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The effect of R&D, technological spillovers and absorptive capacity on productivity and profitability of automobile and electronics firms in Japan

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**The effect of R&D, technological spillovers and absorptive capacity on
productivity and profitability of automobile and electronics firms in Japan**

Nattachai Charusilawong

**Submitted in partial fulfilment of the
requirement for the degree of:**

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Abstract

It is widely accepted that R&D is a key factor explaining performance at both macro and micro-levels. At the micro level, it is thought that firm's R&D activities contribute to productivity and profitability by improving efficiency and delivering new products. What is unclear is the role that technology spillovers play in firm performance and the importance that absorptive capacity plays in helping firms benefit from these spillovers.

This thesis fills this gap by addressing three issues: the impact of firm R&D on performance as measured by labour productivity and profitability; the impact of technological spillovers on this performance; and the formalisation of absorptive capacity in order to examine the indirect effect of the firm's technological effort. Of secondary importance is the bi-directional relationship between R&D and profitability. The empirical context for this study is the Japanese automotive and electronics industries. Japan is an appropriate context because both the automotive and electronics manufacturing industries are considering some of the world leading innovators. Three empirical chapters address these issues in turn. The first explores the productivity effects of internal R&D activities, intra-industry spillovers, inter-industry spillovers and absorptive capacity. It adopts production function framework, and random and fixed effects panel data estimators. The second empirical chapter considers the effect of these factors on profitability. It applies dynamic regression models and autoregressive distributed lag empirical methodologies. Results in both empirical chapters indicate that internal R&D activities undertaken by the firm directly enhance performance and indirectly foster the capability to internalise outside knowledge. The third chapter assesses the reverse impact of profitability on the firm's R&D investments. Little evidence of profitability effect on R&D is found in the automobile industry whereas a fall in profit motivates electronics firms to engage more innovative activities.

This thesis contributes to the literature on the impact of technology on performance at the micro-level. It sheds the light on the significance of technological externalities and the importance of absorptive capacity. The empirical analysis presented in this thesis provides insights into the direct and indirect role of firm R&D on performance, which will be of interest to managers. It also raises policy implications in bolstering the private sector's incentive to undertake R&D in order to cultivate the pool of technological spillovers.

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Chapter 1: Introduction

1.1 The Context

Technological development is vital for competitiveness at both the macro and micro economic level. The amount of funds invested by firms on research and development projects, and by funds allocated by public institutions in industrialised countries to bolster research, suggests that knowledge creation activities are a pivotal source of economic wealth and welfare enhancement. At the micro level, research and development can influence firm performance through the introduction of new and improved product or processes (Morbey, 1988), or new features in existing products and services (Vemuri et al., 2003). To this end, the firm's competitive position can be enhanced even if they are in a mature or declining market. Firms are motivated to invest in R&D by the need to create new products or improve existing products, which could benefit their position in the marketplace and thus their long-term financial viability. Specifically in high-technology industries, R&D activity is regarded as one of the foremost factors that will enable them to gain a competitive position as well as to improve their performance in the market (Tassey, 1983). A number of different strands of literature indicate R&D is making a major contribution to sales performance, productivity and profit of the firm (Griliches, 1988; Geroski et al., 1993; Jones, 1995; Van Reenen, 1997).

The pioneering work of Griliches (1979, 1986) has widely served as an important framework for many authors studying the relationship between technological development and productivity at national, sectoral and firm level. The empirical literature has adopted the Cobb-Douglas production function and adding either knowledge capital stock or R&D expenditures into the model. Other authors have applied structural models by Crepon, Duguet and Mairesse (1998) (CDM), which differs from the production function model as it highlights on output definitions of inventive activities. In this respect, the CDM model involves three steps of estimation regarding firm decisions to conduct R&D and the degree of R&D intensification, the effective innovation yielded from such R&D effort, and the relationship between innovation output and firm productivity (Goya et al., 2012). Given the diversity in productivity estimation models, the economic level being analysed, the available data and the methods used, existing empirical results are inconsistent. Yet the overall evidence at the firm level point toward a positive and significant relationship between innovation and productivity. The role of technology as an issue in firm performance suggests the need to investigate the interrelation between monetary outcomes and technological

investment. Compared with productivity studies, empirical analysis in the literature on the profitability effect of technological innovation does not take a uniform approach.

With a focus on the input side of innovative activity, one strand of the empirical literature estimates R&D in one of three main forms; the amount of R&D investment, R&D intensity (R&D as a percentage of output) and R&D capital stock. But these types of R&D variables present one source of knowledge accumulation - innovative effort made by an individual firm (Verspagen and De Loo, 1999). Other sources of knowledge accumulation include learning by doing and particularly technological diffusion and these can exert influence upon firm performance. The essence of technological spillovers effects are easily understood and not limited to the innovating firm. Inevitably, some benefits acquired from its investment in new technologies tend to spill over to other economic agents such as other firms in the same sector and those in other sectors. Even with the existence of patent protection, the firm cannot prevent others making use of new discoveries of technology or knowledge. Economic transactions across firms and economic sectors, the tacit nature of knowledge and the movements of skilled labour are counted among channels of technological diffusion. Lack of effective appropriability implies a positive externality for a firm, which is a potential recipient of others' diffused technologies. In the perspective of that firm, the presence of numerous firms doing research in related areas may reduce the cost of innovation (Jaffe, 1984).

The recognition of the importance of external knowledge flows is an important phenomenon seen in the organisation of the innovation process within corporations (Rigby and Zook, 2002). Firms are gradually abandoning the idea that the generation of new knowledge is mostly an internal process (Arora et al., 2001; Gans and Stern, 2003). In some industries, the boundaries between the organisation's knowledge stock and extramural knowledge are blurred (Teece, 1998). The theoretical prospects and potential importance of technological spillovers on economic variables; particularly productivity, has been discussed alongside the early modeling of the R&D-productivity relationship. Griliches (1979) stresses that the extent of spillovers is vital to assessing the overall contribution of R&D to productivity growth. This is rational since the productivity of a firm may not only be determined by its own innovative effort but as well by the pool of external knowledge available. Spence (1984) cites R&D intensive industries as examples where the extent of spillovers is an element of market structure with crucial implications for conduct and performance. While it is likely the significance of spillovers was recognised, there is less

empirical evidence on their effect upon performance than those addressing exclusively the effect of inventive efforts made internally by the company. With regard to preceding studies taking into account technological externalities, the direction and magnitude of such spillover effects are still not determined owing to dissimilarities in the level of analysis and variables approximating externalities. A number of studies report a positive and significant relationship whereas other papers point to different conclusions. Commonly found in numerous literatures is either uncategorised externalities or one specific source of technological externality. As there could be different kinds of technological spillovers that exert different rates of return (Griliches, 1979), distinguishing separately the effect of spillovers originating from diverse sources could provide a better explanation of the contributions of each spillover upon economic variables. For micro-level studies, the consequences of technological externalities between firms operating within the same industry are often their exclusive focus. Nonetheless, this might be contentious as technological spillovers from firms operating in other industries possibly occur and also affect the performance of an individual firm. For example, inter-sectoral externalities are reported to cause unit costs to decline substantially more than intra-sectoral externalities do (Bernstein, 1988). Hence, the question arises whether the results obtained from empirical models that take into consideration only intra-industry spillovers remain valid when inter-industry spillovers are also introduced explicitly (Steurs, 1995).

In the contemporary knowledge-intensive business environment, organisations increasingly depend upon external sources of information to promote innovation and improve their performance (Cassiman and Veugelers, 2002; Morgan and Berthon, 2008). Nonetheless, many of them encounter with difficulties in benefiting from external knowledge flows, even in industries of easy-to-access sources of information (Escribano et al., 2009). Even exposed to the same amount of extramural knowledge flows, firms might not derive equal benefits; however (Beaudry and Breschi, 2003; Giuliani and Bell, 2005). It should be noted that such discrepancy in the impact of technological externalities upon firm performance could arise from the ability of the firm itself to assimilate and draw on such external knowledge. Arguably, such ability is interrelated with the magnitude of technological activities internally undertaken by the firm. This has been observed by scholars of technological change over several decades (Allen, 1977; Mowery, 1983; Neary and Leahy, 2007). In order to generate tangible benefits, however, organisations need to identify, process, and exploit these external knowledge flows (Gottfredson et al., 2005). Innovative efforts of the firm can take a dual

role. R&D may exert an indirect effect on economic performance via its role in facilitating internalisation of new technologies. For the semiconductor industry, Tilton (1971) states that motivations behind R&D investment are not only to generate innovation but such R&D effort would also bolster in-house technical capability that allows those firms that have kept up with the latest technology to incorporate new technologies created elsewhere. The second contribution of R&D could be generally termed as the learning or absorptive capacity of a firm. Effective absorption of the knowledge of others is associated with the process of learning that requires a long term commitment and considerable effort. In particular, amassing the firm's absorptive capacity has its root in the successive development of the stock of knowledge. Cohen and Levinthal (1989) consider that this ability might allow the firm to exploit external knowledge of a more intermediate sort, such as basic research that provides the foundation for subsequent applied research and development. In this regard, the essence of absorptive capacity seemingly serves as a type of learning that leads to the creation of novel and original knowledge. The concept of absorptive capacity gradually gains recognition as a key driver of a firm's competitive advantage (Lichtenthaler, 2009). Research on absorptive capacity outcomes still falls short in integrative examinations of productivity and financial measures of performance. Whilst being given little attention in the microeconomic literature on R&D and productivity at the firm or sector level, the value of absorptive capacity has been confirmed in the literature at a more aggregate level and specifically on the potential effects upon productivity performance. For example, Griffith et al. (2004) use sector-level panel data for thirteen OECD nations and report that R&D indirectly increases total factor productivity growth by enhancing technology transfers from countries at the technological frontier. Guellec and Van Pottelsberghe (2001) show that the positive impact of foreign R&D on productivity could be magnified by R&D conducted locally by the business sector. Jaffe (1986), Girma (2005) and Parisi et al. (2006) provide evidence supporting the importance of a technological absorption effect of R&D at the firm level. It could be argued that there is a sizable body of empirical work estimating spillover effects while relatively little investigation has been reported regarding the role of own R&D in internalising others' discoveries. Furthermore, the concept of absorptive capacity might be essential not only for productivity, but also for profitability.

1.2 Research objectives and questions to be addressed in the thesis

The research carried out in this dissertation uses quantitative methods to assess the impact of both economic and technological outcomes of firms. It specifically models the

relation of R&D with productivity and profitability. Additionally, this research extends further to examine the significance of R&D spillovers with respect to these two performance measures and investigate the impact of technological absorptive capacity. The micro-economic nature of the analysis is the main feature of this thesis at the empirical level. For this purpose, a representative sample of Japanese listed companies operating in the automobile and electronics industries is constructed. Automobile and electronics industries are chosen because they are technology-intensive industries whose performance tends to rely substantially upon R&D. In fact, the rapid growth in market performance over the decades of 1970s and 1980s was attributable to the development of innovative and quality products by substantial R&D efforts and the productivity improvement by effective manufacturing operations (Lee and Shim, 1995).

Taking the above discussions in section 1.1 into account, the aim of this thesis is fourfold. First, it seeks to determine the effects of R&D on firm performance; both with respect to productivity and profitability. Without doubt, there is considerable effort into research and development activities in manufacturing firms, especially those in technology-intensive sectors. This gives rise to the question of the efficacy of these innovative activities in terms of production and monetary outcomes. Given the two industries used in this empirical analysis, quantifying the contribution of R&D activities to firm performance, as approximated by rises in productivity and profitability can provide understanding of the extent to which the significance of R&D activities persist. The thesis also wishes to understand whether R&D contribution varies from one technology-intensive industry to the other. While a number of studies have found a relationship between R&D and productivity growth, the evidence of a profitability effect of R&D is unclear and a comparatively smaller body of literature has addressed this aspect. Firm R&D investments represent the level of intra-firm innovative effort whose outcomes appear typically to be associated with private rates of return on R&D. As a private rate of return is within the context of each individual firm, it is likely to be of interest to management scholars as well as economists as both are concerned with firm incentives to engage in technological activities. Since the outcomes associated with R&D projects are generally uncertain it is important to ensure a positive return (Hall et al., 2010). As decision makers at the micro-level, firm managers are keen to use information on the effectiveness of internal R&D efforts to help guide them through decisions on technological investments and the evaluation and selection of future strategies.

The second objective of this study is related to technological externalities originating from innovative efforts of other companies. Specifically, this thesis is concerned with research spillovers in order to determine their direction and impact upon productivity and profitability of firms. The thesis decomposes the total pool of research externalities into intra-industry and inter-industry elements and measures to what extent variation in these components contribute to changes in firm performance. The inter-industry spillover is approximated by the diffusion of technology between automobile and electronics sectors. The association between the two industries is clear. Automobile manufacturing increasingly relies upon fields such as microelectronics (Cohen and Levinthal, 1989). This is reinforced by the growing use of electronics products and technologies in the production of both vehicles and automotive components. This trend is expected to continue in forthcoming generations of automobiles such as hydrogen fuel cell (FCEV) and full electric vehicle (FEV) with the application of electric drive technologies. Hence, firms operating in such an industry are likely to have progressively more input on electronics-technology goods, engage in joint research projects with firms in the electronics sector, as well as expand their own efforts in basic research related to electronics innovation. Within the social context, dissemination of technologies can be considered as collectively advantageous. The measurement and investigation of the impact of technological externalities is beneficial for policy makers who are particularly interested in social returns to R&D that affect a variety of economic agents. In this regard, policy makers would be able to gain a better comprehension of both the direction and size of these segregated externalities so that they can designate effective scientific and technological policy programmes.

The third topic explored in this thesis involves an in-depth examination of absorptive capacity in order to measure the significance of such intra-firm capability. In this respect, a question of interest that the thesis aims to address is the firm's ability to internalise and apply others' technological innovation to its own use and thus improve performance. The study introduces a measure of interaction between the firm's R&D investments and pool of technological spillovers explicitly in the model. The measure links the degree of the firm's own technological efforts to indirect effects of other firms' innovations. In this respect, understanding absorptive capacity could be meaningful particularly for managers and the results provide information on the likely success of internal technological investments that are uncertain and costly. Decisions to undertake R&D activities may not only yield a direct outcome in the form of intra-firm generated innovations or knowledge but also expand the

ability to exploit knowledge gained from various external sources. It should be stressed that this thesis adds to the existing studies on absorptive capacity although the previous literature concentrates largely on technological externalities stemming from either foreign direct investment or of firms some distance from the national technological frontier. However, the majority of spillovers take place nationally. Audretsch and Feldman (1996) and Branstetter (2001) show that spillovers are more importance intra- than internationally. The present study adopts a longitudinal research design which are still missing from most of extant researches (Lane et al., 2006). This implementation could yield a contribution that enhancing the understanding of technological absorptive capacity as an antecedent of competitiveness. In addition, the present study is among a few that examine the profitability effect of absorptive capacity, which is absent from empirical studies at both the industry and firm level. Therefore, this research complements the initial contributions of Jaffe (1986) and Hanel and St.Pierre (2002) which are also based on firm-level data.

As it has been mentioned, findings by a number of studies still lack any consensus regarding both the direction of interconnection between technological development and profitability. The fourth and last objective pursued in this work is thus to further investigate the direction of relationship between R&D and profitability. More specifically, this study attempts to explore whether there is also a reverse effect of profit surges on the degree of technological investment undertaken by the firm. The greater innovative efforts made by the firm could yield higher rate of returns, both privately and socially. The social return to firm R&D essentially implies the flow of research externalities and technical knowledge within the economy. Concurrent with technological externalities, the incentive of the firm to engage in technological activities could be thus another subject of interest to policy makers who might seek to encourage technological activities in the private-sector in order to ensure the continuing enrichment of the pool of spillovers.

Main questions addressed in this thesis are provided as follows:

1. Is R&D related to firm performance as measured by productivity and profitability?
2. What is the impact of technological spillovers on productivity and profitability?
3. Does the firm's internal capability to apply technological externalities contribute to performance?
4. Does profitability change reflect the innovative efforts of the firm?

5. Can we observe differences in patterns of these relationships among technological-intensive industries?

1.3 Outline of the thesis

The second chapter gives an overview of the automobile and electronics industries in Japan, which is important as the sample is comprised of firms from these sectors. This includes a brief summary of the development and industrial organisation of those two industries with some relevant data. The significance of the automobile and electronics industries to the aggregate economy of Japan is clear by their large share in the entire manufacturing sector's production and added value and by their share of exports in the national economy. Further, both sectors are typically technologically intensive given their comparatively high levels of R&D investment and research intensification. The last two sections present likely factors that have affected technological activities and performance of firms operating in those two industries; both domestically and globally. Such factors include environmental issues, the advent of alternative energy innovations, long-standing economic stagnation, and the emergence of international competitors.

The third chapter reviews the literature on the importance of R&D investment on labour productivity and profitability. Since the bulk of the ensuing empirical analysis makes extensive use of these indicators, they are clearly defined and the theoretical foundation underlying the relationship between technological investment and performance measures is established. Whilst some other empirical studies apply empirical investigation at the industry or national-level, firm-level data is used to construct the variables in this thesis and therefore a justification for this level of analysis is presented. Then the analytical framework and empirical applications regarding the relationship between the firm's R&D effort and productivity and profitability measures are discussed in depth. As has been emphasised, technological effort undertaken by the firm can be associated with three possible elements; internally generated innovation, a certain degree of technological diffusion to others, and the intra-firm competencies to exploit external innovations. To address the many aspects of R&D, measurement of technological externalities and absorptive capacity are considered. The following section surveys the literature focused on empirical studies that establish the interrelation between R&D and productivity and profitability and in particular those using Japanese data at both aggregate and micro-levels. The final section of the chapter determines the gaps in the existing literature and presents the contributions of the thesis.

The fourth chapter describes the construction and main characteristics of the data. The chapter begins by explaining the sources and sample selection. The unconsolidated financial data are preferred and the rationale for this is provided. As the data sample is not without flaws such as missing observations and outliers, the approach to rectifying this is explained in detail. The final sample used in the empirical analysis comprises comparable firm-level panel data on 325 publicly listed companies. Segregated into two groups according to NAICS 2007's two-digit industry-classification, the data includes 325 electronics firms and 89 automobile firms. These firms have complete information on R&D expenditures, net sales, profit before taxation, number of employees, tangible fixed assets, total assets, and total liabilities for the period 2000-2009. These micro-level data are accompanied by macro-level data on hours worked and deflators that are used in the subsequent computation of additional variables, in particular, labour productivity, profit margin and R&D intensities. All definitions are given as are descriptive statistics and correlations between variables.

The subsequent three empirical chapters are the core components of this thesis. These chapters share some similar features. Each starts with outlining the econometric and methodological framework. This is followed by diagnostics tests prior to estimation; unit-roots, heteroscedasticity and serial-correlation are checked. Then the empirical results and poolability tests are presented. The last empirical section is dedicated to making inferences from the key findings.

The fifth chapter explores the dynamic structure of the R&D-labour productivity relationship. While the empirical model of this chapter uses the Cobb Douglas production function framework that has been used comprehensively in the existing literature, intra-industry spillovers, distributed lag structure of R&D variables and a control variable for firm size are incorporated. The model considers labour productivity growth as a function of current and lagged values of R&D intensity, tangible capital intensity growth, and market capitalisation growth. Later, inter-industry spillovers and absorptive capacity are taken into account as additional determinants in order to observe their explanation of variation in labour productivity growth. The estimates are based upon conventional econometric techniques; random and fixed effects, which are appropriate to panel-data. The results show evidence of a lagged impact of R&D activities on labour productivity growth. For both industries, these effects appear to take roughly one year to show up in the rate of labour productivity increase. In addition, the immediate impact is negative to production efficiency, possibly owing to the time-gap for the firm to reorganise or adjust its production to suit either new production

innovations or new technological embedded products. As far as technological spillovers and absorptive capacity are concerned, these variables exert a remarkably greater impact on labour productivity than internal R&D. Even so, patterns in the relationship between technological spillovers and labour productivity appear to be dissimilar between the two industries. For example, intra-sectoral externalities are shown to be negative for automobile firms whereas such spillovers display a positive impact in electronics companies. Findings on absorptive capacity support the view that the firm's own R&D is crucial for the development of internal-capability to absorb technological externalities. Here also, further gains in labour productivity are a consequence of the enrichment of absorptive capacity, which could be actually attributed to technological effort made by the firm itself.

The sixth chapter continues the investigation of the contribution of R&D to firm performance. Particularly, it attempts to shed light on the profitability effect of own R&D, technological externalities and absorptive capacity. As a departure from traditional panel-data estimators, this chapter utilises dynamic panel-data estimators and includes a lag dependent variable as a regressor. In this regard, the fundamental empirical model demonstrates profit margin to be a linear function of its lagged level, present and preceding R&D intensities, labour productivity, capital intensity as well as control variables for size, age and leverage. As with chapter 5, technological externalities and absorptive capacity are subsequently added after the poolability tests reveal that both industries should be empirically analysed by separated models.

The 5th and 6th chapters are distinguished from chapter 7 by structure and methodology. In the former two empirical chapters, there are two different estimation results shown. The first are obtained from the empirical model without research externalities and absorptive capacity whereas the second are based on the revised model taking into account these additional variables. The seventh chapter examines determinants of the firm's technological efforts. In particular, it considers profitability as a potential variable that influences incentive to engage in internal R&D activities. Along the lines of chapter 6, the dynamic panel data regression is implemented. The empirical framework is an autoregressive regressive specification in which preceding R&D is also shown as one of the independent variables. The question of whether profit change brings about higher own R&D intensification is addressed. The main findings of this chapter illustrate both similarity and disparity between two technology-intensive sectors. While the impact of profitability on R&D investment is negative in both industries, this could be interpreted as the potential for a

shortfall in future profits that could eventually motivate the firm to put more emphasis on innovative activities in order to retain their competitive stance in the market. Nonetheless, the magnitude of such effect is statistically proven to be relevant for electronics firms only.

The final chapter summaries the empirical results and relates these to the existing literature, emphasising the contribution of the thesis.

