) \tag{3.57}$$

$P_{(t)}^{A\ in}$ and $P_{(t)}^{A\ out}$ denote the probabilities of being acquired in year t by a within market bank and a outside market bank respectively, given that they were not acquired during the previous year. $P_{(t)}^{no\ A}$ is the probability of not being acquired during year t. The explanatory variables are given by the vector X_t and corresponding beta coefficients by $\beta^{A\ in}$ and $\beta^{A\ out}$. The coefficients are likely to vary depending on whether the acquirer is from inside or outside the market. ROR_t represents the rate of return, MS_t is the market share of the bank within its geographical market, CA_t is the capital asset ratio, LA_t is the loan to asset ratio of the bank, BG_t is bank growth calculated based on deposits, MG_t is market growth, CR_3 is the concentration ratio based on deposits of the top 3 banks within the geographical market, $Assets_t$ denotes the size of the bank in terms of assets, RU_t is a dummy that differentiates between urban and rural markets and T is a set of time dummies.

To test the hypothesis that poorly managed banks are more likely targets they assume that bad management is linked to poor performance. Using the rate of return as a performance measure, they estimate the model 4 times using different measures for the rate of return. These measures include the rate of return on net income on assets, rate of return on net income on equity, the ratio of the rate of return on net income on assets to the market average and the ratio of rate of return on net income on equity to the market average. These ratios aim to offset any fluctuations in market conditions that may impact the size of the variable. A negative coefficient on the ROR_t variables would be consistent with the hypothesis, yet the results show no support for the notion that poorly managed firms are more likely to become acquisition targets. The coefficients are not significant in any of the 4 specifications.

A large market share is assumed to indicate good quality to the consumer, which is a favourable characteristic for a potential target, yet competition laws act as a constraint on the extent of market share allowed in each state-defined geographical area. Therefore, it is likely that the coefficients will differ in strength and direction for within state and outside state acquisition. The results show that market share is an important characteristic for outside market acquisitions, with positive significant coefficients in all specifications. This indicates that outside market acquirers may be drawn towards firms with a large market share to benefit from their existing customer reputation. The market share coefficients for the within market acquisitions are not significant. This difference highlights the importance of competition laws in influencing acquisition behaviour.

The capital asset ratio has a negative significant coefficient in all specifications, suggesting that a low capital asset ratio indicates a more attractive target. The coefficient on the loan to asset ratio is not significant. This suggests the extent of risk taking behaviour by the bank does not generally act as a deterrent or to encourage acquisition. The coefficient representing bank size in terms of assets $Assets_t$ is also not significant.

The bank growth and market growth variables are used to test if previous expansion opportunities impact the acquisition decision. BG_t and MG_t are calculated based on deposit growth over the 3 year period $t-4$ to $t-1$. High bank or market growth suggests there had been potential for expansion within the local market previously and that could indicate a good target to acquirers if this potential remained. The coefficients on these variables are not significant, implying that this is not a motivating factor for acquirers. Acquirers may use other sources of information to predict potential for market expansion.

The concentration ratio CR_3 is based on deposits of the largest 3 banks within the geographical market. This variable's coefficient differs according to inside or outside acquisition. The coefficients for inside market acquisition are negative and significant, which implies that high concentration ratios are associated with a lower likelihood of acquisition due to competition laws. Whereas the coefficients on outside market acquisition are not significant, which ties in with the idea that competition laws are no longer a barrier for acquirers from outside the market.

The dummy that differentiates between banks operating in rural and urban markets is significant for outside market acquisitions, but not within market acquisitions. This implies that firms within urban markets may have a desire to expand to more rural settings to have access to a broader customer base.

This study focuses on the banking industry which has clear differences from the manufacturing industry, therefore a large emphasis has been placed on assessing the importance of financial characteristics. A study on manufacturing would benefit from including a broader range of firm characteristics. The distinction between within local and outside local markets is an interesting feature of the study. This allows differences between the two types of acquirers to be taken into account. A limitation to this study is that it only focuses on the characteristics of banks that become targets and pays little attention to the characteristics of the acquirers. Furthermore, endogeneity arising from sample selection bias may be a problem. The sample is relatively small therefore results may be sample specific.

Hay and Liu (1998) aim to investigate behavioural differences between dominant firms within industries and how behaviour differs depending on market structure. They use data consisting of 110 stock market quoted manufacturing firms across 18 3-4 digit industries. The sample includes firms that make at least 1 acquisition during the period 1971-89. The data contains information on whether a firm has made an acquisition and the extent of the acquired assets within a given year. The study focuses on the motives and behaviour of acquiring firms rather than the characteristics of acquired firms.

They highlight various motives behind acquisition related to gaining market share, utilising free cash-flow and a favourable valuation ratio of the target. Firms may aim to increase market share through acquistion in order to increase capacity and customers base simultaneously. This is more likely to be a motive when the industry is growing because there is less incentive to acquire if the industry is declining. When the industry is growing, battles for potential targets may take place. Firms may undertake acquisition with the strategic motive of increasing competitive advantage in oligopolistic markets. Jensen's 'free cash-flow' theory suggests that managers may prefer to utilise spare cash to invest in growth through acquisition, rather than pay dividends to shareholders or invest in new fixed assets. A further motive for acquisition appears if assets can be obtained cheaply through acquisition i.e. when the valuation ratio of the target is less than 1.

Hay and Liu (1998) use 2 different models to address their research question. The first model is a probit model.

$$Acq_t = \alpha + \beta_1 ln\, ProfitRate + \beta_2 ln\, InvestRate + \beta_3 ln\, VRatio + \beta_4 ln\, DARatio + \beta_5 RivalsAcq \tag{3.58}$$

Acq_t is a dummy variable indicating acquisition, $ProfitRate$ represents the gross post-tax profit rate, $InvestRate$ is the investment rate in capital assets, $VRatio$ is the valuation ratio, $DARatio$ is the debt to asset ratio and $RivalsAcq$ is a dummy variable indicating years when there are acquisitions made by other firms within the firm's industry. The explanatory variables are forcasted values for the acquiring firm at time t. Predicted values are used rather than observed variables to avoid endogeneity arising from acquisition. In order to account for unobserved heterogeneity firm fixed effects are used. Despite identifying a low valuation ratio of the target firm as a motive, they use the valuation ratio of the acquirer as a explanatory variable.

The results are reported as coefficients and marginal effects of fixed effects probits. Acquisition and profits are positively related, implying that forecasted rises in cash-flow make acquisition more likely. The debt asset ratio $DARatio$ has a negative coefficient, suggesting that it is free cash-flow that matters. Interest payments on debt absorb cash leaving less available for expansion through acquisition. The coefficient on $InvestRate$ is positive which suggests that internal and external growth may act as complements. Internal growth may be necessary to support expansion through acquisition. The valuation ratio is assumed to reflect managerial competence; the higher the valuation ratio, the more confidence shareholders have in managerial ability. The coefficient on $VRatio$ is positive therefore shareholders of the acquiring firm are more likely to support any acquisition bids when the valuation ratio is high as they are more confident that it will be an advantageous move. The coefficient on the $RivalsAcq$ dummy is negative but not significant. This indicates that high acquisition by rival firms in the same industry does not have a significant impact on the decision to acquire. Firm specific effects are found to be important when comparing random and fixed effects models, suggesting some firms may be more inclined to acquire than others due to unobserved factors.

The estimation procedure is also performed on 3 sub-samples of data to test the robustness of the results and for differences within the sample. The first subsample includes only low growth acquisitions. These are acquisitions that add to existing capital stock of the firm by less than 10%. This is done because large growth acquisitions can be unpredictable and held off for favourable circumstances. The coefficients are generally in agreement with the results for the whole sample, although profit is more responsive and the debt to asset ratio is less responsive. The second subsample includes only single dominant firms or firms which are part of a dominant group. The coefficients have the same sign but the marginal effects are much larger. The third subsample includes only firms in fragmented sectors. Again, the coefficients have the same signs, but marginal effects are slightly smaller than the full sample.

The second model is a 2 step procedure to account for selection; taking the inverse mills ratio from the probit model and using a tobit model to allow for a truncated distribution. The dependent variable has a lower bound of zero.

$$\frac{ValueAcq_t}{ValueInitial_t} = \alpha + \beta_1 ProfitRate_t + \beta_2 InvestRate_t + \beta_3 \frac{MarketVal}{ReplaceVal_{t-1}} + \beta 4 MarketShare_{t-1} \tag{3.59}$$

$ValueAcq_t$ is the value of acquisitions that take place in year t, $ValueInitial_t$ is the initial value of the acquirer in terms of capital stock, $ProfitRate_t$ profit rate is the rate of profit growth after depreciation and interest, $InvestRate_t$ is internal growth by investment in capital stock, $MarketVal$ is the market value of the acquirer, $ReplaceVal$ is the replacement value of assets and $MarketShare_{t-1}$ is the market share occupied by the acquirer during the year prior to acquisition. The dependent variable is the ratio of $ValueAcq_t$ to $ValueInitial_t$, therefore it shows the value of acquisition as a proportion of the existing assets of the firm i.e. the rate of growth through acquisition. Therefore this model focuses on the extent of the acquisition, whereas the probit model focuses on the occurrence of acquisition as a binary event. The predicted values for the profit and investment rates are estimated using lagged values and time dummies.

The results show that the profit rate is positive and very significant in explaining the extent of growth through acquisition. Therefore the higher the profits of an acquirer the larger the acquisition as a proportion of existing assets. This supports the free cash flow theory. The coefficient on the internal investment rate variable $InvestRate_t$ is negative and significant suggesting acquisition and investment are substitutes. This result contrasts the findings from the probit model, although this could imply that growth through acquisition at small levels requires complementary investment and a substitution effect takes over at higher levels. The valuation ratio has no significant effect on the dependent variable. The coefficient on market share is negative and very significant, suggesting that large acquisition is less likely when the firm already has a large market share. This reflects the fact that competition laws prevent market domination.

In summary, the key finding of this paper is that 'free cash-flow' is an important determinant of acquisition and the extent of acquisition. The use of use of the tobit model provides interesting insights into how the variables differ with the extent of acquisition, giving additional information beyond the probit results. This proves to be particularly relevant for the internal investment variable. Firm effects are found to be important, highlighting the need to take account of unobserved firm heterogeneity. A drawback to this study is that they place emphasis on acquirer behaviour and mostly ignore the characteristics of the target firm.

Dickerson et al. (2002) look at the determinants of takeovers with the aim of gaining a deeper understanding of the market for corporate control. Their study uses a sample covering 892 UK quoted companies, during the period 1975 to 1990 and poses two research questions. Firstly, is there evidence of a disciplinary motive for takeover? and secondly, can the channels through which the market for corporate control operates be identified?

The market for corporate control is hypothesised to operate through various channels. One of these channels is profitability; if a firm is working towards an aim other than value maximisation or is poorly managed, profitability is expected to be low. Takeover of these firms is more likely as it is driven by the motivation to increase managerial discipline to enhance profitability. Free cash flow theory presents other channels through which the market for corporate control is expected to operate; via dividends and investment. When a firm has few positive NPV investment opportunities it may pay higher dividends to signal to shareholders that their assets are not being wasted by management. This scenario is likely to be associated with a lower probability of takeover. But if a firm with no positive NPV investment opportunities chooses to invest, firm value will be reduced, highlighting poor management and the likelihood of takeover increases.

Dickerson et al. (2002) criticise the pooled probit methodology used in some of the earlier literature. The weakness of this method is that it does not control for unobserved heterogeneity and does not account for path dependency over time. Failure to control for unobserved firm heterogeneity may imply that older firms are less attractive, whereas, in reality, unattractiveness may be due to an unobserved characteristic. The fact that firms are dynamic entities with path dependent characteristics are not accounted for when observations are assumed to be time independent. Furthermore, they suggest that fixed effects and random effects probits are also inadequate specifications for this type of study. Fixed effects depends on changes, therefore the firms not involved in takeover during the sample period will be ignored. Random effects requires the assumption that the unobservable component is not correlated with the explanatory variables, which is unlikely in most economic models. They propose an alternative methodology to overcome these criticisms.

Given that previous takeover events may impact variables over time, they suggest the hazard model as an appropriate solution. The hazard model is a survival model using the hazard rate, which is the probability of an event occurring at time t conditional on having survived without the event occurring until time t. Their study looks at the conditional probability of taking over another firm and also the probability of being taken over. This study is therefore more thorough than the previous studies as it looks at both acquirer and acquired firms. The hazard rate $g_i(t)$ for firm i at time t is defined as follows.

$$g_i(t) = \lim_{dt \to \infty} \frac{Pr(t \leqslant \; T_i < t + dt \mid T_i \geqslant t)}{dt} \tag{3.60}$$

This model allows them to investigate whether, given that a firm has incurred no takeover event up until a certain point in time, changes in firm characteristics will lead to changes in the probability of takeover. The standard proportional continuous time hazard is defined as follows.

$$g_i(t) = g_0(t) \exp X_i(t)'\beta \tag{3.61}$$

$g_i(t)$ is the probability of takeover for firm i at time t conditional on no previous takeover, $g_0(t)$ represents the underlying baseline hazard at time t, $X_i(t)$ is the vector of explanatory variables and β represents the vector of corresponding parameters. Rather than only using the common Weibull specification to estimate the baseline hazard, they also use a discrete time version to overcome the weaknesses of the continuous time model. This seems appropriate given that the data is recorded annually, therefore a takeover that takes place during year t actually takes place sometime after the beginning of t and before the beginning of $t+1$. The discrete time version allows the hazard to be estimated non-parametrically. The advantages of this more flexible baseline hazard is that it prevents one aspect of misspecification bias and may reduce negative duration bias arising from unobserved heterogeneity. The conditional probability can be written in terms of the hazard as follows.

$$P(t \leqslant T_i < t+1 \mid T_i \geqslant t) = 1 - \exp(-\int_t^{t+1} g_i(s)ds) \tag{3.62}$$

$$= 1 - \exp(-\exp(X_i(t)'\beta) \int_t^{t+1} g_0(s)ds) \tag{3.63}$$

$$= 1 - \exp(-\exp(X_i(t)'\beta) + G(t)) \tag{3.64}$$

Where $G(t)$ gives the underlying hazard at each discrete duration, thus revealing the takeover hazard of a firm surviving t years.

$$G(t) = ln(\int_t^{t+1} g_0(s)ds) \tag{3.65}$$

The non-parametric model is sufficiently flexible to allow for unobserved heterogeneity.

In order to make comparisons with the Weibull continuous time specification, unobserved heterogeneity is incorporated into the hazard multiplicatively.

The explanatory variables contained in vector $X_i(t)$ include size in terms of log net assets[36], leverage measured as the ratio of debt[37], liquidity[38], ratio of tangible assets to total assets, gross pre-tax dividend yield, ratio of gross investment in tangibles to net assets and post-tax profitability[39]. As this study aims to provide a deeper understanding of the operation of the market for corporate control, the important explanatory variables include profitability, dividends and investment. These explanatory variables are used to test the different channels of the mechanism. Furthermore, they calculate Tobin's q to distinguish firms with a low q. Under certain assumptions, $q < 1$ indicates a firm with no positive NPV investment opportunities and $q > 1$ indicates a firm with some positive NPV investment opportunities. If the market for corporate control operates via this channel, for low q firms, the results should show that higher investment increases the conditional probability of takeover. An interaction between investment and the low q indicator is included to test for this. The company accounts data is taken from the EXSTAT database and the dividends, share prices and share capital are taken from the London Share Price Dataset (LSPD).

Unobserved firm heterogeneity is apparent when comparing the results from the Weibull specifications with and without heterogeneity. Whereas the estimated heterogeneity parameter is not significant in the model with a non-parametric baseline hazard. This indicates that the non-parametric specification mitigates some of the unobserved heterogeneity as anticipated. Furthermore, the extent of the bias in the β estimates arising from the monotonic Weibull specification can be seen by comparing them with the estimates from the more flexible non-parametric approach.

The conditional probability of takeover depends non-linearly on the log of size, where

[36] Net assets are calculated as total assets minus current liabilities

[37] Debt consists of short term debt, bank loans and overdraft.

[38] The ratio of net current assets to net assets.

[39] They use a variety of measures of profitability and find results are not sensitive to the chosen measure. The measure displayed in their results is the rate of return on net assets

the coefficient on $log(size)$ is positive and $log(size)^2$ has a negative coefficient, implying an inverted U-shaped relationship. This differs from previous work, but may be due to the loosening of constraints during the 1980s. The coefficients on leverage and liquidity are not significant and the joint significance test for the industry dummies suggests that there does not appear to be sectoral differences, although the individual coefficients suggested that some industries had lower conditional activity rates than others.

The estimated baseline hazard differs depending on the type of specification used. The Weibull monotonic specification results in a negative sloping hazard. When unobserved heterogeneity is incorporated, the slope becomes less negative. The more flexible non-parametric hazard is slightly upward sloping, suggesting that the bias exists in the parametric specification. Given that a large proportion of the sample exists in the beginning of the sample time period, the hazard may be susceptible to time specific effects or shocks from the macroeconomy. They control for this using start dummies and year dummies.

The findings suggest that profitability is an important channel for corporate control, as the coefficient is negative and highly significant. The coefficient on investment is negative and significant and the coefficient on dividends is negative but not significant. This implies the effects of a firm's investment policy are larger that its dividend policy. The signs remain consistent when investment and dividends are interacted with tobin's q indicator dummies. The interaction terms show that, for low q firms, an increase in investment reduces the conditional probability of takeover. This contrasts the free cash flow hypothesis, although the negative coefficient on dividends is consistent with free cash flow theory. Higher dividends appear to indicate to shareholders that managers are not wasting their assets on unprofitable investment opportunities.

In summary, this paper investigates the motivations behind takeover. They introduce an alternative methodology into this literature which is arguably more appropriate than the conventional probit method, particularly with small samples. Although, signs on the probit coefficients are consistent with the hazard models.

Dickerson et al. (2003) is an extension of the previous paper. This follow up paper investigates whether acquisition can be used to reduce the likelihood of being acquired by looking at how these events interrelate. They aim to test if a firm can use acquisition strategically to influence its own fate. The hazard methodology is extended to include competing risks. In each period a firm faces the risk of being acquired, bankruptcy or acquiring another firm.

The continuous time proportional hazard for company i and risk r is defined as follows.

$$\theta_{r_i}(t) = \theta_r r_0(t) \exp(X_{r_i}(t)'\beta_r),\ \ r = 1, ..., R \tag{3.66}$$

$\theta_{r_i}(t)$ represents the instantaneous probability of risk r conditional on survival to t, $\theta_{r_0}(t)$ is the baseline hazard at time t and β is the vector of coefficients corresponding to the vector of explanatory variables $X_{r_i}(t)$. In a similar manner to the previous paper, this continuous time hazard can be estimated parametrically using the Weibull function to impose a monotonic baseline hazard. Alternatively, a more flexible non-parametric discrete time approach can overcome misspecification bias. The discrete time proportional hazard is given as follows.

$$\Phi_{r_i}(t) = 1 - \exp(-\exp(X_i(t)'\beta) + \Theta_r(t)) \tag{3.67}$$

Each hazard has an extreme value distribution where $\Theta_r(t)$ gives the underlying hazard at each discrete duration for risk r.

$$\Theta_r(t) = ln(\int_t^{t+1} \theta_{r0}(v)dv) \tag{3.68}$$

In order to answer their research question they test for proportionality of the competing risks following Narendranathan and Stewart (1991).

$$H_0 \ : \ \beta_r = \beta \ and \ \theta_{r0}(t) = \theta_0(t) \ ; \ r = 1, ..., R \tag{3.69}$$

This provides a formal test of whether the impact of the explanatory variables $X_i(t)$ and baseline hazards $\theta_{r0}(t)$ differs depending on the conditional probability of being acquired, bankruptcy or acquiring another firm. A weaker version is also tested.

$$H_0' \ : \ \beta_r = \beta \ ; \ r = 1, ..., R \tag{3.70}$$

Furthermore, a previous acquisition dummy is included in their model to test the direct effect of making a previous acquisition on the likelihood of takeover. But indirect effects must also be considered. Previous acquisition will impact the characteristics of the firm therefore the indirect effect acts via the explanatory variables $X_i(t)$. These include $log(size)$, $log(size)^2$, profitability, leverage, liquidity, tangible assets, internal investment, dividends, a previous acquisition dummy and a dummy indicating if company i exists at the start of the sample. The net effect of previous acquisition on the probability of takeover consists of the direct and indirect effects. This is estimated by calculating the the relative hazard, the ratio of the post-acquisition hazard to the pre-acquisition hazard.

$$Pr = \frac{\theta_r^{post-acquisition}}{\theta_r^{pre-acquisition}} \tag{3.71}$$

This is evaluated for the mean change in covariates between periods $t-1$ and $t+1$ around an acquisition event that happens at time t.

Two data samples are used in this study. The first spans from 1948 to 1970, covers 2280 companies and is taken from the DTI Databank of company accounts. The second covers 969 companies over the period 1975 to 1990 and is taken from EXSTAT. Both datasets are merged with the London Share Price Dataset (LSPD) to include stock market data. The samples reflect the characteristics of the population. The data is at company level therefore an acquisition leads to an amalgamation of resources and the acquired firm ceases to exist as a separate entity.

Results are shown for two risks; making an acquisition and being acquired. The estimated coefficients show the relationships between the probability that the risk occurs conditional on survival until time t and the explanatory variables. The specifications with the Weibull hazard and non-parametric hazard generate very similar results. Firstly, focusing on the conditional probability of making an acquisition, the coefficients on *log size* and profitability are positive and significant. This is consistent with the literature as larger, more profitable firms tend to be the main acquirers.[40] Internal investment has a negative coefficient implying that internal and external growth are substitutes.[41] The coefficients on liquidity, leverage differ in sign or significance depending on the data sample. The liquidity coefficient is negative and significant for the 1975-1990 sample, but not significant when using the earlier sample. This contrasts Jensen's idea that 'free cash' may increase a firm's inclination to acquire. Leverage has a negative coefficient implying that high debt levels are associated with reduced likelihood of acquisition. This could arise due to difficulties in obtaining additional external finance to fund acquisition. Two methods are used in order to test whether previous acquisition increases the likelihood of acquisition at time t. The first method includes a dummy variable indicating previous acquisition in the model and the second method includes a cumulative[42] number of acquisitions variable. Both methods indicate that acquisition is 'habit forming' with positive coefficients on the variables. There may be scale economies over time in terms of reduced search costs for suitable targets. Acquisition may result in gaining further knowledge from the target or knowledge from the initial target search could identify additional targets for future acquisition.

Secondly, focusing on the conditional probability of being acquired, the coefficient on *log size* differs depending on the sample. A negative and significant coefficient is found in the earlier sample, whereas an inverted U-shape relationship is found in the 1975-1990 sample. This suggests a declining probability of takeover as size increases for

[40] Although some smaller firms may undertake acquisition to gain access to R&D, this only accounts for a small proportion of takeovers.

[41] Hay and Lui (1998) find mixed evidence on this.

[42] Truncated at '6 or more'.

the 1948-1970 sample, whereas medium size firms are more likely to be targets during the 1975-1990 period. Less profitable companies were more likely to be taken over, suggesting acquirers may choose targets with the aim of restructuring the firm to improve profitability. Investment and dividends have negative coefficients, which also ties in with this idea. The coefficient on the start dummy is not significant, suggesting that cohort effects are not important, but significant coefficients on the time dummies imply that macro effects influence the likelihood of being taken over. The previous acquisition dummy implies that previous acquisition does not have a direct effect on the likelihood of becoming a target, but indirect effects could be at work via other explanatory variables, such as size. Proportional risk tests of H_0 and H_0' are performed to test whether making an acquisition is a feasible form of strategic defence against being acquired. These tests suggest that the characteristics of targets and acquirers are distinctly different from each other. This enables a company to act strategically to avoid becoming the victim of acquisition by changing characteristics to differ from a target's profile. The relative hazard test suggests that making a previous acquisition reduces the conditional probability of becoming an acquisition target by around 30%. This is mostly driven by the fact that acquisition increases the size of the company.

In summary, this paper contributes to the literature by using a competing risk framework to look at the characteristics of acquirers and their targets. It highlights the distinct differences in their characteristics and provides insight into how the two event types interrelate. This has been neglected in previous studies. Acquisition is viewed as a potential strategic tool to reduce the likelihood of becoming a target.

Desyllas and Hughes (2009) investigate the motives for high technology acquirers by analysing their choice of targets. They identify two R&D centred motives; the search for superiority and the search for inferiority. Most studies do not take innovation motives into account.[43] This is important because innovation motives are likely to be less important for firms in low technology industries.

[43] Hall (1999) includes R&D intensity as an explanatory variable in her model, but does not distinguish between high and low technology firms.

The search for superiority describes acquisition with the motive of gaining access to superior innovation relative to industry counterparts. This idea originates from resource based theory. Firms may choose to invest in acquisition as a favoured substitute for expansion of in-house R&D. This may be a faster and less risky way of obtaining the latest technology, gaining a competitive advantage by becoming a technology leader or catching-up in terms of competitiveness. In-house R&D requires time and is path dependent. Furthermore, acquisition can be viewed as a method of revitalising a firm's knowledge base.[44]

The idea of the search for inferiority is based on the theory of the market for corporate control. This theory suggests that when product market competition is ineffective in producing perfectly efficient firms, the assets of inefficient firms will be obtained by superior managers through acquisition. The market for corporate control describes the platform where managers compete over the ownership of assets, in order to gain ownership and organise assets more efficiently.

The search for superiority predicts that target firms have better innovation performance than other non-target firms, whereas the search for inferiority has the expectation that target firms will have lower innovation performance than non-targets. These competing hypotheses are tested.

The data is taken from Thompson Financial's SDC Platinum Datasource. High technology firms are defined as those with primary activity in Chemicals and Allied Products (SIC 28), Industrial and Commercial Machinery and Computer Equipment (SIC 35), Electronics and Electrical Equipment (SIC 36), Transportation Equipment (SIC 37), Measuring, Analysing and Controlling Instruments (SIC 38) Communications (SIC 48), Business Services (SIC 73), Engineering, Accounting, Research, Management and related services (SIC 87). The data covers the period 1984-1998 and is aggregated to the parent firm. There are 628 acquired firms and 4,124 non-acquired firms included in the sample. Patents data was taken from the NBER dataset and R&D expenditure from Datastream

[44] Danzon et al. (2007) find that acquisition is used by pharmaceutical firms as a fast response to shortages in innovation projects.

and Compustat.

They chose not to use a hazard model because it requires data on firm age, which is not consistently available in their data. Furthermore, they suggest that results from logistic and hazard models are similar; coefficients are likely to be matched in sign and significance but may differ in magnitude. Therefore they use a logit model to provide results for the following specification.

$$Acq_{it} = \alpha + \beta_1 I^I_{t-1} + \beta_2 I^D_{t-1} + \beta_3 ln(I^S)_{t-1} + \beta_4 size_{t-1} + \beta_5 size^2_{t-1} + \beta_6 growth_{t-1} + \beta_7 Profit_{t-1}$$
$$+ \beta_8 P^D_{t-1} + \beta_9 ln(Tobin'sQ)_{t-1} + \beta_{10} leverage_{t-1} + \beta_{11} liquidity_{t-1} + \gamma Ind + \gamma T + \epsilon \tag{3.72}$$

Acq_{it} is a binary variable indicating acquisition at time t for firm i, I^I represents innovation intensity. This variable is measured in two ways; R&D intensity measured by R&D expenditure to total assets and patent intensity measured as successful patent applications to total assets. Patents are normalised by dividing the number of citations by the cohort average within the same year and technological classification to account for industry differences. I^D is a dummy that indicates zero innovation intensity, I^S is the accumulated innovation output or innovation stock calculated using the perpetual inventory method, $size$, $size^2$ and $growth$ are measured in terms of total assets, $Profit$ represents profitability measured by operating return, P^D is a dummy indicating negative operating return, $Tobin'sQ$ is calculated as the ratio of total assets and market value of common equity minus book value of common equity to assets, $leverage$ is calculated as the ratio of long-term debt to the book value of common equity, $liquidity$ is the ratio of current assets to current liabilities, Ind and T represent vectors of industry and time dummies respectively. All explanatory variables are lagged to avoid endogeneity problems.

The marginal effects for the pooled logit with firm cluster robust standard errors are displayed. Findings from the equivalent panel model suggest that unobserved firm heterogeneity does not have a significant effect in this data and therefore the results remain consistent. The time and industry dummies are jointly significant. The results show a positive significant effect for R&D intensity suggesting that acquired firms are more likely to have higher R&D intensity than non-acquired firms. The effect of the accumulated patent stock is positive and significant, implying that acquired firms tend to have greater stock of patents than non-acquired firms. Whereas, the effect of patent intensity at $t-1$ is not significant. Acquired firms are more likely to have zero patent intensity at $t-1$.

To test the robustness of the results they split the data into two sub-periods. The results suggest that the determinants of the probability of being acquired change overtime. This may relate to stock market valuation waves. Robustness is also tested by using sales rather than total assets to calculate the explanatory variables. The results are not sensitive to this change.

Differences between acquiring firms and targets are investigated using a univariate analysis. The disadvantage of this technique is that it does not account for interactions between explanatory variables. Median values of each explanatory variable are obtained for targets, acquirers and target minus acquirer. These are then repeated using control adjusted targets and acquirers, which are calculated as the difference between the target or acquirer and its matched control. The control firms are taken from the sample on non-target and non-acquiring firms. The results imply that targets are more R&D intensive than acquirers, but this may be due to industry or firm size effects rather than acquisition patterns. Targets are likely to have lower patent stock than acquirers and have poorer economic performance than acquirers.

In summary, this paper adds to the literature by investigating innovation based motives for acquisition. The results suggest that acquirers target firms that are under performing in terms of patent intensity during $t-1$ compared to non-targets and their own previous performance, despite having higher R&D intensity. Patent stock is higher compared to non targets but generally lower than the acquirer. Furthermore, targets tend to have poorer economic characteristics than their counterparts. These findings support the search for inferiority hypothesis, where managers with superior capabilities are motivated by the aim to reorganise failing firms.

The methodology used in this literature has progressed from simplistic models to more complex survival models. The empirical findings indicate that motivations for mergers have changed over time. Financial characteristics are generally found to be important in determining the likelihood of takeover, therefore this consideration must be incorporated into my analysis.

3.4.2 Post-M&A Innovation Outcomes

Cloodt et al. (2006) focus on high-tech industries in their analysis. They distinguish between technological and non-technological motives for M&A by assuming that a technologically motivated acquisition is observed when the target firm has engaged in patenting activity during the 5 years prior to acquisition. They test how post-M&A innovative outcomes differ between the group of technological and non-technological M&As.

The international sample is taken from the Securities Data database and additional data on firm characteristics, R&D expenditure and patents were taken from various sources including Amadeus, Compustat, Worldscope and the US Patent and Trademark Office database. Patents are measured as the number of granted applications. This provides a balanced panel of 347 firms over the period 1985-1994. They identify 2429 M&As within the sample and no entry or exits occur.

The model takes the form of a random effects negative binomial model. The negative binomial model is considered to be appropriate because the dependent variable is measured using the number of patents which takes non-negative integer values.

$$P_{it} = exp(\alpha X_{i,t} + \beta_1 A_{i,t-1} + \beta_2 A_{i,t-2} + \beta_3 A_{i,t-3} + \beta_4 A_{i,t-4}) \tag{3.73}$$

P_{it} represents post-M&A innovation measured by number of patents obtained by firm

i in year t, $X_{i,t}$ is a vector of firm characteristics and $A_{i,t-year}$ is a vector of lagged firm characteristics. Firm characteristics include number of non-technological acquisitions, absolute size of the acquired knowledge base, relative size of the acquired knowledge base, relatedness of the acquired knowledge base, relatedness of the acquired knowledge base squared and cultural distance.

The absolute size of the acquired knowledge base is the number of patents obtained by the acquired firms from $t-5$ to t. Relative size is calculated by dividing the absolute size of the acquired knowledge base by the absolute size of the acquiring firm's knowledge base. Technologically related is measured by the number of identical patent codes between the acquired and acquiring firm, then divided by the absolute size of the acquired knowledge base. Cultural distance is a measure to control for differences between acquired and acquiring firms in international M&A.[45] R&D expenditure, log number of employees and an acquisition dummy are also included as control variables.

The results show that non-technological M&As may have a negative impact on innovation outcomes, whereas technological M&As exhibit an initial positive impact followed by a negative impact. This is indicated by the coefficient on the absolute size of acquired knowledge base. The relative size coefficients are negative and significant, suggesting that integrating a relatively large knowledge base into the existing operating activities of the firm can lead to organisational disruptions leaving less opportunity to focus on improving innovation and utilising synergies. A U-shaped relationship is found between innovation outputs and technological relatedness. This suggests that there must be some overlap of innovation activity between acquired and acquirer to improve innovation outcomes post-M&A. But if the relationship is too close the benefits diminish. Furthermore, the cultural distance variable displays a positive coefficient, suggesting that international M&A increases innovative output. Also, the number of patents is less economically meaningful than the value of patents.

Bertrand (2009) investigates the impact of foreign acquisitions on the R&D activities

[45] This is measured using the Hofstede Index.

of domestic target firms. They use a firm level panel of French manufacturing firms. The data is taken from the LiFi (Enquêtes Liason Financière) and covers the period 1994-2004. They contribute to the literature by looking at the changes in the type of in-house R&D - basic or applied- and differences in domestic and foreign outsourced R&D during the period following a foreign acquisition. The methodological approach aims to estimate the difference between the R&D expenditure following a acquisition by a foreign acquirer and the expected R&D expenditure if the acquisition did not occur. This involves two stages; firstly, an appropriate control group is determined using propensity score caliper matching and secondly, the difference in difference method is applied.

The first stage requires estimation of the probability that a firm is taken over by a foreign owner using the following equation:

$$P(FAcq_{it} = 1) = f(X_{i,t-1}, I_i, T_t) \tag{3.74}$$

$X_{i,t-1}$ provides a vector of firm characteristics. These include domestic market share at the 4 digit industry level, profitability (return-to-sales ratio), profitability squared, debt (EBITDA-to-interest), R&D intensity (R&D expenditure to total sales), R&D skill intensity (wages of R&D workers divided by the number of R&D workers) and capital intensity (productive assets divided by number of employees). The findings from this stage show a positive significant relationship between foreign acquisition and all independent variables, except capital intensity and debt and U-shaped relationship exists between foreign acquisition and profitability. This implies that bidders appear to cherry pick the best targets. The balancing properties of the sample are tested. Those targets with a propensity score beyond the upper and lower limits of the control group propensity score are removed to provide the balanced sample. The sample is composed of 123 matched acquisitions.

The second stage uses the difference-in-difference method to obtain the net difference in outcomes between the acquired and non-acquired after taking the initial pre-acquisition differences between groups into account. (See Blundell and Dias, 2000). Their estimating strategy takes the following form:

$$\Delta R\&D = \beta_0 + \beta_1 FAcq_{i,t} + \beta_2 FAcq_{i,t-1} + \beta_3 FAcq_{i,t-2} + \beta_4 FAcq_{i,t-3} + \epsilon_i \tag{3.75}$$

where

$$\Delta R\&D = R\&D_{i1} - R\&D_{i0} \tag{3.76}$$

Various measures of R&D expenditure are used as the dependent variable including total, internal, domestic external, foreign external, internal basic, internal applied, internal development, financed internally and financed externally. $FAcq_{it}$ is a dummy variable taking the value of 1 for foreign acquired firms and 0 for control group firms. Separate dummies are included to indicate acquisition during the current time period t, also 1, 2, and 3 years post-acquisition.

Results suggest that foreign acquisitions lead to an increase in R&D expenditure in each post acquisition year. He finds nothing to suggest that more R&D is outsourced abroad following foreign acquisition. Post-acquisition, domestic external R&D expenditure increases in line with internal R&D expenditure. This implies complementarities between these types of R&D. The findings imply that foreign firms may use acquisitions as a strategy to access the expertise of external sources within the local economy of the target firm. This suggests that foreign acquisitions could actually encourage R&D investment within the host economy. Furthermore, the results suggest that basic, applied and development R&D are complements. Despite the usual assumption that basic research is likely to be cut following acquisition in favour of less risky investments with short-term returns, basic R&D expenditure increases post acquisition in line with other forms of internal R&D. Internally financed and foreign financed R&D also rises post-acquisition suggesting that R&D could provide a possible channel for foreign injections to be made into the domestic economy. The results are also divided into subsamples of European and Non-European acquirers and by high-tech industry and low/medium-tech industries, but no significant differences are found between groups.

Ornaghi (2009) investigates the impact of mergers and acquisitions on innovative activity and the role that technological and product relatedness plays. The analysis specifically focuses on the Pharmaceutical industry. This industry is characterised by a large number of prominent mergers and has a high R&D intensity which plays a crucial role in inter-firm competition.

Data from 6 sources is combined to provide detailed information on the firms. These sources include Standard and Poor's Compustat, the Bureau Van Dijk's Osiris, Patent data from NBER, British National Formulary, the Orange Book of Food and Drug Administration and the Mergers Book. This provides a panel from 1998-2004 including 27 mergers and acquisitions. Each of these events involves 2 firms, where one is defined as the acquirer and the other as the target.