Chapter 2: Industrial Background

Introduction

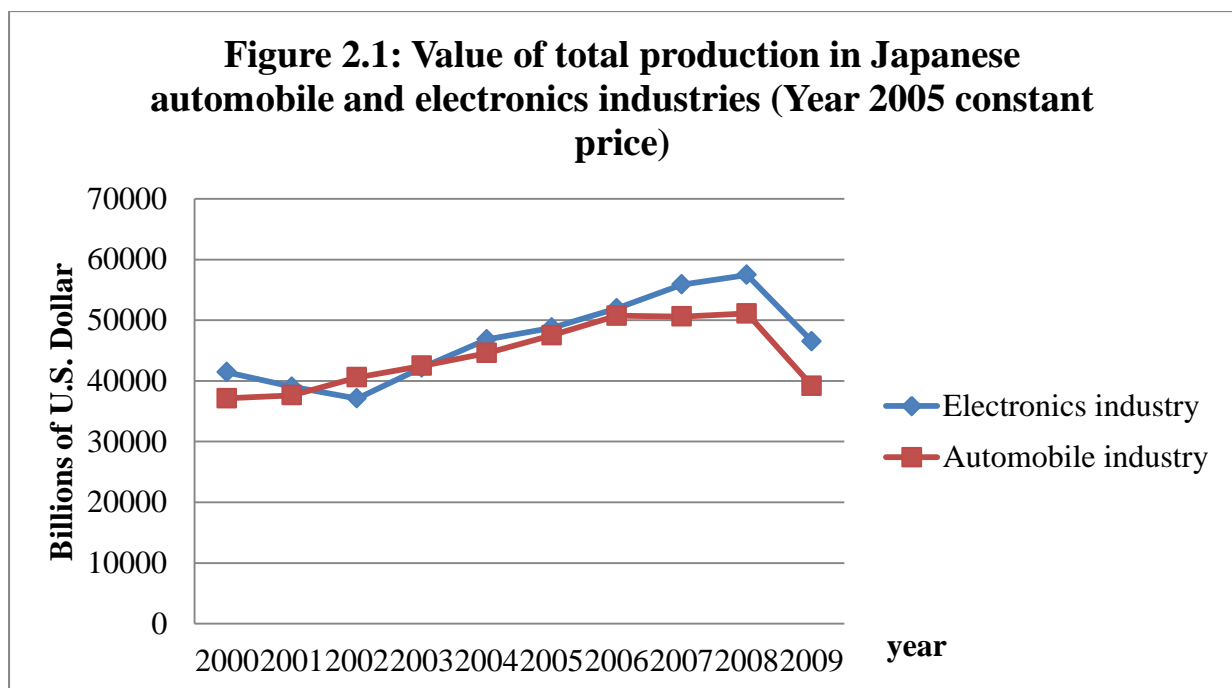
This chapter provides an overview of the two industries that are the focus of this thesis. The first section outlines the growth of both sectors from the end of the Second World War to the present. Then the development of the sectors is discussed before explaining their importance in the overall economy, the major competitors in each sector, their patterns of trade with the rest of the world, the importance of R&D and the different organization structures within them. It also compares the differences between them and the networks that link the two. Finally, the challenges that face the automotive sector in particular are discussed as renewable energy is limited and alternative forms are developed. This is a major issue as the environment is a global responsibility. This chapter is central to the overall understanding of why these two sectors combined are important to the economy of Japan and thus provide a foundation for the further study of labour productivity and the relationship between productivity and performance. These will be described in more detail in the next chapter when the research questions are developed.

2.1 Background to the development of the Japanese automobile and electronics sectors

This section provides an overview of the automobile and electronics industries in Japan and discusses the industrial structure and importance of these manufacturing sectors in the macro-economy. Whilst both sectors appear to share similar characteristics in terms of their development path and consolidated hierarchical structure, organisational diversity and the destination of products differ. To Bailey et al. (2007), the electronics industry in Japan primarily consists of four sub-segments; component makers, office related product manufacturers, large conglomerates offering products that span various electronics categories and other specialised electronics manufacturers.

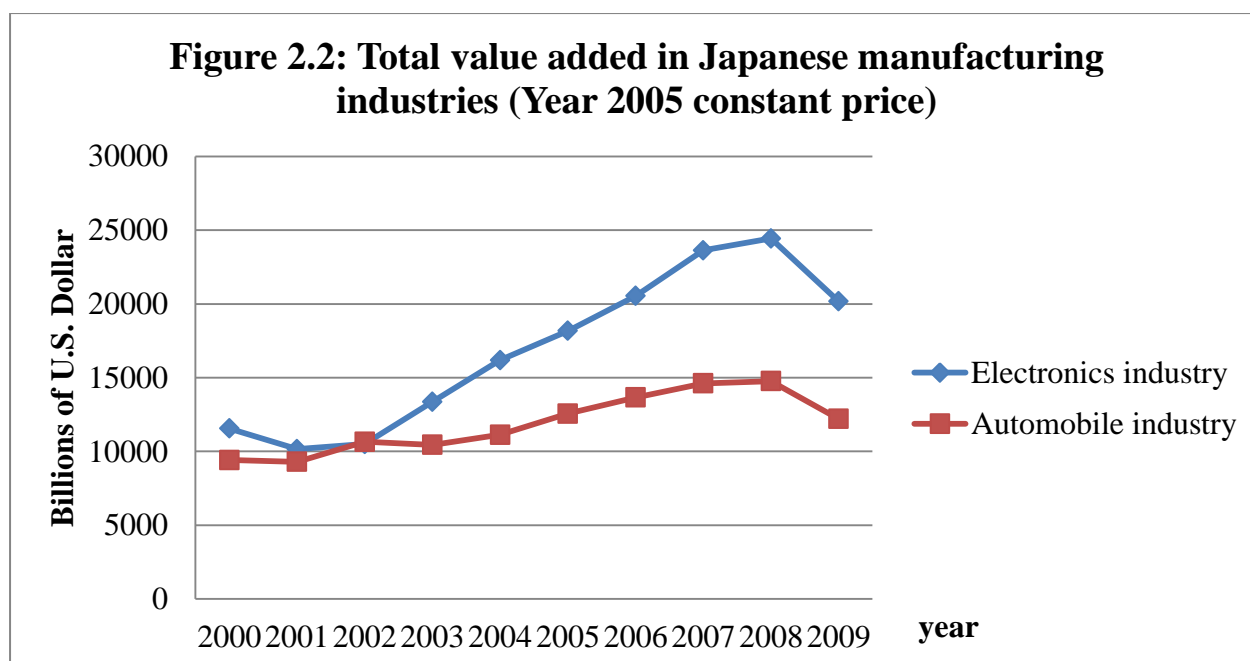
The origins of the automotive sector could be traced to the period before the second world war, with a small number of established domestic car producers and part suppliers, some being joint ventures with foreign firms. The post-war period saw the gradual advance of the industry towards consolidating the home market with products equivalent to those of foreign manufacturers and with an export orientation. Aided by the oil price shocks of the 1970s, Japanese car manufacturers began to focus on international markets. Their vehicles have a reputation for being relatively affordable, low maintenance and high quality (Fuss and

Waverman, 1991). The electronics sector developed in the aftermath of World War II. As with automobiles, the priority was initially the domestic market where demand grew rapidly until 1960s and then moved to the international market by 1970. Exports for the industry were particularly successful during the 1970s and 1980s. The commercial application of transistors and semiconductors, combined with the consistent pursuit of miniaturization and cost-efficiency, helped bring the Japanese electronics sector to the forefront of the international electronics market throughout the second-half of the 20th century as their products could be manufactured relatively fast and offered both high quality and cheaper prices than foreign competitors. As a result of productivity in semi-conductors and applied products, innovation breakthroughs were evident in hardware, particularly portable audio devices, television, camcorders and video-recorders.



Source: STAN database for structural analysis ISIC Rev. 3(OECD, 2012)

Notes: Gross value of industrial output in current price values with 2005 as base year.



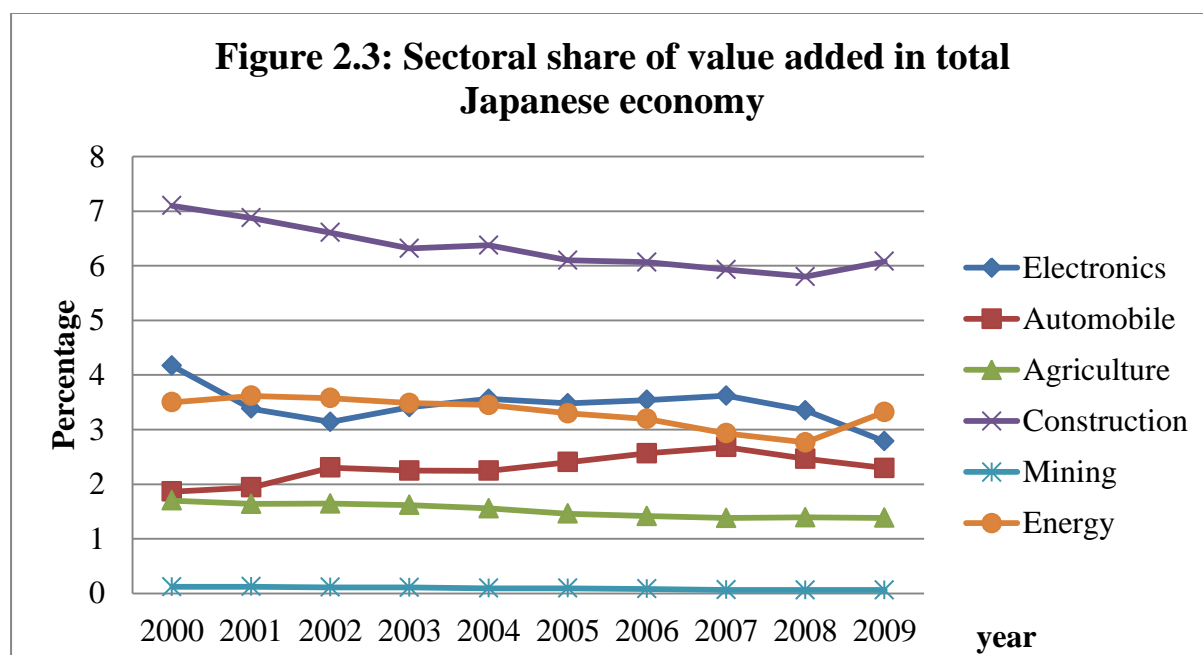
Source: STAN database for structural analysis ISIC Rev. 3(OECD, 2012)

Notes: Value added is computed from the difference between revenues and cost of materials and services. Total value added is in current price values with year 2005 as reference year.

Up until the onset of the global economic recession in the late 2000s, production in both industries followed an overall increasing trend. Figure 2.1 shows that the value of total goods manufactured in the electronics and automotive sectors rose gradually throughout the first half of the decade before reaching a plateau and then fell at the start of the global recession. The growth of both industries is similar with the electronics sector having a relatively higher rate of increase by the middle of the 2000s. Nevertheless, the rise in production in both sectors was offset by the recession and by 2008 and industrial production fell to almost the same level as at the beginning of 2000. Equally, industrial value added in the two industries reflects a rise shown in Figure 2.2. Noticeably, value added in the electronics sector rose substantively whereas the automobile sector also rose but at a lower rate of growth. As with total industrial production, value added in both sectors declined during the global economic recession. The trends from Figures 2.1 and 2.2 suggest that the domestic manufacture of electronics and automotive products continued to expand despite the transfer of assembly plants to other low cost nations such as China and Thailand.

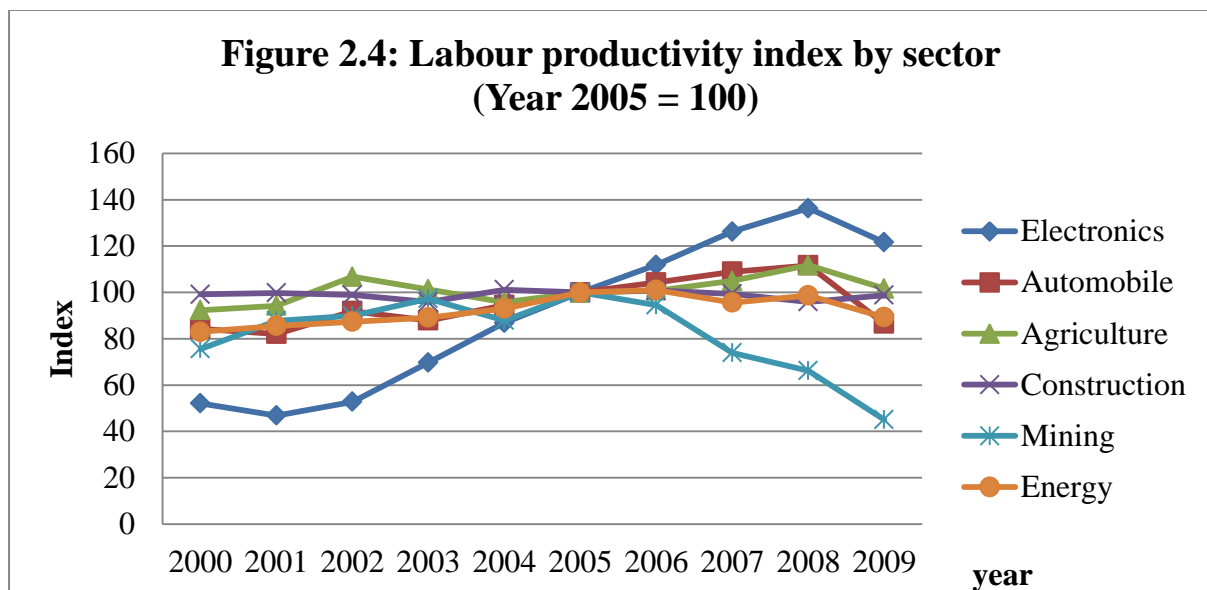
Figure 2.3 shows the total value added in the Japanese economy contributed by the electronics and automobile industries. This was different during the first two years of the

decade but from then on the sectors began to move together and at the end of the period have a similar rising share in gross value added in the economy. Along with total production and value added generated within these two industries, their value added share in the economy fell during the economic problems in late the 2000s. It is clear that the share in total value added by the end of the 2000s in the electronics industry dwindled to about 6% from the level of around 7% in year 2000. On the other hand, the share of automobile gross value added had an upward trend throughout the 2000s. Compared with other major sectors in the economy, electronics and automobiles are considerably larger than agriculture and mining but do not contribute as much value added as construction that is predominantly active in the domestic market. The construction sector generally accounts for the largest share of gross value added created in the Japanese economy throughout the 2000s, in spite of its gradual decline. The energy sector, which focuses on supplying electricity, natural gas and water also mirrors the overall trend in the construction sector. Its share in total gross value added is mostly higher than the automobile industry but lower than the electronics sector from the second half of the decade until the beginning of the global recession.



Source: Structural analysis (STAN) indicators (OECD, 2012)

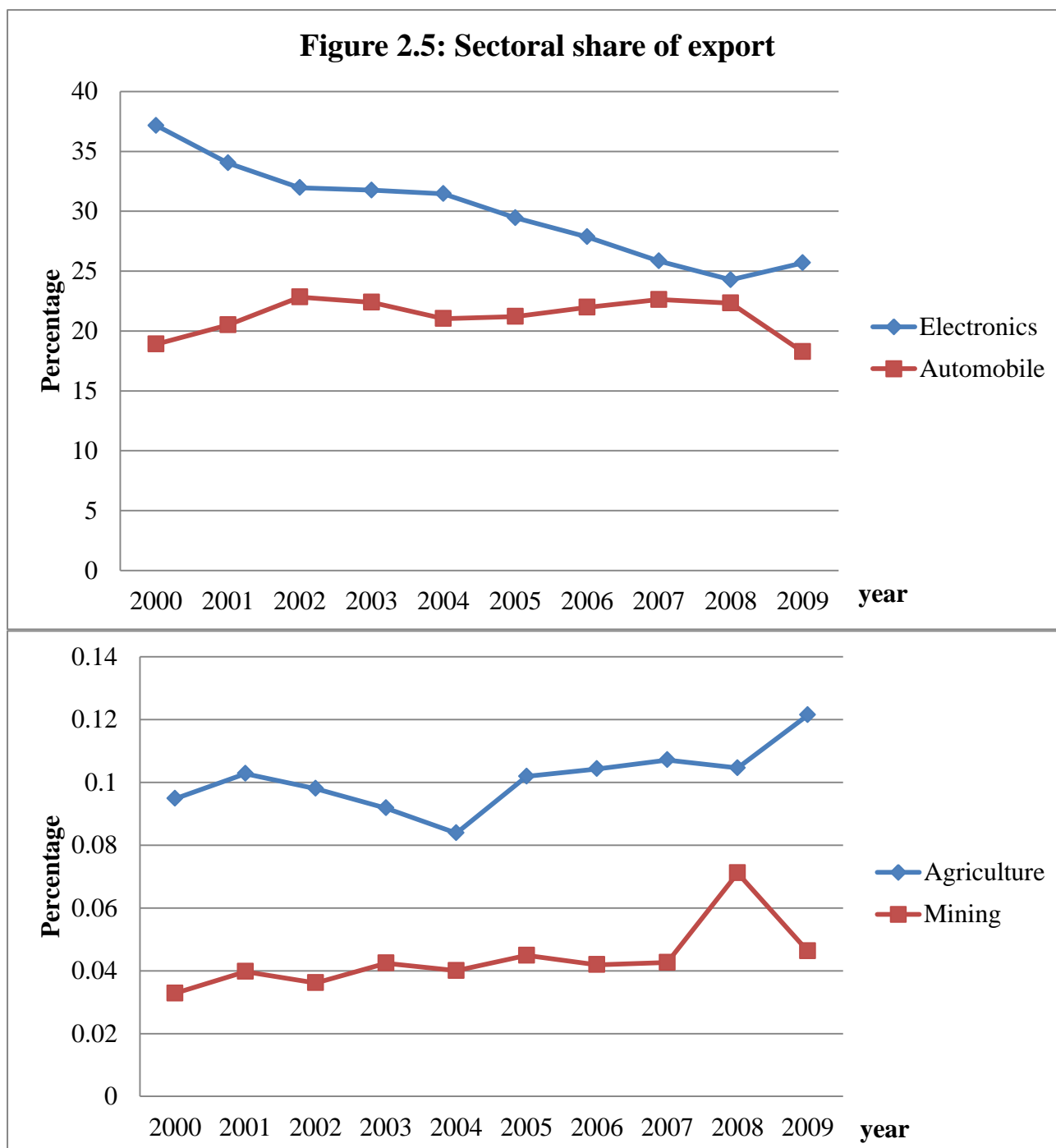
Notes: This indicator is calculated from the ratio of value added by each sector to gross value added in the economy.



Source: Structural analysis (STAN) indicators (OECD, 2012)

Notes: Labour productivity is calculated from the sector's value added divided by total amount of employment. For each year and sector, labour productivity index is measured with reference to year 2005 whose index equals 100.

Labour productivity reflects efficiency in production. Prior to the global recession, it is shown in Figure 2.4 that both the electronics and automobile sector experienced steady growth in the level of value added per employee with the former having a remarkable rate of increase. Nonetheless, it is also obvious that both industries did not have a clear lead in labour productivity over other sectors during the decade. In fact, the electronics industry had somewhat lower labour productivity than automobiles and other non-manufacturing sectors as early in the 2000s but the gap became consistently narrower over time. Subsequently, the electronics industry attained relatively higher labour productivity in comparison to the other sectors. This can be explained by the sharp rise in industrial value added during the same period of time. In spite of persistent growth, labour productivity in the automotive industry is approximately equal to that in the agriculture, construction and energy sectors.



Source: Structural analysis (STAN) indicators (OECD, 2012)

Notes: Export share of each industry as a percentage of total exports of the Japanese economy.

Both the electronics and automobile industries are export-oriented. Figure 2.5 shows that exports clearly surpassed other sectors and the combination of both industries account for half of the entire export value in the Japanese economy. Given their contribution to gross national exports, it is clear that these manufacturing industries are pivotal to the exports of Japan. However, the share of the electronics industry in total Japanese exports has been in decline since 2000. As of 2009, the electronics industry share of total exports in the economy deteriorated about 10% from the level at the beginning of the decade and can be attributed to increasing competition from foreign rivals. Whereas the share of automobile exports was roughly 21% of total exports in the economy, the trend is shown to be fluctuated slightly for most of the time period. The onset of the global recession has led to the contraction of automobile exports between 2007 and 2009 and the automotive share in total exports fell to a level lower than in the year 2000.

2.2 Industrial organisation

In both industries, the production system has been built substantially around just-in-time (JIT) methods. The just-in-time production strategy refers to the emphasis on inventory cost reduction and the elimination of waste and the buyer-supplier relationship. Its primary aim is to eliminate not only the cost associated with keeping excessive inventory but also all costs related to production procedures (Turnbull, 1988). To handle unnecessary inventory, the objective is to reduce stocks to the minimal amount sufficient to keep the production process going. Within the context of JIT, waste stems from faults in parts and materials. To eradicate such product defects in production processes, total quality control during purchasing and production is highlighted. As quality is improved, the time and cost involved with rearranging production as well as dealing with consumer complaints can be lessened. For JIT to be implemented effectively, manufacturers seek to establish good communication and long-term relationships with their suppliers. According to Turnbull (1988), delivery disruptions, quality problems and engineering changes are promptly reported meanwhile both parties work together to cope with technical difficulties. In this respect, producers source from suppliers chosen for their high-quality materials and punctual delivery (Kaneko and Nojiri, 2008). In accordance with the JIT approach in production those suppliers prone to make frequent deliveries of parts and materials while altering their production sequence to match the production schedule of the manufacturers assembly plants (Altenburg et al.,

1999). Further, a JIT strategy is implemented in accordance with an approach to long-term gradual improvement in skills development. Workers are provided with expertise in multiple jobs including quality inspection during the production process. Through various training schemes multi-skilled workers are in control of numerous successive steps that are part of the entire operation.

The adoption of just-in-time methods across both industries has brought about increased efficiency derived from considerable cost and inventory reduction (Lieberman and Demeester, 1999). As the exact quantities of high quality raw materials and components are delivered in time for each stage of production, the firm is able to secure time economies from the use of capital and labour inputs (Sayer, 1986). In other words, a greater number of manufacturing operations conducted in the workshop could be achieved with the same amount of labour input, thus increasing the labour productivity level of the plant. Just-in-time strategy is implemented in conjunction with local and complex industrial organization in the two industries.

Both sectors are noted for the prominent existence of vertical keireisu, defined as a manufacturing conglomerate that comprises of affiliated firms interlocked with each other and with close business relationships and shareholdings (Gilson and Joe, 1993). Vertical keireisu is a production network that centres on a major or core manufacturer and includes various suppliers and subcompanies (McGuire and Dow, 2009). In the automobile industry, the networks within the sector are strong as car-makers and component suppliers have established close relationships and collaboration involving transactions, joint product-development and the accumulation of transaction specific skills or facilities (Asanuma, 1989). To Turnbull (1988), the structure of the automobile industry is highly integrated and pyramidal. Assemblers of motor vehicles and commercial trucks such as Toyota, Honda, Nissan and Hino are at the top of production chain. In addition, there is also a series of proprietorships among Japanese automakers as some smaller independent producers are subsidiaries of automotive industrial groups centering on prominent car manufacturers. For instance, the Toyota Motor Corporation has a majority shareholding in the Daihatsu motor company and Hino motors, makers of small economy cars and trucks and of buses respectively. Whilst the network of suppliers are positioned at the lower tier, major suppliers for each car manufacturer acquire long-term single supplier contracts to supply automakers with critical components and systems. Major suppliers are characterised by their scale of operation and level of technological sophistication. Moreover, car manufacturers may have

strong ties with major suppliers as both could be part of the same industrial group. In this respect, a number of suppliers might be subsidiaries or affiliates of an automobile producing firm but the former are legally separated from the latter regarding their business operations. One example is the Honda motor company, which has shareholdings both wholly and partially in a group of firms supplying components such as shock absorbers, transmissions and brake pedals. Linkages between auto assemblers and major suppliers create a mutually interdependent relationship via crosswise-holdings of shares. Thus, the suppliers rely on the carmakers for sales and finance capital whereas carmakers depend on suppliers for technological progression and uncompromised quality (Lin, 1994).

Finally, below the supplier level are subcontractors that are the bulk of car producers and suppliers of source materials and intermediate goods. Subcontractors manufacture small and basic parts that require relatively more labour intensive production. The lowest tier in the automobile industrial structure is the material industries that supply raw materials required in the production processes of car assemblers, suppliers and subcontractors. Examples of these raw materials include iron, non-ferrous metals and resin.

The electronics industry is similarly characterised by an extensive network of affiliate companies and subcontractors (Chon, 1997). This industry is dominated by the presence of large conglomerates, which substantially make use of suppliers and various affiliates. A range of products is manufactured by large electronics firms, which are orientated towards multiple high technology sub-sectors (Florida and Kenny, 1990). In particular, the same companies that produce consumer electronics goods such as television and stereo systems, also make computers, telecommunication equipment, industrial robots, electronic precision instruments (Gregory, 1986; Steinmueller, 1990). As Engas (1987) notes, the business operations that span across various electronics related products yield advantages in both technological advancement and manufacturing. Thus, the amalgamation of high technology goods and consumer electronics products in the same firms facilitate the easy diffusion of technical development into the production of mass market consumer goods. This leads to widespread sales in the goods markets that in turn helps fuel further innovations (Freeman and Christopher, 1987). A plethora of products covering multiple electronic goods provides the channel for components that electronics conglomerates source from their supply and subcontractors (Ferguson, 1988; Okimoto et al., 1984). Furthermore, like the automobile industry, the electronics sector is characterized by highly structured just-in-time linkages

between electronics conglomerates and their subsidiaries, suppliers and subcontractors (Sheard, 1983; Swyngedouw, 1987).

Despite seemingly similar R&D activities, export orientation and a system of conglomerates that dominate industrial organisation, the automobile and electronics sectors differs in term of their structure. Aoyama (2000) describes the automobile industry as primarily involved with assembling single finished products, particularly both passenger and commercial vehicles, whereas the electronics industry manufactures an assortment of intermediate and finished products for both consumer and industrial use. In addition, the industrial organization of the electronics sector is more horizontal owing to their range of multi-product goods. Products from the electronics industry diverge in term of their technological content, ranging from semiconductors, industrial automation systems to home appliances. As such, some products are distinguished by their technological requirements while others are interconnected by their common use of similar technologies in the production processes.

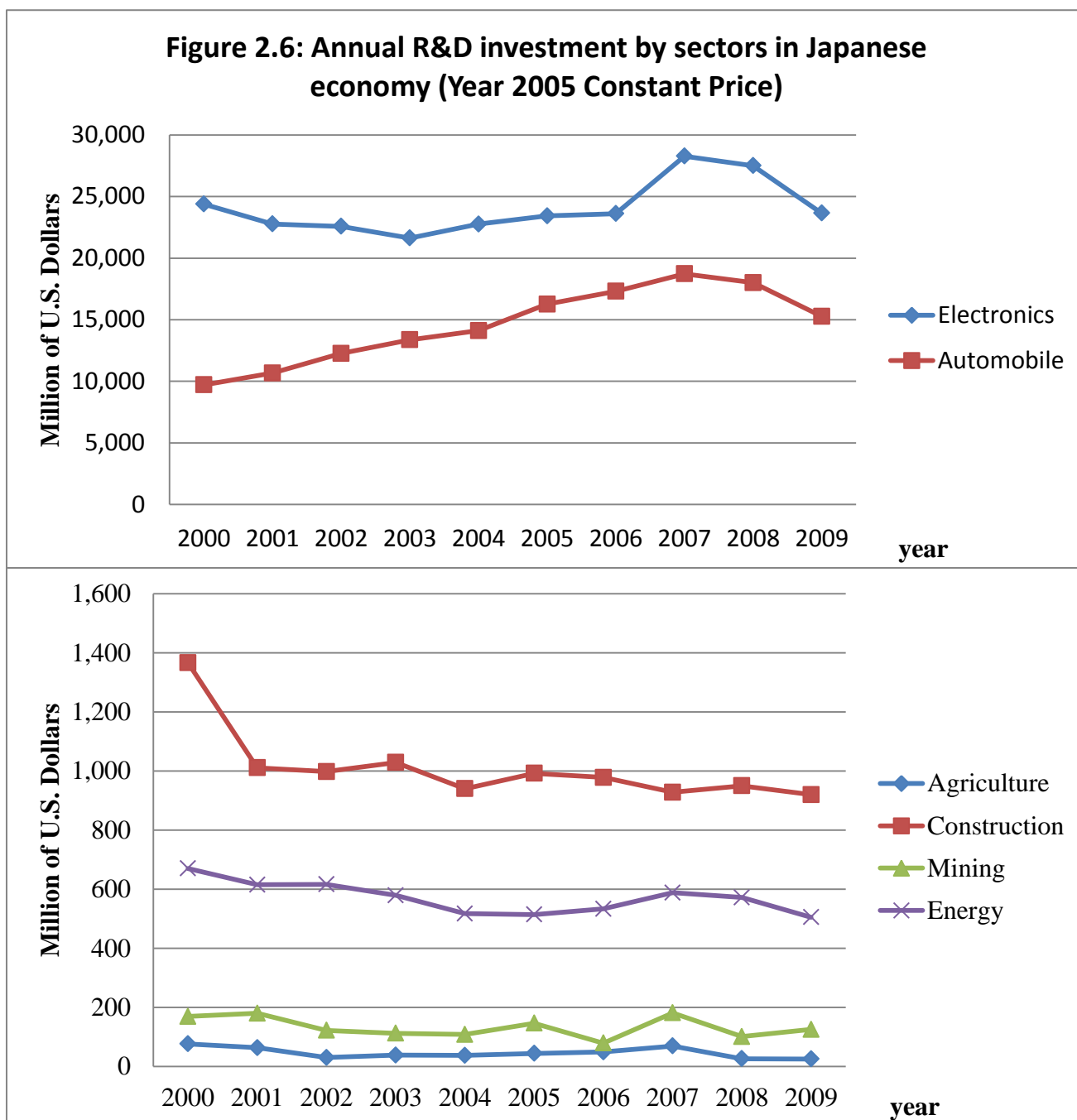
2.3 Research and development in the Japanese electronics and automobile industries

Using industry-level data, this section outlines the development in R&D expenditure and productivity for the electronic and automotive industries in Japan. The period of interest is the decade 2000 to 2009, which saw the protracted consequences of the economic stagnation in Japan from the 1990s and includes the global economic recession. It is also the period that firms in both sectors had to increasingly competition from abroad. The situation in both sectors reflects the climate facing the economy as a whole, particularly given their importance to the export-orientation of Japan and this was the reason they were chosen for special consideration in this thesis. These industries have long been associated with technological innovation, and there is a long history of creativity and the development of new products and improvements in existing ones. However, although there has been extensive investment in R&D this has not resulted in increased profitability and it has proved difficult to slow the loss in market share to low cost competitors.

As technology-intensive industries, both distinguish themselves from the rest of the manufacturing sector by their high expenditure on R&D activities. Between 2007 and 2010, the electronics and automotive industries account for approximately 24% and 19% of total R&D investment made by the entire manufacturing sector in Japan (JAMA, 2012). As shown in Figure 2.6, gross R&D expenditure is also considerably higher than other sectors in the

economy. For example, automotive sector R&D in 2000 is about nine times higher than that of the construction sector. Even during the economic downturn of the 1990s, the automobile industry undertook an increasing level of R&D investment before it was reduced in 2008. The pattern is slightly different in the electronics sector as this did not continue as long and the level of R&D expenditures marginally fell in early the 2000s against the backdrop of the continued economic stagnation from the 1990s onwards. The downward trend in the level of R&D spending is in fact consistent with the similar trend in gross value of production and value added created in the electronics sector as shown earlier in figure 2.6 and 2.7. These trends perhaps reflected the decline in price of computers and telecommunications hardware equipment that affected Japan in 2001 (BBC News, 2001; Tanikawa, 2001). Even so in later years, the electronics R&D began to ascend continually before dwindling in the wake of the recent worldwide economic downturn.

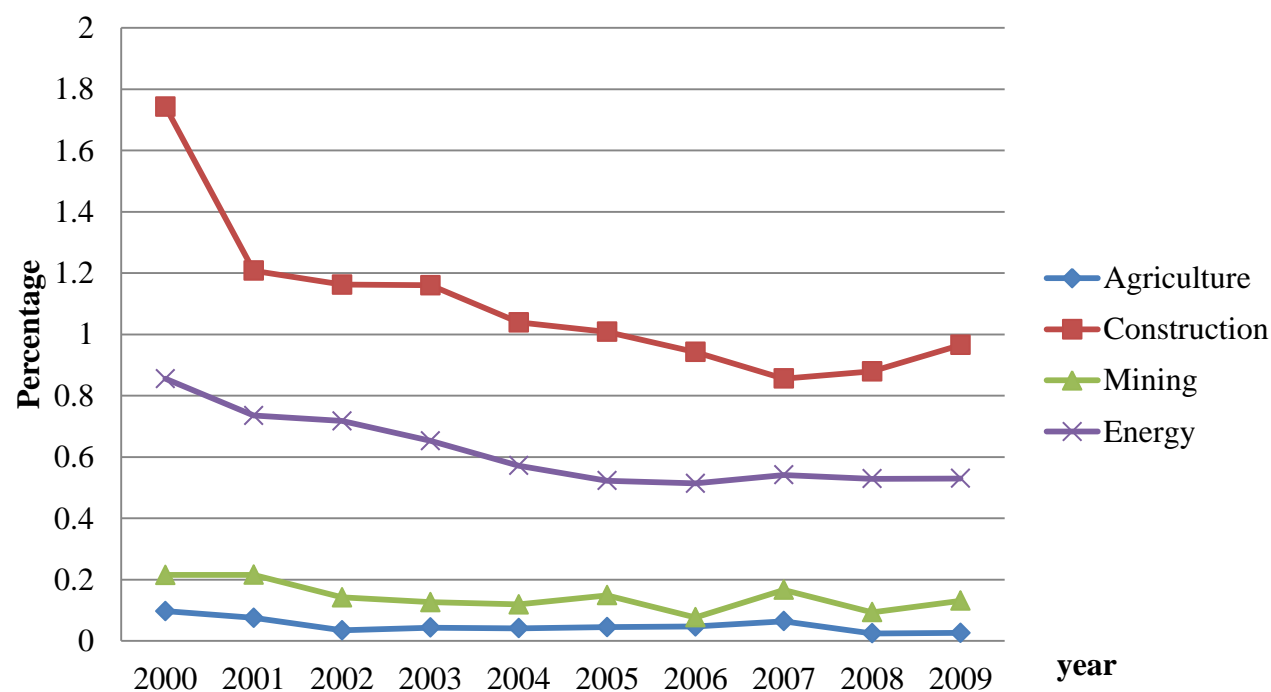
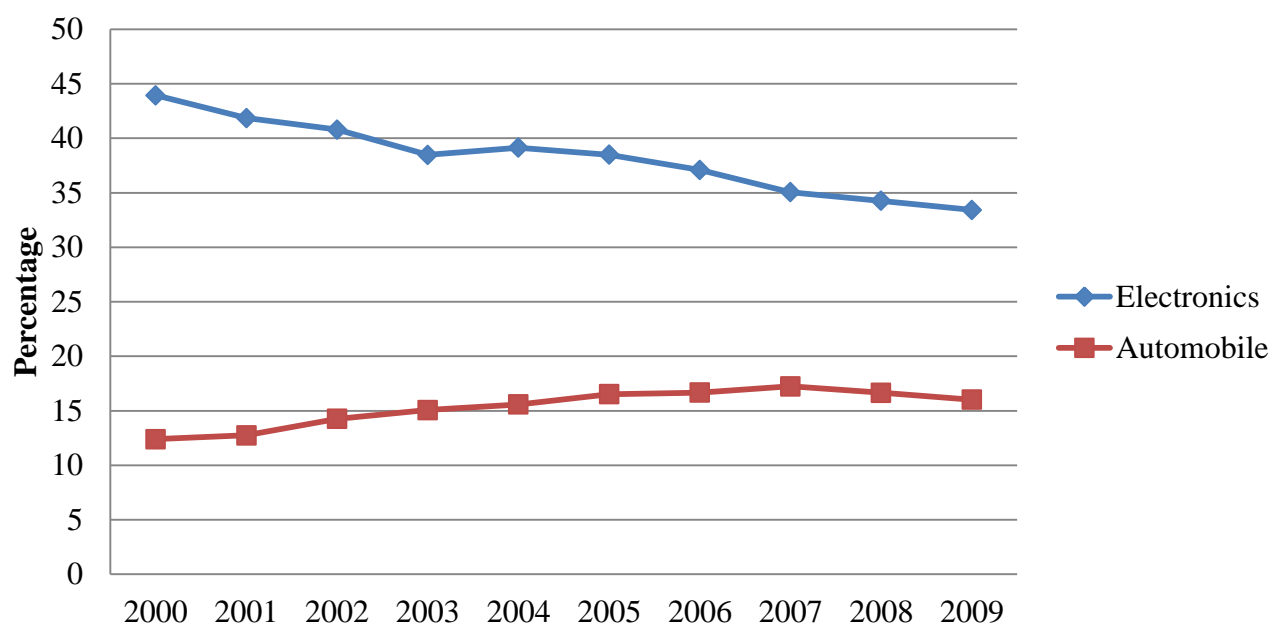
The rise in R&D investment is paralleled by the degree of R&D intensification. Figures 2.8 and 2.9 show that with respect to R&D as a percentage of gross value of industrial output, automotive firms gradually strengthened their research efforts throughout the period. The trend in R&D intensity suggests that R&D investment has become vital in relation to the production of both vehicles and components. This is not surprising since the automobile industry has been moving towards the development of environmental-friendly and fuel economical technologies, which will be discussed in the next section. In addition, the percentage of R&D expenditure as a share of value added demonstrates similar a pattern. Along with the change in automobile industrial value added, the upward trend suggests that the R&D spending augments the value of products and services generated within the automobile industry. That is, R&D investment increases the difference between gross revenue in the total automobile industry and the cost of manufacturing goods. Figure 2.7 shows the ratio of each sectors' R&D and the total R&D in the Japanese economy. Echoing the level of industrial R&D expenses in Figure 2.6, the shares of both the electronics and automobile industries' R&D spending in the whole economy are higher compared to all other sectors. Nonetheless, it is noted that the share of electronics R&D was in continual decline over the decade while there was a gradual increase in the share of R&D in the automobile industry.



Source: STAN R&D expenditures in Industry ISIC Rev. 3 (OECD, 2012)

Notes: Industrial R&D expenditures in real values with 2005 as the base year.

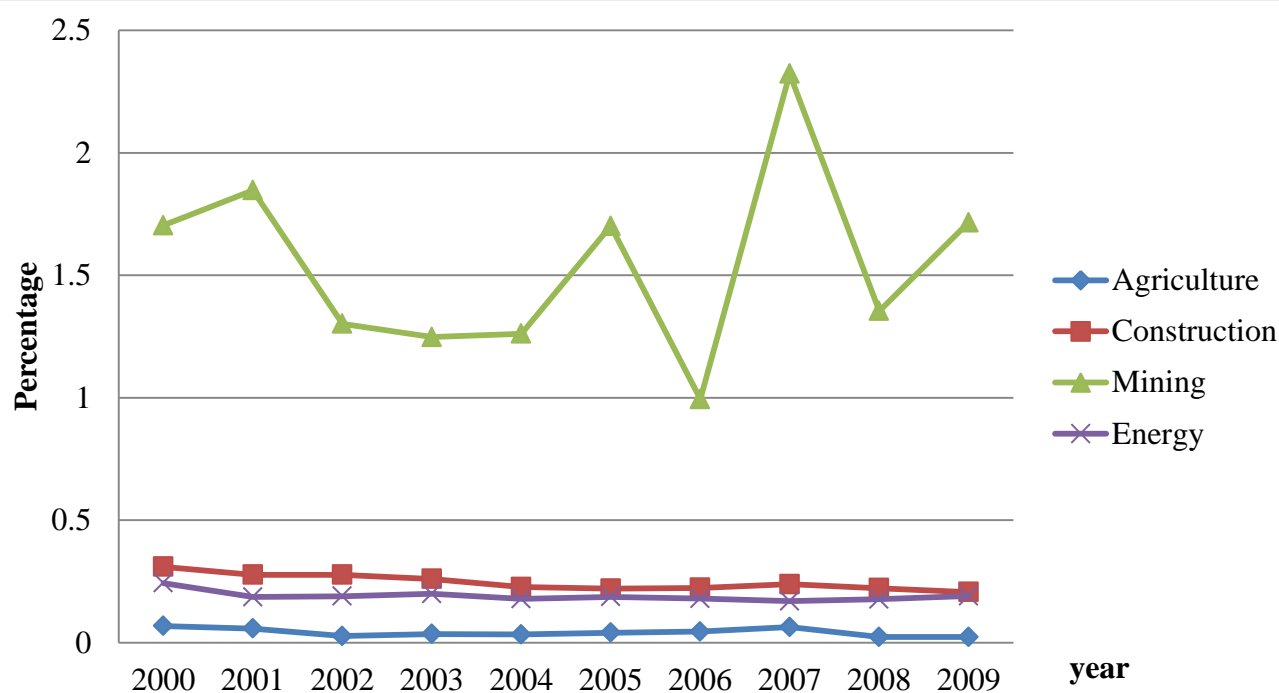
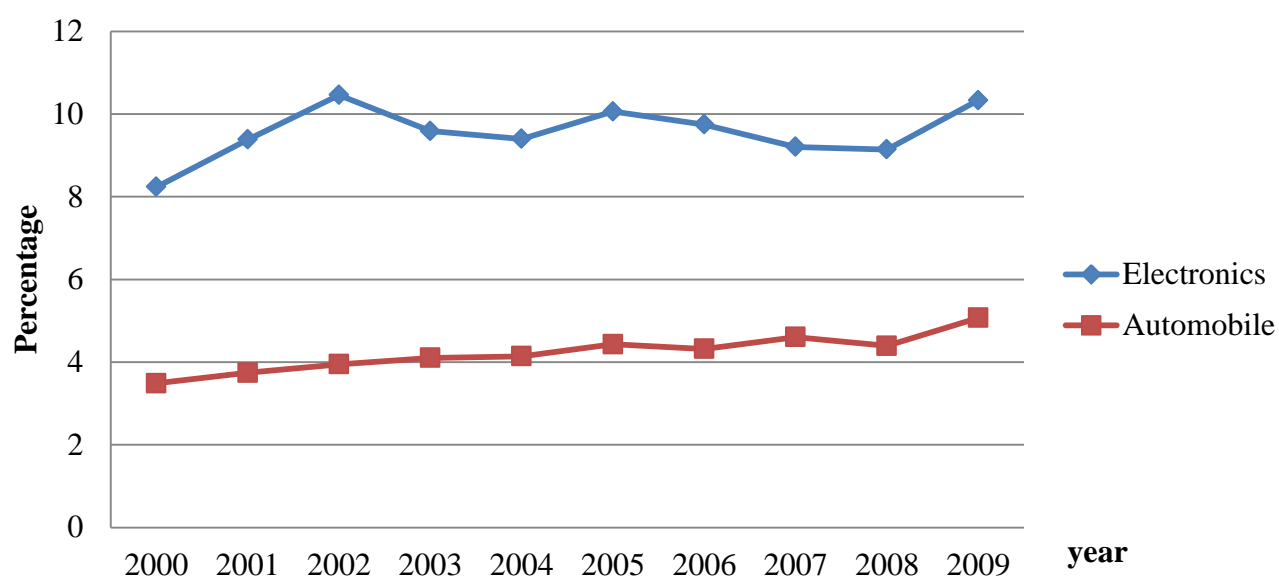
Figure 2.7: Sectoral share of R&D investment in total economy



Source: Structural analysis (STAN) indicators (OECD, 2012)

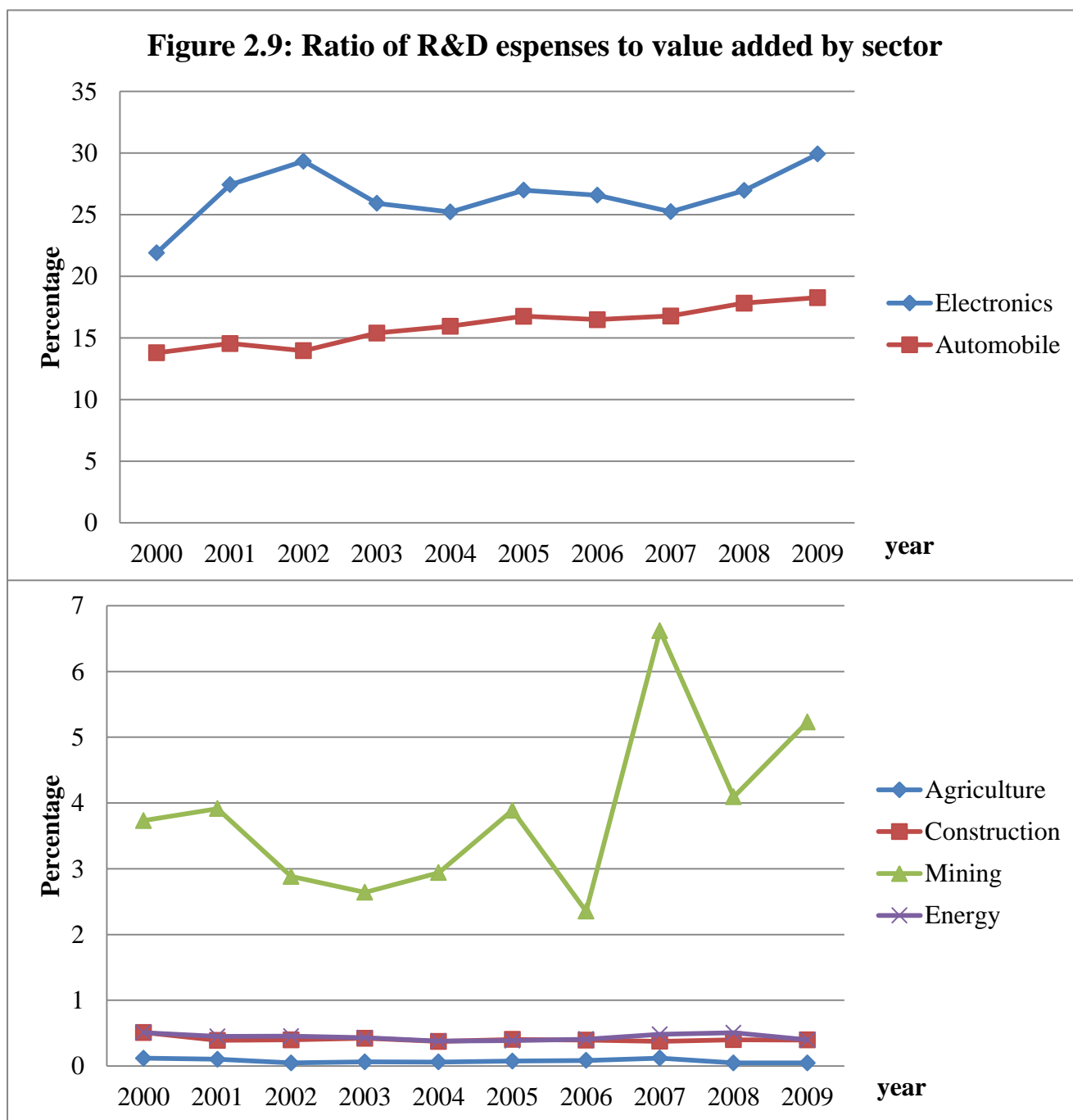
Notes: Industrial R&D expenses for each sector as a percentage of total R&D expenses in the economy.