The estimation strategy proceeds in 2 ways. Firstly, a control sample is defined using propensity score matching and matching based on technological relatedness. Then the difference-in-difference method is applied. This intital estimation strategy aims to investigate the impact of merging on ex-ante innovation activity.

$$\Delta lnY = \beta_1 Acq_{i,t} + \beta_2 Acq_{i,t-1} + \beta_3 Acq_{i,t-2} + \beta_4 Acq_{i,t-3} + \gamma T + \epsilon_i \tag{3.77}$$

Where ΔlnY is the percentage change in innovation. This is measured in various different ways - R&D expenditure, R&D intensity, patents and research productivity (ratio of patents to R&D expenditure). The pharmaceutical industry has a high propensity to patent, therefore "important" patents are identified and used as an alternative patent measure with less noise. Important patents are determined based on the number of citations. Patents in each year are listed by number of citations and the top 40% are considered to be important patents. The stock market value of the firm ΔlnV is also used as a dependent variable to investigate to impact on the value of the firm. *Acq* are a set of acquisition dummies indicating if an acquisition takes place during the current period t, previous period $t-1$, etc.

The propensity score method aims to control for endogeneity by controlling for firm characteristics. The explanatory variables of the logit include percentage of drugs approaching patent expiration, percentage of new drugs introduced into the market, concentration of patents, stock market value, growth of stock market, concentration of products and a set of time dummies. The findings of the logit model suggest that mergers are more likely to take place if current patents will soon expire.[46]

The other approach used to establish a control group is based around technological relatedness. The aim of this is to control for exogenous technological shocks. Firms with a high level of technological relatedness are likely to experience similar shocks. The firms are matched according to the largest overlap between the list of patents cited.

The results are presented for each dependent variable for both methods of control group creation. Tables and graphical representations are used. The findings suggest that innovation outcomes for the merged firms are worse than control group outcomes. But he acknowledges the fact that this type of study is limited due to unobservable outcomes and the assumption that the control group outcomes depicts the behaviour of the firm if the merger did not take place. There is no way of testing the validity of this assumption.

The analysis is extended further by investigating how relatedness of merging partners, in terms of techology and products, impacts post-merger performance. The Heckman two-step method is used.

$$\Delta lnY = \beta_1 TR + \beta_2 PR + \gamma_1 \lambda(X\beta) + \epsilon_i \tag{3.78}$$

Equation (3.78) is estimated on a sample containing only merging firms. Selection

[46] This agrees with another paper that focuses on the pharmaceutical industry Danzon et al. (2007).

bias is controlled for by including the inverse Mills ratio $\lambda(X\beta)$. This is created using the probabilities estimated using the logit model. TR is technological relatedness and PR is product relatedness.

The extent of technological relatedness between acquirers and targets is measured in 4 different ways; the overlap between the list of patents cited, the correlation between patents' technological classes, the importance of cross citations from acquirers to targets and the importance of cross citations from targets to acquirers. Product relatedness is defined according to the "Anatomical Therapeutic Chemical" Classification (ATC) and depends on the correlation of products between acquirer and target. The results imply that technological relatedness has a negative impact on post-acquisition outcomes, whereas product relatedness has a positive effect. He suggests that these findings could potentially be explained by managerial focus on product relatedness to please shareholders, yet neglecting technological aspects leads to negative R&D outcomes.

Desyllas and Hughes (2010) focus on high technology firms. Their paper specifically aims to analyse the impact of acquisition on post-acquisition innovation performance and assess if differences in these outcomes depend on the characteristics of the acquiring firm. They hypothesise that post-acquisition R&D outcomes may depend on the acquirer's ability to identify, exploit and finance research synergies with the target firm. Given that post-acquisition decisions are usually taken by the acquirer, it is likely that acquirers with higher levels of absorptive capacity and lower financial leverage will be better positioned to reap the R&D advantages of an acquisition. Their analysis uses 2 measures of innovation performance. R&D intensity (the ratio of R&D expenditure to assets) and R&D productivity (patent applications to R&D expenditure). They suggest that R&D productivity is the preferred measure of innovation because it combines innovation inputs and outputs.

They use an unbalanced panel of US publicly traded high technology firms from 1984-1998. High technology firms are those in industries such as chemicals, computer equipment, electronics equipment, transportation equipment, measuring, analysing and controlling instruments and communications. Their final sample includes 573 acquiring firms with at least one acquisition and a control group of 850 firms. A total of 2624 acquisitions are included in the 8949 sample observations. This data is taken from Standard and Poor's Compustat database. This dataset provides details of R&D expenditure and financial data. Patent data is taken from the NBER database and the patent application date for granted patents is used. This data is often given at subsidiary level, therefore it is necessary to use Dun and Bradstreet "Who Owns Who" annual issues to establish the parent firm to create a match between datasets. A large number of observations are lost due to missing data or inability to match datasets, but the final sample size is sufficiently large and more substantial than most other studies.

The control group is established using the propensity score matching method. The dependent variable of the first stage is a binary indicator of acquisition. The independent variables represent lagged firm characteristics and include firm size, growth, profitability, leverage, R&D intensity, R&D productivity, knowledge base size and sets of industry and time dummies. The results of the logit estimations are not reported.

Equation (3.79) is estimated using Weighted Least Squares (WLS) in order to identify the impact of acquisition on acquirer R&D intensity and R&D productivity.

$$\begin{aligned} \%\Delta R\&D = \alpha &+ \beta_0 Acq_t + \beta_1 PS_t + \beta_2 PC_t + \beta_3 L_t + \beta_4 Lgrowth_t \\ &+ \beta_5 RelAcq_t + \beta_6 PubAcq_t + \beta_7 FAcq_t + \gamma weight_t + \epsilon_t \end{aligned} \tag{3.79}$$

Two dependent variables are used; the percentage change in R&D intensity and percentage change in R&D productivity. The percentage change is calculated over various different time windows, including t-1 to t+1, t-1 to t+2, t-1 to t+3 and t-1 to the average of t+1 to t+3. This provides 8 different dependent variables. The explanatory variables include $Acq_{i,t}$, a binary dummy indicating the event of acquisition at time t and PS_t is the knowledge base size of the firm. This is measured using a perpetual inventory of patents. PC_t is a measure of knowledge base concentration by 3-digit patent classification. L_t is a measure of financial leverage given by the ratio of long-term debt to the book value of common equity, $Lgrowth_t$ is the growth in leverage between pre and post-acquisition, $RelAcq_t$ is a dummy variable that indicates when the acquirer and corresponding target belong to the same 3-digit industry, $PubAcq_t$ is a dummy indicating if the target is a publicly traded firm and $FAcq_t$ indicates if it is a cross-border acquisition. Weights are generated using the propensity score. Observations are weighted as $1/p$ when an acquisition occurs and $1/(1-p)$ if no acquisition occurs. This measure is taken to account for endogeneity of acquisitions. Furthermore, interaction terms are allowed between $Acq_{i,t}$ and the firm characteristics.

Findings show acquisition has a negative effect on R&D intensity in the post-acquistion period. This is likely to be a result of post-acquisition restructuring. They note that OLS provides biased positive coefficients during the first post-acquisition year when endogeneity is not controlled for. Their results also show that the size of the acquirer's knowledge base has a positive impact on the percentage change in R&D productivity. They suggest this may be because firms with higher absorptive capacity have a greater ability to exploit the potential of their target's knowledge base and utilise synergies between the firms. Furthermore, they find that firms with high pre-acquisition leverage leads to greater post-acquisition R&D intensity and productivity.

Bandick et al. (2010) uses Swedish data to investigate how multinational take-over impacts R&D activity. They suggest three potential outcomes; R&D activity could reduce, remain at consistent levels or increase. They suggest that the observed outcome will depend on the extent that Swedish R&D complements existing R&D activity within the multinational. A reduction in R&D activity will arise if Swedish R&D is less sophisticated or replicates existing R&D activity within the multinational. Therefore diminishing the level of high skill activity in Sweden. If Swedish R&D proves to be superior to existing R&D and the type of activity complements the multinational's existing operations, R&D activity in Sweden is likely to be maintained or even increased.

The data used covers Swedish manufacturing firms for the period 1993-2002. They use a foreign ownership code to identify foreign owned firms and distinguish domestic multinationals using a further dataset indicating Swedish owned firms with foreign owned subsidiaries. This allows them to test if the effect of foreign acquisition is different for pre-acquisition Swedish multinationals and pre-acquisition domestic firms.

In order to address their research question they employ difference-in-difference estimation with propensity score methods. The difference-in-difference estimator assesses the impact of foreign acquisition on the growth of R&D intensity.

$$\beta = (y^A_{t+s} - y^A_{t-1}) - (y^C_{t+s} - y^C_{t-1}) \tag{3.80}$$

y represents R&D intensity, A denotes acquired firms and C denotes non-acquired firms. β can be estimated using the following equation, where $FAcq$ is a foreign acquisition dummy, d_t is a set of time dummies and μ_i captures industry specific fixed effects.

$$\Delta y_{it} = y_{t+s} - y_{t-1} = \beta FAcq_{it} + d_t + \mu_i + \epsilon \tag{3.81}$$

The β estimate gives the average percentage point change in the R&D intensity growth rate arising from foreign acquisition. This assumes that acquired firms are selected at random. Hence, the propensity score technique is required because there may be a relationship between firm characteristics and choice of acquisition target.

The probability of acquisition by a foreign multinational is estimated using a probit model, where explanatory variables include productivity, wages and size. Findings suggest that endogeneity may be a problem as positive selection is observed. These 'good performance' characteristics are likely to be correlated with R&D activity. The probabilities are used to create a matched sample using the nearest-neighbour approach and the balancing properties of the sample are tested. The sample includes 227 observations of foreign-acquired firms. Difference-in-difference estimation is applied to the matched sample. The results suggest that growth in R&D intensity is higher for foreign acquired firms than the non-acquired control group.

Guadalupe et al. (2012) investigate the selection of acquisition targets and the decision to invest in innovation for foreign-owned firms. This paper is one of the minority that relate this literature to innovation. They use a large panel of around 1800 Spanish manufacturing firms for the period 1990-2006. The data distinguishes between product and process innovation.

They initially test if multinational acquiring firms choose the most productive targets or they choose less productive firms and transfer superior technology or organisational structure. In the first stage of analysis they check for selection in the acquisition decision using a probit model. The probability of acquisition, $\hat{p}$, is estimated as a function of firm characteristics. This probability is estimated separately for each industry to allow the relationship to vary. Their findings show that multinationals are more likely to acquire the most productive firms.

The second stage of analysis asks if foreign-acquired subsidiaries invest more in innovation than if the firm had remained domestic? This question is addressed using the following model.

$$I_{it} = \alpha + \gamma F_{it} + d_t + \eta_i + \epsilon_{it} \tag{3.82}$$

Where I_{it} is the measure of product or process innovation, F_{it} is a Foreign ownership dummy, d_t is a year dummy, η_i is industry fixed effects and ϵ_{it} is the error term. A propensity score reweighting estimator is used to control for selection. Each acquired firm is weighted by $\frac{1}{\hat{p}}$ and each non-acquired firm is weighted by $\frac{1}{1-\hat{p}}$. The sample is restricted to firms with common support. They argue that this method is preferable to the propensity score matching technique following Busso et al. (2009). The results show that innovation is increased following acquisition for foreign-owned firms.

García-Vega et al. (2012) also assess the effect of foreign acquisition on R&D behaviour at the firm level. They use annual Spanish data covering the manufacturing and service sectors for the period 2004-2009. Their sample includes only R&D conducting firms. In the first stage of investigation they test for selection in the acquisition decision. They use probit estimation with cluster robust standard errors on pooled cross-sectional data. The dependent variable is a foreign acquisition dummy and explanatory variables include pre-acquisition characteristics such as various R&D variables, number of employees, labour productivity and an export dummy. Pre-treatment lagged values are used to ensure that the characteristics are not influenced by acquisition, thus complying with the conditional independence assumption.

The data provides information on internal and external R&D expenditures, where external expenditures are divided into domestic and foreign[47]. A number of different R&D variables are tested for significance in the model. Version (a) of the model includes log total R&D expenditure and R&D intensity, version (b) includes log of internal and log of external R&D expenditures and version (c) includes the ratio of external to internal R&D and a dummy indicator of pre-acquisition foreign R&D.

Their findings suggest that acquiring foreign firms tend to select more productive, medium size firms with higher R&D expenditures. Version (b) suggests that as external R&D expenditure increases firms are less likely to be acquired, whereas increases in internal R&D make firms more attractive to acquirers. This suggests that foreign multinationals value knowledge generated through in-house R&D. The coefficient on the dummy in version (c) of the model suggests that those with pre-acquisition foreign external R&D are more likely to be acquired. They suggest this indicates a preference for Spanish owned multinationals.

From this first stage they conclude that evidence of cherry-picking prevails. This implies that endogeneity poses a problem for the second stage in their analysis. To address this problem they use the propensity score method to create a matched sample. They pair each foreign acquired firm with the closest non-acquired firm in the same year using caliper matching with replacement. Therefore some control group firms may be matched to more than one foreign-acquired firm. The matched sample includes 295

[47]This is similar to the UK BERD data.

firms, where 141 are non-acquired firms and 154 are acquired by foreign firms. They use balancing tests to confirm the validity of their sample.

They estimate the impact of foreign acquisition on R&D activity using the following equation.

$$Y_{it} = \delta + \gamma FAcq_{it} + \lambda FAcq_{i,t-1} + \phi Z_{it} + \epsilon_{it} \tag{3.83}$$

$FAcq_{it}$ and $FAcq_{i,t-1}$ are foreign acquisition dummies representing acquisition in period t and period $t-1$ respectively. Z_{it} is a set of control variables and Y_{it} represents R&D expenditure. The model is estimated using total, internal, external, external-foreign and external-domestic R&D expenditure. They extend the analysis by using separate acquisition dummies for foreign owners from frontier and non-frontier countries. The initial frontier countries chosen are Japan, USA and Germany. They investigate this further by testing different country groupings.

Their results suggest that firms acquired by foreign owners from leading frontier countries see an increase in foreign R&D transfers, but a decrease in in-house R&D expenditure. Whereas, foreign acquired firms with non-frontier owners experience the opposite trend.

Szücs (2012) investigates the relationship between acquisition and ex-ante incentives to allocate resources to innovation activities. This paper develops the approach used by Ornaghi (2009) by distinguishing between acquirer and target outcomes, rather than grouping both firms together. The data overs a broad range of industries and is geographically diverse, covering 38 2-digit sic codes and 25 nations.

The dataset is created based on acquisitions identified to the European Commission (EC) or Federal Trade Commission (FTC). Therefore it only contains relatively large M&A, where the deal-value exceeds $60 million (USD) to be registered by the FTC or turnover over 5,000 million Euros to be registered by the EC. This acquisitions data is combined with data on R&D expenditure, total assets, sales, debt and employees.

Firms with more than one acquisitions during 4 year period and those without full R&D expenditure data in the years directly before and after the acquisition are dropped. Firms with zero R&D are included to prevent selection bias. This generates a sample containing 265 acquiring firms and 133 targets.

Control groups are defined from a sample of more than 150,000 observations of non-merging firms using 3 different propensity score matching methods. These include (1) Nearest Neighbour Matching within the same year, (2) Mahalanobis Metric Matching with same year and 2 digit sic and (3) global Caliper Matching. Separate estimations are made for acquirers and targets. The dependent variable is a binary acquisition variable and explanatory variables include R&D intensity, R&D growth, total assets, employees, profitability, total debt, *age* and age^2.

The standardized bias is calculated for each method which shows the bias that occurs when comparing treated to non-treated. This is calculated by the difference in means between the treated (T)and non-treated control group (C) divided by the standard deviation of the treated group (σ_T).

$$\frac{\bar{x}_T - \bar{x}_C}{\sigma_T} \tag{3.84}$$

Difference-in-difference estimation is used in the analysis, where R&D expenditure growth is the dependent variable, *acquirer* and *target* indicate the pre and post acquisition period from $t-3$ to $t+6$.

$$\Delta R\&Dexp_{ij} = \alpha + \sum_{6}^{t=1} \beta_t acquirer_{i,j-t} + \sum_{6}^{t=1} \gamma_t target_{i,j-t} + \eta controls + \epsilon_{ij} \tag{3.85}$$

The results from the propensity score stage show acquirers tend to be large and profitable, whereas targets tend to have high R&D intensity and relatively low profitability. This may suggest that acquirers may cherry pick firms with technology capabilities, with the aim of improving their profitability through restructuring and exerting managerial knowhow. The second stage of the estimation reveals that R&D activity is diminished during the post-merger period for both acquirer and target. There is little variation in results between control group construction method.

This overview of the literature suggests that it is important to create a matched dataset to control for endogeneity. Propensity score matching is a suitable method of doing this. There may be differences in post-M&A outcomes between high-tech and low-tech firms and between M&A by foreign and domestic firms. The literature also suggests that it is preferable to measure innovation activity using a combination of R&D expenditure and patent data. Unfortunately patent data cannot be obtained for use in my study. This overview also identifies a gap in the literature. Each study investigates post-event innovation outcomes, but does not investigate mergers and acquisitions separately or compare outcomes of these different types of events.

3.4.3 Productivity and Foreign Acquisition

Conyon et al. (2002) suggest that the finding that foreign owned firms outperform domestic firms may result from omitted variables and compositional factors, e.g. cross-sectional studies. If the observed differences between performance of multinationals domestic firms do solely arise from these factors, this would have serious implications for government policy.

They suggest that many previous papers that perform cross-sectional studies omit important explanatory variables such as firm size and capital vintage. Also, simultaneity bias is problematic as multinational entrants are likely to be attracted to more profitable and productive industries. In their paper they assume that industry and firm specific characteristics remain the same during the observation period and therefore overcome these difficulties by using panel data. This allows firm specific fixed effects to be controlled for.

Multinationals looking to expand into developed countries such as the UK generally opt for acquisition as their chosen expansion strategy, whereas expansion into less developed countries may occur through the creation of a greenfield start-up. Acquisition as a method of breaking into new geographical territory presents less uncertainty than alternatives. The acquisition target already possesses local market knowledge. The take-over of an existing firm prevents the increase in market concentration that may occur by creating a new enterprise. Also, the target firm can be seen as a stand alone unit that can be divested if necessary.

Foreign multinational firms are generally considered to bring a set of intangible assets with them that can potentially lead to advantages over domestic firms. These assets may include organisational capabilities and technological knowledge.

The data is taken form the OneSource database of UK companies. The sample of acquisitions considers firms with an ownership change between 1989 and 1994 and includes only those with 5 consecutive years of data between 1987 and 1996. This creates a sample with 331 domestic and 129 foreign acquisitions. Furthermore, they create an industry-stratified random control sample of firms that did not incur an ownership change during the observation period. This control group includes 642 firms.

They perform a multinomial logit estimation with a binary acquisition variable as the dependent variable and firm characteristics a explanatory variables. This preliminary analysis determines if there is a type of firm that is a more attractive acquisition target to foreign or domestic acquiring firms. The findings show that foreign firms seem to prefer targets with lower than average profitability and domestic firms prefer targets with lower than average wages. This suggests a potential source of endogeneity in their wage analysis.

They perform investigations into the impact of ownership change on labour productivity and on the wage rate. They use fixed effects panel analysis then control for endogeneity using instrumental variables. The chosen instrument for the acquisition dummy is the estimated probability of domestic and foreign acquisition in each year.

Balsvik and Haller (2010) suggest that the performance of the chosen target before and after the acquisition takes place is likely to depend on the underlying motivations behind the acquisition. They provide an outline of three general motivations to acquisition. Firstly, performance is a secondary consideration if management is motivated by the desire to increase firm size. Therefore no specific relationship with firm performance is observed. Secondly, management may possess a comparative advantage in terms of organisational capabilities. Firms will aim to acquire targets that provide the greatest marginal payoff, therefore they are likely to show a preference for "lemons" and post-acquisition performance should improve. Thirdly, a firm may be motivated by the desire to improve current firm performance arising from complementarities with the target firm. This is consistent with the technology sourcing hypothesis to gain access to specialist knowledge. Under these circumstances targets are likely to be "cherries" and performance could be unaffected, reduced or improved depending on the complementarity match between firm and target.

In their empirical analysis they use Norwegian data taken from an annual census of manufacturing plants for their sample period 1992-2004. Their initial sample is obtained by dropping plants with less than 10 employees and plants that do not add to their capital stocks during the sample period. This results in an unbalanced panel of 65,740 observations from 7158 plants. In this data, plants keep the same plant code for their entire life. Acquisitions are recognised in the data through changes in the ownership code for a given plant. Plants are considered to be domestically owned if less than 50% of the plant's assets are foreign owned. An acquisition is defined as a foreign acquisition if the percentage of assets owned by foreigners increases to above 50% and the plant was previously domestically owned before the ownership change. The data should cover the entire population of Norwegian manufacturing plants, therefore entry and exit of a plant should be illustrated through the inclusion and omission of plant codes. In their initial sample they ignore the fact that multiple takeovers may take place during the sample period. Observations do not necessarily exist for the two years before and after acquisition and firms with missing observations are included.

They use the following estimating equation where controls include log employees, plant age, industry, year, foreign and domestic multinational dummies and industry-year interactions.

$$
\begin{aligned}
y_{it} = \sum_{t=t-2}^{t+2} \alpha_{Dt} DomesticAcq_{it} + \sum_{t=t-2}^{t+2} \alpha_{Ft} ForeignAcq_{it} \\
+ \sum_{t=t}^{t+2} \alpha_{Dt} DomesticEntry_{it} + \sum_{t=t}^{t+2} \alpha_{Ft} ForeignEntry_{it} \\
+ \sum_{t=t}^{t+2} \alpha_{Dt} DomesticExit_{it} + \sum_{t=t}^{t+2} \alpha_{Ft} ForeignExit_{it} + controls + \epsilon_{it}
\end{aligned}
\quad (3.86)
$$

y_{it} represents plant performance. They use log employment, log average wage, log labour productivity and log total factor productivity (TPF)[48] They firstly estimate their model on the entire sample using OLS and plant fixed effects. The coefficients in the OLS model show the deviation from the industry-year base group of non-multinationals experiencing the event. Fixed effects looks at the deviation of firms from their own average performance relative to the base group. The base group consists of firms in regular operation, so deviation from the mean is likely to be small. Positive coefficients on an event at time t suggest firms are doing better than usual and negative coefficients imply that are doing worse than their own average.

Their results show a distinctly different picture for foreign and domestic acquisitions. Domestically acquired plants see a fall in employment and labour productivity post-acquisition, whereas foreign acquired plants show post-acquisition increases in employment, average wage and labour productivity. They find significant coefficients on the entry and exit dummies in the initial results which suggests that plant performance differs from the average close to entry and exit. They check the robustness of their acquisition results by applying the model to various subsamples of the data.[49]

Sample 1 removes all firms that are close to entry and exit. Sample 2 removes all firms

[48]Estimates of TFP are the residuals from the OLS regression of a Cobb-Douglas production function with controls for year, industry and year-industry interactions.

[49]Entry and exit dummies are no longer required in the model due to the restricted samples.

with more than one ownership change during the sample period and all firms that are domestic multinationals. This allows for performance comparisons of non-multinationals acquired by foreign owners and wholly domestic owners over time. Sample 3 adds a further restriction by only including firms with a full set of pre- and post- acquisition dummies. Sample 4 includes single acquisition firms that were originally domestically owned and taken over by domestic or foreign multinationals.

They provide OLS results for each of the samples and plot the coefficients on the foreign and domestic acquisition dummies graphically for each period t. Samples 1-3 provide a consistent picture with the results from the entire sample. Firms prior to foreign takeover tend to be larger, have higher labour productivity and higher average wages than the reference group and firms taken over by domestic non-multinationals. This suggests foreign firms "cherry pick" better performing acquisition targets. Firms acquired domestically show diminishing performance in the pre-acquisition period, implying domestic acquirers pick "lemons". Post-aqcuisition performance generally improves for foreign acquired firms but domestic firms fail to return firms to their pre-acquisition peak during the 2-3 year post acquisition period.

Criscuolo and Martin (2009) investigate productivity differences between UK multinationals, US subsidiaries and other foreign subsidiaries in the UK. They highlight three potential effects that may lead to higher observed productivity of foreign-owned subsidiaries. These include the "best firm effect", "plant picking effect" and the "going global effect". The best firm effect occurs when foreign multinationals transfer superior managerial or technological capabilities to subsidiaries. Plant picking effect refers to the selection of more productive plants in the acquisition process and the going global effect arises due to firm-level economies of scale and ability to hedge exchange rate risk.

They use plant-level data from the ARD and use the AFDI to establish multinational status. Their initial sample includes multinationals and non-multinationals and covers the period 1996-2000. They begin their regression analysis with a simple Cobb-Douglas production function approach and apply OLS using the following estimating equation;

$$log\frac{Y}{L} = \beta_1 log\frac{K}{L} + \beta_2 log\frac{M}{L} + \beta_3 logL + \sum \beta_4 Multinational + \sum \beta_5 controls + \epsilon \quad (3.87)$$

Where Y is gross output, L is labour, K is capital and M is input materials. Various multinational dummies are included indicating general multinational status and if the plant belongs to a US owner, other foreign owner, or EU owner. Controls include quadratic plant age term, region and four digit industry time interaction dummies. Standard errors are clustered by establishment. The results show that multinationals are more productive than non-multinationals plants. Furthermore US owned plants are more productive than other foreign owned plants.

The model can be criticised in a number of ways. Firstly, Cobb-Douglas provides a rather restrictive functional form; secondly, factor inputs may be endogenous; thirdly, the model does not account for differences in production technology across industries; and finally, competitive power could differ between multinationals and non-multinationals and across sectors. They address these concerns by using a total factor productivity TFP approach and placing restrictions on the data sample.

They apply two approaches to the calculation of TFP; method 1 follows Klette (1999) and method 2 is a modified version of the Olley-Pakes (1996) approach. They use the estimated TFP values as the dependent variable and include multinational, US and foreign ownership dummies as explanatory variables. They also include the log of capital relative to median capital when the Olley-Pakes measure is used. This allows production technology to vary. A coefficient of less than 1 implies differences in production technology between sectors exist, implying variations in market power. They perform tests on subsamples of the data by sectors to address the issue that market power may vary with industry sectors as well as between sectors, then interact the capital variable with multinational, US and foreign owned to test for differences. These interactions suggest that no differences in this variable exist between multinational sub-groups. The results with regards to multinational, US and foreign ownership dummies remain consistent with the initial OLS findings.

To further study the US productivity leadership observed in the initial results, they control for firm and plant specific fixed effects using a double fixed effects approach. [50] This approach involves two stages. The first stage uses productivity y_{it} as the dependent variable and controls for each firm-plant combination fixed effect to remove time invariant firm and plant specific effects.

$$y_{it} = \alpha_{it} + \gamma_{j(it)} + \beta_{MNE} Mult_{j(it)} + \epsilon_{it} \tag{3.88}$$

α_{it} is the time invariant plant specific effect and $\gamma_{j(it)}$ is the time invariant firm specific effect. $Mult_{j(it)}$ is a multinational dummy which captures the productivity effect of becoming multinational. A positive significant coefficient on the multinational dummy in this first stage will support the “going global effect”. This is because time invariant firm and plant characteristics are removed therefore the β_{MNE} coefficient is identified on changes in multinational status.

In the second stage they use the fixed effects estimates from the first stage as the dependent variable and include a series of dummies as explanatory variables. These include a set of multinational dummies which indicate if the firm or plant was ever part of a multinational, ever US owned or ever foreign owned and a set of greenfield dummies that indicate domestic multinational, US or foreign owned greenfield set-ups during the sample period. These greenfield dummies indicate the extent of the “best firm” relative to the non-greenfield domestic reference group effect because any technological or managerial advantage can be fully attributed to the parent firm. ‘Ever’ multinational dummies provide evidence of the plant picking effect.

In the first stage of estimation they find no significant indications of the “going global effect”. In the second stage they use the fixed effects estimates taken from the first stage as dependent variable. Positive significant coefficients on the ‘ever multinational’ dum-

[50] This approach appear to be similar to Stochastic Frontier Analysis.

mies imply plant picking behaviour and positive significant coefficients on the 'greenfield multinational' dummy suggests transfer of technological and managerial advantages via the "best firm" effect. To check the robustness of these results they limit the sample to include plants that have changed from domestic to multinational during the sample period. Their results see a drop in size and significance of the multinational dummy implying that "best firm" transfers may take time to manifest for newly multinational plants[51].

They develop stage one of the model further by accounting for endogeneity arising from correlation between time varying shocks and likelihood of multinational takeover. This is done by controlling for the probability of multinational selection estimated using a logit binary dependent variable model. They find evidence to suggest that multinational firms select targets that were more productive in the period before takeover.

A criticism of this study is that they do not control for or compare with firms that experience non-multinational ownership changes, or consider the adjustment period once a takeover has occurred, yet this is due to the limitations of the data. The sample period is short covering only 4 years. The number of matches between AFDI and ARD is relatively low in 1996 and 1997 and the ARD only contains production and construction industries pre-1997.

Harris (2009) seeks to answer the following questions: Firstly, do foreign owners prefer high performance plants as acquisition targets, and secondly, how does a change to foreign ownership impact post-acquisition performance? He investigates this using a number of different measures of performance including total factor productivity, profitability, employment and wages. He also looks at the probability of post-acquisition plant closure. The propensity score methodology is used.

The data is taken from the ARD, covering the manufacturing sector for the period 1985 to 2005 and service sector data form 1997-2005. ARD data is recorded at reporting unit level. An enterprise may possess a number of plants and may group its activity

[51] Those firms that became multinational pre-1996 are removed from the sample

into various reporting units, but reporting units do not necessarily correspond to plants. Harris believes it is important to use plant level data, particularly for the calculation of capital stock. Therefore he calculates estimates of plant level observations using local unit employment data from the BSD. Acquisitions are defined as any change in ownership, therefore mergers and acquisitions are grouped together. The foreign ownership code is used to distinguish between UK, US, EU and other foreign acquisitions. The data is split into 6 manufacturing sub-groups and 7 service sector sub-groups.

The investigation of the impact of foreign acquisition on productivity involves a number of steps. Firstly, a dynamic cobb-douglas production function is estimated on the entire sample using the system GMM approach. This technique is used to control for endogeneity of factor inputs and outputs. Harris favours this approach of deriving TFP estimates over the frequently used Olley-Pakes method because it controls for fixed effects. The inputs are instrumented using lagged levels and lagged first differences, which reduces finite sample bias according to Blundell and Bond (1998).

Various ownership dummies are included to capture the impact of ownership subgroups. One set of ownership dummies indicate the period of ownership by UK, US, EU or other foreign owner. The coefficients on these dummies indicate if intrinsic productivity benefits are derived from foreign ownership. A further dummy is included to control for foreign greenfield investment. These dummies are interacted with the input variables to allow for differential effects. A set of acquisition dummies and lagged acquisition dummies are included to identify the year of acquisition and UK, US, EU or other foreign owner. Another set of ownership dummies indicate if the plant has a foreign owner at any time during the sample period. These dummies are used to test if plants acquired by foreigner owners have further productivity advantages that are not attributed to foreign ownership status. Therefore they are used to test the cherry picking hypothesis when the full sample is used. The results show that in most industries foreign owners opt for less productive firms, but cherry picking does occur in some industries,including metals, mechanical engineering and extraction of minerals & chemicals.

Secondly, a matched sample of foreign owned acquired and non-acquired plants is created using the propensity score approach. This involves using a cross-sectional probit model to calculate the propensity score for each plant. The use of a fixed effects probit is avoided to prevent bias resulting from the incidental parameters problem.

$$P(ACQ_{it} = 1) = \phi(lnLP_{it-1}, lnAGE, lnKL_{it-1}, lnIL_{it-1}, size_{it-1}, singleplant,$$
$$lnDiversification, lnaglomeration, lnHerfindahl, \%FO, industry, region) \quad (3.89)$$

The dependent variable is an acquisition dummy ACQ_{it} recorded as 1 if the plant is acquired at time t during 1995-2000. The explanatory variables include LP_{it-1} labour productivity, KL_{it-1} capital-labour ratio, $size_{it-1}$ a set of 4 size dummies and $\%FO$ measures the importance of FDI within the given industry. Plants are then matched year-by-year using the calculated propensity scores and the nearest-neighbour, one-to-one common support approach (PSMATCH command in STATA).

Thirdly, the initial cobb-douglas production function is re-estimated using the matched sample. These results do not show evidence of cherry picking because the acquired and non-acquired plants in the matched sample display similar characteristics. The results show in some industries acquisition by foreign owners leads to higher total factor productivity beyond the expected outcome of the non-acquired plants with matched characteristics.

Fourthly, total factor productivity estimates are derived from the re-estimated production function. Results are presented in the form of cumulative distribution diagrams by industry, where the distributions for acquired plants generally lie to the right of the non-acquired plants suggesting that acquired plants dominate the non-acquired plants in terms of TFP. Although there is some cross over of the distributions at higher levels of TFP. They use the Kolmogorov-Smirnov test to test the validity of the graphical results.

The main strengths of this paper arise from the data and methodology used. The sample covers a long time-period and foreign acquisitions can be distinguished by country.

A criticism of the study is that no distinction is made between acquisitions and mergers, thus assuming no differences exist between the two event types.

In summary, this section emphasises the importance of distinguishing between domestic and foreign M&A. Post-event productivity differences can exist between the two groups because incentives may differ.

3.4.4 Pre-Divestment Characteristics and Post-Divestment Innovation Outcomes

Markides (1995) describes corporate refocusing as a reduction in diversification that usually occurs through divestiture. The study aims to determine if reductions in diversification lead to increases in profitability. A stratified sample of 200 firms is taken from the Fortune 500 list over the period 1981-1987 and variables are obtained from Compustat and TRINET. The estimating equation is given as follows:

$$\Delta Profit_{87-81} = \alpha+\beta_1 Refoc+\beta_2 Aint_{85-81}+\beta_3 R\&Dint_{85-81}+\beta_4 C4_{85-81}+\beta_5 MCh_{86-81}+ \beta_6 DE_{86-81} + \beta_7 For_{87-82} + \beta_8 Emp_{87-81} + \beta_9 Cap_{87-81} + \beta_1 0 Risk_{87-81} + \epsilon \quad (3.90)$$

The dependent variable $\Delta Profit_{87-81}$ is change in profitability over the period 1981 to 1987. Profitability is measured in three different ways to ensure the results are not sensitive to the measure used. These include the industry weighted return on sales, industry weighted return on equity and industry weighted return on assets. $Aint_{85-81}$ represents industry-weighted industry advertising intensity, $R\&Dint_{85-81}$ represents industry-weighted industry R&D intensity, $C4_{85-81}$ is the industry-weighted four firm concentration ratio measured using a Herfindahl index, MCh_{86-81} is a dummy variable that indicates a change in CEO during the period 1981 to 1986, DE_{86-81} is the debt to shareholder equity, For_{87-82} indicates the firm's foreign sales as a proportion of total sales[52],

[52] 1982 is used because 1981 data is unavailable.

Emp_{87-81} represents sales per employee, Cap_{87-81} is capital expenditure as a percent of sales, $Risk_{87-81}$ is risk measured by the standard deviation of the return on sales during the 1981-1987 period and $Refoc$ is a measure of refocusing. It is defined in five different ways to ensure that the results are not sensitive to the definition.

Method 1 identifies refocusing firms as those that announced their intention to refocus in the Wall Street Journal and actually divest at least 10% of their assets. Method 2 follows Rumelt (1974) by classifying those that reduce the number of strategic categories engaged in between 1981 and 1987. Method 3 calculates an entropy index of diversification following Palepu (1985). A decrease in the measure indicates refocusing. Method 4 classifies refocusing firms as those that reduced the number of industries they competed in by at least three. Method 5 uses a broader definition which distinguishes restructuring firms of two types; unrelated-business firms and related-link firms. The related DR and unrelated DU components of the diversification index are obtained and the ratio of these components to the total diversification index DT are calculated. The unrelated-business firms are defined as those which increase diversification to exploit interal capital, where DU/DT is increasing and DR/DT is decreasing. Related-link firms decrease diversification to improve control systems, where DU/DT is decreasing and DR/DT is increasing.

Furthermore, it is also necessary to distinguish over-diversified firms. Again, five different methods are used to identify these firms and verify the robustness of the results. Method (a) firms in the sample were ranked in order of their initial diversification level as defined by the entropy measure. The 70 most diversified firms were selected to represent highly diversified firms. The sensitivity of this dividing point was tested. Method (b) firms were grouped by core industry. Those with higher diversification than the industry median were considered to be over-diversified. Method (c) Unrelated business firms as defined by Rumelt (1974) are identified as over-diversified firms. Method (d) firms that have higher than median diversification within the unrelated business, related business and dominant business groups are classified as over-diversified. Method (e) those firms that have above median related diversification or above median unrelated diversification are defined as over-diversified.

The regressions are run on the sub-samples of over diversified firms. The results show a positive and significant coefficient on the refocusing variable. This indicates that for over-diversified firms, refocusing of activities is associated with increasing profitability. This finding is robust across the different methods of defining over-diversification and refocusing. The results also remain consistent when the dependent variable $\Delta Profit_{87-81}$ is measured using return on sales, equity or assets. When refocusing is split by time period, findings show that refocusing is only significant in the first period. This suggests that the benefits of refocusing may take time to impact profitability. When the sample is split into groups of early, middle and late refocusing firms, the early refocusers achieve higher than industry average profitability, whereas middle and late refocusers are below industry average.