Figure 2.8: Ratio of R&D expenses to total production value by sector



Source: Structural analysis (STAN) indicators (OECD, 2012)

Note: This R&D intensity is equivalent to industrial R&D expenditures as a percentage of total value of output in each sector.



Source: Structural analysis (STAN) indicators (OECD, 2012)

Note: This R&D intensity expresses amount of industrial R&D investment as a percentage of gross value added in each sector.

2.4 The importance of environmental concerns and alternative energy technologies

Growing awareness of global environmental issues as well as industrial and consumer experiences of increased energy price rises are pivotal factors that drive the car-making industry to develop better petroleum-fuel efficiency and alternative fuel technologies. Automotive firms in Japan are not only confronted by consumer demand for fuel efficient cars that face all car-manufacturing sectors across the world, but also by increasingly stringent state requirements on gas mileage proficiency, vehicle exhaust emission regulation and CO₂ reduction targets. To handle with new challenges and stay competitive in the market, research into advanced vehicle technologies is of crucial importance in order to procure innovations such as improved motor efficiency, the use of light weight materials and enhanced vehicle-body design.

Furthermore, basic R&D activity in the automobile sector is committed to developing alternative energy vehicles such as Hybridisation, hydrogen fuel-cell and electric cars. These new types of automobile technology need to be rigorously researched in order to improve their applicability and effectiveness at a price that consumers are prepared to pay. For instance, maximum driving range, life-span and charging time of lithium-ion batteries developed for electric-drive vehicle has become a primary goal. Much has already been done and there is a steady improvement in these areas. However, this investment is very long term and the path of development and modification may take years and necessitates sizable resources. There is also no guarantee of success following these R&D activities and they are not without the risk of failure. Thus, as with any long term R&D programme, a successful innovation can only lead to increased profitability if the economic environment exists to enable firms to exploit their results.

The constant innovation in the field of electrically powered vehicles suggests an increased share of electronics-related components, particularly battery technologies, in the manufacture of new vehicles. In anticipation of this, a number of electronics components and parts have been incorporated into vehicles such as navigation and audio systems, electronic stability control (ESC) and cruise control systems. Electronics account for approximately 30% of the cost of an automobile and it is likely that such share will increase to more than half with the rise in the application of electric vehicles and their steadily improved performance (Santiago, 2007).

2.5 The long-term effect of prolonged economic sluggishness in the market

A) Automobile industry

After the period of continuous growth, the economic bubble burst in the early 1990s. This led to a shortfall in domestic demand for new vehicles, which was followed by a decline in sales and firm profitability. In the waning economic climate, consumer preferences in the home market shifted towards smaller and more affordable cars that meant that only minimal profit margins could be realized. The rise in labour and material costs previously overlooked in the light of consistent growth in sales performance also undermined the profitability of car manufacturers. Levels of domestic sales deteriorated substantially from earlier levels and remained stagnant during the 1990s. Passenger vehicle sales began to recover by the early 2000s, albeit at relatively lower levels and the rate of increase remained below the pre-1990 level. However, although passenger vehicle sales were recovering this was offset by the global economic recession and the steady decline in sales of commercial vehicles (JAMA, 2010). As a consequence, the general trend throughout the 2000s was an overall decline in domestic sales.

While the domestic market condition was hindered by the collapse of the economy, performance at transnational markets was still not affected. This is in fact in line with the continuing growth in production volume until the late 2000s. Nevertheless, by the second half of the 2000s, the constant appreciation in the value of the national currency and the high cost of steel and other materials diluted the profits of Japanese automotive companies. These two factors were reflected in the effect of the economic recession worldwide and resulted in a sharp drop in demand for vehicles in major international markets such as the United States.

B) Electronics industry

In spite of shrinkage in the domestic economy during the 1990s, demand in both the domestic and international markets grew, but at a much lower rate than in the late 1980s (Motohashi, 2004). Particularly notable is that the economic recession in Japan drove down profitability in the electronics industry in spite of high level of research and development activities. Tokuga and Tanaka (2011) also remark on the fact that the amount of R&D spending consistently increased despite the economic difficulties during 1990s, although the rate of growth declined. A further difficulty facing the Japanese electronics industry was the entry of new and innovative firms during the period of economic growth. This was matched

by the emergence of producers in neighbouring countries, many of which had much lower wages and production costs overall. In this respect, the competitiveness of the Japanese electronics industry has deteriorated, with one sign of the decline being the fall in semiconductor manufacturing activities and their failure to maintain the lead in technological development during the 1990s (Okada, 2008).

C) Response from the competitors

In respect of the automobile industry, foreign rivals reacted by reorganizing their production model. They sought to emulate some elements of just-in-time production systems and blend this with their local specific characteristics of management practice and labour conditions. The gap in productivity and vehicle quality between Japan and the rest of the world fell from the beginning of 1990s. As with Japanese car producers, foreign competitors are also driven by global environmental concerns and the rise in CO₂ emission regulation internationally. Automobile firms in North America and Europe have also stepped up their technological research, particularly in engine fuel efficiency and alternate energy vehicles. Some foreign automobile manufacturers have acquired major stake-holdings in leading Japanese firms and this allows them to achieve economies of scale and increased efficiency from joint products and technological development. For example, Renault took a 43.4% stake as part of a strategic alliance with Nissan Motors, a firm which had experienced severe financial difficulties by 1999. Through the partnership with Nissan, French Renault was able to gain further access to Japanese production systems and apply such practices to enhance their own productivity (Newsroom.nissan-europe.com, 2009). In addition, South Korean car manufacturers, which have a history of joint ventures with foreign producers and localized production, began to achieve success abroad and by the early 2000s had gained a major foothold in international markets, reflecting that of Japanese firms' earlier performance. South Korean vehicles are also known for their affordability and good quality in major global markets such as North America.

In past decades, Japanese electronics firms were able to sustain their competitiveness through technological improvements in product innovation and efficient implementation of their just-in-time production systems. Nevertheless, it became clear that international competitors were able to increasingly outperform Japanese firms operating in the same sector in terms of productivity, financial performance and brand value (Bailey et al., 2007). From the beginning of 21st century, the Japanese electronics industry has been overtaken by

Taiwanese, South Korean and Chinese producers. These new entrants in the global marketplace surpassed Japanese firms in the field that they once dominated. Thus, foreign producers not only had the advantage in technological innovations and cost effectiveness, but also penetrated into both Japanese domestic and international markets. By the late 2000s, the domestic market in cell phones was increasingly lost to foreign competitors, particularly Samsung and Apple. In the area of television, including flat panel displays and audio equipment, the sales performance and global market share of South Korean electronics conglomerates have been progressively outstripping Japanese electronics manufacturers. The profitability of foreign competitors is also much more substantive than those of Japanese electronics firms, indeed the operating profit of the prominent South Korean rival, Samsung, was more than twice as high as the aggregate operating profit of the nine largest Japanese electronics firms in 2009 (Simms, 2009).

2.6 Conclusion

This chapter has described the two industries that are the focus of this thesis, the automotive and electronics industries. It has discussed their background and structure and the patterns in their performance individually and with respect to their share of the Japanese economy. Both manufacturing industries epitomized the success of Japanese post-war economic development as they experienced rapid progression in a matter of decades and were able to either catch up with or surpass those of western counterparts in terms of production efficiency, commercialization, innovation and revenue generation. Both industries are characterized by the presence of large industrial conglomerates and interconnected by networks of suppliers and subcontractors. However, the characteristics of their end products are different. The entire automobile industry is associated with assembling vehicles and producing components designated specifically for use as vehicle parts. In contrast, the electronics industry manufactures a multiplicity of product types, ranging from consumer electronics to industrial electric tools and instruments. Therefore, the purpose of an electronics product could be as finished goods such as consumer electronics, or as intermediate goods that are subsequently used as components in production processes of other manufacturing industries, including automobile makers.

In spite of setbacks resulting from the Japanese economic recession during the 1990s, the overall trend in production and value added in the 2000s reveals that the domestic manufacture of both industries is still crucial despite the transfer of production plants in other

countries. Support for this is reflected in the growth of the value of production. Even so, comparisons with other sectors demonstrate that both the automobile and electronics industries contribute a large share in total value added in the economy. However, during the stagnation in Japan, these industries that were at the foremost in terms of R&D and productive efficiency lost their lead over other sectors.

More recently, both industries have regained their prominence and have returned to their high levels of research and development activities as shown by the increasing trend in their annual R&D expenditure and their degree of research intensification. Further, both industries are also shown to invest in R&D significantly higher than other sectors. The extensive R&D investment by the automotive industry is now driven by the realisation of environmental issues and the need for continuing development of new innovations that bolster effective fuel consumption and minimal carbon emissions. As future vehicle technologies tend to increasingly involve electronics components and systems, a great deal of outputs of R&D conducted by the electronics industry can also be implemented by car manufacturers. As both sectors are highly export-oriented, it is not surprising that they contribute a major share in total Japanese exports. Yet, it is noticeable that the export shares of both industries did not generally increase and in fact there is a constant decline in the electronics share and the trend is level in the automotive share. This pattern is largely a function of increased competition from overseas manufacturers. In fact, other Far-East Asian electronics manufacturers have been increasingly credible rivals that have weakened the position of their Japanese counterparts since the 1990s. China, Taiwan and South Korea have caught up technologically to a considerable extent and now no longer lag behind Japan in terms of innovation, efficiency, and ultimately performance.

Chapter 3: Literature review

Introduction

This chapter first presents the literature on innovation and the influence of R&D on firm performance as this clearly is an important component of the thesis. First, definitions and theories relating to technological development, R&D and labour productivity are described in order to understand the importance of these variables in the subsequent analysis. Then the advantages and disadvantages of micro-level data studies are shown to provide justification and for using firm-level in this research. The subsequent two sections review the theories followed by a discussion of the empirical analysis of the relationship between R&D and various measures of profitability and productivity. This chapter will also emphasise the importance of R&D to labour productivity and profitability as these are the focus of the thesis. Next, the empirical models and existing applications regarding spillovers and absorptive capacity are discussed in depth. Given the research is directed to firms operating in the automotive and electronics industry in Japan, firm-level studies of R&D and productivity in these sectors and overall manufacturing will be reviewed. This will allow gaps in the literature to be identified and thus the contribution of this study confirmed. Finally, the applied literature is vast and much of it has focused on approaches to estimating this relationship. These include the construction of productivity indices, a range of production functions, an assortment of spillover measures as well as ways to quantify absorptive capacity. These models are presented and are important here as the estimation in the empirical chapters uses most of them directly.

3.1 R&D, technology and performance

Griliches (1980) describes technology as the currently known ways of converting resources into outputs that are desired by the economy. The advancement in technology could be denoted in terms of new products, new processes of manufacturing, as well as changes in organization, behaviour and management practices of agents within the economic system (Cooke et al., 1997 and Stoneman, 1995). Technological progress might take place in two forms; disembodied and embodied. Disembodied technical change refers to new organizational or managerial practices and scientific advancement whereas embodied technical change is found in the development or design and quality of capital and intermediate products (OECD, 2001). Technological change has been regarded as a crucial factor in the improvement of productivity levels as knowledge which can be created and

accumulated through the R&D efforts of a firm or industry and will subsequently become available through product innovations or in new and improved production processes (Mansfield, 1965; 1969).

While technological progress is often difficult to quantify and measure, it could be nonetheless regarded as a tangible outcome of R&D activities. This leads to the perception that R&D might plausibly represent the development in techniques and products. In Romer (1990) and Grossman and Helpman (1991a), R&D could be treated as a production activity that converts primary inputs such as research spending and experiments into knowledge or innovation output. The investment in R&D is meant to augment the stock of knowledge which could be utilised to find new applications and innovations (Hall et al, 2010). R&D could be distinguished into two types. Process R&D refers to that aimed at inventing new methods of production whereas product R&D is defined as that directed towards the creation of new and more advanced goods (Hall and Hayashi, 1989). To Denison (1985), R&D is yet one of many factors of technological change as it has been estimated to account for merely 20 percent of all technological progress. On the other hand, R&D has the advantage of being quantifiable and measureable and can be used to construct indicators that can then be incorporated explicitly in econometric models (Griliches and Mairesse, 1984). In fact, economic studies often indicate that variables such as R&D expenditure and R&D capital stock have been directly linked to the rate of productivity change (Griliches, 1980 and Mansfield, 1980). Hall et al. (2010) relates R&D to productivity increases as it improves product quality, reducing median cost in manufacturing existing products, as well as widening the spectrum of final goods or intermediate goods available. The observable consequences of successful R&D include increased profits, price reductions, and input reallocations, as well as firm entry and exit (Hall, 2005).

In the composition of growth accounting it is clear that the majority of output growth is accounted for by the growth of total factor productivity that includes R&D and in econometric estimation the residual comprises an unknown factor influencing productivity growth considered to be technological progress (Edquist and Mckelvey, 2000). In neoclassical growth theory (Solow, 1957), technological progress is regarded as from outside the firm and enhances the productivity of labour at a constant rate. According to Comin (2006), technological progress captures the development in productivity levels that is not accounted for by the changes in labour and physical capital use. Without advancement in technology from external sources, output growth is sustained by the accumulation of

traditional capital stock whose marginal productivity declines over time. In this respect, the continual fall in the marginal product of capital might imply that the production of goods and services would enter a stationary state as additional investment in capital will be merely to replace worn-out machinery and equip new workers (Grossman and Helpman, 1994). In the long-run the growth rate of output can only be determined by the exogenous technological improvement, rather than growth in capital stock and total population (Stoneman, 1987).

The framework of the endogenous growth literature is distinguished from neoclassical growth by the fact that improvements in output results from endogenous factors within the economic system, not the result of exogenous technological progress. Romer (1986) and Lucas (1988) postulate that growth is driven by technological change that results from R&D efforts of profit-maximizing agents. It is the repository of knowledge and innovative ideas accumulated over time by economic agents, universities and governments that leads to subsequent technological development and productivity improvements (Borras and Stowsky, 1997). The rise in productivity levels can be attained by the move towards the best available practice or new technologies while also involving changes in management practices and organizational structures to take the advantage of new innovations and change market opportunities (Mundel, 1983). Given the prospect of increasing returns in the manufacture of output, technological innovation gives the incentive for consistent accumulation of capital and the stock of technical knowledge as both factors accounts for much of the rise in output per worker (Romer, 1989). In this respect, it is market incentives that contribute a fundamental role in the advancement of technology over time. Economic agents intentionally engage in R&D activities with the objective of creating new knowledge or innovation which could be subsequently translated into goods with commercial viability. Another element of technological knowledge arises from its natural externalities. As a new technology is created by one firm, it is assumed to exhibit an effect on the production possibilities of other firms because it could not be perfectly patented or concealed from competitors (Romer, 1994).

Since an innovation may allow for the more effective production of goods, it creates monopoly rents that the innovating firms can temporarily capture. Nonetheless, such monopoly rents would not only deteriorate over time by the effect of externalities, but also by the anticipation of forthcoming innovations. Owing to the spillovers of knowledge, the innovating firm would soon face imitation of either product or production techniques by its market rivals aiming to improve the quality of their own comparable products (Grossman and Helpman, 1991b). As Aghion and Howitt (1992) state, new technology or knowledge would

render the existing one outdated and eventually destroy the rents provided by the latter. Specifically, the stock of knowledge accumulated through successive research and development might be depreciated by new discoveries that lead up to the development of even more technologically advanced products or more efficient processes of production. Firms innovate as a means to cope with organisational adaptation, pressures from intense competition, shifting customer demands, and the constant requirement for new and better products and services (Jansen et al., 2006; Prajogo and Ahmed, 2006). Through innovation, companies aim at responding effectively to environmental demands and thereby achieve their goal of maintaining or improving their performance (Damanpour et al., 2009).

3.2 Labour productivity

Productivity is defined by Melitz (2000) as the measure of output from production processes, given a set of factors of production. As a ratio between gross amounts of output to inputs, the change in productivity could refer to movements in performance of a firm or an industry over time (Coelli et al., 2005). Productivity could be categorised into two variants; single factor productivity and total factor productivity (TFP) measures. The former uses either labour or capital as the only input in its computation whereas the latter is calculated by using data of both conventional inputs. Labour productivity is thus considered as a single factor productivity measure as it is conceptualised as the amount of goods and services that a worker produces in a given amount of time. It is generally termed as average output per worker that could be measured in physical or in price terms (OECD, 2001). It provides a measure of the efficiency with which inputs are used in an economy (Freeman, 2008). Within the aspect of labour as an input of production, labour productivity could also reflect the effectiveness of workers regarding their personal capacities or the intensity of their manufacturing efforts.

The choices for measures of output and of input use results in various ways to compute labour productivity. As the numerator in labour productivity ratio, the measure of output could be proxied in two ways; gross domestic product or value added. In micro- level studies, gross domestic product might be generalised as total production output of goods and services generated by a firm or sector. Such total production output could be measured in terms of physical quantity-based output or revenue-based value. Physical based output refers to the actual volume of products manufactured whereas revenue-based output might be represented by gross value of sales or operating turnover. For the denominator the measure of

labour input used reflects the time, effort and skills of the workforce (Freeman, 2008). To this end, there are two different measures of labour input; total hours worked by all employed personnel and total number of labourers employed. While headcount of workers is more readily available than total hours worked, the former input measure does not account for the effects of part-time work, overtime and absence. Also, the number of employees does not reflect changes in multiple job holdings nor labour quality (OECD, 2001).

However, there are drawbacks to using single-input productivity measures, particularly labour productivity. Whilst multiple outputs are manufactured using an assortment of inputs, a partial productivity measure such as output per worker may potentially mislead or misrepresent the performance of a firm or sector (Coelli et al., 2005). Zhang and Parker (2004) points out that labour productivity partially measures the total amount of productivity, this is because it does not take into consideration changes in the quantity and quality of other inputs resulting from investment, particularly in physical capital and raw materials. In contrast, total factor productivity allows for changes in all inputs with TFP measured as the residual change in output not explained by the changes in inputs (Coelli et al., 2003 and Comin, 2006). Nevertheless, labour productivity is regarded relatively more measureable than total factor productivity as the latter measure requires weighted cost shares of labour and capital in gross production output. Meanwhile these data are often available at either sectoral or national level, computing TFP at micro-economic level could be constrained by the notion that inputs cost shares may not be the same across firms and time periods. In fact, the decomposition of labour productivity reveals the linkages between labour productivity and those of physical capital and TFP. Schreyer (2005) illustrates that rate of change of labour productivity is jointly determined by the effect of capital intensity and the rate of TFP change. To this end, investment in traditional capital bolsters the degree of capital intensity while investment in intangible capital such as innovation and organisational change result in TFP change. This implies that labour productivity is determined also by the intensity of use of both conventional and intangible capitals. Two manufacturers could have different levels of labour productivity although they possess similar production technology and this may be due to different intensification of physical capital usage (Syverson, 2011).

3.3 The relevance of analyses: micro vs macro level studies

This research focuses on firms as the unit of measure rather than industries. Thus, productivity is measured at the micro-level, not aggregated or at the macro-level.

Measurement of firm-level productivity therefore necessitates the use of firm data. There are both advantages and disadvantages to using firm data for the analysis of the impact of R&D on productivity. Firm-level data has relatively higher number of observations compared with macro-level data such as industrial data and allows closer investigation into the relationship between economic variables and inter-firm differences such as asset capacity (Odagiri and Iwata, 1986). As noted in the documents from the Office of National Statistics (ONS (2007)) using micro-data allows the researcher to isolate the effects of factors such as firm size, region and foreign ownership on productivity of individual firms. According to Wakelin (2001), by considering the firm, the researcher can also separate productivity improvements which occur as a result of the direct R&D efforts of the firm, from technological improvements and advances that are general to the sector. Consequently, it is possible to pinpoint the contribution of the firm's own technological resources to its productivity growth. It also allows an analysis of how the change in output share or productivity at firm-level affects productivity change in the entire industry (Ito, 2004). Furthermore, the parameter estimation using economy-wide or industrial level data has been interpreted as a measure of collective returns to R&D (Lichtenberg and Siegel, 1991). The analysis using micro-level data is therefore more feasible, since such data allows the examination of private returns to R&D, the benefits of R&D investments that each individual firm could realize.

Nonetheless, company data can be less accurate than industrial data. This problem tends to occur with detailed information, in particular R&D. For Lichtenberg and Siegel (1991), public access files often include no micro-level information on the number of hours worked while energy and materials data are also missing. In the work of Griliches and Mairesse (1990), they point out that one of their public databases, NEEDS, underreported and even missed some firms. As they further argued, the responses to official R&D surveys conducted by government agencies or industrial institutions seemed to be classified and not publicly available. Thus the only R&D data available are R&D expenditures reported as part of company annual reports or filings with the respective securities markets regulatory authorities. Furthermore, there is no universally standardised pattern of the way in which expenses are to be included under the umbrella of R&D expenditures. Keiko (2004) explains another drawback regarding deflators. Virtually all deflators for output and inputs are only available at sectoral and national levels, and hence researchers need strong assumptions that the same price or economic indices are applicable to all firms or micro-establishments.

3.4 Modelling R&D-Productivity

The primary framework that has been used in the literature estimating the relationship and the size of R&D effects on productivity at both micro and macro level are derived from the production function. Fundamentally, a production function determines the relationship between the output of a firm or sector and inputs such as physical capital, labour and materials. In a number of studies, other variables are augmented as additional independent variables. Mansfield (1981) uses a production function framework to investigate the link between R&D spending and three factors; firm size, industrial concentration and types of innovative output. The production function in Smith et al. (2004) also comprises of the effects on productivity of foreign ownership, funding sources, innovative characteristics and ownership dispersion. In the work of Johansson and Loof (2008), dummies for research strategy, technological level and ownership structure are also included to examine the impact of R&D choices upon productivity and profitability of Swedish firms. Despite being extensively used in productivity related studies, the production function framework has limitations. It could be inadequate in situations where elasticities may vary across data points (Coelli et al., 2005). A further point is that the production function may be also problematic when data contains zero values as it is impossible to construct logarithms.

As to the framework of production function, Griliches (1979; 1980) augments the production function with R&D variables which typically enter the model in the form of knowledge or R&D capital stock. He postulates two assumptions that support the presence of R&D capital in the enhanced production function. First, output is a function of total factor productivity and conventional inputs. The total factor productivity term is analogous to the concept of Solow's residual (1957) that constitutes technological change. Second, total factor productivity itself is the function of R&D capital stock and other potential factors. In this respect, the production function supplemented with knowledge capital could be written as:

$$\text{Equation 3.1 } Q_{it} = A e^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} e^{\epsilon_{it}}$$

where i and t denote time and firm/sector respectively. A is a constant parameter, defined as other determinants of TFP independent from technological innovation (Kim, 2009). λt is a time-specific variable and disembodied technical change. It is apparent that equation 3.1 is presented in non-linear form but as an exponential production function. In order to make the model easier to estimate, the natural logarithm is used. This transforms equation 3.1 into a linear model, as follows:

$$\text{Equation 3.2} \quad \ln Q_{it} = \ln A + \lambda_t + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln R_{it} + \varepsilon_{it}$$

Further first differencing equation 3.2 would convert it into a growth rate version where smaller letters denote growth rate of each respective variables and $\ln A$, the constant disappears:

$$\text{Equation 3.3} \quad q_{it} = \lambda + \alpha k_{it} + \beta l_{it} + \gamma r_{it} + \varepsilon_{it}$$

Equation 3.3 presents output growth as the dependent variable and the growth rates of labour, physical capital and knowledge capital as independent variables. However, this form of the equation is not in an expression for productivity growth as a function of production inputs. Referring to Griliches and Mairesse (1984), there is also a choice of assuming constant return to scale (CRS) for a combined labour and capital input in the production function, although it is important to test for this assumption as follows:

$$\text{Equation 3.4} \quad \theta = 1 - \alpha - \beta$$

According to CBO (2005) and Maté-García and Rodríguez-Fernández (2008), if θ is equal to zero (which implies that α and β sum to 1) then constant returns to scale cannot be rejected. However, if θ is significantly different from zero, there are not constant returns to scale for labour and capital, implying either increasing return to scale (IRS) or decreasing return to scale (DRS). If $\theta > 1$, conventional inputs would show IRS. If $\theta < 1$, then combined inputs of labour and capital would indicate DRS. Then with equation 3.4, equation 3.3 could be rearranged into labour productivity growth as the explained variable. Subtracting both sides of the equation 3.3 with l_{it} and replacing β with $1 - \alpha - \theta$ will transform such equation as follows:

$$\text{Equation 3.5 (with CRS)} \quad (q-l)_{it} = \lambda_t + \alpha(k-l)_{it} + \gamma r_{it} + \varepsilon_{it}$$

$$\text{Equation 3.6 (with IRS/DRS)} \quad (q-l)_{it} = \lambda_t + \alpha(k-l)_{it} + \gamma r_{it} + \theta l_{it} + \varepsilon_{it}$$

Another alternative specification of equation 3.2 could be derived by subtracting labour from both sides and then applying the returns to scale assumptions into it. This process would generate two equations similar to equations 3.5 and 3.6 but rather having all variables in level-form.

$$\text{Equation 3.7 (with CRS)} \quad \ln (Q/L)_{it} = \ln A + \lambda_t + \alpha \ln (K/L)_{it} + \gamma \ln R_{it} + \varepsilon_{it}$$

$$\text{Equation 3.8 (with IRS/DRS)} \quad \ln (Q/L)_{it} = \ln A + \lambda_t + \alpha \ln (K/L)_{it} + \gamma \ln R_{it} + \theta L_{it} + \varepsilon_{it}$$

According to Oh et al. (2009), $k-l$, or capital intensity as previously noted, is considered as a measure of firm-specific knowledge embodied in machinery and equipment in production. Thus, high levels of capital intensity imply that the firm has high levels of asset specificity and variability in capital utilisation. Differences in capital intensity could mirror differences in production processes and managerial choices about the degree of process automation (Lieberman and Demeester, 1999). In both equations, R&D capital is treated as directly impacting the production of the firm. Results generated from firm-level R&D efforts are those of patents, copyright and new products developed by firms (Kortum, 2008). Patent counts and data on actual innovations can be used as proxies for knowledge capital.

The coefficient on R&D capital is equal to the output elasticity of R&D capital stock. Nevertheless, the actual physical amount of research capital is highly unobservable; in fact, it is not publicly available on most investor or public relations documents. This difficulty is reflected by Rouvinen (2002)'s views on the drawbacks of the econometric approach based on the modified Cobb-Douglas production function. He argues that analysts are largely unable to obtain knowledge capital stock and firm productivity is only seen after a lag. The lag in R&D effects on productivity was pointed out by Griliches (1979) who found that past R&D efforts contributed to the level of current R&D impacts upon productivity in the future. R&D capital represents cumulative R&D effort and it includes all current knowledge of the firm, past experience of R&D activity as well as commercialisation of R&D results (Johansson and Loof, 2008). In this respect, researchers can directly estimate the amount of R&D capital by using perpetual inventory methods which would require two conditions. R&D expenditures, net investment in R&D related activities for each firm, must be known for long periods of time while the rate of research depreciation or obsolescence are properly estimated (Griliches and Mairesse, 1984). R&D capital depreciates as no further investment is undertaken and this results in the deterioration in returns to previous R&D efforts. To Hall et al. (2010), the depreciation rate is determined by the firm's own behaviour, reactions by other competitors as well as the progress of public research. R&D capital may also depreciate in due course since other firms gain access to it and subsequently imitate it (Grabowski and Mueller, 1978). Following Mansfield (1968), research capital at period t (R_{it}) depreciates at the constant rate (D_R), then the estimates of research capital is as follows:

$$\text{Equation 3.9 } R_{it} = RD_{it} + (1 - D_R)R_{it-1}$$

R&D investment helps generate a stock of knowledge that could yield returns into the future. Following equation 3.9, it could be assumed that the returns on earlier period's R&D capital will eventually diminish. Another variation of the perpetual inventory method is to construct R&D capital stock that does not require information on the level of last period's knowledge stock; even so it would involve a longitudinal series of R&D spending data in preceding periods. In other words, an increase in the stock of R&D capital at the present period would reflect not only the same period's R&D expenses but also those of preceding years (Wang and Tsai, 2004). Hence, the alternative model to construct R&D capital presumes the relationship between the current knowledge capital stock and those of current and past R&D expenses:

$$\text{Equation 3.10 } R_{it} = RD_{it} + (1-D_R) RD_{it-1} + (1-D_R)^2 RD_{it-2} + (1-D_R)^3 RD_{it-3} + (1-D_R)^4 RD_{it-4} + \dots$$

Equation 3.10 shows R&D capital stock as a measure of the distributed lag effect of preceding R&D spending upon productivity. The estimation of the output elasticity of R&D capital is the point of analysis for firm-level studies on R&D-productivity link. The output elasticity of R&D capital denotes the percentage increase in output given a percentage growth in stock of R&D capital. Table 3.1 provides a summary of the empirical literature estimating the output elasticity of R&D. Studies by Mansfield (1980 and 1981) further classify research and development into two sub-categories; basic research and applied research. This gives rise to two respective types of R&D capital in his analytical framework. The work of Griliches (1986) examines the impact of R&D capital upon American manufacturing firms in 1972. The change in level of value added is significantly explained by R&D capital stock. Hall and Mairesse (1995) analyse the relationship between R&D and productivity in 197 French manufacturing firms across 10 industrial sectors. This study is marked by the returns to scale supposition imposed on all inputs, rather than merely traditional inputs. Consequently, their model is similar to equation 3.7 and 3.8 where R&D capital is transformed into a ratio to labour input. With both assumptions of constant returns to scale and non-constant returns to scale, they regress labour productivity on capital intensity and R&D capital intensity. Similarly, Harhoff (1998) uses panel data for West-German manufacturing companies to explore the relationship between R&D capital and labour productivity. Assuming constant returns to scale and all variable in logarithms, his results shows a positive significant impact of R&D capital across both OLS and fixed effects estimations.

Table 3.1: Econometric studies estimating the output elasticity of Research and Development						
Study	Country	Time period	Individual data	Explained variable	Estimation methods	Output Elasticity
Griliches (1986)	U.S.	1972	491 firms	Value added	OLS	0.115**
Hall and Mairesse (1995)	France	1980-1987	197 firms	Labour productivity	Fixed effects (Within)	0.069** (without CRS), 0.08** (with CRS)
Griliches (1998)	U.S.	1966-1977	133 firms	Labour productivity	OLS	0.054** (without CRS), 0.073** (with CRS)
Harhoff (1998)	Germany	1979-1989	443 firms	Labour productivity	OLS, Fixed effects (Within)	0.136** (OLS), 0.15** (Fixed effects)
Beneito (2001)	Spain	1990-1996	501 firms	Output growth	OLS, IV	0.036** (OLS), 0.033** (IV)
Wang and Tsai (2004)	Taiwan	1994-2000	136 listed firms	Capital productivity	Random effects (FGLS)	0.18** 0.3** for high tech, 0.07** for others
Higon (2007)	U.K.	1970-1997	8 industries	Output growth	Fixed effects (ARDL)	0.331**
Smith et al. (2004)	Denmark	1995-1997	684 firms	Value added	OLS	0.088***
Graversen and Mark (2005)	Denmark	2001	2,228 firms	Labour productivity	OLS	0.016-0.019**

Notes: OLS denotes ordinary least square; IV denotes instrumental variable estimation; FGLS denotes Feasible generalised least squares
ARDL denotes auto regressive distributed lag model
CRS denotes constant return to scale assumption for traditional inputs
* 10% significant level; **5% significant level; ***1% significant level

Focusing on 133 large American manufacturing firms, Griliches (1998) assesses the contribution of private R&D spending by individual firms to their own productivity performance. With regards to different returns to scale assumptions imposed in the model, his findings indicate a strong relationship between labour productivity of the firm and the level of accumulated knowledge capital stocks. In investigating R&D impact on productivity growth of Taiwanese listed companies over the period of 1994-2000, Wang and Tsai (2004) estimate output elasticity of R&D with further analysis of the different impacts on productivity between high-technology and conventional firms. Their model is noted for using a physical capital productivity measure as the dependent variable. This model transformation could be achieved by subtracting physical capital from both sides of equation 3.2. Their results show the overall R&D output elasticity is about 0.18. Distinguishing firms into two different technological levels shows that high-technology firms have a considerably higher R&D output elasticity than other firms, at 0.3 and 0.07 respectively.

Beneito (2001) investigates the productivity effect of firm R&D capital by using panel data for Spanish manufacturing firms for the period 1990-96. The model is similar to equation 3.3 and augments it with raw materials. The results show the statistical significance of R&D capital stock with elasticity coefficients around 0.033-0.036. Smith et al. (2004) and Graversen and Mark (2005) examine whether R&D capital leads to a productivity rise in Danish private manufacturing firms, using value-added per employee as a proxy for firm productivity. Robust evidence of a positive and significant link between sectoral stock of knowledge capital and productivity performance is illustrated in Anon Higon (2007), who investigates eight U.K. manufacturing industries.

Modelling the elasticity of R&D capital is not without limitations, which particularly stem from the construction of R&D capital stock. Several previous studies on micro-level data have only a short history of R&D expenditures for individual firms. Another underlying problem is associated with difficulties in determining the depreciation rate of the capital stock. With regards to micro-level studies, depreciation of knowledge capital is not only subject to the firms' own behaviour, but also depends upon competitors' actions and to some extent on the advancement of public research. For this reason, it is likely that depreciation of research capital rates neither remains level over time or is not identical across firms (Hall, 2005). Moreover, pinpointing the depreciation rate separately from the return to R&D entails determination of the lag structure of R&D in generating returns (Hall et al., 2010). To handle complications regarding measurement of R&D capital stock and its depreciation rate, a

number of papers proceed to rearrange the production model to create an alternative approach for estimating R&D-productivity link. Here, R&D capital and its output elasticity coefficient is replaced by R&D intensity and the rate of return on R&D investment coefficient respectively. As with the elasticity coefficient, there is a constant marginal product across firms and over periods (Griliches and Mairesse, 1990).

Wakelin (2001) states that output elasticity (γ) is interconnected to rate of return on R&D (ρ) by the ratio of R&D capital to output, as follows:

$$\text{Equation 3.11} \quad \gamma = \rho(R/Q)_{it}$$

As first demonstrated in the earlier equation 3.3, r represents the growth rate of R&D capital stock and can also be termed as the first difference of R&D capital stock ($\Delta R/R$). Multiplying both sides of equation 3.9 with the r or $\Delta R/R$, leads to the following:

$$\text{Equation 3.12} \quad \gamma r_{it} = \rho(\Delta R/Q)_{it}$$

To Hall et al. (2010) the estimation of the rate of return on R&D is typically based on the assumption that depreciation rate in the stock of R&D capital is approximately zero, thus its stock can be altered with the amount of investment in research and development in the present period (RD_{it}). This means that $\Delta R_{it} = RD_{it}$. As a consequence, equation 3.12 is further revised as:

$$\text{Equation 3.13} \quad \gamma r_{it} = \rho(RD/Q)_{it}$$

Simply substituting equation 3.12 in 3.5 and 3.6, the new relationship in terms of labour productivity could be rearranged as below:

$$\text{Equation 3.14 (with CRS)} \quad (q-1)_{it} = \lambda_t + \alpha(k-1)_{it} + \rho(RD/Q)_{it} + \varepsilon_{it}$$

$$\text{Equation 3.15 (with IRS/DRS)} \quad (q-1)_{it} = \lambda_t + \alpha(k-1)_{it} + \rho(RD/Q)_{it} + \theta l_{it} + \varepsilon_{it}$$

Apart from 3.14 and 3.15, it could be observed that a number of researchers alternatively use the model specification that has total factor productivity growth as the dependent variable. This specification is conventionally associated with a constant returns to scale assumption. In order to derive this model specification, first subtract k_{it} and l_{it} from equation 3.3. This will convert the dependent variable into total factor productivity growth. Thereafter, implementing constant returns to scale and the rate of return coefficient from equation 3.4 and 3.13 would result in the following expression:

$$\text{Equation 3.16} \quad \text{TFPG}_{it} = \lambda + \rho(\text{RD}/\text{Q})_{it} + \varepsilon_{it}$$

An unconventional specification used by some authors is characterised by having output growth in place of labour productivity growth. This model arrangement can be expressed as equation 3.13 and substituted directly into equation 3.17.

$$\text{Equation 3.17} \quad q_{it} = \lambda + \alpha k_{it} + \beta l_{it} + \rho(\text{RD}/\text{Q})_{it} + \varepsilon_{it}$$

With regards to the RD/Q term, this measure of R&D intensity is typically expressed as R&D expenditures as a fraction of sales or value added. The estimate of the rate of return coefficient (ρ) indicates the increment of output that could be manufactured with a monetary value rise in R&D spending.

Reviews of preceding studies documenting the rate of return to R&D estimation are shown in Table 3.2. Applying a model with a total factor productivity specification, Mansfield (1980) discusses 16 American petroleum and chemical companies where the average rate of return on R&D during the period of 1960-1976 is estimated to be about 27.5%. Similarly, labour productivity growth from 1966 to 1977 in Griliches (1986) is linked to firms' R&D expenses, which yields rates of return of about 10.7%. With the sample of 924 manufacturing firms, Clark and Griliches (1984) note results regarding labour productivity growth and R&D expenses for the period 1970 to 1980. Their R&D intensity variable is noted for being lagged one period in both the numerator and denominator. They classify total R&D investment into process and product expenditures as the ratio of product R&D to total R&D investment, and this variable also enters the model as an additional R&D variable. Therein, major findings include some evidence that higher effort into product R&D could in fact diminish the growth rate of firm productivity and that the rate of return to total R&D investment over the course of 1970s was about 18%. Using intensity or the rate of return model, Lichtenberg and Siegel (1991) examine the association between R&D and productivity of U.S. manufacturing firms for the period 1972-1985. By using sales and employment to represent firm size, they also test whether bigger firms are more successful in reaping benefits from their R&D activities than smaller firms. The productivity measure is proxied by the growth rate of total factor productivity which is regressed on R&D intensity and firm size variables. Their results suggest that R&D significantly determined TFP growth over the 1970s and 80s. As well, the rate of return on R&D undertaken by large firms is shown to be higher than in their smaller counterparts.

Table 3.2: Econometric studies estimating the rates of return to Research and Development						
Study	Country	Time period	Individual data	Productivity variable	Estimation methods	Rate of return
Mansfield (1980)	U.S.	1960-1976	16 petrol & chemical firms	TFP growth	OLS	0.275**
Clark and Griliches (1984)	U.S.	1970-1980	924 firms	Labour productivity growth	OLS	0.18**
Griliches (1986)	U.S.	1966-1977	491 firms	Labour productivity growth	OLS	0.107**
Griliches and Mairesse (1991)	U.S.	1973-1980	525 firms	Output growth	OLS	0.41**
Lichtenberg and Siegel (1991)	U.S.	1972-1985	2000 firms	TFP growth	OLS	0.132***
Hall and Mairesse (1995)	France	1980-1987	197 firms	Output growth	Fixed effects	0.273**
Wakelin (2001)	U.K.	1988-1996	170 firms	Labour productivity growth	OLS	0.34*
Parisi et al. (2006)	Italy	1992-1997	465 firms	Labour productivity growth	IV	0.16**
Maté-García and Rodríguez-Fernández (2008)	Spain	1993-1999	1312 firms	Labour productivity growth	GMM	0.27** (without CRS), 0.26** (with CRS)
<p>Notes: OLS denotes ordinary least square; IV denotes instrumental variable estimation; GMM denotes generalised moment methods CRS denotes constant return to scale assumption for traditional inputs * 10% significant level; **5% significant level; ***1% significant level</p>						

In Hall and Mairesse (1995), value added growth is regressed on growth rates of physical capital and labour inputs and on R&D intensity. R&D intensity is approximated with different lag structures of R&D expenses and value added; $t-1$ and $t-2$. It is confirmed in their studies that the positive effect of R&D continues from 1970s, as pointed out in their earlier studies, well into the 1980s. Wakelin (2001) examines the role of R&D expenditure in enhancing labour productivity growth of 170 British listed manufacturing firms from 1988 to 1996. She further categorises firms into two sub-groups; innovating and non-innovating ones. Her empirical results show the significant impact of R&D expenses on productivity, albeit the link is not significant when sector fixed effects are included. Parisi et al. (2006) presents empirical evidence of the effect of total R&D investment, but also the effects of both process and product innovation on productivity in Italy. They find that the effect on labour productivity growth of a process innovation is significant and greater than a product innovation, which contributes negative yet insignificant impact. Maté-García and Rodríguez-Fernández (2008) apply a distributed lag structure for R&D intensity on a production function specification. In their analysis of Spanish manufacturing companies during the 1990s, the empirical findings with both constant returns to scale and non-constant returns to scale indicate a pivotal role for R&D investment in determining labour productivity growth.

Although the estimation of rate of return on R&D investment would be beneficial for productivity studies that avoid difficulties in measuring R&D capital, this approach also has a drawback regarding R&D depreciation. This is because it does not take into account the factor of technological obsolescence. Substituting R&D expenditure for increments in R&D capital not only disregards the reduction in the effective appropriation of knowledge, but also overestimates the rate of return on R&D (Wang and Tsai, 2004). Taking no account of depreciation of knowledge capital means that the term RD_{it} represents the gross R&D investment, rather than net R&D investment. As Hall (2007) pointed out, the use of gross R&D spending in calculating R&D intensity could be problematic, particularly at the micro-level analysis. Since much of firms' R&D investments could be aimed at supplanting outdated stock of innovation or technical knowledge, the R&D intensity computed from net R&D investment may be lower than the one measured by the ratio of gross R&D expenses to output. These arguments are in line with Griliches and Mairesse (1990) that R&D expenditures is a good proxy for R&D capital only on two conditions; if research capital has no or little depreciation, or if the study focuses on the beginning phase of knowledge accumulation and initial stock of research capital is small. Even so, Mairesse and Sassenou

(1991) show that the rate of return values estimated by using net and gross R&D investment could be fairly comparable in the event that depreciation rate of R&D capital is small with respect to the growth rate of R&D expenses. Another restraint could arise from the fact that there may be the costs of adopting a new technology to fully bolster product's quality or manufacturing processes (Bessen, 2002). Unless this extra monetary spending required to apply the technology is taken into consideration, the rate of return on R&D would be lower than what could have been actually estimated (Maté-García and Rodríguez-Fernández, 2008). A further point is that this method of estimation is also flawed by the difficulty in determining the correct timing for the R&D variable. More specifically, there is no consensus regarding the proper lag period for numerator and denominator of R&D intensity variable.

3.5 Modelling R&D-Profitability

Profitability is another indicator of the firm-level performance which reflects the achievement by a firm in terms of economic outcomes. Parallel with productivity measures, profitability is a specific measure of innovation-driven entrepreneurial success and an indicator of successful performance at the firm level (Bogliacino and Pianta, 2012). In fact, the examination of links between technological development and profitability made by a number of papers often postulate the bi-directional relationship between variables. Scherer (1965a) notes that technological advancement taking the form of innovation could enhance profit mainly in two ways. While a successful innovation widens the profit margin earned on the amount of sales, it might also facilitate the growth of profitable sales at the constant rate of profit margin. A process innovation may render a firm more flexible when adjusting to exogenous incidents such as shocks in demand and supply (Nås and Leppälähti, 1997). Conversely, increase in profitability may exert a positive effect on R&D efforts. With less financial restraints, the company would have more equity capital adequate to be self-financed; R&D activities would become less risky and are more likely to be taken up by the company to reinforce its existing market share (Galia and Legros, 2004). Likewise, improvements in productivity, profit and cash flow also bring about better access to external resources that could be used to invest in both physical capital and R&D activities (Baumol and Wolff, 1983). This is because banks and other financial institutions would be more willing to subsidise R&D efforts (Pakes and Griliches, 1984). R&D investment decisions made by the firm could be related to not only the expectation on future levels of profit (Scherer, 2001), but also comparisons of R&D projects' profitability with alternative uses of available funds (Archarungroj and Hoshino, 1999). Both R&D and profits could be

influenced by some third factors, such as government support and exogenous increases in demand (Branch, 1974).

Nevertheless, the commercial success of innovation is not guaranteed. It is uncertain whether customers would adopt the new products and services introduced into the market or whether such innovations will yield the sought-after return for the organisation (Baker and Sinkula, 2005). Conflicting findings regarding the relationship between innovation and financial measures of performance are thus documented by empirical studies (Gatignon et al., 2002; Morgan and Berthon, 2008; Walker, 2004).