Mata and Portugal (2000) investigate the likelihood of market exit and divestiture following foreign entry. Entry can occur by acquisition or through greenfield investment. They use a competing risks model with two latent durations. These durations are time until divestment and time until closure.

$$h(m) = exp(\beta X_m)\gamma_m \tag{3.91}$$

where γ_m represents the hazard rate for the time interval m, X_m is a vector of explanatory variables at time m and β is the vector of corresponding coefficients. A flexible non-parametric specification is used and the model is estimated using maximum likelihood methods. The explanatory variables X_m include a greenfield entry dummy, where greenfield entry is indicated by 1 and acquisition is indicated by 0, proportion of college graduates in the firms work force, log number of employees, fully owned subsidiary dummy indicating firms with 100% of foreign capital, majority joint venture dummy indicating firms with less than 100% but more than 50% foreign capital, limited liability dummy, log number of plants, diversification measured as 1 minus the herfindahl index of firm specialisation calculated using the shares of firm activities in different industries, industry concentration, log of estimated minimum efficient scale calculated following Lyons (1980) to capture scale economies, industry growth, ratio of employment in new firms to total employment in the industry, ratio of employment in foreign owned firms to total employment in the industry.

The study uses data from the Portuguese Ministry of Employment to create a sample of 1033 foreign firms that entered during the 1983-89 period. The results show distinct differences in characteristics between those subsidiaries that exit through divestiture and those that exit through closure. Greenfield investments are more likely to be closed firms than enter through acquisition, whereas entrants through acquisition are more likely to divest than greenfield entrants. The divestiture coefficients on the majority foreign and fully owned foreign subsidiary dummies are negative. This indicates that subsidiaries with a higher proportion of foreign ownership are less likely to be divested than majority domestic owned firms. The coefficients in the closure equations indicate that foreign owned subsidiaries are more likely to close than majority domestic owned firms. With regards to legal ownership form, limited liability firms are least likely to close but more likely to be divested than unlimited liability firms. This may reflect difficulties associated with selling an unlimited liability firm. The negative and significant size coefficient indicates that larger firms are less likely to exit through closure but the size coefficient for divestment is not significant.

The estimates of the baseline hazard parameters are obtained and depicted graphically. Both hazard rates are similar to the pattern observed when covariates are not controlled for. The closure hazard rate and divestment hazard rate evolve differently over time. The closure parameters decrease over time suggesting that continued learning takes place following entry; firms get better at surviving the longer they have existed. The divestment parameters remain relatively consistent overtime, despite a peak during year 2.

In summary, this paper investigates the likelihood of exiting the market for foreign entrants. The competing risks model is appropriate because it accounts for the fact that a firm faces the risk of closure and divestment simultaneously. The results show that it is not appropriate to group these two forms of exit together. The model differs from others by using mostly ownership explanatory variables rather than financial variables. The study may have benefited from the inclusion of these variables if they were available.

Haynes et al. (2002) investigate the impact of divestment on performance using an unbalanced panel of 132 UK quoted companies from 1985 to 1993. They identify various motives for divestment. It can act as a means of correcting over-diversification, when growth has been misdirected or occurs at a faster rate than the organisation can manage. This idea ties in with Markides (1995). Firms with excessive free-cash flow and limited growth opportunities may undertake negative net present value investments. Divestment may act to reduce the risk of total failure of an organisation. This could be achieved because divesting the least profitable parts of the firm may reduce losses and may provide financial value to the divestor in terms of the purchase price. The motivations behind divestment are likely to impact post-divestment performance. They suggest that divestment as a means of reducing diversification to focus on core competencies is likely to lead to improved performance.

The model is specified as follows and estimated using GMM.

$$\Delta(\Pi/K)_{it} = \alpha_1\Delta(\Pi/K)_{it-1} + \alpha_2\Delta CON_{it} + \alpha_3\Delta MS_{it} + \alpha_4\Delta(MS * CON)_{it} + \alpha_5\Delta LEV_{it} + \sum_{r=0}^{3}\delta_r DIV_{it-r} + \sum_{t=1}^{T}\gamma_t Y_t + e_{it} \quad (3.92)$$

First differencing is used to remove fixed effects. The dependent variable $(\Pi/K)_{it}$ represents profitability measured by return on capital. Other measures of profitability are also used to test the sensitivity of results to the measure used. These include the ratio of profit before interest, tax and gains to losses on disposals relative to net assets, the ratio of profit before interest, tax and gains to losses on disposals relative to sales turnover and the ratio of trading profit before interest, tax, depreciation and operating provisions to net assets. The explanatory variables include a lagged dependent variable to capture the persistence of profitability. MS_{it} represents market share of firm i, CON_{it} is market concentration using a Herfindahl index, LEV_{it} is firm leverage measured using the debt to asset ratio, DIV_{it-r} represents a set of divestment variables to capture lagged effects of divestment, Y_t is a set of year dummies to control for macroeconomic effects and e_{it} is an error term.

The results show the lagged dependent variable $\Delta(\Pi/K)_{it}$ has a positive and significant effect implying that persistence in profitability exists. Market concentration ΔCON_{it} also has a positive and significant coefficient, whereas the coefficients on market share ΔMS_{it} and leverage ΔLEV_{it} are not significant. The sets of divestment variables take a different form in each version of the model, including number of divestments, proportion of assets divested and divestment dummies. The coefficients on these variables are mostly positive and significant.

To test the validity of the Markides (1995) argument, the divestment dummies are interacted with *complex* and *noncomplex* dummies. These dummies aim to identify firms with complex and non-complex organisational structures according to size and the extent of diversification. Companies with above median (size*diversification) are classified as complex and those below are defined as non-complex. Three definitions of size are used to ensure robustness. The findings show all coefficients on complex-divestment interactions are positive and significant, although two non-complex-divestment interaction coefficients also have a positive significant effect for the $t-2$ and $t-3$ lags. Wald tests confirm that it is appropriate to distinguish between the two categories. Therefore some support is provided for the idea that the performance impact is more substantial for over-diversified firms, yet it is not conclusive.

In addition, strong and weak governance dummies are defined. Three definitions are used depending on the extent of management's equity stake in the company and the existence of blockholders with at least 5% equity. Strong governance implies that management will be more likely to conform to shareholder value maximisation policies rather than pursue their other objectives. The interaction with divestment terms show all coefficients on the weak governance interactions are positive and significant, indicating that the performance impact for weak governed companies is greater. This could be because they are more likely to over-diversify.

In summary the findings conform to the notion of an optimal diversification level as they show that divestment has an positive impact on profitability, particularly for larger, more diversified firms with weak governance. Although these findings are not robust to all measures and therefore cannot be deemed entirely conclusive.

Haynes et al. (2003) investigate the determinants of divestment using an unbalanced panel of 144 UK firms over the period 1985-1991. The firms were taken from the top 500 firms in the Times 1000 list 1988-89. Corresponding divestment data was taken fom the Centre for Management Buy-out Research CMBOR database, financial statistics from Datastream and data on takeover-threat rumours from Acquisitions Weekly and the Financial Times. The sample excluded foreign owned and trading companies. 91% of firms in the sample had at least one divestment during the sample period.

$$\begin{aligned} Divest_{it} = \beta_0 &+ \alpha_0 Perf_{it-1} + \alpha_1 LEV_{it-1} + \alpha_2 Threat_{it-1} + \alpha_3 NewMD_{it-1} \\ &+ \alpha_4 DIV_{it-1} + \alpha_5 size_{it-1} + \alpha_6 CON_{it-1} + \alpha_7 MS_{it-1} + \alpha_8 ACQ_{it-1} + u_{it} \end{aligned} \tag{3.93}$$

The dependent variable *Divest* is measured in two different ways; the number of divestments and the proportion of assets divested. The model is estimated using Poisson and negative binomial distribution regressions when the number of divestments is used as the dependent variable and estimated using a log-linear specification with random and fixed effects when proportion of assets divested is the dependent variable. Explanatory variables are lagged by a year as performance in the previous period will impact the likelihood of divestment at time t. The Poisson and negative binomial distribution regressions model the non-negative integer property of this dependent variable. These models are estimated with maximum likelihood.

The explanatory variables include $Perf$ is a measure of accounting performance including return on capital employed, return on equity, operating profit margin and the trading profit margin, LEV is leverage measured using the debt to assets ratio or debt to equity, $Threat$ is a dummy variable indicating a threat of takeover, $NewMD$ represents a change in management, DIV is an entropy measure of the level of diversification, $size$ is measured by total sales, total assets or number of employees, CON measures market concentration using a Herfindahl index, MS is market share, ACQ is a dummy variable indicating if the firm has made any acquisitions during the sample period.

The results remain consistent regardless of the specification. Performance has a negative and significant coefficient, indicating that divestment is more likely when performance is poor. The pressure on managers of over-diversified firms to divest increases when performance deteriorates. This finding is supported by Markides (1995). The coefficient on the leverage variable is positive and significant. High levels of debt constrain management's ability to engage in unprofitable investments and as leverage increases firms are more likely to divest assets as a means of paying off debts. The threat of takeover variable has a positive and significant coefficient suggesting that divestment is more likely when a firm faces the threat of takeover. This implies that there is an interrelationship between takeover and divestment, where downsizing may act as a managerial response to prevent takeover. The threat of takeover puts pressure on managers to refocus firm activities. There is no evidence to suggest that a change in management has any effect on the likelihood of divestment because the coefficient on the $NewMD$ variable is not significant. Firm size and diversification both have positive and significant coefficients indicating that divestment is more likely for larger firms experiencing control problems. Furthermore, there is a positive significant coefficient on the ACQ variable suggesting that the firm is more likely to divest if acquisition is undertaken during the sample period. This may be because these firms have more units available to divest or part of a corporate restructuring plan. Market share has a positive significant coefficient in most specifications of the model. This suggests that the larger the core industry market share, the greater the incentive to refocus on core activities. The coefficient on market concentration variable is surprisingly negative. This could indicate that high concentration in core activities reduces the opportunity for within market growth. Although firms may choose to diversify into other markets, the core activities are likely to be profitable therefore reducing any pressures to divest.

Weak and strong governance dummies are interacted with the performance and leverage variables to further investigate the influence of governance regimes on divestment. The governance dummies are defined in the same way as Haynes et al. (2002). The findings show that firms with strong governance are more likely to react to poor performance with divestment than firms with weak governance. The leverage-governance interactions indicate that high levels of debt encourages divestment for firms with weak governance, whereas the coefficient on the leverage interaction term in not significant for strong governance. Firms with weak governance are more responsive to debt as an encouragement to refocus as management have more scope to pursue their own goals and are therefore more likely to engage in riskier projects. Divestment can be used as a means of raising cash to repay loans and correct for over-diversification.

In summary, this paper looks at the determinants of divestment and distinguishes between strategy and governance motives. Both sets of motives are found to have a significant influence on the likelihood of divestment. The results are rigorously tested across different specifications of the model and different definitions of variables. The findings are robust. The sample includes 144 firms which is reasonably small and contains only large firms, therefore it is debatable how far these conclusions can be generalised to population level.

Van Beers and Dekker (2009) also recognise the interrelationship between acquisition and divestment. They examine the determinants of acquisition and divestment and the impact of these events on innovation. Firms expand through acquisition and may restructure through divestment as part of a wider strategy. Divestment may be motivated by a desire to focus on core activities or to correct for over-diversification. Resources freed up by divestiture may be used to pursue alternative projects through acquisition. This could involve expansion of innovation activity if the strategy aims to draw upon the innovative capabilities of the acquisition target.

The technology-searching motive may have direct and indirect effects on innovative performance. Direct effects impact R&D inputs, processes and innovative outputs, whereas indirect effects of innovation occur through enhanced performance and profitability generating funds to reinvest into the R&D process. Acquistions motivated by the desire to spread risk through diversification may also create indirect effects on innovation performance. The outcome of the acquisition-divestment strategy on innovation will depend on the initial motivation behind restructuring, the ability to create synergies with acquired resources and derive value from divestments.

They suggest that innovative firms are more likely to engage in acquisition and divestment than non-innovative firms because they are involved in a dynamic environment. These firms have more incentive to exert control to obtain technological advancement and reduce competitive threats. Furthermore, innovative firms that face knowledge barriers are even more likely to acquire and this should have a positive impact on innovation performance. Also, innovative firms that lack available finance are more likely to divest and this should impact innovation performance positively.

They use data taken from the Community Innovation Survey (CIS) for the Netherlands to test the relationship between acquisition, divestment and innovation. The sample includes 5 waves of the survey covering the period 1996 to 2004. The model consists of two stages. The first stage involves logit equations to determine pre-event characteristics.

$$\begin{aligned} Acq_t = \alpha_0 + \alpha_1 ln(size)_{t-n} + \alpha_2 Export_{t-n} + \alpha_3 Innovation_{t-n} + \alpha_4 Div_{t-n} + \\ \alpha_5 KnowLack_{t-n} + \alpha_6 FinLack_{t-n} + \alpha_7 OtherLack_{t-n} + \alpha_8 Sector + \alpha_9 T \end{aligned} \tag{3.94}$$

$$Div_t = \alpha_0 + \alpha_1 ln(size)_{t-n} + \alpha_2 Export_{t-n} + \alpha_3 Innovation_{t-n} + \alpha_4 Acq_{t-n} +$$
$$\alpha_5 KnowLack_{t-n} + \alpha_6 FinLack_{t-n} + \alpha_7 OtherLack_{t-n} + \alpha_8 Sector + \alpha_9 T \quad (3.95)$$

The dependent variables are binary indicators of acquisition and divestment at time t respectively. $size$ is measure using number of employees at time $t-n$, where n is a lag of 2 or 4 year, $Export$ is a binary export variable indicating if a firm is an exporter at $t-n$, $innovation$ is a binary variable indicating if a firm is an innovator at $t-n$, $Sector$ is a set of sector dummies and T is a set of time dummies. The Div and Acq binary explanatory variables indicate if a divestiture or acquisition occurs at time $t-n$, $KnowLack$, $FinLack$ and $OtherLack$ are binary variables indicating constraints to innovation identified in the CIS survey. $KnowLack$ indicates lack of specialist knowledge and qualified personnel, $FinLack$ indicates lack of financial resources and high innovation costs compared to the initial budget and $OtherLack$ indicates any other innovation barriers.

The second stage equation is specified as follows.

$$ln(InnPerf)_t = \gamma_0 + \gamma_1 ln(size)_{t-n} + \gamma_2 ExportInt_{t-n} + \gamma_3 Coop_{t-n} + \gamma_4 ContR\&D_{t-n}$$
$$+\gamma_5 Acq_{t-n} + \gamma_6 Div_{t-n} + \gamma_7 (Acq_{t-n} * InnCons_{t-n}) + \gamma_8 (Div_{t-n} * InnCons_{t-n}) + \gamma_9 Sector + \gamma_{10} T \quad (3.96)$$

The dependent variable $ln(InnPerf)_t$ represents innovative performance measured by the ratio of 'new to the market' product sales to number of employees. $ExportInt$ is export intensity measured by the ratio of exports to total sales, $Coop$ is a dummy indicating if the firm engaged in any cooperative innovation projects in $t-n$, $ContR\&D$ indicates if a firm consistently engaged in R&D over the sample period, $InnCons$ represents the set of innovation constraints described previously, $KnowLack$, $FinLack$ and $OtherLack$.

Each of these innovation constraints are interacted with the acquisition dummy Acq and divestment dummy Div to test their hypotheses.

The positive significant coefficients on the Acq_{t-n} and Div_{t-n} in the first stage regressions show that firms are more likely to engage in acquisition following divestment and divestment following acquisition. This implies that acquisition and divestment are interrelated and are used together as part of a restructuring strategy. There is more robust support for the acquisition following divestment finding, suggesting that firms free up resources through divestment prior to acquiring.

The coefficient on $KnowLack$ is not significant in the acquisition equation. Therefore no support is provided for the notion that innovating firms constrained by lack of knowledge are more likely to acquire to obtain technological advancement. The $KnowLack$ coefficient in the divestment equation is positive and significant at the 10% level. This suggests that firms faced with knowledge constraints may free up resources through divestment in order to invest in internal R&D. The positive and significant coefficient on $FinLack$ in the divestment equation provides further support for this idea. Firms facing financial constraints to innovation are more likely to sell off assets through divestment.

The coefficients on $ln(size)$ is positive and significant in both equations suggesting that large firms are more likely to engage in restructuring. Coefficients on $Exports$ are positive and significant in the acquisition equation implying that exporting firms are more likely to acquire than non-exporters. The coefficient on the *innovation* variable in the acquisition equation is positive and significant, whereas in the divestment equation it is negative and significant. Acquiring firms are likely to have innovated in $t - n$, whereas divestors are likely to be non-innovators.

The second stage of the investigation uses a Heckman correction for sample selection because the dependent variable is only defined for innovating firms and therefore may create selection bias. The selection equation takes the form of a probit with a binary dependent variable $PosNTMS$ that records positive 'new to the market' sales as 1 and no 'new to the market sales' as 0. Explanatory variables include those included in the second stage equation except $Coop$ and $ContR\&D$ because these are undefined for non-innovators. A binary product innovation variable $ProdInn$ is additionally included to indicate if the firm reports a new product innovation.

$$PosNTMS_t = \gamma_0 + \gamma_1 ln(size)_{t-n} + \gamma_2 ExportInt_{t-n} + \gamma_3 \text{ProdInn}_{t-n} + \gamma_4 Acq_{t-n} + \gamma_5 Div_{t-n} \\ + \gamma_6(Acq_{t-n} * InnCons_{t-n}) + \gamma_7(Div_{t-n} * InnCons_{t-n}) + \gamma_8 Sector + \gamma_9 T \quad (3.97)$$

This equation identifies the determinants of a positive probability of sales of 'new to the market' innovations. The results of this equation show $export$ and $ln(size)$ have positive and significant coefficients. In the 2 year lag version, Acq has a negative coefficient, whereas the $Acq * KnowLack$ interaction and $Acq * OtherLack$ interaction have positive and significant coefficients. This implies acquisition by firms with no innovation barriers has a negative impact on the probability of positive 'new to the market' sales, but acquisition has a positive impact on the probability of positive 'new to the market sales' for firms constrained by lack of knowledge.

The estimated probability from the selection equation is included to control for selection bias in the second stage equation (3.96). The results show $ExportInt$ and $ContR\&D$ have positive and significant coefficients. Other explanatory variables have no significant effect on the dependent variable. This implies acquisition, divestment and the barriers to innovation have no significant effect on innovative performance.

This paper is novel because it looks at both divestment and acquisition. Other papers tend to focus on one event and ignore the interrelationships. It discusses motivations behind acquisition in detail, although does not describe divestment motives in depth. The paper could be improved by testing the robustness of the results with different measures of innovative performance, such are R&D intensity or a patent measure.

Kaul (2012) suggests that divestment can be seen as a firm strategy with reactive or proactive motives. The empirical analysis uses an unbalanced panel of 1290 US manufacturing firms from 1982 to 2002. A set of hypotheses are created in order to test which motivation dominates. The data is taken from Compustat, SDC PLatinum and NBER patent database. Propensity score matching is used to correct for endogeneity. The first step is a probit model with binary divestment as the dependent variable. An indicator of divestment by other firms within the same industry as firm i is included as an instrumental variable. This should control for 'bandwagon' effects increasing the likelihood that firm i makes a divestment but is uncorrelated with the innovation performance of firm i. The second stage equation is estimated using fixed effects and is specified as follows.

$$InnProd_t = \alpha + \beta_1 Div_{i,t-3 \ to \ t-1} + \beta_2 Div_{i,t-3 \ to \ t-1}.M_{it} + \beta_3 InnProd_{i,t-3} + \beta_4 M_{it} + \beta_5 Controls + \eta_t + \gamma_i + \epsilon_{it} \quad (3.98)$$

$InnProd$ is the ratio of patent stock to stock of R&D spending which captures innovation productivity. The stock is calculated using the perpetual inventory method with a depreciation rate of 15% to control for the accumulation of knowledge. Furthermore, patents are weighted to account for differences in importance of patents. Div is a divestment dummy indicating if divestment has taken place during the previous three years. M is a vector of independent variables including performance measured by the return on assets, an entropy measure of diversification, core and non-core divestment dummies, absorbed slack given by the ratio of 'sales and administration' to total sales and available slack measured as the ratio of current assets to total assets. These variables are also interacted with the divestment dummy. $InnProd_{i,t-3}$ is a lagged dependent variable indicating the level of innovation productivity prior to divestment. $Controls$ is a vector of control variables including stock of R&D expenditure, firm size in terms of assets, the debt to asset ratio, total value of divestment transactions, stock of advertising expenditure, acquisition experience, alliance experience and change in performance and diversification over the previous three years. Industry mean of Tobin's Q, rival R&D expenditure and rival productivity are also included to control for industry characteristics.

An alternative dependent variable measuring technological diversity $TechDiv$ is also used. This is measured as 1 minus the Herfindahl index of firm patenting, where the index is calculated using the ratio of patents by firm i at time t in patent class j to total patents by firm i at time t. This dependent variable is used to test how divestment impacts the diversity of technology projects.

$$TechDiv_{it} = 1 - \sum \frac{P_{ijt}}{P_{it}} \quad over\ all\ j \tag{3.99}$$

Results of the first stage probit shows divestment is more likely for highly diversified firms with high R&D stock, high pre-divestment R&D productivity and high debt to asset ratios. Furthermore, divestment is more likely following recent acquisitions and when the firm's industry has high levels of divestment.

The second stage model reveals a positive coefficient on the divestment dummy, indicating that on average innovation productivity increases following divestment as both theories predicted. The interaction between pre-divestment profitability has a positive coefficient. This supports the proactive view, as it indicates the firm's with higher pre-divestment profitability benefited most in terms of R&D productivity from divestment. The negative coefficient on the divestment and pre-divestment diversification interaction indicates that the impact on R&D productivity is greater for less diversified firms, again supporting the proactive view. The binary indicators of core and non-core divestments indicate that firms benefit in terms of R&D productivity following both types of divestment. Robustness checks using alternative measures of innovation support the original findings. The alternatives include firms' citation-weighted patent stock unadjusted for R&D expenditure, unweighted patents to R&D expenditure ratio and patents to R&D expenditure ratio where patents are weighted by non-self citations.

In summary the majority of the findings of this study support the proactive motivation for divestment. This suggests that divestment is mostly motivated by external conditions and the desire to free up resources in order to embark on new opportunities by pursuing technological innovation.

3.5 Summary

This section has outlined the main motivations behind restructuring events and discussed the implications of these events. Strategic, synergistic, refocusing and managerial motivations for joining and separating events were identified in the discussion of the theoretical literature. Strategic motivations concern the industry supply and demand conditions, market share and industry concentration. This provides mixed conclusions in terms of profitability outcomes. Synergistic motivations arise from potential economies of scale and technology transfer opportunities for joining events and refocusing motivations result from dis-economies of scale from over-diversification and excessive growth for separating events. Improved performance is the anticipated outcome following events motivated by these considerations. Managerial motivations occur when the manager pursues alternative objectives to profit maximisation, such as growth or streamlining if these are favourable with shareholders. Managers of firms with high levels of debt may be more inclined to act in the shareholders' interests because they may be at greater risk of being replaced. Various outcomes could occur as a result of this scenario.

Empirical studies in the event motivation literature predominantly use probit, logit or competing risk survival models. The explanatory variables in these models typically include market share, industry concentration, firm size measured using total assets and number of employees, innovation performance, profitability, leverage, liquidity, a measure of diversification and indicators of involvement in previous events. The evidence suggests that differences in pre-event characteristics exist between different event types. Acquisition and divestment are more likely following a previous acquisition or divestment. Some interesting results are found when a distinction is made between foreign and domestic events. These ideas can be investigated in more detail in this study.

Empirical evidence on post-event outcomes show that an initial negative impact in innovation and performance is often incurred during the immediate post-event period. This is likely to be due to the disruption of reorganisation. Overall, post-event innovation outcomes are mixed. Firm performance is generally found to increase following foreign acquisition and refocusing events have a positive impact on profitability.

The main criticism of these papers is that a clear distinction is not always made between different event types. The terms ‘merger’ and ‘acquisition’ are often used interchangeably. Most papers place emphasis on the ‘acquirer’ or ‘acquired’ firm and do not make comparisons between them or with other events. The number of studies investigating separating events is limited and distinctions between different types of separating event are not considered. Firm restructuring events should be clearly defined because differences in motivations can exist between event categories. The data used in this study allows restructuring events to be clearly defined.

Table 3.1: Literature Overview 2

Author	Methodology	Data	Key Variables	Results
Hannan and Rhoades (1987)	Multinomial Logit	Banking data from Texas, US 1971-1982	Dependent: Categorical variable with no acquisition, within market acquisition and outside market acquisition as categories. Explanatory: rate of return, market share, capital-asset ratio, loan to asset ratio, bank growth, market growth, concentration ratio, assets, rural location dummy	Low capital-asset ratio and concentration ratios increase likelihood of acquisition. rural location and a large market share has positive impact on outside market acquisition. Financial performance is not statistically significant.
Hay and Liu (1998)	Probit	110 stock market quoted manufacturing firms 1971-89	Dependent: acquirer dummy. Explanatory: Profit rate, rate of investment in capital assets, valuation ratio, debt to asset ratio, dummy indicating acquisition made by rival firms.	Low debt to asset ratio increases the likelihood of acquiring. External and internal investment are complements. Acquisition bids are more likely when the acquirer has a higher valuation ratio.
Dickerson et al. (2002)	Survival Model using Weibull Hazard Specification	892 UK quoted companies 1975-1990	Dependent: Categorical variable with no event, acquirer and acquired as categories. Explanatory: $log(size)$, $log(size)^2$, $log(Assets)$, debt ratio, liquidity ratio, investment in tangible assets to total assets, dividends, indicator dummies for high and low Tobin's Q values.	Acquisition has an inverted U-shaped relationship with size. Investment within target firms reduces the chance of takeover, particularly for low Q firms. Dividends have no statistically significant effect.
Dickerson et al. (2003)	Competing Risk Model using Weibull Hazard Specification	Sample 1: 2280 companies 1948-1970 DTI database of company accounts, Sample 2: 969 companies EXSTAT	Dependent: categorical variable with no event, acquired, acquirer and bankruptcy as categories. Explanatory: $log(size)$, $log(size)^2$, profitability, leverage, liquidity ratio, tangible assets, internal investment, dividends, previous acquisition dummy	Larger more profitable firms are more likely to acquire. Internal investment and acquisition are substitutes. Acquisition is habit forming. Impact of liquidity and leverage is not consistent across samples.

Table 3.1 (continued): Literature Overview 2

Author	Methodology	Data	Key Variables	Results
Desyllas and Hughes (2009)	Logit	Thompson Financial's SDC Platinum Datasource, NBER dataset, Datastream and Compustat 1984-1998	Dependent: Acquired dummy Explanatory: innovation intensity, zero innovation dummy, innovation stock, size, size^2, growth, total assets, $log(Tobin'sQ)$, leverage, liquidity ratio, industry and time dummies.	Acquired firms are more likely to have higher R&D intensity and patent stock than non-acquired firms, but poorer financial characteristics.
Bertrand (2009)	Probit (PS match)	LiFi French manufacturing firms 1994-2004	Dependent: Foreign acquisition dummy Explanatory: market share, profitability, profitability^2, debt ratio, R&D intensity, capital intensity	Foreign acquisition is more likely for firms with a larger market share, higher R&D intensity and R&D skill intensity. There is a U-shaped relationship with profitability.
Ornaghi (2009)	Logit (PS match)	Standard and Poor's Compustat, Bureau Van Dijk's Osiris, Patent data from NBER, British National Formulary, the Orange Book of Food and Drug Administration and Mergers book.	Dependent: acquisition dummy Explanatory: drugs approaching patent expiration, percentage of new drugs introduced into the market, concentration of patents, stock market value, growth of stock, market concentration, time and industry dummies	Mergers are more likely to occur if current patents are likely to expire.
Desyllas and Hughes (2010)	Logit (PS match)	US publicly traded high-tech firms 1984-1998 from Compustat, NBER and Dun and Bradstreet 'Who Owns Who' Database	Dependent: acquisition dummy Explanatory: Firm size, growth, profitability, leverage, R&D intensity, R&D productivity, knowledge base size, industry and time dummies	Not reported

Table 3.1 (continued): Literature Overview 2

Author	**Methodology**	**Data**	**Key Variables**	**Results**
Bandick et al. (2010)	Probit (PS match)	Swedish manufacturing 1993-2002	Dependent: foreign acquisition dummy Explanatory: labour productivity, plant age, age^2, number of employees relative to the industry mean, R&D and skill intensity, export intensity and a measure of foreign presence in the industry	More productive firms are likely to be taken over
Guadalupe et al. (2012)	Probit (PS match)	1800 Spanish manufacturing firms 1990-2006	Dependent: Dummy variable representing foreign acquisition in given year or foreign acquisition any time during sample period Explanatory: log labour productivity and log real firm sales at various lags	The results suggest evidence of "cherry picking". Foreign acquirers select the most productive targets.
García-Vega et al. (2012)	Probit (PS match)	Spanish manufacturing firms 2004-2009	Dependent: Foreign acquisition dummy Explantory: size, size^2,labour productivity, export dummy, R&D variables	Foreign acquirers select more productive, medium sized firms firms with higher internal R&D expenditures
Szücs (2012)	Probit or Logit (PS match)	European Commission, Federal Trade Commission with 265 acquiring firms ans 133 targets from across 25 nations	Dependent: acquirer dummy or acquired dummy Explanatory: R&D intensity, R&D growth, total assets, employees, profitability, total debt, age and age^2	Acquirers tend to be large and profitable, whereas targets tend to have high R&D intensity and relatively low profitability
Conyon et al. (2002)	Multinomial Logit	OneSource UK companies 1987-1996	Dependent: Categorical variable with no event, UK acquired and foreign acquired as categories Explanatory: Wages, profit, size, concentration and FDI	Small firms are more likely to be targets. Foreign firms seek targets with higher than average profit whereas UK firms have seek targets with lower than average wages

Table 3.1 (continued):2 Literature Overview 2

Author	Methodology	Data	Key Variables	Results
Harris (2009)	Probit (PS match)	ARD UK manufacturing plants 1985-2005	Dependent: acquisition dummy Explanatory: labour productivity, capital-labour ratio, size percentage of foreign ownership in industry	Not reported
Mata and Portugal (2000)	Competing Risks survival model	Data from Portuguese Ministry of Employment 1983-89	Dependent: Categorical variable with no event, divestment and closure as the categories Explanatory: Greenfield dummy, proportion of college graduates in workforce, log employees, foreign subsidiary dummies, limited liability dummy, number of plants, diversification measure, log of minimum efficient scale, industry growth, ratio of employment in foreign owned firms to industry total	Differences between characteristics of those firms that exit through closure and divestment. Foreign owned subsidiaries are more likely to close. Limited liability firms are less likely to close but more likely to be divested than unlimited liability firms. Larger firms are less likely to exit
Haynes et al. (2003)	Negative Binomial and Poisson models	UK firms 1985-1991 Datastream Centre for Management Buyout Research Database and Financial Times	Dependent: Number of Divestments and proportion of assets divested Explanatory: Profitability measures, leverage, presence of takeover threat, change in management, diversification, market concentration, market share, previous acquisitions.	Profit and market concentration have negative and significant coefficients. Firm size, market share, leverage, divestment, threat of takeover, and diversification have a positive and significant impact on the probability of divestment
Van Beers and Dekker (2009)	logit (PS match)	Community Innovation Survey (CIS) from the Netherlands (1996-2004)	Dependent: Acquisition dummy or divestment dummy Explanatory: Number of employees, export dummy, innovation dummy, 'constraint to innovation' dummies, previous acquisition dummy, previous divestment dummy, industry and time dummies	Positive and significant impact of previous acquisition and divestment dummies indicate that acquisitions and divestments may occur as part of broader restructuring policies
Kaul (2012)	Probit (PS match)	Compustat, SDC Platinum, NBER patent database	Dependent: binary divestment variable Explanatory: diversification, leverage, previous acquisition, level of divestment within industry, R&D stock and R&D productivity	Divestment is more likely for diversified firms with high R&D stock, high debt to asset ratios, following previous acquisition and within industries with high levels of divestment

Table 3.2: Literature Overview 3

Author	Methodology	Data	Key Variables	Results
Cloodt et al. (2006)	Random effects and negative binomial	Securities Database, Amadeus, Compustat Worldscope and US Patent Office 1985-1994, 347 firms	Dependent: number of patents Explanatory: size of acquired knowledge base, relative size of acquired knowledge base, relatedness of acquired knowledge base, cultural distance	Technical M&As have initial positive impact on innovation performance followed by a negative impact . Non-technical M&As have a negative impact on innovation.
Bertrand (2009)	Propensity score matching and difference-in-difference	French Manufacturing firms from LiFi 1994-2004	DID Dependent: Change in R&D expenditure Explanatory: dummy variables indicating foreign acquisition at time t, t-1, t-2 and t-3	Foreign acquisition leads to an increase in R&D expenditure in each post-acquisition year
Ornaghi (2009)	Propensity score matching, difference-in-difference and Heckman 2-step	Compustat, Osiris, NBER, British National Formulary, the orange book and the mergers book	DID dependent: Change in log innovation Explanatory: acquisition dummies indicating acquisition at t, t-1, t-2 and t-3	Innovation outcomes decline following merger compared to no event
Desyllas and Hughes (2010)	Propensity score matching and difference-in difference with PS weighting	Compustat, NBER, Dun and Bradstreet 'Who Owns Who' database	DID Dependent: change in log R&D intensity over various different time frames Explanatory: Acquisition dummy, knowledge base of firm, knowledge concentration, financial leverage, leverage growth, publicly traded dummy, foreign acquisition dummy and PS weighting	Acquisition has a negative impact on R&D intensity in the post-acquisition period
Bandick et al. (2010)	Propensity score and difference-in-difference	Swedish Manufacturing firms 1993-2002	DID Dependent: change in log R&D intensity Explanatory: Foreign acquisition dummy, set of time dummies	R&D intensity is higher for foreign acquired firms than the no-acquired control group

Table 3.2 (continued): Literature Overview 3

Author	Methodology	Data	Key Variables	Results
Guadalupe et al. (2012)	Propensity score and fixed effects	Spanish Manufacturing firms 1990-2006	Dependent: Measures of innovation Explanatory: Foreign ownership dummy, time dummies and industry fixed effects	Innovation increases following acquisition by foreign-owned firms.
García-Vega et al. (2012)	Propensity score matching with second stage OLS	Spanish R&D performing firms from the manufacturing and service sector 2004-2009	Dependent: R&D expenditure Explanatory: foreign acquisition dummies by country at t and t-1, control variables	Foreign acquired firms from frontier countries show an increase in foreign R&D transfers and a decrease in in-house R&D expenditure. Firms acquired by firms from non-frontier countries show the opposite
Szücs (2012)	Propensity score matching and difference-in-difference	European Commission and Federal Trade Commission international data	DID Dependent: change in R&D expenditure Explanatory: acquirer and target dummies pre and post-acquisition and control variables	R&D activity falls for acquirer and target in the post event period
Conyon et al. (2002)	Propensity score re-weighting	OneSource Database UK firms 1989-1994	Dependent: Labour productivity and average wages in levels and changes Explantory: Foreign and domestic acquisition dummies, capital intensity, firm size, industry average wages and industry average productivity	Foreign acquisition leads to higher productivity and wages
Balsvik and Haller (2010)	Fixed effects and OLS	Norwegian Manufacturing plants 1992-2004	Dependent: plant performance measures including log employment, log average wage, log labour productivity and log TFP Explanatory: Foreign and domestic acquisition, entry and exit dummies, controls for firm characteristics	Post-acquisition performance improves for foreign acquired firms, but domestic acquired firms show a decline
Harris (2009)	Propensity score matching	UK plant level data ARD 1985-2005	Dependent: TFP Explanatory: acquisition dummy	TFP is greater for acquired plants than for non-acquired plants

Table 3.2 (continued): Literature Overview 3

Author	Methodology	Data	Key Variables	Results
Markides (1995)	OLS	Compustat and TRINET 1981-1987	Dependent: Change in profitability Explanatory: advertising intensity, R&D intensity, market concentration, CEO change dummy, debt-to-shareholder equity ratio, foreign to domestic sales ratio, capital expenditure, sales per employee, risk measured by standard deviation of sales and a refocusing measure	Refocusing leads to increased profitability for over-diversified firms
Haynes et al. (2002)	GMM	UK publicly listed companies 1985-1993	Dependent: change in profitability Explanatory: change in profitability in previous period, market share, market concentration, leverage, divestment dummy, time dummy	Divestment has a positive impact on profitability
Van Beers and Dekker (2009)	Propensity score matching and Heckman selection model	Community Innovation Survey (CIS) Netherlands 1996-2004	Dependent: log innovation performance, log size, export intensity, cooperation dummy, continuous R&D activity dummy, innovation constraints dummies	Acquisition and divestment have no significant effect on innovative performance
Kaul (2012)	Propensity score matching and fixed effects	Compustat, SDC Platinum and NBER database	Dependent: Innovation productivity calculated as the ratio of patent to R&D expenditure Explanatory: Divestment dummies, control variables and their interactions	Innovation productivity increases following divestment

4 An Investigation into Pre-Events Motivations and Firm Characterisitics

4.1 Introduction

The restructuring of firm organisation is an important part of corporate strategy. Motivations behind these actions are not directly observable. This chapter distinguishes between various different types of restructuring event. These include "acquirer", 'acquired', 'merger', 'change of ownership', 'break-up', 'divested', 'divestor' and 'trade sale'. The aim is to investigate the determinants of these restructuring events by identifying the characteristics of the firms involved. A key distinction is made between domestic and foreign events. Further analysis is undertaken on events in high-tech industries since motivations are likely to differ from events involving other manufacturing firms. This will allow inferences to be drawn about the motivations driving the events. A contribution to the literature is made by using detailed data to distinguish between many different event types and considering these restructuring events simultaneously. The majority of prior papers overlook the fact that these events may be interrelated as part of a wider restructuring strategy.

Events may be motivated by different considerations and therefore the characteristics of firms in each group are likely to be different. For example, joining events may be undertaken due to technology seeking motives or as a method of quickly increasing market share (Desyllas and Hughes, 2009). When the acquirer seeks to derive technological benefits from its target, the acquired firm is likely to have strong performance in terms of innovation performance or productivity. This behaviour is described as "cherry-picking". Alternatively, firms may choose lemons as acquisition targets with the aim of reorganising and improving the performance of these failing firms (Balsvik and Haller, 2010). The acquisition of these targets could be motivated by the aim of quickly expanding the firm's current operations to increase market share or a competitive strategy to gain the upper hand over rival firms. This is more likely when the industry is growing (Hay and Liu, 1998). Acquirers are expected to have a good performance record and available finance. Dickerson et al. (2003) find that acquisition acts as a form of defence against becoming a takeover target. This implies that events may be strategically interlinked. Mergers differ from acquisitions because they tend to involve mutual agreements. Firms will seek acquisitions partners to gain from technology synergies and complementarities. A change in ownership can represent a firm changing ownership to a newly created domestic enterprise but also represents new foreign entry into the the UK. There is likely to be distinct differences between domestic and foreign change of ownership.

Separating events may be motivated by the decision to refocus on core activity to either improve productivity or pursue new opportunities in the market (Kaul, 2012). Depending on the motives, divestors will either have poor performance and use divestment to salvage the firm through refocusing or medium to strong performance and aim to divest to free up funds to reinvest as part of a broader strategy. In these circumstances events are interrelated. A breakup is likely to be motivated by the decision to refocus and become independent. The characteristics of firms undertaking this type of event may differ from divested firms. Tradesales and acquirer-divestor describe different type of restructuring events involving simultanteous joining and separating events.

This study uses UK data covering the period 2000-2007. Samples are created by combining the Business Structure Database (BSD), Annual Respondent Database (ARD) and Financial Analysis Made Easy (FAME). Data on R&D expenditure is taken from the Business Enterprise Research and Development (BERD) data. The enterprise and enterprise group reference codes in the BSD are used to identify the occurrence of events. These are established based on changes in the codes between time periods.

This chapter contains a description of the methodology used in section 4.2, the data used and identification of events in section 4.3, descriptive statistics in section 4.6, results are explained in section 4.7 and section 4.8 concludes the study. The results from this chapter inform the following chapter as selection into different event types is observed.

4.2 Methodology

The aim of this analysis is to identify differences in characteristics between the types of firm that undertake restructuring events. Inferences about the motivations to engage in each event can be drawn from this. Events are categorised in 9 different ways, including no event, acquired, acquirer, merger, change of ownership, break-up, divestor, divested, trade-sale or acquirer-divestor. Acquirer-divestor describes the situation where the a firm acts as an acquirer and a divestor during the same period. Events are mutually exclusive and observations are case-specific; one alternative is observed for each firm in each time period.

4.2.1 Discrete Outcome Models

A discrete outcome model is a form of analysis that models the probability of outcome events based on characteristics. The outcome event is chosen from a set of qualitative alternatives. The simplest case offers two outcomes and is estimated with a binary choice model. The binary outcome variable y can take the values of 0 or 1 and x is a vector of characteristics. If y was modelled as a linear function of x, the standard errors and t-statistics would be invalid because the error terms would not be normally distributed and the predicted probabilities may be less than 0 or greater than 1. Therefore it is necessary to base the model around an underlying regression, which includes an underlying continuous latent variable, y^* (Greene, 2000).

$$y^* = \beta x' + \epsilon \tag{4.1}$$

$\beta x'$ is the index function and the error terms ϵ are assumed to be independent and identically distributed. y^* is not observable and meets with the following criteria.

$$y = 1 \text{ if } y^* > 0$$

$$y = 0 \text{ if } y^* \leq 0$$

Therefore if y^* exceeds zero, the binary outcome equals 1 and if y^* is less than or equal to zero, the binary outcome takes the value of zero. This allows the latent variable y^* to take any value from negative to positive infinity, yet the outcome variable remains binary. Given the normalising assumption of the zero threshold and assuming that the distribution of the error term is known, the probability that $y = 1$ is as follows.

$$Prob(y^* > 0|x) = Prob(\epsilon > -x'\beta|x) \tag{4.2}$$

A symmetric distribution for the error terms, such as normal or logistic, ensures that

$$Prob(y^* > 0|x) = Prob(\epsilon < x'\beta|x) = F(x'\beta) \tag{4.3}$$

where $F(\psi)$ is the cumulative density function of the random variable. The following is implied to obtain predictions that are consistent with this theory.

$$\lim_{x'\beta \to +\infty} Prob(y = 1|x) = 1 \tag{4.4}$$

$$\lim_{x'\beta \to -\infty} Prob(y = 1|x) = 0 \tag{4.5}$$

This can be represented using the logistic distribution as follows to obtain the logit model,

$$Prob(y = 1|x) = \frac{exp(x'\beta)}{1 + exp(x'\beta)} = \Lambda(x'\beta) \tag{4.6}$$

or using the normal distribution to obtain the probit model.[53]

$$Prob(y = 1|x) = \int_{-\infty}^{x'\beta} \phi(t)dt = \Phi(x'\beta) \tag{4.7}$$

The choice of distribution may have an impact on the results depending on the character of the sample. The logistic and normal distribution are similar, although the logistic

[53]Other distributions can be used, but these are the most common.

distribution has heavier tails. This implies that the logit model will provide larger probabilities for $y = 1$ than the probit when $x'\beta$ is very small and smaller probabilities when $x'\beta$ is very large. Differences in results may also be observed if there are few observations in an outcome category or an explanatory variable with a large variation across observation.

These models are estimated using the maximum likelihood method. Each observation is treated as a single draw from the Bernoulli distribution. The likelihood function is given by

$$Prob(Y_1 = y_1, Y_2 = y_2, ...Y_n = y_n|X) = \prod_{y_i=0}(1 - F(x_i'\beta)) \prod_{y_i=1} F(x_i'\beta) \tag{4.8}$$

where X represents $[x_i]_{i=1,2...n}$. For a sample of n observations, the likelihood function becomes

$$L(\beta|sample) = \prod_{i=1}^{n}(F(x_i'\beta))^{y_i}(1 - F(x_i'\beta))^{(1-y_i)} \tag{4.9}$$

Logs are taken to give the following.

$$lnL = \sum_{i=1}^{n}(y_i lnF(x_i'\beta) + (1 - y_i)lnF(1 - x_i'\beta)) \tag{4.10}$$

The first order conditions for maximisation are obtained, where f_i is the density, $dF_i/d(x_i'\beta)$.

$$\frac{\partial lnL}{\partial \beta} = \sum_{i=1}^{n}\left[\frac{y_i f_i}{F_i} + (1 - y_i)\frac{-f_i}{1 - F_i}\right] x_i = 0 \tag{4.11}$$

The first and second order conditions for the logit model are specified as follows.

$$\frac{\partial lnL}{\partial \beta} = \sum_{i=1}^{n}(y_i - \Lambda_i)x_i = 0 \tag{4.12}$$

$$\frac{\partial^2 lnL}{\partial \beta \partial \beta'} = -\sum_{i}\Lambda_i(1 - \Lambda_i)x_i x_i' = 0 \tag{4.13}$$

Whereas first and second order conditions for the probit model are given by the following, where $q_i = 2y_i - 1$.

$$\frac{\partial lnL}{\partial \beta} = \sum_{i=1}^{n} \left[\frac{q_i \phi(q_i x_i' \beta)}{\Phi(q_i x_i' \beta)} \right] x_i = \sum_{i=1}^{n} \lambda_i x_i = 0 \tag{4.14}$$

$$\frac{\partial^2 lnL}{\partial \beta \partial \beta'} = \sum_{i=1}^{n} -\lambda_i(\lambda_i + x_i' \beta) x_i x_i' \tag{4.15}$$

Due to their non-linear nature, these models are solved using iterative methods.

4.2.2 Multiple Discrete Outcome Models

The binary model can be expanded for multiple alternatives, where the event variable has discrete responses with unordered categories. The multinomial logit (MNL) is computationally less burdensome than the multinomial probit (MNP) because the MNP requires the evaluation of multiple integrals. The multinomial logit model can be specified as follows.

$$Prob(Y_i = j|w_i) = \frac{\exp(w_i' \alpha_j)}{\sum_{j=0}^{J} \exp(w_i' \alpha_j)'} \tag{4.16}$$

Where j is one of $J+1$ alternative events for firm i, therefore $j = 0, 1, 2, ..., J$. The ordering of events is arbitrary. $Prob(Y_i = j|w_i)$ shows the probability that the outcome for firm i is event j, conditional on the explanatory variables w_i. The model ensures $0 < Prob(Y_i = j) < 1$ and $\sum_{j=1}^{J} p_{ij} = 1$. Only J probabilities can be freely specified. α_j represents the corresponding coefficients and is set to zero for the base category to ensure identification, $\alpha_0 = 0$ where $j = 0$. Therefore the model becomes

$$Prob(Y_i = j|w_i) = \frac{\exp(w_i' \alpha_j)}{1 + \sum_{k=1}^{J} \exp(w_i' \alpha_k)'} \tag{4.17}$$

The model relies on the assumption of independence of irrelevant alternatives. This states that the relative odds of events occurring will not be influenced by the inclusion of additional event categories. It seems reasonable to assume that this will hold in this case.

The log-likelihood equation can be obtained by setting $d_{ij} = 1$ if firm i incurs outcome j and $d_{ij} = 0$ if firm i incurs the base outcome. This is completed for each of the $J+1$ alternatives so each firm has only one $d_{ij} = 1$.

$$lnL = \sum_{i=1}^{n}\sum_{j=0}^{J} d_{ij} lnProb(Y_i = j|w_i) \tag{4.18}$$

The first derivatives are given by

$$\frac{\partial lnL}{\partial \alpha_j} = \sum_{i=1}^{n}(d_{ij} - P_{ij})w_i \quad for \quad j = 1, 2, ...J \tag{4.19}$$

Second derivatives are given as follows, where $1(j = l)$ is equal to 1 if $j = l$ and 0 if $j \neq l$.

$$\frac{\partial^2 lnL}{\partial \alpha_j \partial \alpha_l'} = -\sum_{i=1}^{n} P_{ij}[1(j = l) - P_{il}]w_i w_i' \tag{4.20}$$

The results for the estimated coefficients can be interpreted with respect to the base category, as the multinomial logit is equivalent to a set of pairwise binary logit models. A positive coefficient implies that with an increase in the corresponding explanatory variable the likelihood of event j increases relative to the base event. Relative risk ratios show the risk of an event j occurring relative to the risk of the base event occurring. They can be obtained as follows.

$$\frac{Prob(y_i = j)}{Prob(y_i = 1)} = \exp(w_i'\alpha_j) \tag{4.21}$$

Results can also be obtained in terms of marginal effects. Due to the non-linear form of the logit model, the marginal impact of a change in an explanatory variable is not constant. Marginal effects depend upon the point of evaluation. They are usually evaluated at the sample mean of the regressors $x = \bar{w}$, at a representative value $w = w*$, or the average of the marginal effects at each $w = w_i$.

$$\frac{\partial p_{ij}}{\partial w_i} = p_{ij}(\alpha_j - \bar{\alpha_i}) \tag{4.22}$$

$\bar{\alpha_i} = \sum_l p_{il}\alpha_l$ is the probability weighted average of the α_l coefficients, p_{ij} varies with the point of evaluation in terms of w_i. The signs on the regression coefficients may differ from the signs on the corresponding marginal effects. The marginal effect on variable w will be positive if $\alpha_j > \bar{\alpha_i}$.

4.2.3 The Estimating Equation

The multinomial logit estimating equation can be specified as follows.

$$Event_{it} = \alpha + \beta X_{it-1} + \Psi I_i + \lambda T_t + \epsilon_{it} \tag{4.23}$$

$Event_{it}$ is a categorical dependent variable for firm i at time t. Each category indicates an occurrence of a type of event at time t. The main analysis uses a dependent variable with 10 event categories. These events include 'no event', 'acquired', 'acquirer', 'merger', 'change of ownership', 'break-up', 'divested', 'divestor', 'tradesale' and 'acquirer-divestor'. 'No event' is the base category. The number of categories is increased to 20 in order to distinguish between foreign and UK events, where 'UK no event' is the base category. X is a vector of firm and industry characteristics, I is a vector of industry dummies at the 1-digit level[54], T is a vector of time dummies, β, Ψ and λ are the corresponding parameters, α is the intercept and ϵ is the error term. Events occur between $t-1$ and t, therefore explanatory variables at $t-1$ are used to ensure that pre-event characteristics are captured. The following section describes the data used in this analysis, including the definitions of events and characteristics.

[54] The 1-digit industry level was used to prevent multinomial logit convergence problems.

4.3 Data

The sample used in this analysis is created by merging four datasets. The Business Structure Database (BSD) contains a register of all firms and therefore can be used to identify demographic ownership events. The Annual Respondents Database (ARD) provides details on firm characteristics and Business Enterprise Research and Development (BERD) contains data on R&D. Financial Analysis Made Easy (FAME) includes financial data on firms in the UK. See Chapter 1 and the following subsections for a more detailed discussion of the datasets and the identification of demographic events.

4.4 Definition of Events

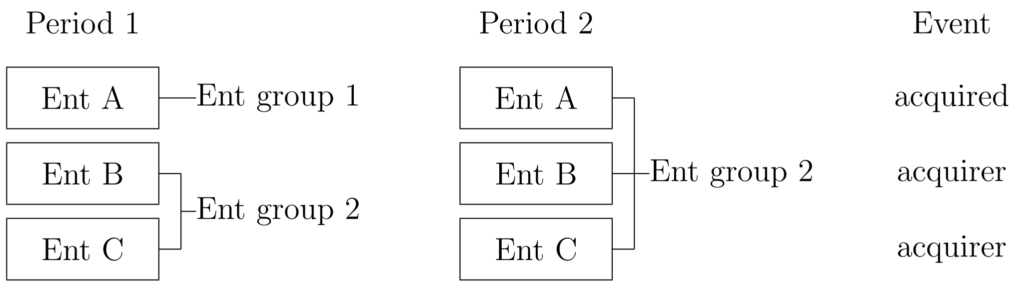
The first stage of creating the dataset involves creating event dummies using the BSD. The BSD exists at enterprise level and local unit (plant) level. For this analysis it is appropriate to use enterprise level observations because BERD data is provided at reporting unit level, therefore plant level observations cannot be directly observed. It is more appropriate to aggregate the reporting unit BERD data upwards to enterprise level because the creation of plant level observations requires assumptions about the division of reporting unit R&D activity between plants. Any assumptions imposed would be unlikely to accurately reflect reality.

The BSD provides a register of all enterprises within the UK. Each enterprise has an enterprise code and an enterprise group code, where the enterprise group is the owner of the enterprise. Demographic events are identified when the enterprise group reference code for a given enterprise changes. These changes in enterprise group references are classified into different groups according to the nature of the change and the number of enterprises involved pre and post change.

It is necessary to generate event indicators using enterprise and enterprise group reference codes because the demvar variable provided within the BSD seems to be unreliable. Inconsistencies are revealed when specific events are observed within the data. The type of event recorded in demvar often differs from the type of event observed based on enterprise and enterprise group codes. Furthermore, the demvar variable is only available for the period 1998-2005.

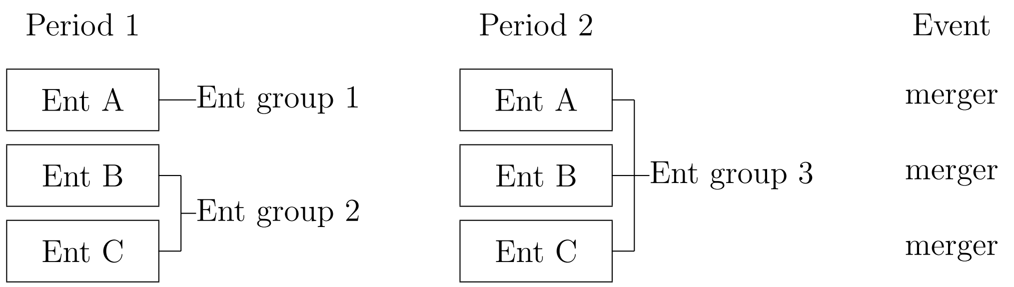
The following figures provide examples of the structural changes over 2 periods. The event column on the right hand side provides an example of the event variable coding for the enterprise in period 2.

Figure 1: Takeover



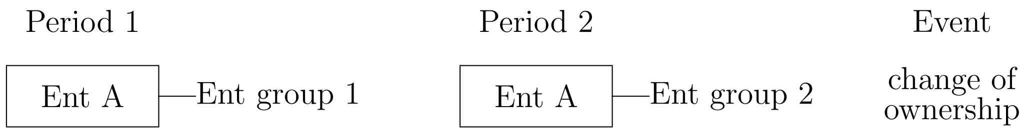
A takeover is identified when 2 or more enterprise groups integrate and one enterprise group retains its enterprise group code. N enterprise groups exist before the event and 1 enterprise group after the event. The 'acquirer' retains the same enterprise group code and the 'acquired' enterprise changes from its original enterprise group code to the code of the 'acquirer'.

Figure 2: Merger



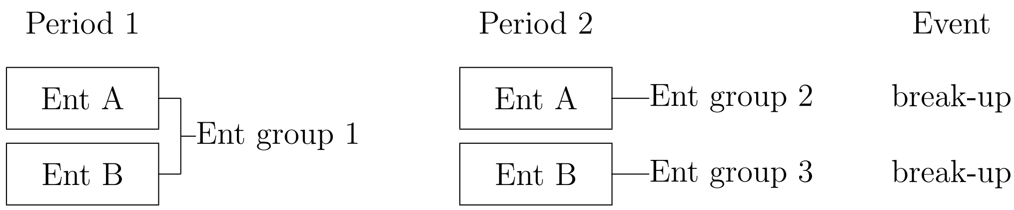
A 'merger' is identified when 2 or more enterprise groups integrate and neither enterprise group retains its enterprise group code. N enterprise groups exist before the event and 1 enterprise group after the event. A new enterprise group code is created that did not previously exist.

Figure 3: Change of ownership



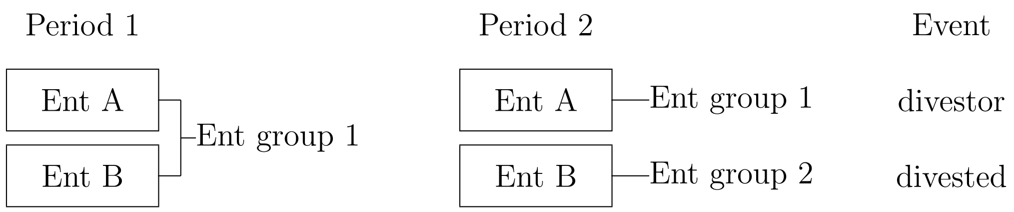
A 'change of ownership' occurs when an enterprise changes enterprise group, the enterprise group code did not previously exist and no other enterprises are involved. 1 enterprise group before the event and 1 enterprise group after the event.

Figure 4: Break-up



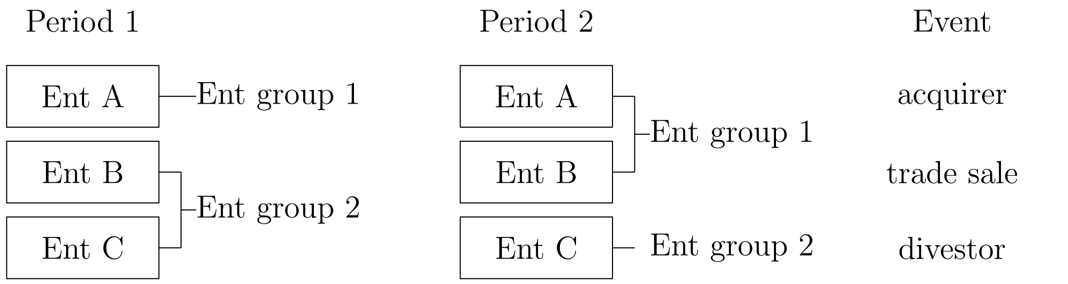
A 'break-up' occurs when an enterprise group splits into two or more enterprise groups and new enterprise group codes are created that did not previously exist. 1 enterprise group before the event and n enterprise groups after the event.

Figure 5: Divestment



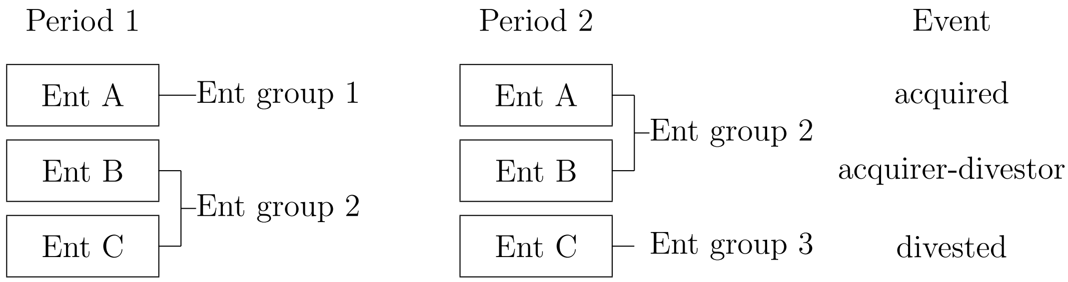
A split-off or divestment occurs when an enterprise group splits into two or more enterprise groups. At least one enterprise group retains previous enterprise group code and the other enterprise group(s) is (are) given a new code that did not previously exist. 1 enterprise group before the event and n enterprise groups after the event. The 'divestor' retains the original enterprise group code, whereas the 'divested' enterprise splits off from the enterprise group and a new enterprise group code is created.

Figure 6: Trade Sale



A 'trade sale' occurs when an enterprise from one enterprise group is transfered to another enterprise group. Both enterprise groups continue to exist after the event. This involves n enterprise groups before the event and n enterprise groups after the event, where n=n. Enterprise B switches from enterprise group 2 to enterprise group 1.

Figure 7: Acquirer-Divestor



The 'acquirer-divestor' event occurs when an enterprise group divests and acquires during the same period. Enterprise group 2 acquires enterprise A and divests enterprise C. Enterprise B remains in enterprise group 2. A new enterprise group code is created for the divested enterprise C .

Table 4.1: List of Variables

Variable	Description
$logY$	log of gross value added output
$logC$	log of capital stock
$logL$	log of the number of employees
R&D dummy	Dummy variable indicating if a firm performs R&D
$logK^R$	log of in-house R&D stock
$logK^{T_F}$	log of knowledge transfer stock from foreign sources
$logK^{T_{UK}}$	log of knowledge transfer stock from UK sources
Market Share	Market share owned by firm
HHI	HirshmanHerfindahl Index measure of market concentration
No. Firms	Number of firms within the enterprise group
Div. Ratio	Diversification measure calculated as the ratio of the number of industies that an enterprise group is active in to the number of firms within the enterprise group
log D	log of dividend payments to shareholders
log TA	log of total assets
log ROTA	log of the rate of return on total assets
log DAR	log of the debt-to-asset ratio
log LR	log of the liquidity ratio
log Age	Age of the firm
Previous. event	Previous event dummy indicating if an event has occured at an earlier time within the sample
Industry Dummies	Set of industry dummies
Time Dummies	Set of time dummies

Zeros and negative values of variables are converted to very small positive numbers to allow logs to be taken.

4.5 Definitions of Firm and Industry Characteristic Variables

Innovation Performance

The R&D dummy is a binary variable where 1 indicates an R&D performing firm and 0 indicates otherwise. The stock of R&D variables are calculated in the same way as described in chapter 2. These variables are included in the models as an attempt to capture the synergistic technology transfer motivation for joining events and the refocusing motive for separating events. Joining events may be motivated by a desire to transfer technology from one joining partner to another to improve performance. Separating events may be motivated by a desire to refocus on core activity, therefore R&D performing firms may be divested to focus on other core activities or other firms may be divested to reinvest funds into R&D activities.

Market Share

This variable is calculated using the turnover variable in the BSD. The BSD covers the entire population of UK firms, therefore industry turnover can be obtained by aggregating turnover for all firms within the industry. The following equation represents market share for firm i, where firm i operates in industry j. Industries are defined at the 5-digit level.

$$MarketShare_{i,t} = \frac{\textit{Turnover for firm } i \textit{ at time } t}{\textit{Turnover for industry } j \textit{ at time } t} \tag{4.24}$$

Market Concentration

The Hirshman-Hirfindahl Index HHI provides a measure of industry level concentration. It is defined for industry j as follows, where N is the number of firms in the industry.

$$HHI_{j,t} = \sum_{i=1}^{N} (MarketShare_{i,t}^{2}) \tag{4.25}$$

The HHI ranges from 1 to $1/N$ and is calculated at the 5-digit industry level. A market becomes more concentrated if market power is shared amongst a small number of dominant firms. A higher HHI indicates higher market concentration. The advantages of the HHI over other measures of market concentration is that it considers all firms within the industry and gives a greater weighting to the largest firms.

Diversification

The diversification ratio acts as a measure of enterprise group level diversification and is calculated using the BSD as follows;

$$\textit{Diversification Ratio}_m = \frac{\textit{(Number of Firms in Enterprise group m) -1}}{\textit{Number of Industries engaged in by Enterprise group m}} \tag{4.26}$$

Highly diversified enterprise groups may be more likely to be involved in a separating event because diversification increases the complexity of an organisation. Over-diversified firms may seek to refocus on core activities. Diversified enterprise groups may also be more likely to engage in joining events as diversification may indicate a trend of managerial growth motives.

Enterprise Group Size

The number of firms variable indicates the number of firms within the firm's enterprise group. If firm i belongs to enterprise group m, this variable records the total number of UK-based firms within enterprise group m at time t. It is identified using the BSD. Firms from larger enterprise groups may be more likely to be involved in a restructuring event due to the size of the enterprise group.

Firm Workforce Size

Firm workforce size is measured using the number of employees. This variable is taken from the ARD.

Assets

Total assets are defined in FAME as fixed assets plus current assets, where fixed assets include investments, tangible and intangible assets. The ARD does not provide a measure of total assets, therefore the capital stock measure as defined in chapter 2 is used as a measure of tangible fixed assets and investment.

Profitability

The rate of return on total assets is a measure of profitability provided in FAME. It is defined as follows;

$$\textit{Return on total assets}_{i,t} = \frac{\textit{Profits before tax}_{i,t}}{\textit{Total Assets}_{i,t}} \tag{4.27}$$

The ARD does not provide a measure of profitability, therefore gross value added is used as a proxy. Gross value added is given by the value of final output minus the value of inputs. The impact of this variable on the likelihood of events depends on the predominant motive behind the event. Joining events may be motivated by synergistic technology transfer motives where a less profitable firm joins with a more profitable firm. The acquired firms may be less profitable and the acquirer may be more profitable. Less profitable firms are likely to be divested from an enterprise group when refocusing strategies are pursued.

Liquidity

The liquidity ratio is a measure of liquidity taken from the financial ratios in FAME.

$$\textit{liquidity Ratio}_{i,t} = \frac{\textit{Current Assets}_{i,t}\text{-}(\textit{Stock and W.I.P})_{i,t}}{\textit{Current Liabilities}_{i,t}} \tag{4.28}$$

Current assets include stock, work in progress (W.I.P), trade debtors, bank deposits, investments and other current assets. Current liabilities include trade creditors, short-term loans, overdrafts, corporation tax, dividends, social security and other current liabilities.

Leverage

The debt-to-asset ratio is a measure of leverage calculated using the financial data from FAME.

$$\textit{Debt-to-Asset Ratio}_{i,t} = \frac{\textit{Long Term Liabilities}_{i,t} + \textit{Current Liabilities}_{i,t}}{\textit{Net Assets}_{i,t}} \tag{4.29}$$

Long term liabilities includes long term debt, hire purchase, leasing, pension liabilities and other liabilities. Net assets is total assets minus longterm liabilities. In circumstances of high debt, managers are more likely to act in the interests of shareholders as their position may be at risk. The literature provides mixed evidence on the impact of leverage on joining events, but suggests that higher leverage increases the likelihood of separating events.

Dividends

The dividends variable is taken from FAME and represents dividend payments made to shareholders during the financial year.

Previous Events

The previous event dummies indicate at least one previous occurrence of an event. Dummies are included for each event type. These variables aim to capture the interrelationships between events.

Control Variables

The firm age variable is calculated using the year of birth given in the BSD and acts as a control variable. Sets of industry and time dummies are included to control for industry and macroeconomic effects.

Table 4.2: Number of Events in BSD population by Year

Year	No Event	Acquired	Acquirer	Merger	Change of Ownership	Breakup	Divested	Divestor	Tradesale	Acquirer-Divestor	Total
1998	2008538	4819	10687	2888	16115	413	1305	1807	457	4815	2051844
1999	2000717	265	325	31230	50565	11541	424	360	0	48	2095475
2000	2042573	4203	8160	4572	13698	1721	3624	4801	462	4093	2087907
2001	2068659	5075	8934	5151	16424	1991	3350	4299	606	4102	2118591
2002	2056038	8551	11104	12198	25077	4919	3836	4134	432	5519	2131808
2003	2088358	6386	9578	7955	18006	3742	4505	5799	348	5598	2150275
2004	2153990	5265	8509	4802	16363	3123	4197	6002	400	4773	2207424
2005	2186606	6896	11656	8332	24204	3164	3541	4401	441	4571	2253812
2006	2263565	4462	9979	3657	11319	364	2546	2608	631	2498	2301629
2007	2326643	6542	11325	6707	16652	556	3558	3626	856	2648	2379113
Total	21195687	52464	90257	87492	208423	31534	30886	37837	4633	38665	21777878
Total (2000-2007)	17186432	47380	79245	53374	141743	19580	29157	35670	4176	33802	17630559
Percent (2000-2007)	97.48	0.27	0.45	0.30	0.80	0.11	0.17	0.20	0.02	0.19	100.00

Creation of the Sample

BSD

Events are defined at enterprise level using enterprise and enterprise group reference codes for each observation in the BSD. A categorical 'event' variable is created where the categories include 'no event', 'acquired', 'acquirer', 'merger', 'change of ownership', 'break-up', 'divested', 'divestor', 'trade sale' and 'acquirer-divestor'. These event categories are mutually exclusive.

Enterprise group codes are available in the BSD for the period 1997 to 2007. Although later years are available for the BSD, enterprise group codes are missing in 2008. If an event occurs between time $t-1$ and time t, the event is recorded at time t in the event variable, therefore events can be defined during the period 1998 to 2007. Table (4.2) shows the number of events taking place by year using the entire BSD sample.

The pattern of events occurring in 1999 appears to differ from other periods. There are far more change of ownership events, mergers and break ups and far fewer acquisitions, divestments and trade sales. This could have arisen due to changes in the recording of enterprise group codes during this year, as it is unlikely that this is the result of a macroeconomic shock during this period. Criscuolo and Martin (2003) report similar problems. It seems sensible to truncate the sample to 2000-2007 to avoid these irregularities in the data.

BSD, ARD and BERD Sample

The BSD data is then merged together with the ARD and BERD. Merging the ARD with the BSD is relatively straight forward because observations exist at enterprise level in both datasets. The number of matches provided by the merging process is shown in table (4.3). The observations with common enterprise references between the ARD and BSD are kept in the sample and unmatched observations are dropped. Over the 2000-2007 period 17,238,323 observations from the BSD and 12,794 from the ARD are

Table 4.3: BSD and ARD Merge

Year	Not Matched		Matched	Total
	From BSD	From ARD	BSD-ARD	
2000	2,037,303	1,724	50,604	2,089,631
2001	2,063,819	2,081	54,772	2,120,672
2002	2,080,170	1,803	51,638	2,133,611
2003	2,099,259	1,802	51,016	2,152,077
2004	2,156,710	1,708	50,714	2,209,132
2005	2,204,416	1,759	49,396	2,255,571
2006	2,261,458	933	40,171	2,302,562
2007	2,335,188	984	43,925	2,380,097
Total	17,238,323	12,794	392,236	17,643,353

Table 4.4: BSD-ARD and BERD Merge

Year	Not Matched		BSD-ARD-BERD	
	From BSD-ARD	From BERD	Matched	Keep
2000	47,963	5,950	2,641	50,604
2001	52,354	6,222	2,418	54,772
2002	48,434	7,577	3,204	51,638
2003	48,538	7,292	2,478	51,016
2004	47,675	8,773	3,039	50,714
2005	46,341	9,415	3,055	49,396
2006	36,789	13,163	3,382	40,171
2007	39,955	14,862	3,970	43,925
Total	368,049	73,254	24,187	392236

Table 4.5: Number of Events in BSD-ARD-BERD Sample by Year

Year	No Event	Acquired	Acquirer	Merger	Change of Ownership	Breakup	Divested	Divestor	Tradesale	Acquirer-Divestor	Total
2000	34447	447	1155	384	1391	198	406	795	97	866	40186
2001	34540	525	1215	398	1567	218	413	730	97	771	40474
2002	35673	681	1606	842	2498	522	485	653	111	1002	44073
2003	35099	523	1298	526	1688	371	381	906	58	778	41628
2004	35643	468	1125	323	1668	284	321	807	37	734	41410
2005	34271	522	1511	482	1846	304	301	593	62	706	40598
2006	35045	326	1208	260	1239	49	308	302	70	323	39130
2007	27377	316	1133	331	1251	84	403	355	94	266	31610
Total	272095	3808	10251	3546	13148	2030	3018	5141	626	5446	319109
Percent	85.27	1.19	3.21	1.11	4.12	0.64	0.95	1.61	0.20	1.71	100.00

unmatched. There are 392,236 matched observations between the BSD and ARD. Merging the BERD data is a little more complex because observations are only given at reporting unit level. The corresponding enterprise reference code for each reporting unit is not included in the BERD data. The look-up table created by Richard Harris is used to provide the corresponding enterprise reference codes for the appropriate reporting units. The data is then aggregated to the enterprise level and merged with the BSD. The matches between the data sets are shown in table (4.4). BERD should include data for all R&D performing firms in the UK, but not all firms perform R&D. Unmatched observations between the BSD-ARD and BERD indicate that no R&D was performed by the enterprise during the year. This assumption is likely to hold in most cases, therefore missing R&D values for these unmatched BSD-ARD observations are replaced with zero. All observations from the BSD-ARD sample are kept and only the unmatched observations from BERD are dropped. The number of observations that are dropped due to the merging process are shown in the "Not Matched From BERD" column in table (4.4). The final sample is obtained by dropping observations with missing lagged variables. The number of observations lost is 73,127. Table (4.5) describes the number of events in the final BSD-ARD-BERD sample.

UK and Foreign Events

Events can be distinguished into UK and Foreign events using the country of ultimate ownership codes available in the BSD. These codes are not available for all observations; 208,767 observations from the BSD-ARD-BERD 2000-2007 sample have missing country of ownership codes. Table (4.6) shows the number of foreign and UK owned enterprises in $t + 1$ by year. The foreign-UK event variable indicates the type of event that occurs and foreign or UK ownership following the event. Event motivations may differ between firms that become foreign owned and UK owned as a result of the event. Table (4.7) shows the number of foreign and UK events in the BSD-ARD-BERD sample by year.