Table 3.3 gives a detailed summary of studies regarding the relationship between R&D and profitability. It could be noted that both directions of such relationship have been comprehensively examined whereas the time-lag effect is also in each model specification. With regards to the empirical literature, most utilise either correlation or regression to examine the impact of technological progress on profit. The former appears to be relatively less used. For the latter analysis, the profitability variable is modelled as a function of potential factors that could explain the variation in profit. Apart from variables representing technological change, independent variables may include productivity, the size of firm and the debt ratio. Existing studies are distinguished by their approach to technological development as a determinant of firm profitability. In this respect, some studies uses number of patents held by a firm as an indicator of innovative efforts whilst alternative innovative measures are the amount of R&D investment or stock of R&D capital. R&D capital stock is measured by using techniques similar to that in the extended production function discussed earlier. Comparing the two approaches, Leonard (1971) explains the advantage of using R&D investment/R&D capital over patent data. Detailed information of R&D expenditures allow for further separation of research effort into basic and applied whereas patents tend to be representative only of development. In addition, R&D investment also provides measures of both successful and unsuccessful R&D efforts of the firm. While the propensity to patent is not alike across firm, industry and time, the quality of innovations on which patents are issued could also vary substantially (Schmookler, 1966).

$$\text{Equation 3.18 } \pi_{it} = \sum_{d=1}^n X_{dit} + \varepsilon_{it}$$

In equation 3.18, profit is a function of explanatory variables from d to n. X_{dit} denotes explanatory variable d for the ith firm and time period t. Explanatory variables represent technological progress and other factors explaining change in profit.

Study	Country	Time period	Individual data	Model specification	Dependent variable	Independent variables	Estimation methods
Scherer (1965a)	U.S.	1955-1960	448 firms	Linear regression	Profit	lagged number of patents firm size, industry structure dummies	OLS
Branch (1974)	U.K.	1950-1965	111 firms	Distributed lag structure	Profit after taxes, Patent/asset ratio	lagged profit, lagged patent/asset ratio	OLS
Grabowski and Mueller (1978)	U.S.	1965-1970	86 firms	Linear regression	Return on assets	R&D capital, advertising capital, firm size, industry growth	OLS
Morbey (1988)	U.S.	1976-1985	800 firms	Correlation	-	-	-
Leiponen (2000)	Finland	1985-1993	209 firms	Autoregressive	Profit margin growth	lagged patent, product and process innovation dummies	GMM
Galia and Legros (2004)	France	1994-1996	2,165 firms	Linear regression	R&D expenses per employee	Profit margin, firm size	ALS
Hokkanen (2006)	Finland	1999-2005	65 firms	Linear regression	Profit margin	lagged values of R&D intensity, labour productivity, debt ratio, industry dummy	OLS

Author(s)	Country	Year	Sample	Method	Dependent Variable	Independent Variables	Estimation Method
Aw et al. (2008)	Taiwan	2002-2004	Electronics producers	Autoregressive	Operating revenue	lagged values of revenue, R&D expenses, capital stock and capital investment	OLS
Heshmati and Loof (2008)	Sweden	1992-2000	1,339 firms	Autoregressive	Profit before tax	lagged values of profit, sales, capital investments, R&D expenses, employment	Within
Natasha and Hutagaol (2009)	Indonesia	2004-2007	106 firms	Linear regression	Profit margin	R&D intensity, Labour productivity, Debt ratio, Firm size	OLS
Coad and Rao (2010)	U.S.	1973-2004	Manufacturing firms	Autoregressive	Operating revenue growth	lagged growth rates of employees, sales, R&D and operating revenue	OLS
Simanjuntak and Tjandrawinata (2011)	U.S.	2003-2010	6 Pharmaceutical firms	Linear regression	R&D expenses	Lagged profit before tax, R&D intensity, cash flow	GLS
Bogliacino and Pianta (2012)	E.U.	1994-2006	38 sectors	Linear regression	Operating revenue	lagged innovative turnover's growth, demand	WLS
Bogliacino and Pianta (2012)	E.U.	1994-2006	38 sectors	Autoregressive	R&D expenses per employee	lagged operating surplus, lagged R&D expenses per employee, size	WLS
García-Manjón and Romero-Merino (2012)	E.U.	2003-2007	754 firms	Autoregressive	Operating revenue growth	lagged values of operating revenue growth, R&D intensity, firm size, industry dummies	OLS, GMM

Notes: OLS denotes ordinary least square; GMM denotes generalised moment methods; ALS denotes asymptotic least squares
WLS denotes weighted least squares; GLS denotes generalised least squares

Scherer (1965a) considers the study of invention patents, profitability and sales growth of American manufacturing companies during 1950's. He suggests that current period profit of the firm is determined by the amount of patents held during earlier periods and the structure of the industry. Applying a distributed lag structure for patents and profitability variables, Branch (1974) provides analysis on a bi-directional relationship between technological development and profits of 111 manufacturing firms. His results indicate that a ratio of patent to assets, as an indicator of the firm's inventive activities, affect the future level of profits. Equally, R&D activities would be slightly stimulated by the level of profit in past-periods. Leiponen (2000) investigates the effect of innovation and education on profitability of Finnish manufacturing firms. This model is an autoregressive and first-differenced logarithmic specification which asserts a firm's profit margin as a function of lagged profit margin, innovation, as well as firm and industry-specific characteristics. Innovation is represented by number of patent applications and three dummies indicating whether the firm generates product innovation or process innovation or both. The results suggest that amount of patents and the introduction of both product and process innovations are associated with better profitability. House and Fries (1992) compare two technology-intensive sectors, manufacturing consumer durable and non-durable goods. They find that both R&D expenses per employee and R&D expenses per sales are related to return on assets; positively for non-durable and negatively for consumer durable producers.

Grabowski and Mueller (1978) is a study of the effect of profitability determinants which include investment in intangible capital such as advertisement-related goodwill and knowledge capital stock. To incorporate both intangible assets, they construct both R&D and advertising capital with perpetual inventory methods and then divide two intangible capital stocks with total assets in order to create R&D capital intensity and advertising capital intensity respectively. In their model, return on total assets is regressed on the two intangible capital variables with controls for size and industry-specific structure. Their results demonstrate that R&D capital is a significant source of above-average profitability and that firms in R&D-intensive sectors tend to experience considerable returns on their R&D capital stock. García-Manjón and Romero-Merino (2012) consider the ratio of R&D investment to net sales as a determinant of firm growth. Using an autoregressive model specification, they regress sales growth on a lagged dependent variable and R&D intensity at the earlier time-period. Their findings give support for a positive association between R&D investment and firm growth.

In Galia and Legros (2004), firm level relationships between R&D investments, innovation, training investments, quality and firm profitability are used in a recursive model. Their results indicate that firm profitability exerts positive and significant on R&D investment. This is possibly owing to the fact that R&D investments are less risky as firms become more profitable. Such R&D efforts by using past profit would be considered as an innovation strategy to enhance firm performance in the long-run. Bogliacino and Pianta (2012) link both R&D investment and innovation to profitability at a sectoral level. Applying the concept of R&D, innovation and productivity relationship, illustrated in Crepon et al. (1998) and Parisi et al. (2006), they use a simultaneous three-equation model which shows that R&D efforts lead to innovation which thereafter has a delayed effect on the increase in firm profit. In reverse causality, lagged profitability would then sustain the level of investment in R&D activities. They provide evidence that change in industrial profits is explained by the rise in successful innovations generated within that industry in the previous period. In addition, their results confirm the positive and lagged feedback effect of profit on R&D investments. Simanjuntak and Tjandrawinata (2011) examine the influence of the determinants of technological efforts, particularly lagged profitability, R&D intensity and cash flow on R&D expenditures of American pharmaceutical companies. Their findings demonstrate that enhancement in all three determinants contribute to the increase in R&D investment. In other extant researches, there is also evidence suggesting a positive link between innovation and financial performance. Walker (2004), in quantitative review of the findings of 30 empirical literatures from 1984 to 2003, demonstrates that in most cases innovation positively influences performance. Jansen et al. (2006) demonstrate that, under different environmental conditions exploratory and exploitative innovations contribute to profitability-based measures of performance. Govindarajan and Kopalle (2006) reports similar positive effects between disruptive types of innovation and total sales and gross profit margin. Positive links between innovation and cash flows and future profitability are documented by Sorescu et al. (2007).

Productivity could be highlighted as one of pivotal determinants of profitability, apart from technological development. Botazzi et al. (2008) stress that productivity interconnects with profitability, as evidenced by strong and positive correlations. Likewise, studies use decomposition methods to investigate determinants of profit (Banker et al., 1993 and Lawrence et al., 2006) also point out that productivity change constitutes one cause of profit change. To Lawrence et al. (2006), increased productivity may imply that more production

output could be attained from given quantity of factor inputs, this leads to more revenue and profit that the firm. Aw et al. (2008) suggest the assumption that each firm's profitability will evolve over time with changes in productivity and physical capital. Thus, productivity is likely to vary as a consequence of R&D investment whereas capital depreciation and the inflow of capital investment will lead to the change in the capital stock. From their theoretical model, R&D is presumed to contribute to the rise in future profits through its effect upon productivity levels. Using an autoregressive model, the growth of profitability describes the firm's revenue in the forthcoming period as a function of current period revenue, R&D expenditures, capital investment and stock of physical capital. In a sample of Taiwanese electronics firms, there is empirical evidence suggesting that investment in both R&D and physical capital tend to bolster the prospective level of firm profitability. Hokkanen (2006) concentrates on the impact R&D investments have on profitability. Regressing profit margin on lagged independent variables, including labour productivity, there is an impact on profitability. Her results and findings provide strong support for the presumption that R&D investment is positively related to firm profitability, however there exists a time lag after which R&D spending is noted. The results regarding labour productivity demonstrate a positive yet not statistically significant impact.

Natasha and Hutagaol (2009) propose a model to investigate research and development, profitability and productivity simultaneously. They examine the impact of R&D investment and labour productivity upon profitability of Indonesian firms. Their results show that labour productivity positively relates to profit margin. In contrast to prior studies, the coefficient of R&D not only is statistically insignificant, but also has a negative sign. However, they consider the current-period effects of explanatory variables upon profitability in the same period. In this respect, it could be noted that R&D may not have significant impact on performance of the firm in the same financial year that it is conducted. Abovementioned negative and irrelevance of R&D is also clarified by House et al. (1994). They stress that R&D outlays could contribute negative impact on profit owing to its uncertainty. There may be a significant lapse of time between the commencement of R&D activities and determination of success so that such negative effect could take even more than a year to pay off (Wild et al., 2007). If R&D investment grows faster than the increase in sales volumes, it is likely that the profitability at the same period would be undermined. Whilst also unable to detect any feedback of R&D expenditure growth on the growth of profits, Coad and Rao (2010) find that R&D growth is positively associated with profit

growth for the second lag period. Their findings support the existence of a time lag for commercially feasible innovation to eventually materialise in increases in firm performance. Perhaps even successful R&D could necessitate further short-term costs; costs related to product development for example, before yielding benefits in the long-run (Coad and Rao, 2008). To Archarungroj and Hoshino (1999), the profitability effect of R&D could be cumulative. This means that rises in profit may not reflect the result of contemporary R&D activities, but rather as the consequence of continuous R&D efforts over periods of time.

Additionally, peculiarities in samples of firm, country, time horizon or choice of independent variables are potential factors causing disparate results of the R&D-profitability relationship (Natasha and Hutagaol, 2009). Morbey and Reithner (1990) use an assortment of profitability measures and R&D investment to examine correlations between variables. Their studies find diverse results in a correlation analysis between two R&D intensity variables and three profitability proxies. The ratio of R&D expenditures to number of employees is strongly correlated with future productivity and all profitability measures. On the other hand, there is no correlation between the ratio of R&D outlays to sales revenues and those of profit margin, return on sales and return on assets. In a study of American companies in the period from 1976 to 1985, Morbey (1988) uses correlations to investigate the existence of a bi-directional relationship between R&D spending and two performance measures; sales growth and profitability. Findings show that R&D investment is associated with increased sales in the following period whilst it has weak correlation with growth rate of subsequent profit. There is also weak reverse causality between the rise in both firm performance measures toward R&D effort in the following period. For Sweden firms, Heshmati and Loof (2008) explore two way causal relationships between research investment and performance indicators including sales and gross profit. They find that both performance measures weakly related to R&D. Their results confirm findings of Klette and Kortum (2004) that there is not only an insignificant relationship between R&D and productivity in the long-run, but also no influence between R&D and profitability was found with respect to each other.

In spite of debates in the existent researches regarding financial outcomes of innovation, a number of theoretical arguments corroborate the positive role of innovation on financial performance of the firm. Due to shifting customer demands and impulsive consumer preferences, organisations that introduce innovative products with advanced features and capabilities, are more likely to remain up to date and achieve higher levels of sales and firm growth (Bayus et al., 2003; Srinivasan et al., 2009). Such firms could also gain first or early

mover advantages that have been associated with superior long-term firm profitability (Lieberman and Montgomery, 1988; Roberts and Amit, 2003). Additionally, innovating firms may realise performance benefits through penetrating further on their existing customer base, particularly in those segments of high financial margins or shifting demands, thus offsetting potential costs of targeting and attracting new customers (Bayus et al., 2003). To Srinivasan et al. (2009), firms with a more long-term orientation could reduce the vulnerability of their cash flows by launching innovative products to new customers. A further point, by planning and implementing innovation on continuous basis organisations may also benefit indirectly (Kostopoulos et al., 2011). Steady engage in technological activities bolsters the effectiveness of technological absorption. If a firm consistently ,and as a part of its corporate strategy, explores and develops new products and services, then is more likely to recognise and acquire new knowledge that could generate successive rounds of innovation with corresponding financial benefits over time (Cohen and Levinthal, 1990). In other words, through continuous innovation, firms are able to build a set of dynamic capabilities (Eisenhardt and Martin, 2000; Teece et al., 1997) that allows the reconfiguration of their competencies to changing market conditions, hence enhancing the prospect of benefiting from future innovation activities (Damanpour et al., 2009; Roberts and Amit, 2003). Such benefits ould create, over time, economic advantages that competitors would find very difficult to achieve (Bayus et al., 2003).

3.6 R&D spillovers and absorptive capacity

One of the characteristics of technology or innovation is its degree of appropriability which leads to subsequent diffusion. More specifically, knowledge produced by one firm may not be entirely non-excludable and others may access or imitate it. Research spillovers is defined by Antonelli (1994) as the effects upon technological capacity of each firm stemming from corresponding R&D activities of other firms. Research spillovers might arise as R&D activity not only influence the performance of the firm undertaking the research effort but may as well have ramification on the performances of other firms (Wieser, 2005). The presence of technologically related R&D efforts of other companies may allow a firm to achieve innovative results with less R&D effort than otherwise (Jaffe, 1986). According to Griliches (1979), there are two distinctive types of technology spillovers; knowledge and rent spillovers. Knowledge spillovers are associated primarily with general knowledge that the original inventor could not prevent another company from exploiting. Knowledge spillovers originate from the disembodied form of R&D. This type of spillover takes place without any

economic transaction between counterparties and the beneficial firms have not paid for the use of technical knowledge generated via R&D efforts of another company (Bernstein and Nadiri, 1989). The possible channels of transmission of such general knowledge include the publication of scientific journals, intra-firm movement of skilled workers as well as product reverse-engineering (Wakelin, 2001). When there are low barriers to entry and imitation costs, new technology might leak out rapidly and innovating firms reap only a small fraction of the welfare from their own R&D investment (Mansfield, 1985). In contrast to knowledge spillovers, rent spillovers relate to R&D embodied in commodities traded and used between firms or industries. Blueprints of new products or new variants of existing products are appropriable, typically by patents or licenses (Los and Verspagen, 2000). Rent or market spillovers happen in the presence of strong competition and imperfect price discrimination (Scherer, 1982). In this respect, the economic benefits of an innovation are nevertheless not fully captured by the original producer via its price. Indeed, the gain from the superior new products or technologies could be passed on to buyers or users in form of productivity improvement (Wakelin, 2001). External knowledge enables the firm's internal knowledge to be extended by enhancing competitiveness and innovation (Matusik and Heeley, 2005).

Research externalities could be across firms within the same industry, across sectors in the economy and at transnational level. The technology of a firm within an industry could be not only positively affected by others in the same industry, but also by R&D efforts of firms in other industries that have no trade or technological relations with it (Antonelli, 1994). Potential effects of research spillovers are manifold. To Spence (1984), the externalities from R&D investment of a firm might lessen the cost of production of other firms and thus subsequently triggering the prevalent cost-reduction for the whole industry. Likewise, Wolff and Nadiri (1993) point out likely effects of cross-industry research spillovers. R&D conducted in an industry could affect technology of both producers and users. Such research spillovers emerge from close collaboration in R&D between consumers and suppliers of new products. For an industry, its R&D efforts and subsequent development of technology may also have an effect on linkages with other industries in the supply chain and the economy. Product development in the automobile and computer manufacturing sectors are noted for bolstering steady growth in both forward and backward linkages. Apart from productivity improvement, technological advancement in a particular sector could affect the production structure of others. Production inputs and distribution methods of other industries are substantively altered by the advent of automotive vehicles. In particular, the

spillover effects upon recipient industries may change their pattern of demand for labour, materials, traditional capital as well as their own R&D spending (Nadiri, 1993).

Production and cost functions are two models commonly used to examine the size of research spillovers and their impact upon productivity growth. The first is regarded as an extension to the typical production function model that investigates the relationship between R&D and productivity. It involves parameter estimations of the production function which includes not only traditional inputs and the firm's own R&D capital stock, but also the pool of R&D spillovers accrued to that particular firm. Close to the productivity effect of firms or industries own R&D efforts, changes in research spillovers also alter the quantity of output. Based on the Cobb-Douglas production function, the model is further augmented by technological spillovers and has two variants of estimation; elasticity and rate of return/marginal productivity. Griliches (1979) stated that the external technology available for an individual firm rely on the stock of knowledge accumulated through the process of R&D efforts made by other firms. To quantify R&D spillovers into the model, a simple way is to take the unweighted sum of all other firms' R&D capital or R&D spending. For instance, intra-sectoral spillover variables can be computed by adding together either R&D capital stock or R&D expenditures of other firms within that industry, expressed as follows;

$$\text{Equation 3.19 } S_{it} = \sum_{j \neq i}^n K_{jt}$$

$$\text{Equation 3.20 } S_{it} = \sum_{j \neq i}^n RD_{jt} \text{ or } \sum_{j \neq i}^n (RD/Q)_{jt}$$

In the investigation of spillovers in a regional cluster of Italian firms during 1980s, Antonelli (1994) uses a simple production function which has a slight alternation from the traditional production function in R&D-productivity analysis. This focuses on the impact of spillovers upon overall companies operating within the same region. Output growth proximate productivity growth of each individual company and labour, physical capital and R&D variables are on the ride hand side of the equation. Both internal and external R&D follow in the rate of return on R&D estimation approach as both types of R&D variables are shown as a fraction of production output. The spillover variable is the unweighted sum of R&D investment made by other firms divided by total output. This spillover variable is an additional independent variable in the model specification in which R&D intensity of a particular firm is already shown. The model specification is along the lines of Cohen and Levinthal (1989) and hypothesises the combined effects on a firm's output of R&D activities

both internally and externally. Raut (1995) analyses the R&D spillover effect upon productivity growth of Indian manufacturing firms over the period of 1975-1986. As with Antonelli (1994), Raut estimates output on two conventional inputs and internal and spillover R&D variables. While also based on the extended production function augmented by unweighted R&D spillovers, Raut's model is formulated in line with the estimation of R&D capital's output elasticity. Thus, the industry-level spillover R&D capital is computed in a similar manner as R&D capital. Even though both examples of preceding studies could be noted for straightforward model specification and spillover variable construction, they do not segregate the effect of intra-industry and inter-industry spillovers.

In addition, the use of unweighted spillover variables could be a limitation. It is arguable that not every R&D investment undertaken by others are pertinent for a given firm (Aiello and Cardamone, 2005). A technology or innovation could be critically relevant to one firm while it is somewhat extraneous to another. Therefore, the alternative and more refined measure of both intrasectoral and intersectoral R&D spillovers can be generated by assigning a weighting scheme onto those of spillover variables. Weights indicate the relevance of R&D of other firms or industries to a particular firm or industry. The weighting scheme is derived from the concepts of technological proximity, a measure of how diffusible knowledge is among firms or industries. This concept was originally suggested and developed by Griliches (1979) and Jaffe (1984; 1986). It is noted that technology and know-how developed by an industry could be utilised by other industries that have the level of technology close to that of the innovating industry. In particular, the new technology would be applied rapidly and effectively by an industry that shares relatively similar technological capabilities.

$$\text{Equation 3.21 } S_{it} = \sum_{j \neq i}^n W_{ji} K_{jt}$$

$$\text{Equation 3.22 } S_{it} = \sum_{j \neq i}^n W_{ji} RD_{jt} \text{ or } \sum_{j \neq i}^n W_{ji} (RD/Q)_{jt}$$

Equation 3.21 and 3.22 are modeled on 3.19 and 3.20, but are further incorporated with weights. S_{it} is the potential pool of research spillovers available for firm i , w_{ji} is the weight used to define the significance of R&D by firm j upon firm i .

There are two approaches to calculating weights and then to position companies or industries in a matrix of technological linkages (Nadiri, 1993). The first approach is to construct a matrix of technological proximity based on input-output link among companies or industries. This implies that commodities made by a firm or an industry are regarded as its

production output while those commodities simultaneously become inputs for other firms or industries for their own production. It is then assumed that the amount of R&D that spills over from one sector to another is proportional to the amount of output that the former sector sells to the latter. Terleckyj (1974) argues that the use of commodities in manufacturing processes may reflect the use of technical knowledge or innovation associated with those traded commodities. As input supplying firms or industries conducting R&D activities, their R&D outcomes may enhance the quality of inputs which subsequently result in the growth of productivity in the industry receiving those inputs (Goto and Suzuki, 1989). As this type of technological proximity indicator highlights economic transactions regarding intermediate inputs, the use of input-output table data solely captures rent spillovers rather than knowledge spillovers (Griliches, 1992). Despite this, it could be argued that any measure of rent spillovers incorporate some elements of knowledge spillovers, due to difficulties in quantitatively disentangling the two types of spillovers (Guellec and Van Pottelsberghe de la Potterie, 2004).

Terleckyj (1974, 1980) are early papers that estimate the stock of external R&D of an industry by using a weighting scheme using sectoral purchases of materials and capital from other sectors based on input-output tables. These R&D spillovers are notable for taking into account technological innovation embodied in customer inputs of production. In industry-level studies, total factor productivity is regressed on both intra-sectoral R&D and externally funded R&D. Both variables are expressed as a fraction of sectoral output and give estimates in terms of rate of return to R&D. The rate of return to external R&D is considerably larger than that of own R&D and this pattern is confirmed by Postner and Wesa (1983) and Mohnen, 1990). Scherer (1982, 1984) uses a similar approach in his measure of external R&D, but this weighting scheme is based on the number of patents originally issued by a sector that fall in another sector's industrial classification. In constructing the weighting scheme, patent data is used to distinguish between industry of origin and industry of user of technical knowledge. Spillover variables are distributed proportionally to patents instead of sales. Griliches and Lichtenberg (1984) also examine the role of inter-sectoral technology flows in fostering productivity growth, albeit using more detailed and better productivity data than in Scherer's earlier studies. Their findings are generally in line with Scherer's results as both demonstrate relatively larger estimates of spillovers than of internal R&D.