Table 4.6: UK and Foreign Ownership by Year in BSD-ARD-BERD Sample

Year	UK		Foreign		Total
	Frequency	Percent	Frequency	Percent	
2000	10325	75.43	3363	24.57	13688
2001	10010	74.56	3416	25.44	13426
2002	10300	72.10	3985	27.90	14285
2003	10170	72.31	3894	27.69	14064
2004	10240	72.21	3941	27.79	14181
2005	10289	72.19	3964	27.81	14253
2006	10152	71.84	3980	28.16	14132
2007	8728	70.88	3585	29.12	12313
Total	80214	72.70	30128	27.30	110342

Table 4.7: Number of Foreign and UK Events in BSD-ARD-BERD Sample by Year

Year	No Event		Acquired		Acquirer		Merger		Change of Ownership		Total
	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	
2000	6651	2485	154	69	947	190	138	47	491	176	13688
2001	6265	2579	241	66	994	201	145	48	511	162	13426
2002	5547	2568	289	88	1290	310	281	93	793	311	14285
2003	6364	2674	193	73	1029	263	163	64	571	212	14064
2004	6923	2818	203	77	855	259	115	33	539	189	14181
2005	6644	2846	204	68	1165	346	149	37	660	174	14253
2006	7820	3164	152	51	888	313	120	36	390	152	14132
2007	6294	2755	147	57	862	254	106	47	472	146	12313
Total	52508	21889	1583	549	8030	2136	1217	405	4427	1522	110342
Percent	47.59	19.84	1.43	0.50	7.28	1.94	1.10	0.37	4.01	1.38	100.00

Year	Breakup		Divested		Divestor		Tradesale		Acquirer-Divestor		Total
	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	
2000	157	33	309	88	653	137	80	17	745	121	13688
2001	176	36	342	68	584	141	79	17	673	98	13426
2002	374	104	375	105	479	167	83	26	789	213	14285
2003	249	95	287	91	700	201	44	13	570	208	14064
2004	213	66	227	92	635	171	23	14	507	222	14181
2005	255	44	214	87	418	174	42	20	538	168	14253
2006	34	15	198	107	220	79	56	14	274	49	14132
2007	60	21	274	112	236	116	63	26	214	51	12313
Total	1518	414	2226	750	3925	1186	470	147	4310	1130	110342
Percent	1.38	0.38	2.02	0.68	3.56	1.07	0.43	0.13	3.91	1.02	100.00

BSD-ARD-BERD R&D Performing Firms Subsample

Table (4.8) shows the number of observations by event for a subsample of the BSD-ARD-BERD dataset containing R&D performing firms only. R&D performing firms are defined as those that engage in R&D activity during at least one period within the sample time frame, therefore the number of observations within this subsample exceeds the number of matches between BSD-ARD and BERD shown in table (4.4).

Table 4.8: Number of Foreign and UK Events in R&D Performing Firms Subsample

Event	UK		Foreign		Total	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
No Event	10663	40.24	5435	20.51	16098	60.75
Acquired	464	1.75	211	0.80	675	2.55
Acquirer	1859	7.02	849	3.20	2708	10.22
Merger	332	1.25	134	0.51	466	1.76
Change of Owner	1087	4.10	472	1.78	1559	5.88
Breakup	382	1.44	138	0.52	520	1.96
Divested	570	2.15	294	1.11	864	3.26
Divestor	1141	4.31	472	1.78	1613	6.09
Tradesale	145	0.55	53	0.20	198	0.75
Acquirer-Divestor	1380	5.21	416	1.57	1796	6.78
Total	18023	68.02	8474	31.98	26497	100

Joining and Separating Events

Some events can be grouped together as ‘Joining’ and ‘Separating’ events. The‘Joining’ events group includes ‘Acquired’, ‘Acquirer’ and ‘Merger’. The‘Separating’ events group includes ‘Breakup’, ‘Divested’ and ‘Divestor’. The data can also be analysed in reference to these aggregated events. Tables (4.9) and (4.10) show the number of observations by year for each of these events. ‘Change of Ownership’, ‘Tradesale’ and ‘Acquirer-Divestor’ events are not included in this sample.

Table 4.9: Joining and Separating Events BSD-ARD-BERD Sample

Year	**No Event**	**Joining**	**Separating**	**Total**
2000	34447	1986	1399	37832
2001	34540	2138	1361	38039
2002	35673	3129	1660	40462
2003	35099	2347	1658	39104
2004	35643	1916	1412	38971
2005	34271	2515	1198	37984
2006	35045	1794	659	37498
2007	27377	1780	842	29999
Total	272095	17605	10189	299889
Percent	90.73	5.87	3.40	100.00

Table 4.10: UK and Foreign Joining and Separating Events BSD-ARD-BERD Sample

Year	**No Event**		**Joining**		**Separating**		**Total**
	UK	**Foreign**	**UK**	**Foreign**	**UK**	**Foreign**	
2000	6651	2485	1239	306	1119	258	12058
2001	6265	2579	1380	315	1102	245	11886
2002	5547	2568	1860	491	1228	376	12070
2003	6364	2674	1385	400	1236	387	12446
2004	6923	2818	1173	369	1075	329	12687
2005	6644	2846	1518	451	887	305	12651
2006	7820	3164	1160	400	452	201	13197
2007	6294	2755	1115	358	570	249	11341
Total	52508	21889	10830	3090	7669	2350	98336
Percent	53.40	22.26	11.01	3.14	7.80	2.39	100.00

FAME

As identified in the literature review, the likelihood of an event occurring will be partly influenced by the financial characteristics of a firm. This includes variables such as profitability, leverage etc. Unfortunately data on these variables are not available in the ARD. The failure to include these variables could result in omitted variable bias, therefore an additional sample is created to include financial variables taken from the FAME database.

The Financial Analysis Made Easy (FAME) Database contains data on firms registered at Companies House in the UK. The data is mainly sourced from government statistics and compiled by Bureau Van Dijk (BvD). It contains information taken from company records including profit and loss accounts, balance sheets, number of employees and industry codes. This data is available for the period 2004-2008 and the original FAME sample contains 670,883 observations. The Secure Data Service (SDS) used a lookup table to match the BvD company reference with the IBDR enterprise reference code. 127,974 observations were linked to the corresponding Entref. There may be a number of reasons why some of the matches were not successful. Enterprise references cannot be obtained if the company is not included in the IDBR database. This would occur if the company is too small or not operating at the time of the survey. Table (4.11) shows the number of FAME observations with an identifiable IDBR enterprise reference number by year.

Table 4.11: Number of Observations in FAME by Year

year	Frequency	Percent	Cumulative Percentage
2004	24,247	18.95	18.95
2005	24,992	19.53	38.48
2006	25,652	20.04	58.52
2007	26,373	20.61	79.13
2008	26,710	20.87	100
Total	127,974	100	

Table (4.12) shows the number of matches between the BSD and FAME. Although the IBDR lookup table provided enterprise reference codes for 127,974 observations, only 67% of these observations could be matched to the BSD. This indicates that IDBR and BSD codes are not entirely consistent with each other. Table (4.13) shows that 17% of the FAME sample can be matched with the BSD-ARD-BERD sample. A large number of observations are lost due to the small overlap of the two samples and others may be lost due to inconsistencies between the IDBR and BSD codes.

Table 4.12: BSD and FAME Merge

Year	Not Matched		Matched	Total
	From BSD	From FAME	BSD-FAME	
2000	2,087,907	0	0	2,087,907
2001	2,118,591	0	0	2,118,591
2002	2,131,808	0	0	2,131,808
2003	2,150,275	0	0	2,150,275
2004	2,187,042	3,865	20,382	2,211,289
2005	2,232,751	3,931	21,061	2,257,743
2006	2,279,983	4,006	21,646	2,305,635
2007	2,356,755	4,015	22,358	2,383,128
Total	17,545,112	15,817	85,447	17,646,376

Table 4.13: BSD-ARD-BERD and FAME Merge

Year	Not Matched		Matched	Total
	From BSD-ARD-BERD	From FAME	BSD-ARD-BERD-FAME	
2000	50,604	0	0	50,604
2001	54,772	0	0	54,772
2002	51,638	0	0	51,638
2003	51,016	0	0	51,016
2004	45,164	18,697	5,550	69,411
2005	43,812	19,408	5,584	68,804
2006	34,941	20,422	5,230	60,593
2007	37,989	20,437	5,936	64,362
Total	369,936	78964	22,300	471,200

Table 4.14: Number of Foreign and UK Events in BSD-ARD-BERD-FAME (2005-2007)

Event	UK		Foreign		Total	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
No event	4,741	40.06	2,984	25.22	7725	65.28
Acquired	138	1.17	60	0.51	198	1.67
Acquirer	1,098	9.28	453	3.83	1551	13.11
Merger	138	1.17	49	0.41	187	1.58
Change of Owner	403	3.41	198	1.67	601	5.08
Breakup	98	0.83	33	0.28	131	1.11
Divested	210	1.77	123	1.04	333	2.81
Divestor	302	2.55	168	1.42	470	3.97
Tradesale	45	0.38	24	0.20	69	0.58
Acquirer-Divestor	437	3.69	132	1.12	569	4.81
Total	7610	64.31	4224	35.69	11,834	100

The final BSD-ARD-BERD-FAME sample is obtained by dropping observations with missing lagged variables. Lagged variables were created in the FAME sample prior to matching to minimise the number of observations dropped. 8085 observations are dropped from the 4 year sample to create a 3 year sample of lagged variables. Table (4.16) shows the number of observations for each event by year in the BSD-ARD-BERD-FAME sample and distributions of the events. Table (4.14) shows the distribution of foreign events in the BSD-ARD-BERD-FAME sample. The distribution remains fairly consistent with the distribution of events in the BSD-ARD-BERD sample. Table (4.15) shows the number of joining and separating events in the sample.

Table 4.15: Joining and Separating Events BSD-ARD-BERD-FAME Sample

Year	**No Event**	**Joining**	**Separating**	**Total**
2005	2,986	800	370	4156
2006	3,495	651	233	4379
2007	3,169	641	339	4149
Total	9,650	2092	942	12684
Percent	76.08	16.49	7.43	100.00

Table 4.16: Number of Events in BSD-ARD-BERD-FAME Sample by Year

Year	No Event	Acquired	Acquirer	Merger	Change of Ownership	Breakup	Divested	Divestor	Tradesale	Acquirer-Divestor	Total
2005	2,986	108	578	114	347	82	78	210	17	287	4,807
2006	3,495	83	502	66	247	18	102	113	22	139	4,787
2007	3,169	78	481	82	299	33	158	148	30	143	4,621
Total	9,650	269	1,561	262	893	133	338	471	69	569	14,215
Percent	67.89	1.89	10.98	1.84	6.28	0.94	2.38	3.31	0.49	4.00	100.00

4.6 Descriptive Statistics

The data section describes the creation of 3 samples; BSD-ARD-BERD sample, BSD-ARD-BERD R&D performing firms sample and BSD-ARD-BERD-FAME sample. This section provides descriptive statistics for the key variables used in the model for each of the data samples.

Table (4.17) provides an overview of pre-event descriptive statistics for the BSD-ARD-BERD sample for 'no event', 'joining events' and 'separating events'. 'Joining events' include 'acquired', 'acquirer' and 'merger'. 'Separating events' include 'breakup' 'divested' and 'divestor'. Comparisons across these groups reveal that events tend to involve larger firms than the 'no event' group. This is illustrated by the larger mean and median values for gross value added, capital stock and number of employees. The larger standard deviations for 'joining' and 'separating' events imply that there is a larger variation within these groups. Furthermore, events tend to be experienced by firms that belong to larger enterprise groups. Single firm enterprise groups are less inclined to engage in events. The mean and median values for the number of firms within the enterprise group are higher for the joining and separating events groups than for the no event group. These values are particularly high for separating events, which ties in with the idea that separating events may be motivated as a response to over-diversification. The relatively high diversification ratios for separating events provides further support for this notion. The descriptive statistics for market share and HHI reveal a tendency for firms with a larger market share and within more concentrated industries to engage in 'joining' or 'separating' events. Firm age remains relatively consistent regardless of event involvement.

Table (4.18) provides descriptive statistics by event for the BSD-ARD-BERD sample. Dividing the joining events into 'acquired', 'acquirer' and 'merger' reveals that the mean values for each type of 'joining event' are consistently higher than the 'no event' group. In particular, acquirers are generally larger than acquired and merging firms with higher mean and median gross value added, capital stock and number of employees. They enjoy a larger market share and belong to larger more diversified enterprise groups.

Splitting the 'separating events' into 'breakup', 'divested' and 'divestor' shows that mean and median values for each type of 'separating event' are consistently higher than the 'no event' group and each 'joining event' group. On average, 'divested' firms are smaller than breakups and divestors, but come from larger enterprise groups.

The 'change in ownership' group has the smallest mean and median values in terms of gross value added, capital stock and number of employees compared to the other event types. Firms involved in a 'change of ownership' mostly come from small enterprise groups. 'Tradesale' is the combination of 'divested' and 'acquired' in one event. The mean and median values for gross value added, capital stock and number of employees is similar to the values for the divested and acquired group. The average values for number of firms within the enterprise group and the diversification ratio are much higher than the 'acquired' group and more in line with the mean and median values for the'divested' group. The 'acquirer-divestor' group has the largest average and median values compared with the other event groups. Firms that acquire and divest during the same period, on average, have larger gross value added, capital stock and number of employees, a greater market share, come from more concentrated industries and very large enterprise groups.

Table (4.19) displays the descriptive statistics for the BSD-ARD-BERD R&D performing firms sample. The sample contains 33,936 observations. R&D performing firms tend to be larger. Comparisons of the descriptive statistics for the total samples reveals that, on average, R&D performing firms are larger with a larger market share, from larger and more diversified enterprise groups and operate in more concentrated industries than the average firm within the BSD-ARD-BERD sample. This finding is reflected in the descriptive statistics for each event. Events are more frequent for larger firms, therefore 66.27% of observations incur 'no event' in the R&D performing sample, compared to 85.27% of observations in the full BSD-ARD-BERD sample.

Table (4.20) shows the descriptive statistics for the total BSD-ARD-BERD-FAME sample. FAME contains publicly listed firms therefore firms within this sample tend to

Table 4.17: Descriptive Statistics for BSD-ARD-BERD Joining and Separating Events

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
No Event (N=272095)					
Gross Value Added	5299.79	61344.03	497	64.9	6104.85
Capital Stock	2207.06	32460.2	32.26	62.27	5525.66
Number of Employees	155.27	1342.97	19	62.56	6801.45
Market Share	0	0.02	0	20.07	568.59
Age	17	9.58	16	0.18	1.75
HHI	0.04	0.07	0.01	4.85	40.05
Number of firms in enterprise group	1.46	2.13	1	22.01	1338.65
Diversification Ratio	0.12	0.31	0	2.33	6.63
Joining Event (N=17605)					
Gross Value Added	40158.23	440295.2	4986	80.78	8518.06
Capital Stock	17941.37	202786.7	988.81	57.8	4638.82
Number of Employees	785.96	4505.66	133	26.18	930.54
Market Share	0.02	0.05	0	7.82	82.18
Age	17.91	9.29	16	0.12	1.8
HHI	0.05	0.08	0.02	3.88	24.8
Number of firms in enterprise group	6.03	8.97	2	3.43	18.78
Diversification Ratio	0.44	0.41	0.47	0.14	1.38
Separating (N= 10189)					
Gross Value Added	43176.77	235217.4	6061.81	18.82	507.52
Capital Stock	23838.84	202307.7	1518.66	40.47	2483.91
Number of Employees	884.56	4212.61	167	21.46	733.39
Market Share	0.02	0.07	0	7.12	68.97
Age	18.78	8.81	18	0.06	1.78
HHI	0.05	0.09	0.02	3.83	23.94
Number of firms in enterprise group	12.55	17.62	7	5.32	48.08
Diversification Ratio	0.69	0.27	0.71	-0.7	2.96
Total (N= 299889)					
Gross Value Added	8633.06	129548.6	605.15	196.81	67364.36
Capital Stock	3865.71	69196.14	42.92	126.13	26601.64
Number of Employees	217.08	1862.42	22	51.94	4227.83
Market Share	0	0.03	0	16.1	356.1
Age	17.11	9.54	16	0.17	1.75
HHI	0.04	0.07	0.01	4.73	37.8
Number of firms in enterprise group	2.11	4.94	1	14.51	404.61
Diversification Ratio	0.16	0.34	0	1.83	4.6

Table 4.18: Descriptive Statistics for BSD-ARD-BERD Events

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
No Event N=272095					
Gross Value Added	5299.79	61344.03	497	64.9	6104.85
Capital Stock	2207.06	32460.2	32.26	62.27	5525.66
Number of Employees	155.27	1342.97	19	62.56	6801.45
Market Share	0	0.02	0	20.07	568.59
Age	17	9.58	16	0.18	1.75
HHI	0.04	0.07	0.01	4.85	40.05
Number of Firms in Enterprise Group	1.46	2.13	1	22.01	1338.65
Diversification Ratio	0.12	0.31	0	2.33	6.63
Acquired N= 3808					
Gross Value Added	16510.2	55773.97	3905.64	12.58	244.11
Capital Stock	7837.97	61008.62	712.74	35.8	1603.78
Number of Employees	401.5	1423.57	106	17.14	437.62
Market Share	0.01	0.04	0	9.52	120.3
Age	16.27	9.5	15	0.25	1.85
HHI	0.05	0.08	0.02	3.57	20.2
Number of Firms in Enterprise Group	2.19	4.28	1	13.24	251.96
Diversification Ratio	0.23	0.39	0	1.22	2.67
Acquirer N= 10251					
Gross Value Added	55848.42	571873.7	6850.74	63.2	5133.6
Capital Stock	23592.47	255373.4	1581.32	48.96	3156.55
Number of Employees	1030.11	5431.36	181	22.75	694.91
Market Share	0.02	0.06	0	7.08	67.5
Age	19.14	8.95	18	0.06	1.77
HHI	0.05	0.08	0.02	4.05	27.77
Number of Firms in Enterprise Group	8.59	10.44	5	2.69	12.13
Diversification Ratio	0.59	0.36	0.67	-0.47	1.92
Merger N= 3546					
Gross Value Added	20195.34	109679.6	2537.14	15.39	306.92
Capital Stock	12454.68	106842.6	362.75	19.76	483.33
Number of Employees	493.03	3594.87	71	26.94	869.91
Market Share	0.01	0.04	0	8.74	98.26
Age	16.13	9.48	14	0.27	1.85
HHI	0.05	0.08	0.01	3.67	20.52
Number of Firms in Enterprise Group	2.75	4.31	1	4.14	27.44
Diversification Ratio	0.23	0.37	0	1.22	2.74

Table 4.18 (continued): Descriptive Statistics for BSD-ARD-BERD Events

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
Change of Ownership N=13148					
Gross Value Added	10735.16	54254.85	2129.84	19.98	562.73
Capital Stock	4726.75	42843.43	258.15	35.49	1655.04
Number of Employees	274.45	1286.72	60	21.2	667.92
Market Share	0.01	0.03	0	11.68	185.96
Age	16.38	9.45	15	0.27	1.83
HHI	0.04	0.07	0.01	4.2	27.69
Number of Firms in Enterprise Group	1.76	2.38	1	8.03	107.4
Diversification Ratio	0.2	0.38	0	1.42	3.17
Breakup N=2030					
Gross Value Added	50425.5	304127.1	6041.37	20.36	547.98
Capital Stock	33027.04	348162.8	1450.25	34.19	1360.11
Number of Employees	939.67	6259.44	175	23.63	659.99
Market Share	0.02	0.07	0	8.08	84.28
Age	18.31	8.79	17	0.07	1.78
HHI	0.06	0.1	0.02	4.21	26.53
Number of Firms in Enterprise Group	10.8	14.72	5	3.42	17.99
Diversification Ratio	0.7	0.29	0.75	-0.78	2.86
Divested N=3018					
Gross Value Added	24785.44	121223.2	4596.09	22.6	665.55
Capital Stock	12389.8	97751.97	1044.49	27.1	850.43
Number of Employees	576.78	2153.46	128	11.85	190.74
Market Share	0.02	0.05	0	8.13	96.02
Age	18.14	9.05	17	0.14	1.82
HHI	0.05	0.08	0.02	3.67	22.11
Number of Firms in Enterprise Group	15.73	25.48	7	4.76	32.41
Diversification Ratio	0.67	0.28	0.69	-0.65	2.82
Divestor N=5141					
Gross Value Added	51111.05	253465.8	7283	14.37	274.49
Capital Stock	26931.85	165968.3	2007.22	17.17	388.23
Number of Employees	1043.48	4111.46	195	11.72	191.32
Market Share	0.02	0.07	0	6.16	51.01
Age	19.34	8.63	18	0.02	1.76
HHI	0.05	0.08	0.02	3.58	21.46
Number of Firms in Enterprise Group	11.37	11.83	7	2.63	13.59
Diversification Ratio	0.7	0.26	0.71	-0.68	3.07

Table 4.18 (continued): Descriptive Statistics for BSD-ARD-BERD Events

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
Tradesale N=626					
Gross Value Added	21447.76	56731.07	5443.52	7.27	75.16
Capital Stock	12898.86	88409.86	1606.45	20.44	466.78
Number of Employees	558.24	1633.15	175.5	10.04	138.31
Market Share	0.01	0.03	0	5.32	41.7
Age	18.31	9.03	17	0.15	1.83
HHI	0.05	0.09	0.02	4.18	28.47
Number of Firms in Enterprise Group	16.15	23.89	8	4.49	32.08
Diversification Ratio	0.67	0.27	0.68	-0.59	2.8
Acquirer-Divestor N=5446					
Gross Value Added	92980.85	475818.5	12200.23	13.15	218.12
Capital Stock	57337.1	521699.3	3023.15	26.56	858.98
Number of Employees	1906.56	10032.84	289.5	15.03	280.62
Market Share	0.03	0.08	0	5.93	48.06
Age	19.04	8.84	18	0.05	1.73
HHI	0.06	0.09	0.02	3.97	25.56
Number of Firms in Enterprise Group	30.33	32.99	21	3.27	17.06
Diversification Ratio	0.57	0.21	0.55	0.17	2.64
Total N=319109					
Gross Value Added	10184.31	141004.5	675	152.42	45605.12
Capital Stock	4831.46	96347.25	50.19	116.83	19408.06
Number of Employees	248.94	2258.03	24	50.77	3773.14
Market Share	0.01	0.03	0	15.12	313.45
Age	17.12	9.53	16	0.17	1.76
HHI	0.04	0.07	0.01	4.69	37.07
Number of Firms in Enterprise Group	2.6	7.52	1	13.38	285.47
Diversification Ratio	0.17	0.34	0	1.73	4.24

Table 4.19: Descriptive Statistics for BSD-ARD-BERD R&D Performing Firms Sample

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
Total N=33936					
Gross Value Added	39232.15	273266.9	5117.11	21	576.03
Capital Stock	25265.5	273172.4	1762.79	46.26	2784.54
Number of Employees	687.65	4764.76	147	29.6	1132.05
Market Share	0.02	0.07	0	6.55	58.46
Age	20.04	8.76	19	-0.06	1.78
HHI	0.06	0.09	0.03	3.37	19.87
Number of Firms in Enterprise Group	5.36	11.71	2	8.01	109.12
Diversification Ratio	0.4	0.43	0	0.3	1.33

Table 4.20: Descriptive Statistics for BSD-ARD-BERD-FAME Total Sample

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
Total N= 14215					
Gross Value Added	75775.72	542817.9	12595.71	54.89	4568.24
Capital Stock	33444.18	318401.1	2462.56	45.17	2582.86
Number of Employees	1308.9	6396.01	256	19.4	507.45
Market Share	0.02	0.07	0	6.11	51.14
Age	22.33	9.3	22	-0.23	1.79
HHI	0.05	0.09	0.02	3.74	21.9
Number of Firms in Enterprise Group	5.38	12.63	2	9.14	125.38
Diversification Ratio	0.41	0.42	0.33	0.28	1.35
Debt-to-Asset Ratio	1.86	5.97	1.26	41.93	2167.05
Dividends	2398.58	71964.36	0	69.18	5737.22
Total Assets	1444002	29600000	30856.01	41.19	1982.52
Rate of Return on Total Assets	14.28	34.84	6.71	16.25	437.43
Liquidity Ratio	1.55	2.68	1.06	14.65	372.47

be the larger firms from the BSD-ARD-BERD sample. The statistics show larger mean and median gross value added, capital stock, number of employees, market share, greater market concentration, number of firms within the enterprise group and level of diversification. These trends remain consistent across the different event types. The financial statistics provided by FAME are displayed in table (4.21). The median debt-to-asset ratio remains relatively stable across groups, although mean values are slightly higher for 'acquirer' and 'acquirer-divestor'. The mean dividend values fluctuate dramatically across groups, whereas the median values remain consistently at zero. 'Acquirer', 'breakup', 'divestor' and 'acquirer-divestor' have high mean dividend values, whereas 'acquired', 'change of ownership' and 'tradesale' have low mean dividends. The distribution of total assets across the event groups is similar to the distribution of capital stock in the BSD-ARD-BERD sample, where the groups with the largest total assets are 'divestor', 'breakup', 'acquirer' and 'acquirer-divestor'. The 'acquirer-divestor' group has highest average pre-event profitability indicated by the rate of return on total assets. The 'joining event' group has a higher average rate of return on total assets than the 'separating event' group. The average liquidity ratio values are lowest for 'merger' and highest for 'acquirer-divestor'.

Table (4.22) shows descriptive statistics for the BSD-ARD-BERD sample by foreign and UK ownership status. The values indicate that foreign owned firms tend have greater value added output, capital stock and market share than UK owned firms. The mean number of employees is slightly lower for foreign owned firms, but the median is higher. UK owned firms tend to come from larger UK-based enterprise groups and are more diversified within the UK.

Table 4.21: Descriptive Statistics for BSD-ARD-BERD-FAME Events

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
No Event N= 9650					
Debt-to-Asset Ratio	1.81	3.15	1.28	29.66	1396.63
Dividends	911.67	26992.61	0	53.64	3124.48
Total Assets	717500	20300000	22172.51	59.44	3776.98
Rate of Return on Total Assets	12.54	26.57	6.39	14.8	392.54
Liquidity Ratio	1.52	2.54	1.04	15.77	450.68
Acquired N= 269					
Debt-to-Asset Ratio	1.77	3.67	1.22	13.29	199.21
Dividends	606.8	4932.6	0	11.64	153.49
Total Assets	848795.9	8491572	40301	14.82	230.04
Rate of Return on Total Assets	16.66	36.06	6.62	5.89	45.55
Liquidity Ratio	1.63	3.61	1.15	13.85	213.61
Acquirer N= 1561					
Debt-to-Asset Ratio	2.12	13.07	1.22	25.6	685.48
Dividends	2583.55	27191.95	0	23.27	660.73
Total Assets	2368103	30700000	73869.01	25.43	718.98
Rate of Return on Total Assets	18.12	34.91	8.11	6.92	81.02
Liquidity Ratio	1.66	2.94	1.07	8.78	104.35
Merger N= 262					
Debt-to-Asset Ratio	1.47	0.96	1.22	2.35	10.68
Dividends	1039.96	9860.36	0	14.42	221.45
Total Assets	397365.1	1611974	43340.52	9.03	101.02
Rate of Return on Total Assets	20.79	86.17	7.63	13.71	205.52
Liquidity Ratio	1.26	0.96	1.05	2.81	15.13
Change of Ownership N = 893					
Debt-to-Asset Ratio	1.82	3.46	1.25	19.27	475.04
Dividends	153.18	1240.81	0	13.08	201.44
Total Assets	762495.6	10700000	26632.99	21.01	454.69
Rate of Return on Total Assets	15.04	26.71	7.37	5.62	47.23
Liquidity Ratio	1.68	3.77	1.06	15.86	343.10

Table 4.21 (continued): Descriptive Statistics for BSD-ARD-BERD-FAME Events

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
Breakup N= 133					
Debt-to-Asset Ratio	1.37	0.95	1.18	2.76	14.54
Dividends	4106.17	40873.94	0	11.33	129.84
Total Assets	8167076	83600000	63376.02	11.36	130.36
Rate of Return on Total Assets	13.84	21.08	4.72	2.55	10.25
Liquidity Ratio	1.54	2.39	0.97	5.64	41.09
Divested N= 338					
Debt-to-Asset Ratio	1.77	2.36	1.26	9.28	116.79
Dividends	646.81	6962.33	0	16.87	299.43
Total Assets	1454338	14600000	65844.99	16.94	300.38
Rate of Return on Total Assets	13.69	34.88	5.64	8.98	99.09
Liquidity Ratio	1.59	2.46	1.08	9.01	111.47
Divestor N= 471					
Debt-to-Asset Ratio	1.77	3.04	1.22	8.78	92.8
Dividends	6279.32	68038.98	0	16.48	301.9
Total Assets	2800445	29900000	104799	20.17	425.23
Rate of Return on Total Assets	16.54	38.19	6.89	9.37	130.51
Liquidity Ratio	1.48	2.14	1.07	8.09	88.80
Tradesale N= 69					
Debt-to-Asset Ratio	1.6	1.5	1.2	4.13	24.83
Dividends	551.59	2247.4	0	4.8	26.15
Total Assets	522825.6	2736409	57440.98	7.58	60.73
Rate of Return on Total Assets	13.91	24.63	7.71	4.84	32.04
Liquidity Ratio	1.48	1.37	1.11	3.49	18.70
Acquirer-Divestor N= 569					
Debt-to-Asset Ratio	2.65	14.65	1.23	15.1	240.01
Dividends	29758.22	331770.1	0	16.79	309.92
Total Assets	10500000	97200000	161739	15.03	256.9
Rate of Return on Total Assets	26.6	86.66	9.61	9.76	115.15
Liquidity Ratio	1.75	2.84	1.13	9.48	124.55

Table 4.22: Descriptive Statistics for BSD-ARD-BERD Foreign and UK Owned

	Mean	**Standard Deviation**	**Median**	**Skewness**	**Kurtosis**
UK Owned N= 80214					
Gross Value Added	23950.81	188378.80	3268.00	31.52	1347.76
Capital Stock	12223.98	182328.60	581.12	67.52	5998.29
Number of Employees	628.30	4166.59	99	29.77	1233.83
Market Share	0.01	0.04	0.00	10.62	155.96
Age	19.69	8.83	19	-0.02	1.76
HHI	0.05	0.08	0.02	4.25	30.22
Number of Firms in Enterprise Group	6.11	13.45	2	8.02	99.37
Diversification Ratio	0.51	0.43	0.60	-0.12	1.31
Foreign Owned N= 30128					
Gross Value Added	34530.45	335614.30	5564.50	104.42	14660.28
Capital Stock	16219.98	96061.53	1398.34	16.77	373.00
Number of Employees	602.31	2466.64	156	25.71	1063.98
Market Share	0.02	0.06	0.00	7.26	72.32
Age	19.91	8.86	19	-0.03	1.71
HHI	0.05	0.08	0.02	3.63	22.02
Number of Firms in Enterprise Group	4.18	7.75	1	4.73	32.46
Diversification Ratio	0.32	0.41	0.00	0.66	1.68
Total N= 110342					
Gross Value Added	26839.49	237851.40	3752.00	91.51	16262.15
Capital Stock	13315.05	163368.90	739.91	69.15	6775.54
Number of Employees	621.21	3779.11	112	30.96	1378.24
Market Share	0.01	0.05	0.00	9.28	118.43
Age	19.75	8.84	19	-0.02	1.75
HHI	0.05	0.08	0.02	4.05	27.48
Number of Firms in Enterprise Group	5.58	12.19	2	8.24	109.67
Diversification Ratio	0.46	0.43	0.50	0.08	1.27

4.7 Results

The literature review in chapter (3) identified four broad motivations for restructuring events. These are strategic, synergistic, refocusing and managerial motivations. In this section the results from the multinomial logit model are analysed in reference to these motivations. The results are reported as average marginal effects (AME) in table (4.25) to table (4.29). Three different dependent variables are used in the estimations. These dependent variables include the 'Joining and Separating Event' variable with 'no event', 'joining event' and 'separating event' categories, 'Event' variable with 'no event', 'acquired', 'acquirer', 'merger', 'change of ownership', 'breakup', 'divested', 'divestor', 'tradesale', and 'acquirer-divestor' categories and 'UK and Foreign Event' variable which distinguishes between foreign and UK post-event ownership status in each event category. The estimations are performed on three different samples. These are the BSD-ARD-BERD sample, BSD-ARD-BERD R&D performing firms sample and the BSD-ARD-BERD-FAME sample. The variables included in the specification for each dataset are indicated in table (4.23).

Profitability is proxied by gross value added in the BSD-ARD-BERD sample. The results in table (4.24) are derived using the 'Joining and Separating' event dependent variable. They show a negative AME on the gross value added variable for 'no events'. This finding is consistent with other tables. 'Joining' events demonstrate a positive relationship with profitability indicating that more profitable firms are more likely to engage in 'joining' events. Tables (4.25) and (4.26) indicate that this effect is mostly driven by 'acquirers'. This supports the findings by Dickerson et al. (2003) and Szücs (2012). The return on total assets is the measure of profitability used in the BSD-ARD-BERD-FAME sample. Table (4.28) shows that the AME and coefficients on the log return on total assets for 'acquirer' and 'merger' are positive and significant giving further support to this viewpoint. More profitable firms are in a better financial position to engage in growth through merger and acquisition. This may act as an indication of managerial incentives for growth. Profitability has little impact on the likelihood

Table 4.23: List of Specifications

Variable	**BSD-ARD-BERD**	**BSD-ARD-BERD** R&D Performing	**BSD-ARD-BERD-FAME**
$logY$	✓	✓	
$logC$	✓	✓	✓
$logL$	✓	✓	✓
R&D dummy	✓		✓
$logK^R$		✓	
$logK^{T_F}$		✓	
$logK^{T_{UK}}$		✓	
Market Share	✓	✓	✓
HHI	✓	✓	✓
No. Firms	✓	✓	✓
Div. Ratio	✓	✓	✓
log D			✓
log TA			✓
log ROTA			✓
log DAR			✓
log LR			✓
log Age	✓	✓	✓
Previous. event	✓	✓	✓
Industry Dummies	✓	✓	✓
Time Dummies	✓	✓	✓

of a ‘separating’ event occurring, indicated by a AME of zero (to 3 d.p) on the gross value added variable in table (4.24). This finding is supported by the results in table (4.25) with no significant AMEs on gross value added for each of the separating events. This remains consistent when the ‘Foreign and UK events’ dependent variable is used. Results for the R&D performing firms and the BSD-ARD-BERD-FAME sample indicate a negative significant AME on the profitability variable for ‘divested’ firms. This implies that lower profit R&D performing and publicly-listed firms have a higher risk of becoming divested for. This is consistent with Haynes et al. (2003) and provides an indication of managerial motives. Managers may be endeavor to keep shareholders happy by divesting less profitable enterprises.

The labour, capital stock and total assets variables capture the impact of firm size on the likelihood of incurring a restructuring event. The AME of capital stock and labour on the probability of ‘no event’ occurring are consistently negative across samples. This implies that smaller firms are less likely to experience an event. The results in table (4.24) show that capital stock and labour have a positive impact on the probability of ‘joining’ and ‘separating’ events occurring. The AME for ‘joining’ events is greater than for ‘separating’ events. Table (4.25) shows that the ‘divestor’ is driving the positive significant AME on firm size, whereas the AME on ‘divested’ and ‘breakup’ are zero (to 3 d.p.). Total assets are used in the analysis of the BSD-ARD-BERD-FAME sample as an alternative measure to capital stock. In this sample of publicly listed firms, the probability of being an ‘acquirer’, ‘merger’, ‘divestor’ or ‘acquirer-divestor’ increases as total assets increase. This ties in with the idea that ‘acquirers’ and ‘acquirer-divestors’ are more likely to be larger financially stable firms.

Firms belonging to a smaller enterprise group are less likely to experience an event, indicated by the negative significant AME of the number of firms within the enterprise group on ‘no event’. The AME and coefficients are positive and significant for other events in the BSD-ARD-BERD sample.[55] This implies the likelihood of an event occurring

[55] Except ‘acquired’, which is not significantly different from zero.

increases with the number of firms within the enterprise group. The results from the R&D performing firms sample and the BSD-ARD-BERD-FAME sample present negative and significant coefficients and AME of number of firms within the enterprise group for ‘acquired’ and ‘change of ownership’. These samples are more inclined to contain larger firms. This suggests that larger firms that belong to enterprise groups with few other firms are at more risk of becoming an acquisition target or changing ownership. The result that acquiring and merging events are more likely for large enterprise groups gives support for the notion of managerial motivated joining events. Managers may be motivated by the prestige of managing large enterprise groups. The result that separating events are also more likely for large enterprise groups provides an indication of the refocusing motivation in action for these events.

Table (4.24) displays positive and significant AME on each of the ‘previous event’ dummies for ‘joining’ and ‘separating’ events. The magnitude of the AMEs on ‘joining’ events are larger than for ‘separating’ events. Negative and significant AME are found on the ‘previous event’ dummies for ‘no event’, implying that it is more likely that a firm will not be involved in a restructuring event if it has not previously been involved in restructuring events. These findings are supported by the ‘previous event’ dummy results displayed in table (4.25) *continued* using the ‘event’ dependent variable. The results provide strong evidence that restructuring events are interrelated and involvement in restructuring events is habit forming. Some managers may be more inclined to repeatedly engage in reorganisation. This finding is consistent with Dickerson et al. (2003), which finds that acquisition is habit forming.

The theoretical literature and empirical studies suggest that market share and market concentration provide strategic motivations for restructuring, although there is no consensus on the expected influence of the impact. The results in table (4.25) show that the AME on market share is positive for ‘no event’ and ‘acquirer-divestor’, implying that the probability of ‘no event’ or ‘acquirer-divestor’ occurring increases as market share increases once firm size is controlled for. The coefficients and AME are negative and significant for 'joining' events, 'change of ownership', 'divested' and 'tradesale'. There is no significant impact on 'break-up' or 'divestor'. The Hirshman-Herfindahl Index (HHI) measures market concentration at the 5-digit industry level. The AME of HHI on 'no event' is negative and significant, therefore a lower market concentration increases the probability of 'no event' occurring. The coefficients and AME on HHI for 'acquired', 'merger', 'change of ownership', 'breakup' are positive and significant. This implies that these events are more likely to occur within industries where market power is concentrated amongst a small number of firms.

The AME on log age is positive and significant for no event and AME and coefficients are negative and significant for all other events in the BSD-ARD-BERD sample. These findings are reflected in other samples, with less significant marginal effects and coefficients due to fewer observations. Younger firms are far more likely to engage in joining events, particularly as 'acquired' firms or through 'merger'.

The coefficients and AME on log dividends are positive and significant for 'acquirer' and 'acquirer-divestor', there is also a positive and significant coefficient for'divestor'. A negative significant effect for log dividends is found for 'change of ownership'. These findings remain consistent when the 'UK and Foreign Event' dependent variable is used. The distinction between UK and foreign no event reveals that the probability of 'UK no event' to occur increases as dividends increase, whereas a 'Foreign no event' is more likely to occur as dividends fall.

The debt-to-asset ratio is a measure of leverage. The AME on the leverage variable is positive and significant at the 10% level for 'no event' and negative and significant at the 10% level for 'acquirer' and 'change of ownership'. This implies that an increase in debt relative to assets increases the probability that 'no event' occurs, whereas a lower debt-to-asset ratio increases the probability of being an 'acquirer' or incurring a 'change of ownership'. The finding for 'acquirers' is consistent with the results from the Meeks Data 1949-70 sample in Dickerson et al. (2003).

The AME on the liquidity variable is positive and significant for 'change of ownership' and negative and significant at the 10% level for 'merger' and 'acquirer-divester'. The AME on the liquidity variable are negative and significant for 'merger', 'divestor' and 'acquirer-divestor'. This implies that the probability of these events increases when the liquidity ratio is lower. Enterprise groups may divest to generate funding for investment elsewhere. Merger may be the preferable joining event when liquidity is low because acquisition may require larger cash investments.

The diversification ratio aims to quantify the level of diversification within the enterprise group. It is calculated as the number of industries engaged in by the enterprise group divided by the number of enterprises within the enterprise group. The findings are consistent across samples. The AME on the diversification ratio for 'no event' is negative and significant, the AME and coefficients for 'acquired' and 'merger' are negative and significant and positive and significant for 'breakup', 'divested', 'divestor', 'tradesale' and 'acquirer-divestor'. This shows support for the refocusing motivation to correct for over-diversification and supports assertions by Markides (1995).

The R&D dummy variable is included to distinguish between R&D performing and non-R&D performing firms when using the BSD-ARD-BERD and BSD-ARD-BERD-FAME samples. This aims to capture synergistic motives for joining and refocusing motives for separating. The marginal effects for a binary variable shows how the probability of the outcome event is predicted to change as the explanatory variable changes from 0 to 1, holding other things constant. The 'Joining and Separating' event results in table (4.24) show that the AME on the R&D dummy are not significantly different from zero for 'no event' and 'joining events', whereas the AME is positive and significant for 'separating events'. This implies that probability of a separating event occurring is higher for R&D performing firms, implying the presence of a refocusing motivation.

The results in table (4.25) suggest that the AME on the R&D dummy are positive and significant for 'divested' and 'divestor'. The AME for 'divested' and 'divestor' are smaller in magnitude than the positive significant AME for 'no event'. This implies that performance of R&D increases the likelihood that'no event' occurs or the firm is involved in a divestment event. The coefficients and AME are negative and significant for 'merger', 'change of ownership' and 'breakup'. The positive impact of performing R&D on 'divested' and 'divestor' must offset the negative impact on 'breakup', resulting in an overall positive coefficient for separating events. This implies it is important to distinguish between events because differences exist. The coefficients and marginal effects on the performing R&D dummy for 'acquired', 'acquirer', 'tradesale' and 'acquirer-divestor' are not significantly different from zero.

The findings from the R&D performing firms subsample in tables (4.26) support these results. The AMEs on the log of in-house R&D stock are negative and significant for 'acquired', 'acquirer', 'merger', 'change of ownership', 'breakup' and 'acquirer-divestor'. This suggests that an increase in the stock of in-house R&D expenditure reduces the probability of these events occurring for R&D performing firms, suggesting that joining events do not appear to be motivated by innovation synergies. This finding contrasts with studies by Desyllas and Hughes (2009) and Szücs (2012), that find that firms with a high R&D stock are more likely to be involved in a joining event. A positive AME is reported for 'divested' but the AME on 'divestor' is no longer significant in the R&D performing firms subsample. This implies that although performing R&D increases the chance of being a 'divestor', the amount of R&D performed has little impact. These result ties in with the study by Kaul (2012), which identifies a positive relationship between R&D stocks and divestment. The AME and coefficients on the knowledge transfer variables are not significant. This implies that expenditure on R&D from external sources has no impact on the probability of an event occurring.

The results in table (4.27) use the 'UK and Foreign Events' dependent variable. Distinguishing between foreign and UK events makes a considerable difference to the coefficients and AME on the R&D dummy for each event. Positive significant coefficients and AME are found for 'foreign no event', 'foreign acquirer', 'foreign merger', 'foreign change of ownership', 'foreign divested' and 'foreign divestor' suggesting that involvement in foreign events is more likely for R&D performing firms. This finding concurs with French and Spanish studies by Bertrand (2009) and García-Vega et al. (2012), which find positive relationships between pre-event R&D and foreign acquisition. This suggests that foreign joining events may be motivated by innovation synergies and foreign separating events may consider refocusing in innovation as a motive. The results from the BSD-ARD-BERD-FAME sample with the 'UK and Foreign Events' dependent variable agree with these findings, although there are fewer significant coefficient and AME due to the smaller sample size.

Table 4.24: Multinomial Logit Results using BSD-ARD-BERD Sample

	No Event	Joining Event		Separating Event	
	AME	Coefficient	AME	Coefficient	AME
log Y_{t-1}	-0.003***	0.068***	0.003***	0.037***	0.000**
	(0.000)	(0.005)	(0.000)	(0.007)	(0.000)
log C_{t-1}	-0.007***	0.151***	0.006***	0.111***	0.001***
	(0.000)	(0.004)	(0.000)	(0.006)	(0.000)
log L_{t-1}	-0.006***	0.129***	0.005***	0.078***	0.001***
	(0.000)	(0.007)	(0.000)	(0.010)	(0.000)
R&D dummy	-0.001	-0.017	-0.001	0.082***	0.002***
	(0.001)	(0.026)	(0.001)	(0.033)	(0.001)
Market Share_{t-1}	0.079***	-1.947***	-0.078***	-0.629***	-0.001
	(0.009)	(0.202)	(0.008)	(0.236)	(0.005)
HHI_{t-1}	0.001	-0.031	-0.001	0.025	0.001
	(0.005)	(0.116)	(0.005)	(0.152)	(0.003)
No. Firms_{t-1}	-0.007***	0.125***	0.004***	0.179***	0.003***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Div. Ratio_{t-1}	-0.062***	0.567***	0.005***	2.711***	0.057***
	(0.001)	(0.021)	(0.001)	(0.042)	(0.001)
log Age_{t-1}	0.017***	-0.368***	-0.014***	-0.234***	-0.003***
	(0.001)	(0.013)	(0.001)	(0.020)	(0.000)
Previous Acquired	-0.042***	0.812***	0.029***	0.856***	0.014***
	(0.002)	(0.038)	(0.002)	(0.043)	(0.001)
Previous Acquirer	-0.030***	0.624***	0.023***	0.508***	0.007***
	(0.001)	(0.025)	(0.001)	(0.029)	(0.001)
Previous Merger	-0.046***	0.890***	0.031***	0.908***	0.014***
	(0.001)	(0.028)	(0.001)	(0.032)	(0.001)
Previous ChangeOwner	-0.019***	0.463***	0.018***	0.176***	0.001
	(0.001)	(0.023)	(0.001)	(0.034)	(0.001)
Previous Breakup	-0.046***	0.893***	0.032***	0.927***	0.015***
	(0.002)	(0.036)	(0.001)	(0.042)	(0.001)
Previous Divested	-0.036***	0.764***	0.028***	0.568***	0.007***
	(0.002)	(0.043)	(0.002)	(0.057)	(0.001)
Previous Divestor	-0.032***	0.634***	0.023***	0.609***	0.009***
	(0.001)	(0.033)	(0.001)	(0.039)	(0.001)
Previous Tradesale	-0.043***	0.830***	0.029***	0.844***	0.013***
	(0.005)	(0.099)	(0.004)	(0.117)	(0.002)
Previous Acq-Div	-0.034***	0.749***	0.028***	0.483***	0.006***
	(0.002)	(0.037)	(0.001)	(0.042)	(0.001)
constant	- - - -	-4.307	- - - -	-6.268***	- - - -
		0.050		0.082	

Table 4.25: Average Marginal Effects using BSD-ARD-BERD Sample

	No Event	Acquired	Acquirer	Merger	Change of	Break-up	Divested	Divestor	Tradesale	Acquirer-
			Joining Events		Ownership		Separating Events			Divestor
log Y_{t-1}	-0.005***	0.000**	0.001***	0.000**	0.003***	0.000	0.000	0.000	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log C_{t-1}	-0.010***	0.002***	0.001***	0.001***	0.004***	0.000***	0.000	0.001***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log L_{t-1}	-0.009***	0.001***	0.002***	0.001***	0.004***	0.000	0.000***	0.000***	0.000*	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D dummy	0.005***	0.000	-0.001	-0.001***	-0.004***	-0.001***	0.001***	0.001**	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Share_{t-1}	0.214***	-0.031***	-0.022***	-0.023***	-0.137***	0.000	-0.006**	0.005	-0.005***	0.006***
	(0.012)	(0.004)	(0.005)	(0.004)	(0.010)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
HHI_{t-1}	-0.047***	0.009***	-0.004	0.011***	0.030***	0.004***	0.001	-0.003	0.000	-0.002
	(0.006)	(0.002)	(0.003)	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
No. Firms_{t-1}	-0.007***	0.000***	0.002***	0.001***	0.000**	0.001***	0.001***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div. Ratio_{t-1}	-0.065***	-0.006***	0.017***	-0.004***	0.001	0.009***	0.014***	0.022***	0.003***	0.008***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
log Age_{t-1}	0.025***	-0.006***	-0.001	-0.004***	-0.012***	-0.001***	-0.001***	0.000	0.000***	-0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	272095	3808	10251	3546	13148	2030	3018	5141	626	5446

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 4.25 (continued): Average Marginal Effects using BSD-ARD-BERD Sample

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
		Joining Events				Separating Events				
Previous Acquired	-0.039***	0.009***	0.012***	0.004***	-0.001	0.001**	0.004***	0.003***	0.001***	0.006***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Previous Acquirer	-0.017***	0.006***	0.012***	0.000	-0.009***	0.000	-0.001**	0.004***	0.000	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Previous Merger	-0.048***	0.009***	0.014***	0.005***	0.004***	0.003***	0.002***	0.004***	0.000	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Previous ChangeOwner	-0.038***	0.005***	0.011***	0.004***	0.019***	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Previous Breakup	-0.058***	0.012***	0.008***	0.009***	0.013***	0.004***	0.003***	0.003***	0.001***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Previous Divested	-0.043***	0.013***	0.006***	0.006***	0.010***	0.000	0.004***	0.001	0.001***	0.002**
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Previous Divestor	-0.030***	0.007***	0.011***	0.001	0.000	0.001	0.001**	0.004***	0.000	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Previous Tradesale	-0.035***	0.012***	0.009***	0.005**	-0.007	0.001	0.000	0.005***	0.002***	0.007***
	(0.008)	(0.002)	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Previous AcquirerDivestor	-0.024***	0.010***	0.011***	0.004***	-0.009***	0.000	0.000	0.002***	0.000	0.007***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 4.26: Average Marginal Effects using BSD-ARD-BERD R&D Performing Firms Sample

	No Event	Acquired	Acquirer	Merger	Change of	Break-up	Divested	Divestor	Tradesale	Acquirer-
			Joining Events		Ownership		Separating Events			Divestor
log Y_{t-1}	-0.005***	-0.001	0.004***	0.001*	0.002**	0.000	-0.002***	0.000	-0.001***	0.001*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
log C_{t-1}	-0.009***	0.002***	0.002**	0.000	0.002***	0.001	0.000	0.002***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
log L_{t-1}	-0.018***	0.004***	0.006***	0.001	0.003**	0.001	-0.001	0.001	0.000	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log K^{R}_{t-1}	0.015***	-0.001***	-0.003***	-0.001***	-0.007***	-0.001**	0.001***	0.000	0.000	-0.001***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
log $K^{T_{UK}}_{t-1}$	-0.002	-0.001	0.000	0.001*	0.001	0.000	0.000	0.000	0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
log $K^{T_{F}}_{t-1}$	0.000	0.000	-0.001	-0.001	0.001	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Market Share_{t-1}	0.086***	-0.028**	-0.013	-0.004	-0.055**	-0.002	-0.010	0.020	-0.018*	0.025**
	(0.035)	(0.013)	(0.019)	(0.011)	(0.024)	(0.007)	(0.012)	(0.013)	(0.010)	(0.012)
HHI_{t-1}	-0.077***	0.020**	-0.026	0.009	0.068***	0.012*	-0.010	-0.006	0.006	0.004
	(0.024)	(0.010)	(0.016)	(0.009)	(0.014)	(0.006)	(0.009)	(0.012)	(0.004)	(0.011)
No. Firms_{t-1}	-0.013***	-0.002***	0.006***	0.001***	-0.003***	0.001***	0.003***	0.004***	0.001***	0.004***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div. Ratio_{t-1}	-0.120***	-0.015***	0.023***	-0.009***	-0.006**	0.013***	0.032***	0.055***	0.009***	0.017***
	(0.005)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.002)	(0.006)
log Age_{t-1}	0.043***	-0.011***	0.002	-0.009***	-0.022***	-0.002**	0.001	0.002	0.000	-0.004**
	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Observations	22488	861	2713	641	2229	526	865	1615	199	1799

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 4.27: Average Marginal Effects using BSD-ARD-BERD Sample

	No Event		Acquired		Acquirer		Merger		Change of Ownership	
	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign
log Y_{t-1}	-0.007***	0.003***	0.000	0.000**	0.002***	0.002***	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log C_{t-1}	-0.022***	0.014***	0.001***	0.001***	-0.001***	0.002***	0.000***	0.001***	0.000	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log L_{t-1}	-0.010***	0.002**	0.001***	0.000	0.002***	0.000	0.001***	0.000**	0.001*	0.001*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
R&D dummy	0.000	0.008***	-0.001***	0.000**	-0.004***	0.001***	-0.001**	0.000***	-0.002***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Market Share_{t-1}	-0.315***	0.250***	-0.011	0.000	0.024	0.018***	-0.011	0.001	0.002	0.010
	(0.034)	(0.024)	(0.008)	(0.004)	(0.018)	(0.006)	(0.008)	(0.003)	(0.018)	(0.007)
HHI_{t-1}	-0.269***	0.194***	0.011**	0.005*	-0.044***	0.004	0.009**	0.002	-0.003	0.011***
	(0.019)	(0.015)	(0.005)	(0.003)	(0.011)	(0.005)	(0.004)	(0.003)	(0.009)	(0.004)
No. Firms_{t-1}	-0.009***	-0.008***	-0.001***	0.000**	0.006***	0.001***	0.000***	0.000***	-0.002***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div. Ratio_{t-1}	0.061***	-0.178***	-0.003***	-0.004***	0.005**	0.000	-0.004***	-0.003***	-0.001	-0.012***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
log Age_{t-1}	0.064***	-0.014***	-0.005***	-0.002***	-0.008***	-0.001*	-0.004***	-0.001***	-0.010***	-0.006* **
	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	52508	21889	1583	549	8030	2136	1217	405	4427	1522

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 4.27 (continued): Average Marginal Effects using BSD-ARD-BERD Sample

	Break-up		Divested		Divestor		Tradesale		Acquirer-Divestor	
	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign
log Y_{t-1}	0.000	0.000**	0.000	0.000*	0.000	0.000**	0.000**	0.000	0.001	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log C_{t-1}	0.000	0.000***	-0.001***	0.000***	0.000	0.002***	0.000	0.000**	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log L_{t-1}	0.000	0.000	-0.001***	-0.001***	0.001	0.000	0.000	0.000	0.003***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D dummy	-0.001*	0.000	0.000	0.001***	0.000	0.001***	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Share_{t-1}	0.004	0.004*	0.002	-0.003	0.053***	0.006	-0.016**	-0.002	0.034***	0.016***
	(0.007)	(0.002)	(0.010)	(0.005)	(0.010)	(0.005)	(0.008)	(0.003)	(0.008)	(0.004)
HHI_{t-1}	0.008*	0.004**	-0.004	0.004	-0.019***	0.002	-0.001	0.001	-0.002	-0.008**
	(0.004)	(0.002)	(0.006)	(0.003)	(0.008)	(0.004)	(0.002)	(0.001)	(0.007)	(0.004)
No. Firms_{t-1}	0.001***	0.000***	0.002***	0.001***	0.003***	0.001***	0.000***	0.000***	0.003***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div. Ratio_{t-1}	0.016***	0.003***	0.025***	0.007***	0.038***	0.012***	0.005***	0.001***	0.012***	0.004***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.003)	(0.002)
log Age_{t-1}	-0.003***	0.000	-0.003***	-0.001***	-0.001	0.000	-0.001**	0.000**	-0.004***	-0.001**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	1518	414	2226	750	3925	1186	470	147	4310	1130

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 4.28: Average Marginal Effects using BSD-ARD-BERD-FAME Sample

	No Event	Acquired	Acquirer	Merger	Change of	Break-up	Divested	Divestor	Tradesale	Acquirer-
			Joining Events		Ownership		Separating Events			Divestor
log L_{t-1}	-0.011***	0.003***	0.001	0.002**	0.001	0.001*	0.000	-0.001	0.000	0.003**
	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D dummy	-0.008	0.008**	-0.004	-0.003	-0.003	0.001	0.004	0.004	-0.001	0.002
	(0.009)	(0.004)	(0.006)	(0.003)	(0.006)	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)
Market Share_{t-1}	0.150**	-0.026	-0.030	-0.022	-0.086**	0.004	0.017	0.012	-0.002	-0.015
	(0.064)	(0.028)	(0.038)	(0.022)	(0.041)	(0.012)	(0.017)	(0.020)	(0.021)	(0.019)
HHI_{t-1}	0.051	-0.009	-0.021	-0.008	0.033	0.002	-0.018	-0.010	-0.008	-0.012
	(0.048)	(0.023)	(0.033)	(0.017)	(0.024)	(0.011)	(0.017)	(0.019)	(0.013)	(0.018)
No. Firms_{t-1}	-0.012***	-0.002***	0.008***	0.001**	-0.003***	0.001***	0.002***	0.003***	0.000***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div. Ratio_{t-1}	-0.102***	-0.012***	0.016**	-0.015***	-0.008	0.013***	0.040***	0.034***	0.009***	0.026***
	(0.010)	(0.003)	(0.008)	(0.003)	(0.005)	(0.004)	(0.006)	(0.006)	(0.003)	(0.009)
log Age_{t-1}	0.041***	-0.010***	0.001	-0.005**	-0.028***	-0.002	-0.003	0.004	0.000	0.003
	(0.007)	(0.002)	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.001)	(0.004)
log DAR_{t-1}	0.011*	-0.002	-0.007*	0.002	-0.005*	-0.002	0.002	0.001	0.000	0.000
	(0.006)	(0.002)	(0.004)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
log D_{t-1}	-0.001	-0.001	0.002*	0.000	-0.003**	0.000	-0.001	0.001	0.000	0.002***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
log TA_{t-1}	-0.013***	0.001	0.004**	0.002*	0.001	0.001	0.000	0.003***	-0.001*	0.003***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log ROTA_{t-1}	-0.003	0.000	0.003**	0.002**	0.003**	-0.001	-0.003***	-0.001	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
log LR_{t-1}	0.002	0.001	0.001	-0.003*	0.002**	0.000	-0.001	-0.001	0.000	-0.001*
	(0.002)	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	22488	861	2713	641	2229	526	865	1615	199	1799

Table 4.29: Average Marginal Effects using BSD-ARD-BERD-FAME Sample

	No Event		Acquired		Acquirer		Merger		Change of Ownership	
	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign
log L_{t-1}	0.017***	-0.030***	0.003***	0.001	0.004	-0.003*	0.002*	0.000	0.003	-0.001
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
R&D dummy	-0.006**	0.009***	0.000	0.001*	-0.005***	0.003***	-0.002**	0.000	-0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Market $Share_{t-1}$	-0.148*	0.223***	-0.018	-0.002	-0.060	0.035	-0.023	0.003	-0.060	-0.003
	(0.080)	(0.063)	(0.024)	(0.021)	(0.046)	(0.023)	(0.022)	(0.011)	(0.038)	(0.018)
HHI_{t-1}	-0.079	0.108**	0.011	-0.005	-0.007	-0.006	-0.003	-0.006	0.022	0.012
	(0.059)	(0.049)	(0.018)	(0.021)	(0.035)	(0.025)	(0.013)	(0.015)	(0.021)	(0.014)
No. $Firms_{t-1}$	-0.003***	-0.012***	-0.001*	-0.001**	0.007***	0.002***	0.000*	0.000	-0.002***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div. $Ratio_{t-1}$	0.023**	-0.133***	-0.005**	-0.003	-0.008	0.003	-0.007***	-0.002	0.004	-0.004
	(0.011)	(0.009)	(0.003)	(0.002)	(0.008)	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)
log Age_{t-1}	0.068***	-0.039***	-0.003	-0.002	-0.001	-0.005	-0.003	-0.001	-0.010***	-0.004
	(0.009)	(0.008)	(0.002)	(0.001)	(0.006)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
log DAR_{t-1}	-0.032***	0.046***	-0.003*	0.001	-0.013***	0.004	0.000	0.000	-0.006**	0.002
	(0.007)	(0.006)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
log D_{t-1}	0.019***	-0.020***	0.000	0.000	0.005***	-0.003***	0.000	0.000	-0.002**	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
log TA_{t-1}	-0.040***	0.028***	-0.001*	0.001	0.000	0.003**	0.001	0.001	0.000	0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
log $ROTA_{t-1}$	0.010***	-0.016***	0.001	0.000	0.005***	-0.001	0.001*	0.000	0.003***	0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log LR_{t-1}	0.005**	-0.002	0.001**	0.000	0.002*	-0.001	-0.001	-0.001	0.001***	0.000
	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	6461	4067	188	82	1469	617	188	67	549	270

Table 4.29 (continued):Average Marginal Effects using BSD-ARD-BERD-FAME Sample

	Break-up		Divested		Divestor		Tradesale		Acquirer-Divestor	
	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign	UK	Foreign
log L_{t-1}	0.001	0.000	0.002*	-0.001	-0.001	-0.001	0.000	0.000	0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D dummy	0.000	0.000	0.000	0.001*	0.000	0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Market Share_{t-1}	0.013	-0.004	0.022	0.004	0.021	0.003	-0.006	0.002	-0.017	0.014
	(0.014)	(0.017)	(0.018)	(0.014)	(0.019)	(0.015)	(0.024)	(0.034)	(0.021)	(0.014)
log Age_{t-1}	-0.003	0.001	-0.001	-0.003*	0.002	0.001	0.000	0.000	0.001	0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)	(0.003)
HHI_{t-1}	0.008	-0.002	-0.019	-0.002	-0.006	-0.001	-0.005	-0.005	0.014	-0.030*
	(0.012)	(0.019)	(0.017)	(0.015)	(0.019)	(0.016)	(0.017)	(0.025)	(0.020)	(0.016)
No. Firms_{t-1}	0.000***	0.000	0.002***	0.001***	0.002***	0.001***	0.000***	0.000***	0.003***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div. Ratio_{t-1}	0.011***	0.003	0.028***	0.016***	0.021***	0.014***	0.006	0.004	0.023**	0.006
	(0.004)	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.004)	(0.009)	(0.010)	(0.007)
log DAR_{t-1}	-0.001	-0.001	0.001	0.002	-0.001	0.003	-0.001	0.001	0.000	0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
log D_{t-1}	0.000	0.000	0.000	-0.001	0.002***	-0.001	0.000	0.000	0.003***	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
log TA_{t-1}	-0.001	0.001**	-0.002*	0.001	0.001	0.003***	-0.001	-0.001	0.002**	0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log ROTA_{t-1}	-0.001	0.000	-0.002**	-0.001	0.000	-0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log LR_{t-1}	0.000	0.000	0.000	-0.001	0.000	-0.002**	0.000	0.000	-0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	134	45	286	167	411	299	61	33	595	180

4.8 Conclusion

This analysis aims to investigate the motivations behind firm restructuring events by focusing on pre-event characteristics of the firms engaging in this activity. A contribution to the literature is made by distinguishing between distinct restructuring events. The benefit of the careful identification of these events is that motivations may differ between groups. Although the differences between groups may appear to be subtle, it is important to establish if differences in motivations exist between groups to improve understanding of restructuring behaviour.

The study uses a multinomial logit model to obtain the average marginal effects of the explanatory variables on the probability of a restructuring event occurring. Other papers in the literature have employed competing risk models. Although these methods are sometimes favoured, in this case the multinomial logit model is preferred for a number of reasons. Firstly, the duration to the event is not of particular interest for this study. Secondly, the data has a large cross-sectional dimension, but the time period available is relatively short, particularly when using the BSD-ARD-BERD-FAME dataset. Thirdly, the large number of event types involved in the analysis and the fact that firms can experience an event in each time period would result in an extremely computationally burdensome competing risk model.

The literature review highlights four main motivations for restructuring events. These are strategic, synergistic, refocusing and managerial motivations. These motivations are not mutually exclusive. The analysis uses a range of variables to indicate the presence of these motives. The finding that higher profits increases the likelihood of acquiring or being involved in a merger suggests a role for managerial motivations. Managers may choose to reinvest profits to pursue growth through external investment. Acquirers are likely to be high dividend paying firms, suggesting that managers involved in these events may aim to keep shareholders happy to provide more opportunity to pursue their own goals. Mergers may be the preferred joining event when liquidity is low. Acquiring and merging firms are more likely for large enterprise groups providing further evidence for managerial growth motives. Indications of managerial motives also exist for separating events. Lower profit firms have a higher risk of becoming divested. Managers may feel pressured by shareholders to divest less profitable enterprises in order to maintain their managerial position. The findings suggest there is a strong relationship between the probability of an event occurring and involvement in previous events. This indicates that firm restructuring is habit forming. Some managers may be more inclined to repeatedly engage in restructuring.

The refocusing motive arises from the desire to streamline an enterprise group when excessive growth or diversification has occurred. The results show that separating events are more likely to occur within larger, more diversified enterprise groups. Refocusing motivations in terms of innovation are indicated for divestors and divested firms but not presented for breakups. Further investigation indicates that this result is driven by foreign- owned divestors and divested firms. Foreign firms are more likely to divest R&D performing enterprises from their enterprise groups. The evidence suggests that foreign joining events may be motivated by innovation synergies. This indicates that foreign firms may engage in restructuring to absorb new knowledge and provides evidence of "cherry picking" in terms of innovation. There is no evidence with regards to other forms of synergy motivations. The findings reveal no significant evidence of "cherry" or "lemon" picking in terms of profitability of acquisition targets.

As in previous empirical studies, the results regarding strategic motivations are less conclusive. This could be due to fact that supply and demand characteristics and other intricacies of the industry cannot be observed. Although the market concentration and market share variables are calculated at the 5-digit industry level, products within these industries may not be substitutable.

It would also have been preferable to use measures of innovation productivity to consider the effectiveness of a firm's innovation performance. Innovation productivity measures require data on R&D inputs and outputs, such as patent citations. Unfortunately data on R&D outputs were unobtainable for this study due to secure data merging considerations and time constraints.

This study focused on identifying motivations behind restructuring events and found differences between the types of firms involved in these events. These results can be used to inform the analysis in the following chapter which investigates the impact of restructuring events on post-event innovation activity and productivity outcomes.

5 The Impact of Ownership Events on Productivity and R&D Activity

5.1 Introduction

The reorganisation of firm structure is likely to have an impact on outcomes in terms of productivity and innovation. The outcomes may depend on the type of restructuring and motives. The impact of joining events on productivity and innovation has been previously examined in the literature, although little attention has been paid to the impact of separating events. This chapter distinguishes between various different types of ownership events and uses propensity score matching to establish the impact on post-event productivity outcomes and innovation activity.

The impact of joining events on innovation is ambiguous. Positive outcomes may be observed if the aim of the merger or acquisition is to enhance the firm's knowledge or asset base. This method of expansion may be deemed preferable by management because it provides an immediate expansion, rather than the slower process of growth from within (Cloodt et al., 2006). Speed may be particularly important in high tech industries, where new products are continually developed and innovation is an important part of competition. Innovation and productivity is particularly likely to improve if the joining firms have complementary knowledge bases, where similarities exist but their knowledge is not identical. This provides opportunities to create synergies.

Another motive for joining events is to take advantages of economies of scale and scope. R&D projects often require large investments and are indivisible. By combining resources firms are able to undertake larger scale R&D projects or spread risk across numerous projects. These circumstances are likely to induce a positive impact on post-joining innovation in terms of outputs per unit of R&D expenditure, but may not necessarily lead to increased R&D expenditure because there will be a reduction of duplication.

Negative impacts on post-joining outcomes may be observed if the event causes disruptions to production or to the R&D process during reorganisation. Differences between the organisational structures of joining firms or lack of technological relatedness may present integration problems. Managerial efforts may be diverted away from R&D, leading to reduced incentives for R&D workers to come up with new inventions. Job uncertainty surrounding joining events may encourage key employees to seek alternative employment, taking their accumulated R&D knowledge with them.

Separating events can be seen as a reactive response to poor performance or as a proactive response to opportunities in the market (Kaul, 2012). Separating events can correct for over-diversification by reducing bureaucracy and freeing up resources. If divestment acts to refocus towards core activities, it is likely that firms may invest more in innovation activity and increase productivity as managerial burden is reduced. Separating events can be part of a wider strategy involving acquisition or internal investment. Alternatively, innovation investment activity may reduce following divestment if the event was the result of poor performance. Managerial effort may be directed away from R&D towards the short-term survival of the firm.

This chapter aims to address the following questions. Firstly, does productivity and innovation activity increase following a restructuring event? Secondly, do differences in post-event outcomes exist between foreign owned firms and domestic firms? This chapter contributes to the literature by considering different events simultaneously and allowing comparisons to be drawn across groups. Furthermore, the data used is very detailed and provides larger samples than most previous studies on UK data or elsewhere.

Propensity score matching (PSM) methodology is used to overcome the issue of sample selection bias. A multiple treatment approach is employed following Lechner (2002). Firms are matched with a partner that has similar characteristics during the pre-event time period. This generates a control group allowing post-event outcomes to be compared with estimated counterfactual outcomes.

The data used in this study is taken from the BSD-ARD-BERD sample described in the previous chapter and event definitions remain consistent. The methodology is explained in section 5.2, descriptive statistics of the data are provided in section 5.3, results in section 5.4 and conclusions in section 5.5.

5.2 Methodology

5.2.1 Estimating Average Treatment Effects on the Treated

The aim of this study is to understand how ownership events impact R&D activity and productivity outcomes. Ideally this question could be answered by looking at the difference between post-event outcomes for a firm and outcomes if no ownership event occurs, for the same firm and time period. The problem lies in the fact that both scenarios cannot simultaneously occur within the same firm. Firms that experience an event are likely to exhibit different characteristics to groups of firms that experience other events or no event, therefore direct comparisons between any two groups may suffer from selection bias. Matching can be used to address this problem by identifying a control group of firms with characteristics that match the event group. The simple single treatment group case described by Roy (1951) and Rubin (1974) is expanded to the more complex multiple treatment group case following Lechner (2002). The methodology and implementation of these steps are explained in subsequent sections.

5.2.2 Multiple Treatment Groups Case

The single treatment framework describes a scenario where the group of firms experiencing the event are known as the treated group and the non-event firms are referred to as the non-treated group. Lechner (2002) expands the single treatment model for the multiple treatment case, where pairwise comparisons can be made between outcomes of each treatment state. Assuming there are $(M + 1)$ mutually exclusive states, potential outcomes can be defined as $Y^0, Y^1, ...Y^M$. Only one of these outcomes is observable for each firm. The remaining M outcomes are counterfactuals for firm i.

$$\tau_i = Y_i(m) - Y_i(l) \tag{5.1}$$

$Y_i(S_i)$ is the potential outcome for firm i, where S indicates the treatment undertaken by the firm, $S \epsilon\ 0, 1...M$. Equation (5.1) indicates the pairwise comparison between the outcomes of treated group m and comparison group l, where $m \neq l$. τ_i is the individual treatment effect derived from the difference between the two outcomes for firm i. As previously explained, one of these outcomes is unobserved. This unobserved outcome is known as the counterfactual outcome.

The estimation of the average treatment effect on the treated (ATT) is required to address the research question.

$$\tau_{ATT} = E(\tau|S = m) = E[Y(m)|S = m] - E[Y(l)|S = m] \tag{5.2}$$

The expected outcome Y(l) is unobserved when S=m, therefore assumptions must be imposed to estimate the counterfactual mean $E[Y(l)|S = m]$. Non-random treatment occurs when selection into the treatment group depends on pre-treatment characteristics. Therefore average pre-treatment characteristics of the treated and comparison groups are different. When treatment is non-random $E[Y(l)|S = l]$ will provide a biased estimate of $E[Y(l)|S = m]$. Hence, a naive comparison between the treated and non-treated groups would result in a biased estimate of the ATT because selection bias is not accounted for.

$$\underbrace{E[Y(m)|S = m] - E[Y(l)|S = l]}_{\text{Observed difference}} = \tau_{ATT} + \underbrace{E[Y(l)|S = m] - E[Y(l)|S = l]}_{\text{Selection bias}} \tag{5.3}$$

The previous chapter indicates that the pre-event characteristics of firms differ across event types, therefore it is necessary to invoke identifying assumptions to take account for the problem of non-random selection. Matched samples must be obtained to provide unbiased estimates of counterfactuals. The sample must comply with the necessary assumptions in order to estimate average treatment effects on the treated.

5.2.3 The Conditional Independence Assumption

The conditional independence assumption (CIA) states that conditional on a set of variables X, the outcomes Y are independent of treatment S.

$$Y(0), Y(1), ...Y(M) \perp S|X \tag{5.4}$$

The set of variables X should not provide any information to indicate which treatment will occur. This suggests that when all variables influencing treatment and outcomes are taken into account selection bias is removed and treatment S is considered exogenous. This strong assumption is required to estimate the population-average treatment effect (ATE).

$$Y(l) \perp S|X \tag{5.5}$$

Equation (5.5) shows a weaker version of the CIA, sufficient to estimate the average treatment effect on the treated (ATT). For a given set of characteristics X, the outcomes for the comparison are independent of treatment.

5.2.4 The Common Support Assumption

The common support assumption states that the probability of being treated given X is greater than 0 and less than 1.

$$0 < Pr[S = m|X] < 1 \tag{5.6}$$

This ensures that treated and non-treated cases exist for each set of X values, creating an overlap of treated and comparison group subsamples. For each treated firm there is a corresponding comparison group firm with similar X values and those with the same X

values have equal probability of experiencing event m.

$$Pr[S = m|X] < 1 \tag{5.7}$$

The weaker assumption that the probability of being treated given X is less than 1 is sufficient for identification of ATT.

5.2.5 Matching Procedure

The first stage of the estimation procedure involves creating matched samples which comply with the conditional independence and common support assumptions described in subsections (5.2.3) and (5.2.4). There are two methods of obtaining event probabilities in the multiple treatment case; either by using a multinomial model or a series of pairwise binary models. These models can be specified as follows.

$$Event_{it} = \alpha + \beta X_{it-1} + \Psi I_i + \lambda T_t + \epsilon_{it} \tag{5.8}$$

$Event_{it}$ is a categorical variable in the multinomial logit case or a binary variable where 1 indicates event group ‘m’ and 0 indicates event group ‘l’ in the binary logit case. X_{it-1} is a vector of pre-event characteristics and I and T are industry and time dummies. Matching is performed on a year-by-year basis to ensure that a firm does not get matched with itself in another year.

The multinomial method is described by Lechner (2002). A multinomial logit model is used to estimate a set of probabilities conditional on pre-event characteristics using the full sample $P_N^0(X), P_N^1(X), ...P_N^M(X)$. The conditional probability of l from the subsample of m and l is denoted by $P^{l|ml}(X)$ and is calculated using the estimated conditional probabilities to provide an estimated propensity score.

$$P^{l|ml}(X) = \frac{P_N^l(X)}{P_N^l(X) + P_N^m(X)} \tag{5.9}$$

Propensity score matching can be performed using $P^{l|ml}(X)$ on pairwise samples for each m and l event combination. Alternatively, mahalanobis matching can be performed using $\hat{P}_N^m(X)$ and $\hat{P}_N^l(X)$.

The binary method involves performing binary logit estimations on each pairwise m and l sample to obtain a propensity score estimate. Lechner (2002) shows that there is little difference between probabilities derived from using the multinomial model on the full sample and probabilities derived from using a binary model on each m and l sample. Comparisons following the application of each of these methods suggest this is also true for this study.