Although also constructing R&D spillovers on the basis of trade flows between sectors, Wolff and Nadiri (1993) use another formulation of R&D spillover. They assume

that the spillover benefit that a recipient industry gains from a supplying industry's R&D effort is proportional to R&D or knowledge importance in the former's production input structure and the gross amount of R&D spending relative to total output of the recipient sector. Using industry level data, they regress total factor productivity growth on sectoral R&D intensity and inter-sectoral R&D spillover intensity. Results show the significance of both sectoral R&D intensity and R&D spillovers embodied in intermediate inputs on the rate of sectoral productivity growth. Anon Higon (2007) presents evidence on the long-run impact of domestic cross-sectoral and transnational spillovers on eight U.K. manufacturing industries. The domestic external R&D variable is weighted by industries' total R&D expenses by a technology flows matrix based on input-output data of intermediate goods. The pool of international spillovers measure is constructed by weighting industries' R&D capital stock with bilateral import shares of intermediate input transactions. Her findings are that only domestic R&D efforts, both by an industry internally and by other industries within the same national boundary, have positive and significant impact on a sector's productivity growth.

The second approach deals with the use of patent classifications to pinpoint those firms or industries that benefit from patents and those of firms or industries appropriating such patents (Mohnen and Lepine, 1991). The distribution of firm patents across patent classes provides a useful account of the technological position of each firm (Jaffe, 1989). Even so the construction of technological distance based on patents requires a lot of detailed information and this approach could thus require substantial time resources (Wieser, 2005). Jaffe (1984, 1988) proposes the concept of technological closeness of each company to others with regards to their position in patent space. Tests are performed to determine for the effects of research spillovers on the firm's own R&D effort, inventive output and total factor productivity growth. In examining the growth of TFP, a model consisting of logarithmic differences are used in a production function. Yet this model differs from a typical R&D-productivity model. Rather, it proxies TFP growth by output growth as a function of traditional inputs, R&D intensity and R&D spillovers. For each firm, the pool of knowledge spillovers is the sum of the weighted R&D effort of others. The weight is represented by technological distance based on firm patent data. This weighting scheme is used to multiply external R&D effort to create a spillover variable. In Jaffe's subsequent study (1989), the focus is also on the effects of external R&D on the growth of firm productivity. The study uses data for 434 American firms for 1972 to 1977 but extended the investigation regarding

the spillover effects on firm patents, profits, gross revenues and market value. Given that productivity is represented by revenues, results show that productivity growth of a firm relates positively with both its own R&D effort and the R&D of others firms that are closely related in technological space. The pool of R&D externalities displays significant effects across all firm types categorised by the intensiveness of R&D effort. Branstetter (2001) applies the concept of technological closeness to a stratified sample of 209 American firms for 1983-1989. The spillover effects are divided between domestic and foreign. The major findings are that own R&D capital stock and the domestic pool of external knowledge exerts positive influence on the growth rate of firm sales. On the other hand, spillovers from abroad are insignificant owing to multicollinearity. Los and Verspagen (2000) address both rent and knowledge spillovers in their production function. In their study of panel data for American manufacturing firms, they proxy rent and knowledge spillovers by weighing other firms' R&D with input-output flows and patent data respectively whilst a basic spillover variable is also constructed by using an unweighted sum of R&D expenditures. All three different spillover variables are found to be positive and significantly related to labour productivity.

Apart from examining the R&D-productivity growth relationship in UK manufacturing firms, Wakelin (2001) extends the production function by adding two spillover variables to represent both intra-industry and inter-industry spillovers. The total amount of R&D investment undertaken by other firms in the same sector is used to proxy for the pool of industry-wide knowledge in that sector. This sectoral R&D spending is net of the firm's own R&D and is divided by gross sectoral sales to generate sectoral R&D intensity. To represent inter-industry spillovers, weighted sum of other firms' R&D expenditures is divided by the recipient sector total sales. The results are different from other firm level studies as inter-sectoral spillovers of innovation are not found to contribute to labour productivity growth of the firm although they may utilise external knowledge. A similar study by Aiello & Cardamone (2005) assesses the link between R&D spillovers and labour productivity of 1017 Italian manufacturing companies between 1995 and 2000. The effects of external R&D are separated into intra-sectoral and inter-sectoral effects. The model uses first differenced logarithms in a production function, and regresses labour productivity growth on the growth rates of traditional capital and knowledge capital stock plus lagged R&D spillovers. As with internal R&D capital, technological spillovers are termed spillover capital. They are determined by the weighted sum of knowledge capital stock of other firms within the same

industry or across sectors. Their results indicate a positive and significant effect of external R&D upon productivity growth of the firms.

An unconventional weighting scheme is found in Beneito (2001). The study constructs spillover variables by weighting the knowledge capital stock of innovation generating firms with a dummy variable indicating whether a knowledge producer has accomplished innovations during the present or previous years. If there is no successful result in a year, then the amount of spillovers to users of technologies in that particular year would be zero. Otherwise, an innovation result is added to the pool of available spillovers. Firms are separated into those using advanced technologies from those that do not, creating different spillover measures for the two groups. The results illustrate the significant effect of spillovers from those that use advanced technologies, as opposed to other sources of knowledge. Since both patent and input-output information relate to market transactions at firm and sectoral level, it is apparent that both approaches to construct technological proximity is feasible for the embodied form of R&D rather than the disembodied form. The production function and its technological distance concepts are flawed as they do not take into account technological developments achieved by different firms in different industries that have virtually no market interaction with a particular firm or industry. Likewise, technological proximity is criticised by Antonelli (1994) as underestimating the effects of technological convergence and the role of generic technologies. To Nelson (1991), generic technologies are know-how and information resulting from R&D efforts of third parties, and such technologies would affect the production function for many firms regardless of intra-sectoral trade flows and technological proximity. As demonstrated in table 3.4, a considerable number of empirical studies using an extended production function framework have reported a positive and significant effect of spillovers on productivity. Early studies could be characterised for not specifying the source of spillovers whereas subsequent attempts have been made to separate total spillover effects into each potential source of knowledge.

The argument behind cost functions is based on the potential effect of research spillovers not only on manufacturing costs but also on the demand for labour, capital and intermediate goods (Griliches, 1992). The flow of R&D externalities could cause factor substitution among production inputs. Notably, the existing stock and investment level of traditional capital and R&D capital may adjust to the change in research spillovers, and inputs may be complements or substitutes to the pool of R&D externalities (Bernstein and Nadiri, 1989). However, main disadvantage of the cost function is data availability. Nadiri

(1993) argues that the cost function requires detailed information on physical quantities and price of output, relative factor prices for conventional inputs as well as R&D capital and the stock of R&D capital owned by other companies or industries. It could be problematic to acquire good input price data that varies across firms and across time-periods, particularly prices of physical capital and R&D capital stock.

As proposed by Bernstein and Nadiri (1988), production costs and the demand for factors of production in an industry is influenced by R&D capital of other industries. They note that the cost shares of labour, physical capital and materials are determined by inter-sectoral spillovers as the inflows of external knowledge could lead to changes in demand for each of three production inputs. In their studies of five American high-technology sectors between 1958 and 1981, it is shown that manufacturing costs diminished as a consequence of inter-industry spillovers. In response to spillovers, there was a decline in the demand for labour and material as opposed to a rise in demand for physical capital. Bernstein (1988) estimates both intra-sectoral and inter-sectoral spillovers in Canadian industries and found a greater cost-reducing effect from inter-sectoral spillovers relative to intra-sectoral spillovers. Also, it was noted that the largest magnitude of inter-industry spillovers' impact was demonstrated in those sectors with substantial levels of R&D effort such as electrical apparatus and chemical products. Bernstein (1989) investigated the effects of inter-sectoral spillovers on production costs of nine Canadian manufacturing sectors and found that production costs of an industry is determined by R&D capital stocks of other industries in the economy. Due to the inappropriability of knowledge, the benefit from new technology created by one industry could be realised by others in form of cost reduction. In his paper, production cost of an industry is defined as the sum of the cost of materials, labour, physical capital and sectoral R&D capital. An additional variable is the unweighted sum of inter-industry spillovers, computed from multiplying the recipient sector's R&D capital with each of the other sectors' R&D capital stock. The cost function is estimated in logarithm form and the results indicate the dependence of each spillover-receiving industry's production cost upon the stock of knowledge capital generated externally.

Table 3.4: Econometric studies assessing the impacts of research and development spillovers upon productivity

Study	Country	Time period	Individual data	Weighting scheme	Estimation methods	Output elasticity/ rate of return of spillover variable
Terleckyj (1980)	U.S.	1948-1966	20 industries	Input-output flow	OLS	0.81**
Scherer (1982)	U.S.	1973-1978	443 firms	Input-output flow	OLS	0.818***
Scherer (1984)	U.S.	1973-1978	443 firms	Input-output flow	OLS	0.249**
Griliches and Lichtenberg (1984)	U.S.	1964-1978	193 industries	Input-output flow	OLS	0.736* (1964-1969), 0.504* (1973-1978)
Jaffe (1984 and 1988)	U.S.	1972-1977	434 firms	Position (firm) in patent space	OLS	0.099**
Jaffe (1989)e	U.S.	1972-1977	434 firms	Position (firm) in patent space	OLS	0.128**
Jaffe (1989)e	U.S.	1972-1977	Low-tech firms	Position (firm) in patent space	OLS	0.13**
Jaffe (1989)e	U.S.	1972-1977	Average-tech firms	Position (firm) in patent space	OLS	0.15**
Jaffe (1989)e	U.S.	1972-1977	High-tech firms	Position (firm) in patent space	OLS	0.17**
Wolff and Nadiri (1993)	U.S.	1947-1977	19 industries	Input-output flow	OLS	0.09*
Antonelli (1994)	Italy	1984-1985	92 firms	unweighted	OLS	0.176
Raut (1995)e	India	1975-1986	192 firms	unweighted	OLS	0.06-0.36**
Los and Verspagen (2000)e	U.S.	1974-1993	680 firms	Position (firm) in patent space	Fixed effects (Within)	0.558** (knowledge S), 0.42** (rent S), 0.56** (unweighted)

Table 3.4: Econometric studies assessing the impacts of research and development spillovers upon productivity (continued)

Beneito (2001)e	Spain	1990-1996	501 firms	Advanced/ non-advanced technology level	OLS, IV	0.007** (OLS) 0.012** (IV) (Advanced tech S)
Branstetter (2001)	U.S.	1983-1989	209 firms	Position (firm) in patent space	LD	0.83 (domestic S)*, -0.24 (Foreign S)
Wakelin (2001)	U.K.	1988-1996	170 firms	Position (firm) in patent space	OLS	0.31 (intra-sectoral S) -0.08 (Inter-sectoral S)
Aiello and Cardamone (2005)e	Italy	1995-2000	1,017 firms	Input-output flow	Random effects (FGLS)	0.007**(intra-sectoral S) 0.002*** (Inter-sectoral S)
Aiello and Cardamone (2005)e	Italy	1995-2000	1,017 firms	Input-output flow	GMM	0.017**(intra-sectoral S) 0.017*** (Inter-sectoral S)
Anon Higon (2007)e	U.K.	1970-1997	8 industries	Input-output flow	Fixed effects (ARDL)	0.942** (domestic inter- sectoral S) -0.048 (Foreign S)

Notes: OLS denotes ordinary least square; IV denotes instrumental variable estimation; GMM denotes generalised moment methods; LD denotes long-differences, FGLS denotes Fesible generalised least squares

ARDL denotes auto-regressive distributed lag; e indicates the estimation of elasticity of R&D

Advanced tech S denotes spillover stemming from advanced technology sector

* 10% significant level; **5% significant level; ***1% significant level

Table 3.5: Econometric studies assessing the impacts of research and development spillovers upon profitability

Study	Country	Time period	Individual data	Weighting scheme	Estimation methods	Output elasticity/ rate of return of spillover variable
Jaffe (1986)e	U.S.	1973 and 1979	432 firms	Position (firm) in patent space	OLS	- 0.078**
Megna and Mueller (1991)e	U.S.	1967-1988	10 firms	unweighted	OLS	0.009 (intra-sectoral S)
Megna and Klock (1993)e	U.S.	1972-1990	11 firms	unweighted	NLS	- 0.007*** (patent S), 0.003*** (R&D capital S)
Geroski et al. (1993)e	U.K.	1972-1983	721 firms	unweighted	GMM	0.0003 (Production S), 0.001 (Use S)
Hanel and St-Pierre (2002)e	U.S. And Canada	1988	278 firms	Input-output flow, Position (firm) in patent space	OLS	- 0.015 (knowledge S), 0.046*** (rent S)

Notes: OLS denotes ordinary least square; GMM denotes generalised moment methods; NLS denotes non-linear least square

e indicates the estimation of elasticity of R&D

* 10% significant level; **5% significant level; ***1% significant level

The concept of technological externalities is applied to empirical studies of profitability determinants. From table 3.5, it is apparent that the spillover effect on profitability has been largely ignored. Typically, both firm internal R&D and spillover variables are incorporated into the linear regression model as additional explanatory variables. As in productivity studies, spillover variables are constructed in the spirit of the approaches discussed above. Jaffe (1986) presents a profit equation in which the estimation shows that firm profit is negatively affected by technological discoveries of others. Megna and Mueller (1991) regress traditional capital, advertising capital and R&D capital on profit. They take into account R&D capital stock of both the firm and competitors within the same sector. The second R&D capital, representing the potential pool of intra-industry spillover, is found to have a small positive coefficient. In Megna and Klock (1993), the profitability effects of both patent and R&D capital and intra-sectoral spillovers are studied on semiconductor companies. For each firm, it is assumed that patents and R&D capital stock are two forms of intangible capital. In their findings, evidence suggests that the stock of rival firm patents and R&D capital explain the variation in Tobin's Q (Tobin, 1978). The negative contribution of other firms' patents upon Tobin's Q could reflect appropriability of patents in the industry.

Geroski et al. (1993) consider the impact of two types of innovation variables on profit margins. The first is the amount of innovations generated via the firm's own R&D effort. The second captures the effect of spillovers stemming from innovations produced and used elsewhere in the two-digit sector that the company is operating in. In contrast to other papers, they observe small positive effects of both spillover variables on profit margin. They argued that their innovative spillover variables measure only rent spillovers embodied in commercial products whereas the potential spillover effect may have emerged from knowledge that is commonly disembodied and widely diffused. Hanel and St-Pierre (2002) examine the profitability effect of both knowledge and rent spillovers. Knowledge spillovers are the pool of quasi-public knowledge, measured according to firms' proximity to each other in technological space (Jaffe, 1986). Rent spillovers represent inter-industry technology externalities which is the ratio of the weighted sum of other sectors' R&D to the gross value of industry output. Their major findings are that firm's own R&D effort and rent spillovers contribute to profitability and that knowledge spillovers are detrimental to profitability. As they stressed, the intense competition amongst firms operating in similar technological space can extend the positive effect of knowledge diffusion that each individual firm may gain.

In reference to Mohnen (1996), technological spillovers are expected to yield beneficial effects since it is reasonable to assume that firms are not likely to adopt new technologies that diminish their revenues. Although empirical literatures appear to be in conformity regarding the positive effect of technological spillovers, there is also a possibility that innovative effort of any given company can constitute a negative externality for other companies. In fact, external knowledge can be hindrance on profits, productivity growth and welfare. To make this concrete, negative externalities may arise from rivalry. To Jensen (2009), the concept of patent race is where two or more companies competing to be the first to discover an invention in order to secure a patent that will safeguard its invention from imitation. In this respect, the first innovator will be granted monopolistic rights which would rule out the possibility of competitors' success with similar technologies and guarantee advantageous interests like rents (Yao, 2006). To Yao, the firm's chance in creating successful innovation before others is determined by the magnitude of technological effort by the firm per se and this in turn reduces the probability of others' success. The failure to secure the first position in patent competition might imply that there would be negative effect of rival's R&D upon a firm's innovative effort. In the presence of race to win the patent, innovating firms are likely to over-invest. They spend more than in the research outcome where there are research cooperation and patent sharing. However, it could be argued that only one firm eventually secures the patent while the rest of competing firms are burdened with enormous R&D expenditures which do not lead to materialised innovative results. For strategic reasons, firms are obliged to participate in R&D races without necessarily benefited from it or to merely keep up with the technological pace (Cincera, 2005).

Another antecedent of negative spillovers might be related to the adjustment costs which stem from the emergence of external technologies. Firms would encounter sizable adjustment costs to learn and adapt to new technologies. In fact, adjustment costs could arise owing to the costs of giving up prior technologies, introducing new ones, acquiring new machines and equipment, and hiring and firing workers (Mamuneas, 1999). The interrelationship between adjustment cost and extramural technology has been pointed out in cost-function literatures. According to Bernstein and Nadiri (1989), given the output and factor quantities in the production function, changes in research externalities cause the adjustment in quasi-fixed factors of production as their rate of investment change. A quasi-fixed factor is defined as a production input whose total employment is partially variable and partially fixed (Oi, 1962), taking for instance labour. The presence of adjustment costs would

prevent manufacturers to immediately attain the long-run equilibrium while they have to adjust toward such equilibrium through successive short-run or temporary equilibria (Morrison and Berndt, 1981; Bernstein and Mohnen, 1998). Such short term feedback might include negative effect stemming from the process of adapting to new external knowledge; either acquired or learnt from other firms, suppliers, and customers.

Technological spillovers determine the price that a manufacturer can charge for its product. To this end, the direction and magnitude of price change is depended on whether outside knowledge is substitute or compliment of existing in-house knowledge. The essence of negative R&D spillovers could be also explained from the concept of creative destruction. Rather than being the application of other firms' knowledge, the improved products of the firm might be a byproduct of its own innovative effort. According to Jaffe (1996), the introduction of a new technology is likely to render some preceding investment in R&D obsolescent. Owing to superior performance of its product, the firm could be able to take away part of the others' market. Consequences of the firm's technological discovery are multi-folds. As the innovator of superior technology, the firm would experience the rise in its revenues. Besides, consumers are those who without doubt gain benefit from better product specification and price competition among firms. Contrariwise, other firms lose a stream of revenues or market rent that if otherwise could have enjoyed. The impact of creative destruction could be injurious if the other firms do not have sufficient time to recover their past R&D investments (Cincera, 2005). This negative social effect is often not considered by the firm during its technological investment decision and there is possibility that its magnitude may dominate the social benefits of new technology. Although the innovating firm sought to earn substantial rents, the net externality benefits are likely to be modest or even negative.

Whilst the pool of publicly available knowledge is created as the consequence of the spillovers from private efforts in R&D by each firm or sector in the economy, the adsorption of external R&D into an individual firm is not costless. The presence of others' R&D capital stock does not guarantee the straightforward diffusion of technology. In fact, some technical knowledge is tacit since it is difficult to codify in manuals or textbooks and hard to acquire without direct investigation (Griffith et al. 2003). To understand and implement ideas and concepts of others, organisations must have the competencies that enable them to understand, decodify and utilise these ideas (Grunfeld, 2003). It could be argued that the firm itself has to actively engage in technological activities in order to effectively reap benefits from spillovers

(Evenson and Kislev, 1973). In other words, the firm's internal R&D investment enables the firm itself to keep up with relevant technological knowledge discovered elsewhere (Von Hippel, 1988). In this respect, the firm must utilise its own laboratories, scientists and engineers to incorporate technical knowledge acquired via spillovers into its own manufacturing process (Rosenberg, 1974 and Nelson, 1982).

Absorptive capacity implies learning and acting on scientific discoveries and innovative activities outside the organisation's limits (Deeds, 2001; Sun and Anderson, 2010). To this end, it is the dynamic capacity that allows companies to generate value and to gain and sustain a competitive advantage through the management of external knowledge (Camisón and Forés, 2010). It represents the link between an organisation's internal capability to develop new product and improve existing ones, and external base of information and opportunities on the other side (Murovec and Prodan, 2009). If the probabilities of success of a specific project change owing to new discoveries outside the firm's limits, firms with greater absorptive capacity would be sensitive to these changes and adjust their innovative efforts quickly in accord with the new information (Jiménez-Barrionuevo et al. 2011). With the capability to absorb and adopt external technology, a recipient firm would be able to reverse-engineer the technology embodied in improved products and afterwards use that knowledge to further its own R&D activities (Branstetter, 2001). Lane et al. (2002) and Van den Bosch et al. (2006) view absorptive capacity as a multidisciplinary concept which serves to link and mediate between related field of knowledge, such as organisational learning, knowledge management and innovation management. Absorptive capacity is qualitatively different from technology development as it involves learning and acting on the scientific discoveries and technical activities occurring outside the firm's boundaries (Deeds, 2001). External knowledge gathered could be afterwards used to redirect scientific discovery and technology development activities (Fichman, 2004). Absorptive capacity improves the speed, frequency, and magnitude of innovation (Helfat, 1997; Kim and Kogut, 1996).and enhances learning within an organisation (Autio et al., 2000; Rosenkopf et al., 2001; Simonin et al., 1999). In turn, this change encourages innovations that improve productivity or effectiveness (Deng et al., 2008).

To Cohen and Levinthal (1994) and Gambardella (1995), if R&D activities are viewed as investments, then superior absorptive capacity will lead to more effective R&D expenditures. In essence, absorptive capacity enhances a firm's ability to judge the probability of successfully turning a given piece of basic research into profitable product

(Keller, 1996). To this end, companies with greater absorptive capacity are more likely to pursue projects with a higher probability of success due to their superior knowledge (Daghfous, 2004). As Deeds (2001) stressed, if the probabilities for a particular research stream change owing to external technological discoveries, then firms with higher absorptive capacity would sense this change faster and be quicker to adjust their innovative efforts in line with the new outside knowledge. Likewise, absorptive capacity substantiates the productivity of the firm's technological investments. By consistently internalising knowledge from beyond the firm's boundaries, the firm per se could chronically re-evaluate its portfolio of R&D projects in accordance with those of new information.

Extant researches have noted a positive interrelationship between absorptive capacity and a firm's innovation performance. Absorptive capacity promotes the speed, frequency, and magnitude of innovation, which in turn may produce knowledge that becomes part of a firm's future absorptive capacity (Zahra and George, 2002). Besides, absorptive capacity can act as a conduit of transferring knowledge between different organisational units, knowledge that can be instrumental in facilitating a firm's innovation activities (Tsai, 2001). Kostopoulos et al. (2011) postulate another role of absorptive capacity as the mediator in the relationship between external knowledge inflows and innovation performance. Drawing from existing models of absorptive capacity (Todorova and Durisin, 2007; Zahra and George, 2002), there is supposition that new outside knowledge functions as an antecedent of absorptive capacity, which, in turn, impacts innovation performance of the firm. In this respect, absorptive capacity enables companies to derive innovation benefit from, otherwise purposeless, external knowledge flows. Conversely, innovation performance facilitates the link between absorptive capacity and firm performance. Absorptive capacity substantiates the development of new cognitive schemas and the modification of existing organisational practices (Kostopoulos et al., 2011). Through these changes, firms are better able to pursue new product developments and product line extensions (Kazanjian et al., 2002), which, in turn, would promote financial performance and contribute to the achievement of competitive advantage (Lane et al., 2006). Nevertheless, it could be marked that the mere processing and assimilation of external knowledge, without the effective introduction and commercialisation of specific innovation output, could not result in tangible financial outcomes for the firm over time (Kostopoulos et al., 2011).