The psmatch2 command in stata provides a wide selection of matching options and algorithms. The 'common' option is selected in stata to ensure that the common support assumption is adhered to. Observations falling outside the common support region are removed from the sample. Caliendo and Kopeinig (2008) provide a detailed discussion of alternative matching algorithms.

Nearest-neighbour matching takes the closest match from the comparison group in terms of the propensity score for each observation within the treated group. One-to-one matching obtains one match for each observation. This can be done with or without replacement, where replacement allows observations from the comparison group to be matched with multiple partners if they provide the closest propensity score. An advantage of replacement is that the comparison sample contains only observations with the closest propensity score to the treated group, therefore reducing bias. A problem with replacement is that if an observation acts as a matched partner a large number of times, the comparison group becomes smaller and the variance of the estimator will increase.

A caliper can be imposed to prevent bad matches occurring. The caliper places a restriction on the difference between matched partners in terms of the propensity score values to ensure that matches have close partners. Unmatched observations are removed from the sample. Radius matching can be used as an alternative to nearest-neighbour one-to-one matching, where all matches within the caliper radius are included in the control group. The difficulty with the radius method is identifying a suitable caliper range.

5.2.6 Testing the Matched Samples

Tests can be performed to assess the quality of the matches within the matched samples. Matching is performed using the propensity score therefore it is appropriate to check that the matching procedure has successfully generated a balanced distribution of the control variables in the comparison and treated groups. If matching is successful, there should be no way that the comparison and treated groups can be distinguished based on the set of characteristics X.

The standardised bias and t-tests for each of X can be obtained using the pstest command following psmatch2 in stata. The standardised bias was suggested by Rosenbaum and Rubin (1985) and is calculated as follows, where $\bar{X}_s$ is the mean value of the covariate X in sample s and $V_s(X)$ is the corresponding variance.

$$StandardisedBias = 100.\frac{(\bar{X}_m - \bar{X}_l)}{\sqrt{0.5(V_m(X) + V_l(X))}} \tag{5.10}$$

The standardised bias is calculated before and after the matching procedure to identify the reduction in bias resulting from matching.

The t-test approach compares the differences in the means of the two groups, where the null hypothesis is that no differences exist between the comparison and treated group in terms of X. Differences are expected in the pre-matched sample but not in the matched sample. If p values are greater than 0.1, the null hypothesis cannot be rejected.

Tests for joint significance of X variables can also be performed. These include the pseudo-R^2 and F-test. Following matching, equation (5.8) can be re-estimated on the matched sample. A low pseudo-R^2 and rejection of the F-test for joint-significance indicate that the sample is balanced.

5.2.7 Estimating ATT on Matched Samples

Identification of common support groups suggests that treatment can only occur for a subsample of the population in most cases, therefore the average treatment effects for the population cannot be estimated. Average treatment effects on the treated can be estimated on the matched samples using difference-in-difference estimation.

$$\Delta_{t-1}^{t+n} Dependent = \alpha + \beta EventDum_t + \phi X_t + \epsilon_t \tag{5.11}$$

Δ_{t-1}^{t+n} indicates a change in the dependent variable over time periods from pre-event $(t-1)$ to post-event $(t+n)$. The analysis is repeated for $n = 0, 1, 2$ for various different dependent variables including log total factor productivity, log labour productivity, log R&D expenditure and log R&D intensity. These variables are used to investigate the impact of events on productivity and innovation outcomes. Changes are used because they take into account pre-event levels of the variables. $EventDum_t$ is a binary variable where 1 indicates observations from the treated group and 0 indicates observations from the comparison group. The analysis is also performed with X_t a set of firm and industry characteristics and dummies to control for other events. Although differences in characteristics should be removed by the matching process, the matching tests reveal that some differences between treated and comparison groups in terms of these variables still remain in some samples. These variables are included to ensure that these differences are controlled for and the ATT estimates are not biased by the differences.

5.2.8 Estimating Total Factor Productivity (TFP)

Total factor productivity is a measure of productivity derived from the production function. The production function can be specified as follows.

$$Y_{it} = A_{it} L_{it}^{\beta_L} K_{it}^{\beta_K} \tag{5.12}$$

Y_{it} is value added output of firm i at time t, L_{it} is number of employees, K_{it} is capital stock and A_{it} i s the unobservable Hicks neutral efficiency level of firm i at time t.

Olley and Pakes (1996) suggest that endogeneity may arise due to simultaneity of input and output decisions, selection bias resulting from firm exit or unobserved differences across firms. Estimation of TFP using OLS will result in biased estimates. They propose an alternative framework to overcome these issues.

$$lnY_{it} = \beta_0 + \beta_L lnL_{it} + \beta_K lnK_{it} + \varphi_{it} + \eta_{it} \tag{5.13}$$

φ_{it} is productivity and η_{it} is the true measurement error. Productivity is assumed to be a determinant of input decisions and firm survival. Labour is assumed to be a fixed factor, capital is related to productivity and investment is strictly increasing in productivity. This implies the following, where I is investment.

$$\varphi_{it} = h_{it}(I_{it}, K_{it}) \tag{5.14}$$

Equation (5.14) can be substituted into equation (5.13) to give equation (5.15),

$$lnY_{it} = \beta_L lnL_{it} + \phi_{it}(I_{it}, K_{it}) + \eta_{it} \tag{5.15}$$

where $\phi_{it}(I_{it}, K_{it}) = \beta_0 + \beta_K lnK_{it} + h_{it}(I_{it}, K_{it})$ and ϕ is a polynomial function of investment and capital. This first stage of estimation attempts to correct for endogeneity arising from simultaneity and obtain a consistent estimate of the coefficient on labour.

The following stages of estimation aim to remove the endogeneity from selection bias which arises from firm exit. This is done by exploiting the firm dynamics. Productivity is assumed to evolve as an exogenous Markov process.

$$E[lnY_{it} - \beta_L lnL_{it} | lnK_{it}, X_t = 1] = \beta_0 + \beta_K lnK_{it} + E[\varphi_i t | \varphi_{it-1}, X_t = 1]$$

$$lnY_{it} - \beta_L lnL_{it} = \beta_0 + \beta_K lnK_{it} + E[\varphi_i t|\varphi_{it-1}, X_t = 1] + \epsilon_{it} + \eta_{it}$$

$$lnY_{it} - \beta_L lnL_{it} = \beta_K lnK_{it} + g(P_{t-1}, \phi_{t-1} - \beta_K lnK_{it}) + \epsilon_{it} + \eta_{it} \tag{5.16}$$

ϵ is the efficiency shock for surviving firms and is defined as follows.

$$\epsilon_{it} = \varphi_i t - E[\varphi_i t|\varphi_{it-1}, X_t = 1] \tag{5.17}$$

In step 2 the probability of firm survival P_{t-1} is estimated as a function of investment and capital. Step 3 involves estimating equation (5.17) using P_{t-1} from step 2 and $(\phi_{it-1} - \beta_K lnK_{it-1})$ from step 1. These 3 stages of estimation can be performed using the *opreg* command in Stata and $lnTFP$ can be obtained using the postestimation *predict* command with the *tfp* option.

5.3 Descriptive Statistics

5.3.1 Matching

Various different matching algorithms were compared using the tests for match quality described in subsection (5.2.6). Nearest-neighbour one-to-one matching with replacement and a caliper of 0.005 was chosen as the prefered method. The 'common' option was selected to ensure that the matched samples adhere to the common support assumption. The chosen method reduces bias by selecting matches with the closest propensity score, but variance may be increased if multiple observations from the treated group are repeatedly matched with the same observation from the comparison group.

Tables (5.1) and (5.2) shows the number of treated and comparison observations in each matched sample using the full BSD-ARD-BERD sample and the R&D performing firms subsample respectively. The treated groups are indicated down the side of the table and the comparison groups along the top. The number of observations in each matched sample declines as the period of change investigated is extended from two periods, to three or four. Some matched samples have similar numbers of observations in the treated and comparison groups, whereas others have far fewer comparison group observations relative to the corresponding treatment group. When the 'no replacement' option is applied without a caliper, the number of observations in the treated and comparison groups are equal. This method results in a higher level of bias than with replacement, but variance is reduced.

The quality of the matched samples was tested using the standardised bias, t-tests, pseudo R^2 and F-tests. Tables (5.3) and (5.4) provide pseudo R^2 values for each matched sample. These tests indicate how well the matched samples fulfill the conditional independence assumption. The values are low for each matched sample indicating that the estimated model provides little explanation of the differences between treated and control group in terms of pre-event characteristics. However, the F-tests for joint significance of the explanatory variables indicate that differences in pre-event characteristics exist between comparison and treatment for some matched samples. F-test statistics are provided in tables (5.5) and (5.6). Comparisons of matched samples indicate that this method provides the greatest reduction in bias, but the bias is still present. In order to account for these differences, a set of pre-event characteristics controls are included in the second stage difference-in-difference estimation. This aims to reduce the bias incurred on the average treatment effects on the treated estimates.

Table 5.1: Number of Observations in BSD-ARD-BERD Matched Samples

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		39909	39359	39379	41903	25145	23980	23362	12512	10995
		(1030)	(2522)	(965)	(3396)	(492)	(639)	(1174)	(143)	(662)
Acquired	1045		980	991	1036	612	699	633	410	388
	(999)		(634)	(528)	(784)	(213)	(226)	(297)	(82)	(167)
Acquirer	3236	2682		2981	2966	2830	3080	3264	2080	2852
	(2403)	(639)		(630)	(1106)	(496)	(671)	(1103)	(154)	(847)
Merger	981	942	944		968	703	759	775	398	492
	(941)	(519)	(595)		(769)	(234)	(253)	(333)	(92)	(237)
Change of Ownership	3465	3391	3309	3338		2109	2008	1941	1158	1098
	(3226)	(789)	(1066)	(803)		(320)	(333)	(506)	(99)	(229)
Break-up	555	447	600	492	483		566	590	355	577
	(481)	(218)	(474)	(241)	(312)		(324)	(429)	(108)	(358)
Divested	753	556	783	619	633	696		770	575	765
	(633)	(222)	(640)	(263)	(343)	(333)		(549)	(137)	(459)
Divestor	1504	1111	1563	1337	1282	1444	1486		1048	1550
	(1151)	(299)	(1052)	(351)	(510)	(445)	(568)		(143)	(725)
Tradesale	152	110	161	124	120	144	156	155		159
	(136)	(75)	(149)	(89)	(98)	(107)	(129)	(137)		(126)
Acquirer-Divestor	1350	709	1619	971	911	1459	1761	1588	1093	
	(657)	(173)	(870)	(230)	(236)	(378)	(501)	(733)	(137)	

Number of observations in the treated group are provided above and the number of observations in the comparison group are given below in parentheses.

Table 5.2: Number of Observations in R&D Performing Matched Samples

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		10834	11100	10806	12158	4633	5889	5950	2534	4538
		(457)	(1177)	(349)	(1111)	(236)	(386)	(666)	(84)	(353)
Acquired	463		427	414	459	125	206	207	35	120
	(438)		(268)	(196)	(327)	(68)	(88)	(127)	(21)	(56)
Acquirer	1510	925		1241	1292	1150	1288	1385	726	1315
	(1157)	(278)		(274)	(478)	(223)	(357)	(562)	(94)	(410)
Merger	356	314	324		333	126	179	249	57	158
	(336)	(201)	(249)		(262)	(79)	(101)	(145)	(24)	(103)
Change of Ownership	1127	1048	1010	1010		325	497	531	131	321
	(1060)	(328)	(464)	(276)		(120)	(164)	(225)	(39)	(107)
Break-up	253	123	279	192	190		261	268	139	266
	(226)	(70)	(222)	(85)	(113)		(147)	(197)	(45)	(159)
Divested	440	196	484	263	288	372		457	289	476
	(370)	(86)	(349)	(109)	(163)	(163)		(311)	(79)	(287)
Divestor	877	354	915	672	616	718	846		514	903
	(631)	(131)	(552)	(149)	(225)	(209)	(326)		(86)	(375)
Tradesale	93	26	105	33	49	59	100	91		102
	(84)	(19)	(95)	(26)	(42)	(42)	(82)	(80)		(85)
Acquirer-Divestor	700	117	900	329	338	668	908	835	592	
	(353)	(59)	(411)	(102)	(105)	(171)	(297)	(390)	(93)	

Number of observations in the treated group are provided above and the number of observations in the comparison group are given below in parentheses.

Table 5.3: Pseudo R^2 for BSD-ARD-BERD Matched Samples

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		0.07	0.20	0.05	0.03	0.17	0.18	0.20	0.12	0.05
Acquired	0.00		0.02	0.00	0.00	0.08	0.11	0.09	0.07	0.04
Acquirer	0.03	0.08		0.06	0.09	0.01	0.03	0.02	0.02	0.08
Merger	0.00	0.01	0.02		0.01	0.08	0.11	0.11	0.05	0.11
Change of Ownership	0.00	0.02	0.08	0.01		0.14	0.14	0.13	0.09	0.01
Break-up	0.01	0.05	0.01	0.02	0.03		0.01	0.01	0.01	0.01
Divested	0.02	0.04	0.01	0.04	0.05	0.01		0.00	0.01	0.02
Divestor	0.03	0.06	0.01	0.04	0.06	0.01	0.01		0.01	0.01
Tradesale	0.02	0.04	0.02	0.07	0.02	0.01	0.02	0.01		0.01
Acquirer-Divestor	0.05	0.13	0.04	0.08	0.11	0.04	0.03	0.03	0.01	

This table shows Pseudo R squared statistics. These values indicate the explanatory power of the logit model when performed on the matched samples. A value of zero indicates that the model has no explanatory power and the conditional independence assumption holds because treatment is independent of the pre-event characteristics.

Table 5.4: Pseudo R^2 for R&D Performing Matched Samples

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		0.02	0.11	0.02	0.01	0.04	0.10	0.11	0.07	0.16
Acquired	0.01		0.02	0.01	0.01	0.06	0.06	0.07	0.10	0.06
Acquirer	0.02	0.05		0.07	0.06	0.00	0.01	0.00	0.03	0.05
Merger	0.00	0.02	0.01		0.00	0.03	0.03	0.06	0.02	0.04
Change of Ownership	0.00	0.01	0.03	0.00		0.02	0.05	0.05	0.05	0.04
Break-up	0.04	0.01	0.03	0.02	0.03		0.03	0.01	0.05	0.02
Divested	0.02	0.02	0.02	0.02	0.02	0.00		0.00	0.02	0.01
Divestor	0.03	0.03	0.01	0.04	0.04	0.01	0.01		0.01	0.02
Tradesale	0.06	0.10	0.02	0.04	0.03	0.04	0.04	0.03		0.04
Acquirer-Divestor	0.05	0.07	0.05	0.04	0.11	0.04	0.02	0.02	0.03	

This table shows Pseudo R squared statistics. These values indicate the explanatory power of the logit model when performed on the matched samples. A value of zero indicates that the model has no explanatory power and the conditional independence assumption holds because treatment is independent of the pre-event characteristics.

Table 5.5: F-Tests for BSD-ARD-BERD Matched Samples

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		648.838	3757.293	427.829	623.484	843.49	1093.788	1918.952	186.594	126.047
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquired	8.302		39.665	5.96	10.638	76.423	114.777	109.948	33.083	35.406
	(0.823)		(0.000)	(0.948)	(0.641)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
Acquirer	229.329	246.281		192.355	405.621	41.93	95.172	92.603	17.991	155.839
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.158)	(0.000)
Merger	13.161	10.887	40.798		21.134	86.079	126.71	150.866	22.838	69.435
	(0.435)	(0.620)	(0.000)		(0.070)	(0.000)	(0.000)	(0.000)	(0.044)	(0.000)
Change of Ownership	8.554	67.922	375.504	20.528		267.019	263.761	331.758	61.101	137.144
	(0.806)	(0.000)	(0.000)	(0.083)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Break-up	19.279	42.416	21.171	20.957	29.813		10.119	7.823	3.971	18.389
	(0.115)	(0.000)	(0.070)	(0.074)	(0.005)		(0.684)	(0.855)	(0.991)	(0.143)
Divested	33.494	33.725	10.352	42.919	63.161	7.316		3.261	4.28	19.442
	(0.001)	(0.001)	(0.665)	(0.000)	(0.000)	(0.885)		(0.997)	(0.988)	(0.110)
Divestor	92.431	84.277	36.014	73.987	126.482	11.666	16.042		6.897	48.464
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.555)	(0.247)		(0.907)	(0.000)
Tradesale	9.609	11.066	10.021	21.067	5.891	4.409	7.241	3.621		4.501
	(0.726)	(0.605)	(0.692)	(0.072)	(0.950)	(0.986)	(0.889)	(0.995)		(0.985)
Acquirer-Divestor	126.047	110.641	113.191	95.082	132.262	69.127	72.663	84.772	9.619	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.725)	

This table shows the chi-squared statistics and corresponding p- values in parentheses. These are the results from the post-estimation F-tests performed following the logit model on the matched samples. The F-test is a test for joint-significance of the explanatory variables. A low chi-squared statistic and high p-value (above 0.10) indicate that the explanatory variables are not jointly significant and the conditional independence assumption should hold.

Table 5.6: F-Tests for R&D Performing Matched Samples

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		95.634	833.25	46.683	82.601	82.916	278.515	471.308	55.104	397.221
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquired	11.818		20.466	9.222	5.939	15.455	22.548	31.66	7.242	12.977
	(0.543)		(0.084)	(0.756)	(0.948)	(0.280)	(0.047)	(0.003)	(0.889)	(0.450)
Acquirer	75.764	58.94		93.342	117.315	3.517	22.374	9.972	17.811	88.36
	(0.000)	(0.000)		(0.000)	(0.000)	(0.995)	(0.050)	(0.696)	(0.165)	(0.000)
Merger	3.311	10.368	7.476		3.574	7.193	12.253	33.469	2.423	14.914
	(0.997)	(0.664)	(0.876)		(0.995)	(0.892)	(0.507)	(0.001)	(0.998)	(0.313)
Change of Ownership	8.117	17.913	60.445	5.867		8.498	37.546	46.329	8.929	21.619
	(0.836)	(0.161)	(0.000)	(0.951)		(0.810)	(0.000)	(0.000)	(0.778)	(0.062)
Break-up	25.083	3.777	18.729	8.398	12.757		13.736	3.767	10.181	10.955
	(0.023)	(0.993)	(0.132)	(0.817)	(0.467)		(0.393)	(0.993)	(0.679)	(0.615)
Divested	16.842	5.609	20.566	8.286	10.994	2.446		2.936	6.589	10.119
	(0.207)	(0.959)	(0.082)	(0.825)	(0.611)	(0.999)		(0.998)	(0.922)	(0.684)
Divestor	67.444	19.698	25.905	34.462	43.496	5.728	9.096		3.545	31.251
	(0.000)	(0.103)	(0.018)	(0.001)	(0.000)	(0.956)	(0.766)		(0.995)	(0.003)
Tradesale	13.734	6.155	6.375	2.953	3.79	6.106	9.516	6.572		10.011
	(0.393)	(0.908)	(0.931)	(0.996)	(0.993)	(0.942)	(0.733)	(0.923)		(0.693)
Acquirer-Divestor	64.043	15.238	74.197	20.578	52.266	32.672	31.312	26.889	15.918	
	(0.000)	(0.293)	(0.000)	(0.082)	(0.000)	(0.002)	(0.003)	(0.013)	(0.254)	

This table shows the chi-squared statistics and corresponding p- values in parentheses. These are the results from the post-estimation F-tests performed following the logit model on the matched samples. The F-test is a test for joint-significance of the explanatory variables. A low chi-squared statistic and high p-value (above 0.10) indicate that the explanatory variables are not jointly significant and the conditional independence assumption should hold.

5.3.2 Dependent Variable Descriptive Statistics

In this section, descriptive statistics in terms of the number of observations, mean, standard deviation and median values are presented for each dependent variable for time periods $t-1$, $t+1$, $t+2$ and $t+3$. Events occur at time t, therefore $t-1$ are pre-event observations and $t+1$, $t+2$ and $t+3$ are post-event observations. The number of observations declines as the number of post-event years is extended due to attrition from the sample. Attrition occurs if the firm was not included in the ARD sample. This is mostly due to non-returned surveys, but also partly due to firm closure.

Total factor productivity (TFP) is derived using the Olley-Pakes Method, where inputs and outputs are deflated using industry deflators. Descriptive statistics are provided in table (5.7). For 'no event' firms, the mean, median and standard deviation of TFP remain relatively stable over time. TFP values are lower than the total sample averages. This stability is to be expected for the 'no event' group as there is no observable restructuring effect on TFP during this period. 'Acquired' and 'acquirer' firms have higher mean and median TFP values and larger standard deviations than the 'no event' group. The mean and median values decrease following the acquisition event for both event types. This decline following an acquisition event is not expected, particularly for acquisition targets that may experience technology transfer. This observation may be due to changes in the composition of the sample as attrition occurs. In contrast to the other 'joining' events, the average values for'merger' firms remain relatively consistent over time.

The 'change of ownership' and 'break-up' subsamples both experience a declining mean TFP between $t-1$ and $t+2$ to below the average 'no event' TFP. Both groups of firms experience an increase in mean TFP in $t+3$, but this remains below initial levels. This trend is replicated by the median for 'break-up', whereas the median for 'change of ownership' firms continually declines.

'Divested' firms show an increase in mean TFP in each period following the event, but median values show a slight decline. The increasing standard deviations suggest that there may be large differences in TFP outcomes following this event. 'Divestor' firms show an decline in TFP following the event. 'Tradesale' displays a decrease in mean from $t-1$ to $t+1$ followed by an increase on initial levels in $t+2$ and $t+3$. The median peaks at $t+2$. The mean TFP values for 'acquirer-divestor' firms are initially high relative to total sample averages and at a similar magnitude to 'acquirer' and 'divestor' firm groups. The mean level remains high in period $t+1$, but then falls in the subsequent periods. Median values remain relatively stable during the post-event periods.

Table (5.8) provides descriptive statistics for labour productivity. This variable is calculated as the ratio of value added output to number of employees, where output is deflated using industry deflators. The patterns shown by labour productivity over time for each event generally reflect the patterns exhibited by TFP.

R&D expenditure descriptive statistics for R&D performing firms sample are displayed in table (5.9). Inflation is removed from the data using industry level deflators. The statistics indicate the inconsistent volatile nature of R&D expenditure; fluctuations are observed in the 'no event' category. Mean and medians appear to vary independently overtime in most of the event categories without an apparent pattern. High standard deviations indicate a high level of variability within the groups. The 'acquirer-divestor' group has greater mean and median R&D expenditure than other groups and displays an increase in expenditure in each of the post-event periods.

Table 5.7: TFP Descriptive Statistics by Event

	t-1	**t+1**	**t+2**	**t+3**
No Event				
n	272095	91588	37524	23377
mean	2.289	1.999	2.290	2.058
sd	36.544	24.616	41.606	34.520
median	1.099	1.066	0.990	0.984
Acquired				
n	3808	2145	1194	798
mean	6.152	4.868	4.119	3.485
sd	86.392	82.755	54.512	48.754
median	1.188	1.138	1.084	1.080
Acquirer				
n	10251	6550	3969	2756
mean	7.243	4.035	3.242	2.914
sd	179.049	68.381	31.835	24.331
median	1.212	1.172	1.136	1.155
Merger				
n	3546	1962	1044	720
mean	2.858	2.435	2.212	2.265
sd	14.508	13.122	8.743	12.616
median	1.230	1.149	1.092	1.119
Change of Ownership				
n	13148	7068	3532	2364
mean	3.628	2.845	1.878	2.457
sd	48.832	51.182	14.701	26.706
median	1.260	1.114	1.056	1.039

Table 5.7 (continued): TFP Descriptive Statistics

	t-1	t+1	t+2	t+3
Break-up				
n	2030	1249	797	614
mean	3.467	3.101	1.812	2.214
sd	27.544	28.502	3.405	8.091
median	1.143	1.137	1.101	1.140
Divested				
n	3018	1810	1022	694
mean	4.181	4.331	5.156	7.753
sd	59.489	77.821	89.727	123.167
median	1.156	1.084	1.056	1.039
Divestor				
n	5141	3355	2140	1616
mean	5.151	3.089	2.494	2.262
sd	90.121	37.345	11.855	8.861
median	1.144	1.110	1.082	1.082
Tradesale				
n	626	388	213	152
mean	2.364	2.076	2.381	6.107
sd	9.510	6.392	11.262	46.089
median	1.096	1.086	1.117	1.080
Acquirer-Divestor				
n	5446	3670	2464	1880
mean	5.167	6.096	2.454	2.378
sd	57.736	196.657	8.692	8.514
median	1.208	1.174	1.157	1.164
Total				
n	319109	119785	53899	34971
mean	2.676	2.422	2.436	2.349
sd	49.390	48.202	39.035	35.610
median	1.113	1.082	1.021	1.019

Table 5.8: Labour Productivity Descriptive Statistics by Event

	t-1	t+1	t+2	t+3
No Event				
n	272095	92951	38240	23882
mean	78.437	70.864	95.976	74.362
sd	2318.412	1603.415	2369.688	1469.082
median	24.373	26.525	27.358	28.078
Acquired				
n	3808	2189	1221	819
mean	588.809	396.426	398.206	214.996
sd	10664.130	6996.233	6875.237	2816.786
median	33.235	33.617	32.193	32.591
Acquirer				
n	10251	6667	4039	2808
mean	436.529	397.553	297.216	179.453
sd	12000.540	11554.550	7599.665	3064.524
median	35.018	34.592	34.849	35.825
Merger				
n	3546	1991	1064	734
mean	116.618	148.602	173.018	140.379
sd	867.732	2384.304	2763.914	2439.388
median	33.018	32.367	31.749	33.016
Change of Ownership				
n	13148	7217	3611	2429
mean	170.388	128.455	68.717	73.938
sd	3255.097	3548.655	683.362	870.507
median	32.000	28.776	29.176	30.316

Table 5.8 (continued): Labour Productivity Descriptive Statistics

	t-1	**t+1**	**t+2**	**t+3**
Break-up				
n	2030	1267	816	628
mean	307.128	472.065	66.566	85.941
sd	8097.330	12535.450	171.852	535.258
median	33.501	35.000	34.783	37.983
Divested				
n	3018	1852	1039	706
mean	278.109	369.597	374.069	512.395
sd	5417.854	7087.764	6271.983	8259.929
median	33.119	32.859	33.723	34.360
Divestor				
n	5141	3413	2196	1654
mean	464.468	227.481	200.076	183.731
sd	9808.920	3256.447	2746.832	2476.317
median	34.372	34.680	35.438	36.377
Tradesale				
n	626	392	218	153
mean	86.830	87.417	167.043	548.882
sd	410.465	398.048	1504.177	6198.083
median	31.421	32.783	35.098	36.536
Acquirer-Divestor				
n	5446	3734	2511	1915
mean	440.749	221.540	164.803	158.385
sd	8280.470	3426.075	1739.872	1589.969
median	37.154	36.103	36.808	36.824
Total				
n	319109	121673	54955	35728
mean	116.006	117.105	129.589	107.631
sd	3663.026	3750.484	3252.273	2115.570
median	25.500	27.948	29.102	30.038

Table 5.9: R&D Expenditure Descriptive Statistics by Event

	t-1	**t+1**	**t+2**	**t+3**
No Event				
n	16098	12694	11246	8352
mean	2027.51	1832.72	1657.29	1426.06
sd	15623.86	15409.87	15387.77	9229.89
median	133.85	113.45	76.61	74.68
Acquired				
n	675	468	411	311
mean	1729.33	2040.94	1996.82	2198.30
sd	7879.29	12699.95	11447.06	13359.67
median	231.17	225.21	188.00	224.86
Acquirer				
n	2708	1582	1350	1034
mean	5198.59	6400.55	5452.04	3986.08
sd	37630.73	50404.02	44892.02	24212.13
median	252.52	239.21	185.69	166.58
Merger				
n	466	362	317	237
mean	4663.60	5613.80	6452.85	7843.28
sd	30304.92	36906.86	45929.80	50500.19
median	201.14	210.26	124.79	152.83
Change of Ownership				
n	1559	1137	995	764
mean	1582.77	1748.26	1911.82	1463.68
sd	6359.87	15514.76	21123.48	6220.31
median	160.35	151.87	111.80	119.97

Table 5.9 (continued): R&D Expenditure Descriptive Statistics

	t-1	**t+1**	**t+2**	**t+3**
Break-up				
n	520	302	258	208
mean	7562.53	6227.87	7393.94	10995.53
sd	43555.95	39015.18	44033.47	62728.21
median	332.21	281.66	288.56	342.76
Divested				
n	864	525	456	351
mean	3076.29	2866.24	2830.66	3285.09
sd	14949.14	13855.20	15163.60	19487.57
median	270.02	260.79	194.73	212.27
Divestor				
n	1613	962	833	665
mean	7708.04	8607.11	7606.21	9652.61
sd	43390.51	51823.11	48392.69	61197.90
median	327.97	300.46	253.30	292.75
Tradesale				
n	198	122	98	72
mean	2880.10	2946.71	3074.92	1866.28
sd	11232.22	20936.80	19570.68	9405.93
median	229.00	238.34	187.64	171.50
Acquirer-Divestor				
n	1796	1045	893	729
mean	10504.49	11791.75	12195.27	15770.05
sd	48140.13	66471.25	68646.82	83439.70
median	364.14	388.36	395.38	454.83
Total				
n	26497	19199	16857	12723
mean	3433.77	3266.46	3054.68	3236.87
sd	24437.98	28715.13	28267.66	29005.11
median	168.90	145.40	106.41	109.13

5.4 Results

The results of the average treatment effect on the treated (ATT) reported in this section were performed on matched samples created using nearest-neighbour one-to-one matching with a caliper of 0.005 with replacement. This caliper restriction level was decided on after a number of trials with different levels. Other matching algorithms were compared, but this method was preferred because it provides a greater reduction in bias.

In this data, restructuring events occur at enterprise group level and enterprise units remain consistent before and after every type of event. For instance, when an acquisition occurs, the effect on the acquired enterprise unit can be distinguished from the effect on the acquirer. Post-acquisition capital or R&D stock of the acquired firm is not combined with that of the acquirer; these values remain distinct and representative of the individual enterprise. This applies to all forms of joining event. Similarly, pre and post-separation event stock values are also representative of individual enterprises. This is a strong advantage of this dataset over other sources, such as Compustat, where the post-merger or acquisition firms combine into one unit and the individual effects cannot be observed.

The previous chapter indicates that joining events predominantly result from managerial motives. These motivations do not lead to a clear theoretical post-restructuring outcome. Managers may seek growth or re-invest profits to smooth dividend payments or keep shareholders happy. These growth aims will not necessarily lead to improvements in performance. This will be determined by managerial competence. The tables show the coefficients on the binary $EventDum_t$ variable from equation (5.11) for each of the matched samples. The corresponding treated groups are indicated down the side of the table and comparison groups across the top. Table (5.10) show ATT using $\Delta lnTFP$ over periods $t-1$ to $t+1$. Column 1 contains ATT for each event relative to 'no event' comparison groups. The findings suggest that the impact of being 'acquired' relative to the 'no event' comparison results in a 3% increase in TFP growth. This finding is significant at the 5% level. The reverse situation shown in row 1 concurs with this. When 'no event' is the treatment and 'acquired' is the comparison there is a decrease in TFP during the period, although this result is not statistically significant. The results also suggest that the 'acquired' treatment relative to a 'change of ownership' results in an increase in productivity. Labour productivity results for the same period shown in table (5.12) also comply with these findings, although these results are also not statistically significant. Table (5.11) shows ATT using $\Delta lnTFP$ over periods $t-1$ to $t+2$ and indicates that there is no significant effect of being 'acquired' relative to 'no event' after the initial post-event adjustment period. Although the ATT coefficient is not significant, it is negative suggesting that being acquired may reduce productivity growth in some cases. This finding is also consistent when the period $t-1$ to $t+3$ is considered.

Comparisons between the 'acquirer' and 'no event' groups in table (5.10) also show an initial increase in productivity for an 'acquirer' over the period $t-1$ to $t+1$. When 'no event' is the treated group and 'acquirer' is the comparison, becoming an 'acquirer' results in a 3% increase in TFP growth as a result of the acquisition. The results suggest that an 'acquirer' is worse off in terms of productivity by only acquiring, rather than acquiring and divesting in the same period. This is indicated by the negative significant coefficient on the ATT when 'acquirer-divestor' is the treated and 'acquirer' is the comparison group. When the results for the $t-1$ to $t+2$ period and the $t-1$ to $t+3$ period are considered, the findings show that there are no statistically significant differences in terms of changes in productivity between 'acquirer' and other events. Overall, these results show that both types of acquiring event result in an initial increase in TFP growth. The coefficients for 'mergers' present contrasting findings indicating a post-event decrease in the change in TFP, but this result is not statistically significant.

Table (5.13) show the results of the analysis when UK and foreign events are compared. The difference between 'foreign no event' and 'UK no event' is highly statistically significant. 'Foreign no event' firms incur a greater rise in productivity growth than 'UK no event' firms. There are few other statistically significant ATTs, but some patterns are observed based on the signs of the coefficients. The impact of being 'acquired' by a UK owner is positive, but a larger positive impact is incurred following acquisition by a foreign owner relative to 'UK no event' firms. This finding is not statistically significant but is consistent with Conyon et al. (2002), which finds that foreign acquisition leads to higher productivity. 'Foreign acquirers' show a greater increase in the change in productivity than 'UK no event' and 'UK acquirer' comparison groups, but less than 'foreign no event' comparisons. The findings for 'merger' are not consistent when treatment and comparison groups are reversed therefore interpretations cannot be drawn.

The literature review in chapter 3 indicates that separating events may arise due to managerial, refocusing or strategic motives. Managerial motives for engaging in separating events may be inspired by the desire to keep shareholders happy in order to maintain a managerial position. This motivation is likely to dominate if the enterprise group is experiencing poor performance. This decline in performance may continue or recovery may occur depending on the success of the separating event. The refocusing motive acts as a correction for over-diversification or excess growth. It is likely to lead to an improvement in performance due to the removal of excess communication and co-ordination of activities between enterprises resulting in a more simplistic structure or to free up funds for alternative investments. These benefits are unlikely to be received immediately. Strategic motives may arise from changes in industry conditions such as a decline in demand, increases in supply costs or competition. This may result in a decline in performance for all firms within the industry.

The results in table (5.10) show that the 'break-up' treatment compared to 'no event' results in a 5.3% increase in the change in productivity over the $t-1$ to $t+1$ period. This result is significant at the 5% level. When the 'acquired' treatment is compared to the 'break-up' comparison, a decrease of 10% results from the treatment. This implies that the post-event increase in productivity is greater for 'break-up' firms than 'acquired'. The results for 'divested' firms indicate that being divested results in a 5% increase in TFP growth relative to the 'change of ownership' comparison group. There is a significant coefficient at the 1% level on the ATT when 'divestor' is the treatment and 'no event' is the comparison group. The 'divestor' treatment leads to a 4% increase in the change in productivity than if no event occurs. The ATT results when'no event' is the treated and 'divestor' is the comparison concur with this finding, although the coefficient is not significant. This finding continues to persist when the period $t-1$ to $t+2$ is considered.

UK and foreign 'divested' firms both show a positive change in TFP relative to 'UK no event' comparison groups in table (5.13), although these results are not statistically significant. This effect appears to be negative when comparing 'foreign divested' firms to 'foreign no event' firms. UK and foreign 'divestors' also show a rise in the change in productivity relative to 'UK no event' comparison groups. This impact is greater for foreign firms and remains present for 'foreign divestors' in relation to the 'foreign no event' comparison.

When 'change of ownership' firms are compared to the 'no event' comparison groups in table (5.10), the effect of treatment results in a 4% decrease in the change in TFP. A negative impact of 'change of ownership' is also found when compared to 'acquired', 'acquirer', 'breakup', 'divested' and 'divestor'. These impact are not significant when the period of change is expanded to subsequent periods. 'Tradesale' does not provide any significant ATTs in relation to the 'no event' group for $t-1$ to $t+1$ period. The 'tradesale' comparison relative to the 'acquired' treatment group indicates that treatment results in a 23% reduction in the change in productivity. This suggests that the post-event increase in productivity is greater following 'tradesale' than for 'acquired' firms. This finding remains significant in the $t-1$ to $t+2$ period. Results from this period also indicate that 'tradesale' results in a decrease in the change in productivity relative to 'no event'. 'Acquirer-divestor' results in a rise in the change in productivity relative to 'no event'. This increase is also present in relation to 'acquired' and 'acquirer' treatment groups. This relationship is not present when the period of change is extended to '$t-1$ to $t+2$' and '$t-1$ to $t+3$'.

Table 5.10: ATT using dependent variable Δ ln TFP (t-1 to t+1)

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		-0.017	-0.032**	0.014	0.040***	-0.066**	-0.011	-0.034	-0.010	-0.053**
		(0.025)	(0.013)	(0.023)	(0.012)	(0.031)	(0.029)	(0.021)	(0.062)	(0.025)
Acquired	0.030**		0.001	0.021	0.081***	-0.101***	-0.010	-0.020	-0.213**	-0.098**
	(0.014)		(0.023)	(0.030)	(0.021)	(0.040)	(0.044)	(0.037)	(0.089)	(0.049)
Acquirer	0.017*	0.018		-0.009	0.039**	-0.023	0.004	-0.043**	-0.056	-0.047**
	(0.010)	(0.028)		(0.026)	(0.018)	(0.027)	(0.028)	(0.022)	(0.062)	(0.023)
Merger	-0.003	-0.001	-0.004		0.026	0.008	0.026	0.006	-0.052	-0.010
	(0.014)	(0.031)	(0.022)		(0.019)	(0.035)	(0.039)	(0.033)	(0.073)	(0.038)
Change of Ownership	-0.036***	-0.091***	-0.007	-0.021		-0.099***	-0.031	-0.041	-0.096	-0.041
	(0.008)	(0.026)	(0.019)	(0.026)		(0.033)	(0.034)	(0.029)	(0.070)	(0.041)
Break-up	0.053***	0.052	0.027	0.026	0.070**		0.007	-0.004	-0.081	-0.025
	(0.021)	(0.046)	(0.024)	(0.039)	(0.030)		(0.032)	(0.029)	(0.058)	(0.032)
Divested	0.018	-0.011	-0.002	-0.009	0.050*	0.018		-0.022	-0.009	-0.041
	(0.019)	(0.044)	(0.022)	(0.041)	(0.030)	(0.035)		(0.027)	(0.061)	(0.028)
Divestor	0.039***	0.031	0.019	-0.042	0.056**	0.009	0.036		0.024	-0.009
	(0.015)	(0.045)	(0.018)	(0.037)	(0.027)	(0.031)	(0.030)		(0.069)	(0.025)
Tradesale	0.048	0.102	0.052	0.018	0.040	-0.024	0.024	0.013		-0.023
	(0.038)	(0.070)	(0.039)	(0.062)	(0.044)	(0.041)	(0.046)	(0.048)		(0.046)
Acquirer-Divestor	0.024	0.037	0.046**	0.003	0.055	0.032	0.045	-0.005	0.071	
	(0.020)	(0.053)	(0.021)	(0.041)	(0.040)	(0.035)	(0.029)	(0.025)	(0.066)	

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 5.11: ATT using dependent variable Δ ln TFP (t-1 to t+2)

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		0.040	0.000	-0.030	0.025	-0.034	-0.044	-0.043	0.186*	-0.027
		(0.046)	(0.027)	(0.066)	(0.029)	(0.071)	(0.064)	(0.041)	(0.098)	(0.059)
Acquired	-0.014		-0.057	-0.015	0.009	-0.071	-0.084	-0.114	-0.232*	-0.056
	(0.031)		(0.048)	(0.075)	(0.043)	(0.111)	(0.108)	(0.077)	(0.120)	(0.100)
Acquirer	0.010	0.000		0.032	0.057	0.006	0.023	-0.047	-0.101	0.024
	(0.021)	(0.060)		(0.070)	(0.039)	(0.065)	(0.066)	(0.041)	(0.111)	(0.047)
Merger	-0.032	0.101	-0.071		-0.024	-0.028	-0.076	-0.117	0.075	-0.144
	(0.033)	(0.063)	(0.049)		(0.048)	(0.117)	(0.105)	(0.074)	(0.134)	(0.097)
Change of Ownership	-0.062***	-0.060	-0.013	0.035		0.068	-0.008	0.010	0.000	-0.013
	(0.019)	(0.050)	(0.039)	(0.058)		(0.080)	(0.073)	(0.055)	(0.117)	(0.084)
Break-up	-0.017	0.022	-0.031	0.005	-0.039		-0.015	0.038	-0.026	-0.006
	(0.045)	(0.093)	(0.052)	(0.117)	(0.061)		(0.086)	(0.054)	(0.126)	(0.068)
Divested	0.039	0.074	-0.040	0.140	-0.046	-0.054		-0.036	0.001	-0.026
	(0.044)	(0.088)	(0.048)	(0.102)	(0.069)	(0.090)		(0.050)	(0.125)	(0.065)
Divestor	0.060**	0.108	0.026	-0.015	-0.034	0.071	0.094		0.129	0.073
	(0.031)	(0.083)	(0.036)	(0.092)	(0.056)	(0.075)	(0.060)		(0.124)	(0.050)
Tradesale	-0.013	0.168	-0.033	-0.041	-0.024	0.035	0.019	-0.037		-0.037
	(0.082)	(0.142)	(0.078)	(0.194)	(0.111)	(0.094)	(0.118)	(0.091)		(0.101)
Acquirer-Divestor	0.002	0.110	-0.024	0.092	0.086	0.038	-0.048	-0.042	0.138	
	(0.042)	(0.114)	(0.044)	(0.110)	(0.078)	(0.077)	(0.078)	(0.053)	(0.114)	

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 5.12: ATT using dependent variable Δ ln LP (t-1 to t+1)

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		-0.002	0.039	0.093	0.081	-0.034	-0.004	-0.107	-0.190	-0.059
		(0.087)	(0.060)	(0.111)	(0.058)	(0.099)	(0.123)	(0.111)	(0.322)	(0.116)
Acquired	0.038		0.104	0.054	0.086	-0.042	-0.257	-0.157	-0.131	-0.039
	(0.070)		(0.097)	(0.124)	(0.083)	(0.155)	(0.200)	(0.198)	(0.454)	(0.189)
Acquirer	0.032	0.236*		-0.003	0.067	-0.009	0.008	-0.168	-0.206	-0.066
	(0.046)	(0.125)		(0.112)	(0.076)	(0.105)	(0.123)	(0.104)	(0.247)	(0.093)
Merger	-0.013	-0.042	-0.062		-0.058	0.120	0.007	0.046	-0.310	-0.006
	(0.074)	(0.106)	(0.094)		(0.084)	(0.146)	(0.156)	(0.177)	(0.348)	(0.161)
Change of Ownership	-0.021	-0.003	-0.065	-0.068		-0.061	-0.116	-0.204	-0.183	-0.037
	(0.042)	(0.094)	(0.079)	(0.105)		(0.137)	(0.147)	(0.156)	(0.323)	(0.174)
Break-up	0.038	0.106	0.034	0.078	0.057		0.042	0.233	-0.315	-0.102
	(0.098)	(0.153)	(0.103)	(0.164)	(0.119)		(0.145)	(0.149)	(0.281)	(0.123)
Divested	0.019	-0.129	-0.002	-0.161	-0.155	-0.070		-0.165	-0.066	-0.039
	(0.093)	(0.172)	(0.098)	(0.184)	(0.133)	(0.122)		(0.147)	(0.335)	(0.118)
Divestor	0.084	-0.069	-0.071	-0.340*	0.210*	0.084	0.102		0.471	-0.084
	(0.068)	(0.152)	(0.083)	(0.190)	(0.117)	(0.125)	(0.150)		(0.478)	(0.108)
Tradesale	0.094	0.082	0.110	-0.046	0.020	-0.207	0.118	0.052		-0.089
	(0.184)	(0.229)	(0.187)	(0.238)	(0.210)	(0.197)	(0.217)	(0.273)		(0.212)
Acquirer-Divestor	0.014	0.097	0.040	0.132	0.137	-0.058	0.107	-0.110	-0.023	
	(0.087)	(0.185)	(0.086)	(0.150)	(0.138)	(0.118)	(0.138)	(0.127)	(0.343)	

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 5.13: ATT using dependent variable Δ ln TFP (t-1 to t+1)

Comparison	UK Event	Foreign Event	Foreign Event	UK No Event	UK No Event	Foreign No Event	UK Event	Foreign Event
Treated	UK No Event	UK No Event	Foreign No Event	UK Event	Foreign Event	Foreign Event	Foreign Event	UK Event
No Event	-	-0.079***	-	-	0.066***	-	0.066***	-0.079***
	-	(0.019)	-	-	(0.017)	-	(0.017)	(0.019)
Acquired	-0.112*	-0.146	-0.099	0.076	0.125	0.037	0.056	-0.122
	(0.063)	(0.091)	(0.093)	(0.048)	(0.074)	(0.073)	(0.105)	(0.110)
Acquirer	0.029	-0.027	0.060	0.009	0.050	-0.018	0.021	-0.065
	(0.030)	(0.047)	(0.050)	(0.024)	(0.039)	(0.040)	(0.041)	(0.050)
Merger	0.038	0.110	0.170	0.024	0.017	-0.044	0.105	0.021
	(0.066)	(0.109)	(0.111)	(0.052)	(0.087)	(0.091)	(0.109)	(0.120)
Change of Ownership	-0.005	0.030	0.089	-0.019	0.005	-0.059	0.054	0.036
	(0.039)	(0.064)	(0.064)	(0.030)	(0.046)	(0.046)	(0.059)	(0.074)
Breakup	-0.060	-0.114	0.056	-0.007	0.044	0.013	-0.004	0.099
	(0.072)	(0.121)	(0.129)	(0.053)	(0.091)	(0.102)	(0.111)	(0.123)
Divested	-0.057	-0.016	0.113	0.011	0.027	-0.024	-0.021	-0.039
	(0.067)	(0.093)	(0.111)	(0.048)	(0.074)	(0.085)	(0.093)	(0.099)
Divestor	-0.011	-0.046	-0.032	0.024	0.096*	0.021	0.059	-0.030
	(0.047)	(0.068)	(0.073)	(0.036)	(0.055)	(0.057)	(0.067)	(0.079)
Tradesale	-0.182	0.030	0.324	0.044	-0.074	-0.068	-	-
	(0.152)	(0.265)	(0.332)	(0.107)	(0.152)	(0.178)	-	-
Acquirer-Divestor	-0.068	-0.004	0.079	0.082*	0.047	-0.127	-0.044	0.048
	(0.055)	(0.092)	(0.103)	(0.048)	(0.072)	(0.089)	(0.062)	(0.073)

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

The findings from the previous chapter indicated that foreign joining events may be motivated by innovation synergies. The ATT results for change in log R&D expenditure as the dependent variable are reported in table (5.14). There are no significant coefficients on the ATTs for joining events and the signs on the coefficient are not consistent when treatment and comparison group are reversed. This suggests that there is no observable impact of joining events on R&D expenditure. Although the coefficients for joining events in table (5.16) are also not significant, they provide weak evidence to imply that foreign-owned 'acquired' and 'acquirer' firms show a rise in post-event R&D expenditure relative to foreign and UK-owned 'no event' firms. The evidence for merging firms is mixed. The findings weakly imply that post-acquisition innovation activity may increase for foreign-owned firms, which is consistent with the motivation indicated in the previous chapter and concurs with the results found by Bertrand (2009), Bandick et al. (2010) and Guadalupe et al. (2012).

The previous chapter also indicated that the innovation refocusing motive for separating was present for R&D performing firms. This may imply that separating events may lead to a reduction in innovation activity if firms are reacting to a change in demand circumstances. Alternatively 'divestors' may use funds from divestment pro-actively, to re-invest in alternative projects. These alternative motives for refocusing are described by Kaul (2012).

Although few significant differences between treated and comparison groups are found, the coefficients imply that R&D expenditure may rise following separating events, particularly divestments. When 'divestor' is the comparison and 'no event' is the treated group, 'divestor' results in an increase in the change in R&D expenditures relative to the 'no event' case. In the $t-1$ to $t+2$ period reported in table (5.15), the impact of 'divestor' relative to 'no event' is positive but no longer significant. Positive and significant coefficients are found for 'divestor' in comparison to 'acquirer' and 'break-up' events. This implies that 'divestor' events lead to higher R&D expenditure than 'acquirer' and 'break-up' events. This pattern continues into the $t-1$ to $t+1$ period. These findings may indicate a proactive response and are consistent with the empirical findings by Kaul (2012), which found evidence of an increase in innovation activity following divestment. 'UK divested' firms show an increase in post-event R&D relative to 'UK no event' in table (5.16), whereas the coefficients for 'foreign divested' firms are negative relative to 'UK no event' and 'foreign no event'. This suggests that foreign owned firms reduce R&D expenditure after being divested indicating refocusing. This is not the case for 'divestors'; both foreign and UK owned 'divestors' show an increase in R&D expenditure, which suggests that the divestments may have been undertaken to free up funds for re-investment in innovation.

The ATT on the 'no event' treatment relative to the 'acquirer-divestor' comparison is positive and significant at the 10% level. This suggests that the change in R&D expenditure for an 'acquirer-divestor' is lower than if the firm experienced 'no event'. This result remains positive but not significant in the $t-1$ to $t+2$ period. When 'acquirer-divestor' is the comparison group in this period, the 'acquirer' and 'divestor' event treatment results in a reduction in R&D expenditure.

Table 5.14: ATT using dependent variable Δ ln R&D (t-1 to t+1)

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		-0.049	0.024	0.069	0.023	-0.111	-0.020	-0.128**	-0.053	0.121*
		(0.071)	(0.042)	(0.08)	(0.046)	(0.101)	(0.073)	(0.055)	(0.15)	(0.07)
Acquired	0.022		0.028	-0.025	0.079	0.001	0.066	-0.083	-0.271	-0.080
	(0.053)		(0.074)	(0.095)	(0.067)	(0.168)	(0.138)	(0.114)	(0.266)	(0.163)
Acquirer	0.011	0.059		0.084	0.047	0.140	-0.070	-0.061	-0.007	-0.043
	(0.034)	(0.081)		(0.082)	(0.056)	(0.096)	(0.069)	(0.058)	(0.133)	(0.062)
Merger	0.000	0.066	0.007		0.017	0.047	-0.009	-0.066	-0.104	0.059
	(0.057)	(0.084)	(0.069)		(0.069)	(0.128)	(0.117)	(0.097)	(0.25)	(0.103)
Change of Ownership	0.013	0.008	0.073	-0.013		-0.015	0.053	-0.145*	0.074	-0.014
	(0.035)	(0.072)	(0.056)	(0.083)		(0.122)	(0.1)	(0.083)	(0.16)	(0.114)
Break-up	-0.019	0.070	0.028	0.052	0.173*		-0.012	-0.096	-0.228	-0.046
	(0.071)	(0.16)	(0.076)	(0.124)	(0.106)		(0.091)	(0.086)	(0.198)	(0.089)
Divested	0.044	-0.144	0.033	0.059	0.028	0.053		-0.045	-0.230*	0.004
	(0.057)	(0.149)	(0.062)	(0.121)	(0.095)	(0.101)		(0.07)	(0.14)	(0.069)
Divestor	0.041	0.105	0.126**	0.089	0.078	0.195**	-0.019		0.046	0.081
	(0.043)	(0.135)	(0.052)	(0.11)	(0.08)	(0.095)	(0.075)		(0.16)	(0.068)
Tradesale	-0.103	0.048	0.050	0.023	-0.048	0.039	0.047	-0.035		0.126
	(0.117)	(0.257)	(0.109)	(0.206)	(0.177)	(0.164)	(0.13)	(0.125)		(0.111)
Acquirer-Divestor	-0.063	0.063	0.012	-0.017	-0.144	0.023	-0.106	-0.087	-0.013	
	(0.058)	(0.163)	(0.059)	(0.109)	(0.108)	(0.096)	(0.077)	(0.068)	(0.129)	

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 5.15: ATT using dependent variable Δ ln R&D (t-1 to t+2)

	No Event	Acquired	Acquirer	Merger	Change of Ownership	Break-up	Divested	Divestor	Tradesale	Acquirer-Divestor
No Event		0.102	0.038	0.055	-0.062	0.051	0.069	-0.021	-0.157	0.070
		(0.088)	(0.054)	(0.098)	(0.056)	(0.114)	(0.093)	(0.072)	(0.218)	(0.084)
Acquired	-0.054		-0.096	-0.059	-0.045	0.062	-0.049	-0.122	-	0.177
	(0.063)		(0.097)	(0.124)	(0.083)	(0.205)	(0.171)	(0.152)	-	(0.21)
Acquirer	0.014	0.135		-0.012	0.095	0.146	-0.260***	-0.003	-0.025	-0.161**
	(0.043)	(0.105)		(0.112)	(0.072)	(0.109)	(0.087)	(0.076)	(0.195)	(0.078)
Merger	0.006	0.148	0.019		-0.031	0.115	0.096	-0.165	0.037	0.044
	(0.072)	(0.113)	(0.093)		(0.086)	(0.152)	(0.148)	(0.14)	(0.368)	(0.137)
Change of Ownership	0.055	0.019	0.064	0.185*		0.099	0.001	-0.043	0.473	0.180
	(0.043)	(0.089)	(0.072)	(0.098)		(0.136)	(0.139)	(0.111)	(0.306)	(0.158)
Break-up	-0.157*	0.062	-0.047	-0.177	-0.134		-0.146	-0.180*	-0.453	-0.301***
	(0.09)	(0.202)	(0.094)	(0.161)	(0.121)		(0.101)	(0.106)	(0.319)	(0.104)
Divested	0.100	0.127	0.080	0.183	0.198	0.219*		-0.010	-0.086	-0.034
	(0.073)	(0.176)	(0.079)	(0.15)	(0.125)	(0.121)		(0.088)	(0.21)	(0.081)
Divestor	0.022	0.228	0.082	0.067	0.111	0.261**	0.030		0.114	0.120
	(0.056)	(0.176)	(0.07)	(0.146)	(0.103)	(0.116)	(0.095)		(0.198)	(0.081)
Tradesale	-0.234	-	0.070	-0.294	-0.177	0.116	-0.170	-0.124		0.019
	(0.157)	-	(0.159)	(0.22)	(0.248)	(0.243)	(0.178)	(0.178)		(0.153)
Acquirer-Divestor	-0.101	0.201	-0.023	-0.127	-0.139	-0.027	0.014	-0.060	-0.249	
	(0.072)	(0.225)	(0.075)	(0.136)	(0.136)	(0.116)	(0.087)	(0.086)	(0.217)	

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 5.16: ATT using dependent variable Δ ln R&D (t-1 to t+1)

Comparison	UK Event	Foreign Event	Foreign Event	UK no Event	UK no Event	Foreign no Event	UK Event	Foreign Event
Treated	UK No Event	UK No Event	Foreign No Event	UK Event	Foreign Event	Foreign Event	Foreign Event	UK Event
No Event	-	-0.005	-	-	0.023	-	0.023	-0.005
	-	(0.030)	-	-	(0.027)	-	(0.027)	(0.030)
Acquired	-0.134	0.012	-0.061	-0.028	0.081	0.108	0.036	-0.206
	(0.092)	(0.123)	(0.126)	(0.069)	(0.096)	(0.098)	(0.146)	(0.152)
Acquirer	0.038	-0.042	-0.026	0.004	0.065	0.041	0.082	-0.070
	(0.051)	(0.072)	(0.073)	(0.042)	(0.056)	(0.059)	(0.065)	(0.071)
Merger	-0.151	-0.089	-0.042	0.050	-0.067	-0.038	-0.328	0.247
	(0.108)	(0.139)	(0.162)	(0.073)	(0.125)	(0.120)	(0.212)	(0.222)
Change of Ownership	-0.008	-0.107	-0.039	0.053	0.017	-0.006	-0.034	0.039
	(0.061)	(0.085)	(0.081)	(0.046)	(0.068)	(0.069)	(0.085)	(0.095)
Breakup	-0.107	0.013	-0.051	-0.003	0.062	0.096	0.086	0.086
	(0.117)	(0.209)	(0.129)	(0.086)	(0.130)	(0.135)	(0.237)	(0.229)
Divested	-0.237**	0.044	0.104	0.113	-0.106	-0.164*	-0.152	0.202
	(0.102)	(0.095)	(0.107)	(0.072)	(0.082)	(0.097)	(0.119)	(0.138)
Divestor	-0.055	-0.009	-0.012	0.076	0.061	0.050	-0.022	-0.210**
	(0.068)	(0.094)	(0.106)	(0.054)	(0.073)	(0.083)	(0.096)	(0.106)
Tradesale	0.354**	-0.304	-0.095	-0.234*	0.138	0.092	-	-
	(0.162)	(0.239)	(0.279)	(0.144)	(0.248)	(0.311)	-	-
Acquirer-Divestor	0.005	0.293***	0.035	-0.103	-0.070	-0.087	-0.100	0.116
	(0.079)	(0.111)	(0.136)	(0.072)	(0.101)	(0.116)	(0.098)	(0.109)

Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

5.5 Conclusion

This study investigates the impact of firm restructuring events on post-event outcomes in terms of innovation activity and productivity. Previous studies have mostly focused on one event type. This study contributes to the literature by comparing outcomes for various joining and separating events. Propensity score matching and difference-in-difference is used to reduce bias arising from differences in pre-event firm characteristics.

Results indicate that most restructuring events lead to an increase in productivity. Support for this finding is particularly strong during the initial post-event period. An initial increase in productivity is found following acquired, acquirer, break-up, divestor and acquirer-divestor events. This may be the result from the realisation of synergies and streamlining of the organisation. This increase may persist for divestors into subsequent periods. A persistent fall in productivity is found following a change in ownership.

The findings also show that foreign-owned firms generally show greater increases in productivity over-time than UK-owned firms. There is some weak evidence to suggest that firms acquired by foreign owners also show increases in productivity relative to their UK-acquired outcome. This implies that foreign acquirers may apply superior knowledge to their acquisition targets, which conforms with findings in other studies. There is also weak evidence to suggest that the positive effect on productivity may be greater for foreign-owned divestors than UK-owned divestors.

The findings relating to innovation activity of R&D performing firms indicate that divestors tend to display increases in R&D expenditure following the event, which ties in with the idea of refocusing motives. This motive appears to be present for foreign and UK-owned divestors. There is weak evidence to imply that post-acquisition innovation activity increases for foreign-owned firms. This is consistent with the innovation synergy motivation indicated in the previous chapter and concurs with other studies in the literature. The results show fewer significant coefficients than the productivity analysis which may be a result of the volatility of R&D expenditure and difficulties in obtaining suitable matches in terms of innovation activity. The analysis may benefit from applying patent data to obtain measures of R&D productivity, but unfortunately this data is unavailable in this study.

The validity of this analysis rests on the suitability of the comparison samples to provide an accurate counterfactual for the treated sample. Tests indicate that the matching quality varies across matched samples, therefore some results are more reliable than others. Control variables are included in the difference-in-difference stage to account for pre-event differences within the matched samples. This aims to reduce the bias on the average treatment effects on the treated in order to make the comparisons between event types as reliable as possible.

6 Conclusion

The aim of this thesis was to investigate the relationships between globalisation, firm structure, productivity and innovation. The study makes three empirical contributions to the literature. The first empirical analysis in chapter 2 poses two research questions. One aims is to investigate if productivity and knowledge differences exist between multinational and non-multinational firms. The other aim is to investigate whether complementarities exist between internal and external sources of knowledge. The second and third contributions of the thesis focus on firm restructuring events. A distinction is made between foreign and domestic restructuring events. The second empirical analysis in chapter 4 investigates the motivations behind restructuring events by focusing on the pre-event characteristics of the firms. The aim of this chapter is to identify if differences exist between the types of firms that are involved in each type of restructuring event and make inferences about the motivations driving these events. Results from this analysis inform the third contribution in chapter 5, which looks at the impact of restructuring events on productivity and innovation activity.

The key themes in chapter 2 are globalisation, knowledge and productivity. The analysis specifically aims to understand if differences in multinational status are associated with differences in knowledge and productivity. Various measures of knowledge are used including stock of in-house R&D expenditure, stock of R&D expenditure on knowledge transfers from external sources, knowledge spillovers emanating from the local area calculated by summing in-house R&D of other firms within a local radius and number of R&D employees. R&D stock measures recognise that knowledge is path-dependent and labour measures acknowledge that knowledge can be embedded in human capital. The study also aims to ascertain whether the complementarities exist between these different sources of knowledge.

A contribution to the literature is made by analysing these questions using a unique combination of highly detailed UK firm-level datasets. These include the AFDI, ARD and BERD. The majority of previous UK studies in this literature have used the CIS to investigate innovation. The benefit of using BERD is that a large consistent panel can be created, whereas CIS questions change across waves, limiting samples to shorter time frames. Furthermore, BERD R&D expenditure may be considered a more accurate indication of R&D activity than self-reported responses to the CIS questionnaire.

International trade theory suggests that multinational firms posses intrinsic intangible knowledge which has allowed them to break into foreign markets and compete with domestic firms. The results of the study are consistent with this idea and show that multinational firms are more productive than non-multinational firms. Furthermore, foreign-owned multinationals are more productive than domestic-owned multinationals. This finding also concurs with the majority of existing empirical literature. Differences in productivity between multinationals and non-multinationals are partly due to differences in labour and capital. Multinationals derive higher returns to capital and lower returns to labour than non-multinational firms. This may imply that these firms transfer superior technology from other countries, in terms of more effective machinery and equipment. The remaining differences in productivity can be attributed to intangible knowledge such as managerial competence, which is not captured by the R&D knowledge stock.

Findings regarding the relationship between knowledge and productivity are also consistent with the majority of previous studies. A positive relationship between the stock of in-house R&D expenditure and output is found indicating that increases in internally created knowledge stock leads to an increase in productivity. Conversely, a negative relationship is found between stocks of external knowledge transfers and output. This is likely to reflect difficulties in absorbing knowledge from external sources. These results persist for multinational and non-multinational firms. An increase in the number of skilled R&D employees shows a small positive impact on productivity in the short run. This impact is likely to be greater in the medium to long term because results may take time to manifest.

The theory of absorptive capacity suggests that performing in-house R&D improves a firm's ability to absorb knowledge from external sources. This implies that complementarities exist between internal and external sources of knowledge. The study provides little evidence to support the presence of absorptive capacity as the results suggest that increases in the stock of in-house R&D expenditure or number of R&D employees do not increase a firm's ability to productively utilise knowledge from external sources. These findings contrast results from earlier studies and may reflect the fact that these measures do not perfectly represent the quality of innovation.

It is clear that differences exist between multinationals and non-multinationals, but whether this is a causal effect is not conclusive. There are three ways that a multinational firm can be created; expansion of UK-owned firms overseas, greenfield investment by foreign firms or takeover of existing firms by foreign owners. The observed differences in productivity may arise if foreign owners join with more productive firms and separate from less productive firms. In this case the productivity difference cannot be attributed to knowledges advantages associated with becoming multinational, it may be a case of "cherry picking" in terms of selection based on productivity. The subsequent analyses investigate this notion further.

Chapter 4 seeks to obtain a greater understanding of the motivations driving firm restructuring events. These motivations cannot be directly observed therefore they must be inferred based on the the pre-event characteristics of the event participants. Previous empirical studies have mainly focused on the motivations behind joining events and few have looked at motivations behind separating events. The identification of detailed firm restructuring events distinguishes this analysis from previous work in the literature. Ten distinct event types can be identified. The events are identified using enterprise and enterprise group reference codes in the BSD. The BSD provides data on the population of firms with operations in the UK, therefore this data allows the restructuring events to be identified as reliably as possible. A further distinction is made between foreign and UK event to identify differences in restructuring motivations between foreign and domestic owners.

Four main motivations for restructuring events are identified in the literature review in chapter 3. These are strategic, synergistic, refocusing and managerial incentives. Strategic motivations arise from industry circumstances such as competition, demand and supply. Synergistic incentives relate to potential benefits from economies of scale and combining knowledge that may arise from joining events. Refocusing incentives refer to streamlining of activity through separating events as a response to excessive growth or over-diversification. Managerial incentives for restructuring events refer to the pursuit of the managers own objectives. These may involve growth associated with prestige and managerial hubris or actions that are favourable with shareholders to maintain a managerial position. These motivations are not mutually exclusive.

The model is estimated using a multinomial logit, where the categorical event variable is a function of pre-event characteristics. Average marginal effects are obtained to indicate how the average probability of an event is expected to change with an increase in an explanatory variable, holding other things constant. Although the competing risks model has been used in some recent studies, the application of this methodology with many competing events would be computationally burdensome and would add little explanatory power as the sample period is relatively short. Duration time to the event is not of particular interest in this case and it can be argued that the restructuring event is more likely to be a function of its pre-event characteristics than the duration that no event has occurred.

The results show indications that managerial, synergistic and refocusing motivations for restructuring are present. Higher profit firms are more likely to acquire or merge and low profit firms face a greater risk of being divested. This suggests managers may be performing restructuring events to please shareholders and retain their position as manager. The likelihood of an event occurring increases for those firms that have had involvement in previous events, suggesting that engagement in restructuring events is habit forming.

Separating events are more likely to occur for larger, more diversified enterprise groups indicating the presence of refocusing motives. Innovation refocusing is observed for divestors and divested firms, but not for break-ups. This motive is particularly present for foreign divestments. Foreign joining events may be motivated by innovation synergies, but this motive does not appear for UK joining events. This suggests evidence of "cherry picking" in terms of innovation by foreign owners.

After investigating the motivations behind restructuring events, it seems logical to investigate post-event outcomes, focusing on the themes of productivity and innovation. The findings from chapter 4 provide evidence that firm characteristics differ across event types. The analysis in chapter 5 uses propensity score matching in order to account for endogeneity from selection bias. This method is preferred to propensity score reweighting as it provides a more suitable control for endogeneity. Matched samples are created to enable comparisons between 'no event' firms and each event type. Difference-in-difference estimation is performed on the matched samples to obtain average treatment effects on the treated. This method is used to control for pre-event differences in terms of the dependent variable. Control variables are also included in the estimation to capture differences in pre-event characteristics which may remain in the matched samples. The reliability of the estimates rests on the validity of the common support and conditional independence assumptions.

The findings show that most restructuring events result in an increase in productivity, which may reflect the realisation of refocusing and streamlining motivations. These findings are more robust when the change from $t-1$ to $t+1$ is assessed in comparison to the change to subsequent periods. This may be partly due to the reduction in the number of observations as fewer firms are observed over longer time periods. The study finds weak evidence to suggest that firms acquired by foreign owners show greater rises in productivity than if they were acquired by a UK-owned firm. This is consistent with findings in previous studies and suggests that foreign firms may apply superior knowledge to their target firm.

The results on innovation activity show that divestors invest more in R&D expenditure than they would have if they had not restructured. This implies that the action of divestment released funds for reinvestment in innovation. There is also weak evidence to suggest that foreign firms show increases in post-acquisition innovation activity. These findings tie in with the innovation refocusing motives and innovation synergy motives indicated in chapter 4. Fewer statistically significant results are derived in the innovation activity analysis than the productivity analysis. This is likely to be the result of the volatility of R&D expenditure and difficulties associated with finding appropriate matches in terms of innovation activity. This analysis could possibly be improved by placing a greater emphasis on innovation characteristics of firms in the matching process.

The sophistication of the empirical methods used develops as the thesis progresses. Chapter 2 looks at the differences between multinational and non-multinational firms, but does not acknowledge the restructuring mechanisms that may lead to multinational creation. Identification of distinct restructuring events in the data allowed for larger methodological contributions to be made by the second and third empirical chapters. Chapter 4 makes a methodological contribution by applying a multinomial logit model with 10 categories. The results are reported as average marginal effects AMEs rather than coefficients as generally reported in the literature. These AMEs are likely to provide a more general representation of the effect of a variable on the likelihood of an event occurring as the entire distribution is taken into account. The empirical method could be further developed to account for differences between the sample and the BSD population by including a weighting. This would ensure that the results more accurately reflect the entire population of firms. Chapter 5 provides a further methodological contribution by applying the multiple treatment propensity score matching method suggested by Lechner (2002) to this literature. Lechner (2002) previously applied this method to investigate the impact of multiple labour policies. The difference-in-difference method including pre-event control variables is applied to the matched samples to account for remaining endogeneity within the matched samples.

Access to ONS data via the Secure Data Service (SDS) has played a crucial role in this thesis. Initially, this data was only available at the Virtual Micro-data Lab (VML) which involved expensive trips to London and time restricted access. Although there have been some problems with the SDS, data access at my own university desktop was far more convenient and allowed sufficient time to understand the datasets and perform detailed analysis and robustness checks.

The Micro-level data from the ARD, BERD and BSD have proved vital in understanding motivations and behaviour at the firm-level. The data from these surveys are detailed and very useful for most of the purposes of this study. Lack of documentation in the foreign ownership codes made identification of ownership country unfeasible beyond the UK-foreign split. The lookup table provided by Richard Harris was very useful to improve the quality of the merges between these datasets. The AFDI was much more difficult to merge as enterprise group codes where coded in a manner that was not consistent with the other datasets. This made merging more complicated. FAME data was relatively easy to compile from the Bureau Van Dijk database. The data merging was performed on my behalf by the people at the SDS to ensure that disclosive information about firms was not revealed during the merging process.

A limitation in each of these investigations is the unavailability of patent data for the empirical analysis. R&D expenditure provides a measure of inputs into the R&D process, but there is no way of identifying how productively this expenditure is used by focusing on this input alone. Patent measures represent innovation outputs and the ratio of inputs to outputs can act as a indication of innovation productivity. This would greatly benefit the analysis. Patent data proved too difficult to merge with this data, because each patent is recorded by name and address of the firm. The lack of firm identification code makes merging problematic as the SDS data is anonymised and SDS postcodes are not consistent with actual postcodes. Without additional information, it is impossible to merge these datasets. Furthermore, the SDS would not permit any activity that could potentially disclose the name of a firm.

In summary, the key message from this thesis is that it is important to distinguish between foreign and domestic firms and also between different types of restructuring events, because differences in terms of productivity and motivations exist. These differences have important implications for firms, the UK economy and government policy.

The finding that in-house R&D activity increases productivity implies that government policy should encourage in-house R&D, because increased productivity improves the competitiveness of UK based firms in the international market and leads to increased profits for the firm. Although, this finding does not imply that the same incentives should be given to UK and foreign owned firms. The benefit of this for the UK economy depends on the extent that this increase in productivity leads to increased profits and the extent that these profits are re-injected into the UK economy. Profits for UK owned firms may stay in the UK, whereas profits from foreign-owned firms may be taken abroad.

Foreign firms enter the UK either by Greenfield investment or via merger or acquisition. The impact of foreign ownership of firms in the UK economy remains uncertain. The main channels of impact for the UK economy are via the labour market, impact on UK competitors and impact on consumers. The effects on the labour market are associated with job creation or losses and changes in wages. The impact on UK competitors can lead to displacement of firms and further job losses or lead to technology spillovers which benefit local firms. Although the findings of this study suggest foreign multinationals are more productive than UK firms, there does not appear to be any benefit of multinational presence in the UK in terms of knowledge spillovers to UK-owned firms in this study.

Foreign acquisition appears to have a positive impact on productivity of the firms involved in the restructuring event, but the statistical significance of this finding is weak. This implies that the impact may vary within this group. Furthermore, increases in productivity may occur alongside job losses, which may have a negative impact on the local area. Additional analysis in this area can be investigated using the data in this study.

The investigation into the motivations behind restructuring events indicates that the majority of joining events appear to be motivated by managerial growth motives. This is not necessarily a problem as findings indicate that restructuring leads to improved performance in terms of productivity, but there may be implications for the UK economy in terms of labour and competition. Within the managerial growth motivation, there may be unobservable differences in management style and ruthlessness of corporate behaviour. Separating events revealed refocusing as a motive, which also leads to increased productivity. This appears to be beneficial for the economy to minimise the negative effect of over-diversification, particularly if the alternative to separation is firm closure, but also highlights the fact that excessive growth should be limited to minimise the need for refocusing as a result of poor performance.

R&D performing firms are more attractive acquisition targets to foreign firms. The post-event outcomes weakly indicate that R&D expenditure increases following a foreign acquisition event. This event should be studied more closely and investigations by industry could be performed to ensure that UK-based innovation is maintained or expanded.

This thesis presents many possibilities for future research. There are clear indications that deeper analysis by industrial sector would be useful and informative because firm characteristics and behaviour are likely to differ across industries. Additional distinctions between countries of ownership would also be beneficial, particularly to distinguish between developed and developing countries. Firms from highly developed countries are likely to possess a greater level of technological knowledge and act as technology leaders. The motivations for joining events and post-event outcomes are likely to differ greatly between these developed and developing groups. Further investigation into these aspects would be a beneficial extension for each of the three empirical chapters.

Alternative measures of innovation could be used. The BSD restructuring data could be merged with the CIS to provide additional measures of innovation and explore the impacts further. A way of merging patent data with SDS data may also become available in the future. The high level of R&D volatility noted in chapter 5 may be due to the choice of R&D expenditure variables. BERD provides expenditure data on R&D wages, R&D capital and basic, applied and experimental research. R&D wages are likely to provide a less volatile measure of R&D expenditure, therefore it may be useful to compare all available measures.

Additionally, wages and number of employees could also be used as dependent variables in order to understand the broader impacts of these restructuring events on the labour market and the UK economy. It would be useful to understand which restructuring events lead to redundancies and if the effect is larger following foreign events, because this would impact employment, economic growth and would be very informative from a policy perspective.

As AFDI, ARD, BERD and BERD data becomes available for more recent years, this opens up the potential for post-event outcomes to be observed over longer periods. This will allow comparisons of the impacts of restructuring events on innovation and productivity over the long-run and short-run, and will establish if the initial impacts have a lasting effect.

Further analysis related to chapter 4 could expand the potential outcomes to include firm exit and investigate the relationship between restructuring events and firm exit using duration analysis. This analysis would address a different research question to the one posed in chapter 4, focusing on the propensity to exit and therefore duration analysis would be deemed appropriate.

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