The concept of absorptive capacity displays flexibility to be applied to different level of analysis and in a range of research fields such as industrial organisation, organisational

learning, strategic management and innovation management (Zahra and George, 2002). The concept of absorptive capacity has its root in the macroeconomics, where it refers to the ability of an economy to utilize and absorb extramural information and resources (Adler, 1965). The definition of the absorptive capacity and its antecedents is sometimes ambiguous, and most empirical studies do not validate it (Lane et al., 2006; Van den Bosch et al., 2006). Due to the intangible nature of this construct, it is difficult to conceptualise while the definition of the dimensions that shape such construct is complicated. Not only is there no consensus regarding the number of dimensions or phases that compose the construct of absorptive capacity, but no firmly tested measure has been developed to differentiate the phases of the process by which recipient unit absorb knowledge from innovating unit (Todorova and Durisin, 2007).

The definitions of absorptive capacity; introduced by Cohen and Levinthal (1989, 1990), have been regarded as cardinal to the conceptualisation of this variable. Cohen and Levinthal (1989) refer absorptive capacity as the ability to learn from external knowledge via processes of knowledge identification, assimilation and exploitation. They follow Allen (1977) in holding that absorptive capacity is a by-product of an organisation's innovative efforts. To this end, the internal R&D is viewed as critical to the organizational learning. In Cohen and Levinthal (1990), they redefine the absorptive capacity construct as the capacity of an organisation to value, assimilate and apply, for commercial ends, knowledge from external sources. In this respect, absorptive capacity is a by-product not only of internal R&D, but could be also of the diversity or breadth of the organisation's knowledge base, its prior learning experience, the existence of cross functional interfaces, and the mental models and problem solving capacity of the organisation's members (Camisón and Forés, 2010). Likewise, Mowery and Oxley (1995) describe absorptive capacity as a broad array of skills, reflecting the need to deal with the tacit components of transferred technology, as well as the frequent need to modify a foreign-sourced technology for domestic applications. To Kim (1998), absorptive capacity is learning capability that the organization could utilise to assimilate outside knowledge for imitation and problem-solving skills to create new knowledge. Also deriving the basic definition of Cohen and Leventhal, Murovec and Prodan (2009) propose two distinctive types of absorptive capacity; science-push and demand-pull types. According to them, science-push absorptive capacity is based on technological opportunities and available scientific information originated from universities, non-profit research institutes and commercial R&D enterprises. While demand-pull absorptive capacity

is based upon the factors determining market demands such as customers, suppliers, competitors and fairs.

Lane and Lubatkin (1998) provide a different interpretation of absorptive capacity to the construct that Cohen and Levinthal (1989) coin. Their new definition departs from those of Cohen and Levinthal (1989, 1990) in the aspect of the role of internal R&D. Whilst focusing on the capacity of organisations to absorb from other organisations, they argue that in-house R&D explains merely 4% of variation in inter-organisational learning. According to them, absorptive capacity might be determined by the relative organisational characteristics, and the relation between their knowledge processing and application systems. Zahra and George (2002) provide a further reconceptualisation of absorptive capacity by relating the construct to a set of organisational routines and strategic processes through which firms acquire, assimilate, transform and apply knowledge with the aim of creating a dynamic organizational capacity. In line with Teece et al. (1997), these four processes represent the four dimensions of absorptive capacity which combine naturally and build upon one other to generate a dynamic organizational capability. Such four dimensions of absorptive capacity include acquisition, assimilation, transformation and application. Acquisition capacity is an organisation's ability to locate, identify and acquire outside knowledge that is crucial to its operations (Liao et al., 2003). Assimilation refers to the processes that allow the acquired external knowledge to be analysed, understood and finally internalised (Szulanski, 1996). Transformation is the capacity to transfer and combination of previous knowledge and the newly acquired knowledge (Kogut and Zander, 1992). To Van den Bosch et al. (1999), transformation could be achieved by adding or phasing out knowledge, or by interpreting existing knowledge in a different, innovative way. Application or exploitation refers to the capacity to incorporate external knowledge into their operations and routines. This dimension of absorptive capacity would eventually result in new operations, competences, goods and organisational forms (Lane and Lubatkin, 1998). As to four dimensions of absorptive capacity, Zahra and George (2002) categorise them into two subsets of complementing components; potential absorptive capacity and realised absorptive capacity. The first component consists of acquisition and assimilation whereas the latter comprises of knowledge transformation and application. Potential absorptive capacity affects competitive advantage through management flexibility and the development of resources and capacities, meanwhile realised absorptive capacity does so through the development of new products and processes (Camisón and Forés, 2010).

Not only definitions, but operationalisation of absorptive capacity appears to vary greatly as well. Either a quantitative or a qualitative approach is adopted by extant study towards gauging absorptive capacity. Although the multidimensionality of absorptive capacity is noted in the original conceptualisation by Cohen and Levinthal (1989, 1990), the uni-dimensional construct has been often used to measure absorptive capacity in a number of empirical studies. The most popular proxy used by researchers is R&D effort made by the firm. It is proxied by R&D spending divided by annual sales (Cohen and Levinthal, 1990; Stock et al., 2001; Tsai, 2001; Zahra and Hayton, 2008). The effectiveness and magnitude of technology absorption rely upon the level of prior related knowledge that the organisation possesses and is developed cumulatively, through a long process of research and knowledge accumulation (Jiménez-Barrionuevo et al. 2011). Empirical studies have used R&D intensity not only as a measure of internal learning, but also as a prerequisite for external learning (Bierly and Chkrabarti, 1996).

Absorptive capacity is alternatively measured by using data taken from variables that related to R&D investment. Other authors use the firm's possession of its own R&D departments with full-time personnel (Veugelers, 1997), percentage of technical and professional personnel over the total number of employees (Luo, 1997), number of patents (George et al., 2001), total number of publications per dollar spent on research annually (Cockburn and Henderson, 1998), R&D effort in training personnel (Petroni and Panciroli, 2002), the kinds of knowledge sought outside the organisation relative to the organisation's own knowledge bases (Shenkar and Li, 1999), the existence of formal R&D laboratories and the regularity of R&D activities (Becker and Peters, 2000), the number of employees with university education (Grimpe and Sofka, 2009), and R&D activities aimed at developing new knowledge and other activities such as knowledge intelligence and knowledge dissemination (Spithoven et al., 2010). Nevertheless, firm's R&D expenditure and other simple technological indicators might not reflect the richness of the absorptive capacity construct in its totality (Zahra and George, 2002). In fact, the use of crude proxies may have contributed to conflicting and misleading finding about the nature and contribution of absorptive capacity (Flatten et al., 2011). Despite being variables that have been widely used to construct absorptive capacity, R&D investment and patent still have shortcomings. The use of firm R&D as a single variable to gauge a multidimensional construct such as absorptive capacity might not be passably effective. Firm R&D is not the sole source of absorptive capacity while factors namely employee skills, organisational memory, and prior organizational experiments

and experiences may contribute significantly to a firm's overall absorptive capacity as well (Flatten et al., 2011). Due to the firms' difference in propensity to patent their innovation, the use of patent may actually understate the absorptive capacity. Besides, it is nebulous whether the use of patents would fully capture absorptive capacity since patents differ substantially in term of their knowledge content (Coombs & Bierly, 2006).

The interaction term between firm R&D and external knowledge is a relatively more sophisticated construct of absorptive capacity. It is built upon the two facets of R&D; originally termed by Cohen and Levinthal (1989). Previous studies not only suggest the importance of the recipient firm's own R&D efforts regarding the internalisation of R&D spillovers, but also the interaction and complementarity between the levels of internal R&D activities and the external supply of information and know-how that is made available within the economy (Antonelli, 1994). Likewise, it is also implied that the contribution of the firm's own R&D investment has two dimensions. First, R&D efforts are critical for generating original knowledge for the firm itself, and such knowledge would subsequently leak out and become the source of technological spillover for other firms (Terleckyi, 1982). Second, it is necessary for the firm to acquire and apply related know-how and technological information that are spilled from other firms' inventive activity.

To take into account two facets of R&D, Griffith et al. (2000, 2003) uses a model specification that distinguishes the effects of internal R&D into technological development and the enhancement of absorptive capacity. They investigate both roles of R&D on sectoral productivity growth in OECD nations. The absorptive capacity is a function of the size of a quality-enhancing innovation and the distance from the technological frontier of that firm. In this respect, technology is transferred from countries on the frontier of innovation development to those lagging behind the frontier. As Griffith et al. argued, R&D activities engaged by non-frontier countries foster the incorporation of knowledge from the technological frontier. The greater distance from the frontier increases the prospective of technological transfer and the size of home-grown innovations that arise. Productivity convergence could occur rapidly as non-frontier countries commit substantially to their own R&D efforts. The interaction term between R&D and distance from the technological frontier is used to represent absorptive capacity. Since the frontier country is associated with the highest productivity level, this thus leads to the use of distance from the productivity frontier to proximate the distance from technological frontier. The distance from the productivity frontier is computed from the difference between the productivity level at the frontier and the

productivity level of a country behind the frontier. This amount is then multiplied by R&D intensity to generate absorptive capacity in the production function.

Apart from emphasising research spillover effects, Jaffe (1986; 1989) sheds light on the interaction term between firm's own R&D and a measure of the potential technology spillover pool. In both equations for patents and for profits, this interaction term is created by multiplying the firm's own R&D by the weighted sum of others' R&D. His results indicate the positive and significant role of absorptive capacity in explaining the rise of firm productivity. In a firm-level study of the Czech manufacturing sector between 1995 and 1998, Kinoshita (2001) examines the significance of firm R&D and technology spillovers resulting from FDI in explaining productivity growth. The paper considers foreign ownership and foreign firms' presence in the sector to represent intra-firm and intra-sectoral technological spillovers, respectively. Although the empirical model is similar to Griffith et al. (2000), the absorptive capacity term is the interaction between firm R&D and two proxies of FDI. Thus, each absorptive capacity variables are constructed by the product of R&D intensity and the two FDI variables. Estimation of the production function shows that the ownership of domestic companies and the presence in the industry of foreign companies alone do not constitute a significant effect on productivity growth. Whilst the interaction between foreign ownership and firm R&D has a positive and significant impact, this could imply the role of the firm's own R&D in enhancing its capacity to exploit intra-industry spillovers from FDI and subsequently in explaining productivity growth.

Absorptive capacity has been also measured by a large and broad set of variables. Considering absorptive capacity as a global construct, Szulanski (1996) measures it by using scale formed of 9 items and without differentiating its different phases. Nieto and Quevedo (2005) concentrate on the determinants of the accumulation of absorptive capacity. They use variables representing communication with the external environment, the firm's knowledge and experience level, diversity and coincidence between structures of knowledge and strategic position.

Reflecting the multi-dimensional absorptive capacity of Zahra and George (2002), some researchers identify absorptive capacity as a process while taking into consideration a varying number of dimensions. To this end, there is no consensus among empirical studies regarding the amount of phases to be measured and variables used to proxy each phase. Heeley (1997) and Liao et al. (2003) measure absorptive capacity via the processes of

acquisition of outside knowledge and dissemination of such externality within the organisation. Chen (2004) uses scale of 5 items to construct absorptive capacity in accordance with the assimilation and reproduction of external knowledge obtained. In Lin et al. (2002), absorptive capacity is measured through scale formed of 15 items representing the capacity to adapt, replicate and apply external knowledge. Highlighting on the recognition of the value, assimilation and application of knowledge, Thuc Ahh et al. (2006) consider absorptive capacity as a construct that incorporates organisational issues as well as human capital. Jansen et al. (2005) address all four dimensions of absorptive capacity; acquisition, assimilation, transformation and exploitation of the knowledge. They use scale of 21 items to measure potential absorptive capacity and realised absorptive capacity accordingly. Similarly, Fosfuri and Tribó (2008) also recognise the distinction between potential and realised components of absorptive capacity. They choose to empirically explore the organisational antecedents of potential absorptive capacity and its impact on innovation performance.

Among empirical studies, the scales or items used to measure each dimension of absorptive capacity diverge considerably. The capacity of acquisition has been measured through openness towards the environment (Caloghirou et al., 2004; Soo et al., 2007; Tu et al., 2006); research collaboration (Arbussà and Coenders, 2007; Liao et al., 2003; Mangematin and Nesta, 1999) and internal development of technological competences (Arbussà and Coenders, 2007; Tu et al., 2006). Assimilation capacity is proxied by human resources (Caloghirou et al., 2004; Hayton and Zahra, 2005; Vinding, 2006); industrial benchmarking (Tu et al., 2006); involvement in spreading the knowledge (Fosfuri and Tribó, 2008; Soo et al., 2007); attendance at training courses and professional events (Jansen et al., 2005) and knowledge management (Matusik and Heeley, 2005; Soo et al., 2007). Factors representing knowledge transformation capacity include transmission of information-technology based knowledge (Wong et al., 1999); exchange of scientific and technological information (Lenox and King, 2004) and integration of R&D (Vinding, 2006). The dimension of applicability is measured via the degree of new knowledge exploitation (Jansen et al., 2005); application of prior experience (Lenox and King, 2004); patents' development (George et al., 2001; Mangematin and Nesta, 1999; Zahra and George, 2002) and technological proactiveness (Jansen et al., 2005).

Table 3.6: Econometric studies estimating the effects of Research and Development on productivity within Japanese context

Study	Time period	Individual data	Productivity variable	Estimation methods	Output elasticity/ rate of return	Spillovers
Odagiri (1983)	1969-1981	123 firms (scientific sectors)	TFP growth	OLS	0.256**	-
Odagiri (1983)	1969-1981	247 firms (other sectors)	TFP growth	OLS	-0.475	-
Odagiri and Iwata (1986)	1966-1973	135 firms	TFP growth	OLS	0.201*	-
Odagiri and Iwata (1986)	1974-1982	135 firms	TFP growth	OLS	0.169**	-
Sassenou (1988)e	1973-1981	394 firms	Value added	Between effects	0.04	-
Sassenou (1988)e	1976	394 firms	Value added	OLS	0.10**	-
Sassenou (1988)e	1976	112 firms (scientific sector)	Value added	OLS	0.16**	-
Sassenou (1988)	1973-1981	394 firms	Output growth	OLS	0.22**	-
Goto and Suzuki (1989)	1976-1984	13 firms (drugs)	TFP growth	OLS	0.42***	-
Goto and Suzuki (1989)	1976-1984	5 firms(electronics)	TFP growth	OLS	0.22*	-
Goto and Suzuki (1989)	1976-1984	3 firms (motor vehicles)	TFP growth	OLS	0.33**	-
Goto and Suzuki (1989)	1978-1983	50 industries	TFP growth	OLS	0.255**	0.8**
Goto and Suzuki (1989)	1978-1983	50 industries	TFP growth	OLS	0.293**	0.11 (electronics rent S), 0.043*** (electronics knowledge S)
Griliches and Mairesse (1991)	1973-1980	406 firms	Labour productivity growth	OLS	0.56**	-

Table 3.6: Econometric studies estimating the effects of Research and Development on productivity within Japanese context (continued)

Suzuki (1993)	1982-1988	9 firms (electrical machinery)	Variable cost	GMM	0.12**	0.08 (from other cores)
Suzuki (1993)	1983-1986	17 firms (electrical machinery)	Variable cost	GMM	0.07**	0.0106 (from other sub) and 0.008 (from own core)
Cincera (1998)e	1987-1994	133 firms	Output growth	OLS	0.28**	- 0.23 (domestic S) 1.46** (foreign S)
Branstetter and Sakakibara (1998)e	1983-1989	230 firms	Output growth	Fixed effects (Within)	0.079**	0.362**
O' Mahony and Vecchi (2000)e	1993-1997	107 firms (machinery)	Output growth	OLS	0.107	-
Branstetter (2000)e	1983-1989	208 firms	Output growth	Fixed effects (Within)	0.062**	0.125** (Intra-K S) 0.489 (Extra-K S)
Branstetter (2001)e	1985-1989	205 firms	Output growth	LD	0.007	0.5 (domestic S)**, 0.4 (Foreign S)
Kwon and Inui (2003)	1995-1998	3,830 firms	Labour productivity growth	Fixed effects (Within)	0.084**	-
Kwon and Inui (2003)e	1995-1998	3,830 firms	Labour productivity growth	OLS	0.163**	-
Ito (2004)e	1981-1996	210 plants	TFP growth	OLS	-	5.262**
O' Mahony and Vecchi (2009)	1988-1997	2,096 firms	Output growth	GMM	-0.099	-
O' Mahony and Vecchi (2009)	1988-1997	2,096 firms	TFP growth	OLS	-	0.049**

Notes: OLS denotes ordinary least square; GMM denotes generalised moment methods; LD denotes long-differences, e indicates the estimation of elasticity of R&D

* 10% significant level; **5% significant level; ***1% significant level

3.7 Empirical studies of Japanese firms or industries

A summary of R&D-productivity studies using Japanese industry and firm-level data are in table 3.6. Odagiri (1983) used panel data to study the relationship between R&D expenditures and the rate of sales growth over 370 manufacturing firms. The analysis is divided between innovators, which are in scientific sectors, and non-innovators. Findings show that amongst the two groups of firms the innovating firms' R&D effort positively contributes to their sales growth, with the rate of return at 25.6% during the period from 1969 to 1981. On the contrary, R&D investment made by non-innovating companies show insignificant and negative effects upon sales' growth rate. Odagiri and Iwata (1986) analyse the relationship between R&D and productivity growth of 135 manufacturing firms in Japan in two consecutive periods; from 1966 to 1973 and from 1974 to 1982 respectively. They use a Cobb-Douglas function with deflated sales as the measure of output and three inputs including labour, physical capital and knowledge capital. Total factor productivity (TFP) was used as a proxy for productivity growth while R&D intensity, R&D expenses-value-added ratio, represented R&D. They regressed the rate of TFP increase on R&D intensity. Results show that R&D activity initially increases productivity via its contribution to TFP growth. The rise in productivity then enhances output growth owing to lowered price or quality improvements. In subsequent periods, the findings suggested that the R&D effects on productivity will decline when output growth showed a highly significant impact on productivity. Thus, the accumulation of skills, know-how and experience through learning processes increasingly becomes the source of productivity increase.

Sassenou (1988)'s dissertation considers both output elasticity and rate of return to R&D. In a cross-sectional study of all firms plus a group exclusively in scientific related sectors, he estimates a production function in levels. R&D capital stock is found to have a significant positive effect on value added in both cases, although the magnitude of the impact is relatively greater for scientific firms than in the full sample. With regard to the rate of return estimation, his findings demonstrate the rate of return to R&D investment to be about 22% during the period of 1973-1981. Goto and Suzuki (1989) estimate rates of return of R&D investment in 40 firms across 50 industrial sectors. Regressing TFP productivity growth on R&D intensity, they separate the results for each industry. For electronics and automobile industries whose R&D intensity exert a positive and significant effect on productivity growth of a firm, their estimated rate of return to R&D between 1976-1984 was about 22% and 33% accordingly. Griliches and Mairesse (1991) studied Japanese and

American manufacturing firms in the period between 1973 and 1980. They investigate the differences in the rate of labour productivity growth in relation to the level of R&D intensity. Their results show the contribution of R&D expenditures to labour productivity growth was about the same for both countries. Further, there is evidence implying the possible presence of spillover across companies as the rate of return on R&D in both cases appear to decline dramatically after sector dummies are included in the regression.

O'Mahony and Vecchi (2000) estimate the output elasticity of R&D capital in Japanese machinery firms during the period of 1993-1997, although it is found to be positive but not significant. One explanation for the irrelevance of R&D capital stock to productivity growth of the firm is that the time period of their study follows the 1990s economic downturn in Japan. Kwon and Inui (2003) do a similar study, also covering the time period where the Japanese economy underwent stagnation during 1990's. They focus on a large sample of 3,083 Japanese manufacturing firms, between 1995 and 1998. Like earlier papers, they also used a Cobb-Douglas production-function with labour productivity as the depended variable. They investigate differences in R&D-productivity across firms in, including firm size and the characteristics of technology. They estimate the elasticity of output with respect to R&D and the rate of return to R&D. In both cases, they find that there was a positive and significant role for R&D expenses and productivity during the late 1990s period. They also show that the effects of R&D on productivity improvement are larger for large sized and high-technology firms and smaller for small sized and lower-technology firms.

With respect to the effect of spillovers, Goto and Suzuki (1989) consider the flow of R&D externalities at the industry level. Inter-industry flow of technologies takes the form of rent spillovers. In particular, they presume that such inter-sectoral spillovers are embodied in intermediate goods supplied by one industry to another. Their findings are in line with Terleckyj (1982), Griliches and Lichtenberg (1984) and Scherer (1982) in that the coefficients on rent spillovers are considerably larger than on internal R&D. They also investigate the impact of R&D conducted by the electronics sector on the productivity growth of other sectors. Apart from rent spillovers they include a variable representing knowledge spillovers which is constructed with respect to the concept of technological distance. Their results regarding these specific spillovers suggest that the electronics technology impacts other firms' productivity growth via knowledge spillovers rather than the economic transaction of intermediate goods between the electronics sectors and others.

Suzuki (1993) concentrates entirely on firms in the electrical machinery industry. The cost function approach is used to estimate knowledge spillovers both within and across keireisu groups in the manufacturing sector. In his study of 26 firms for the period from 1982 to 1989, there is evidence suggesting the presence of three potential sources of technological flows that result in a firm's cost reduction. It is shown that there is positive and substantial knowledge transfer from the parent firms into its own subcontractors or subsidiaries. Another two sources stem from R&D activities of subsidiaries of other keireisu groups to a subsidiary firm and occurs between keireisu firms. Because his sample is limited to solely firms of the keireisu conglomerates, the effects of being a part of a keireisu group on the ability to gain research externality are not examined and compared with results of non-keireisu firms. Branstetter (2000) applies the concept of technological proximity in the investigation of knowledge spillovers stemming from keiretsu linkages. He formulates two different spillover variables. The first is the potential pool of spillovers generally available for a firm regardless of its ties with the keireisu. This spillover is constructed in the spirit of Jaffe (1986) by using patent information to identify firms' similarity. This assumes the second source of spillover to be from an affiliation with the keireisu's production chain. It is defined as the sum of other firms' R&D spending within the same keireisu group, weighted by a dummy indicating whether a particular firm is part of the same group. Findings suggest strong evidence that an affiliated company is able to access not only the pool of keireisu-unrelated spillovers, but also knowledge created by other keireisu members. This would allow a keireisu member to achieve higher revenue growth rate than a non-keireisu counterpart.

In a dissertation on economic and technological performances of international firms, Cincera (1998) sheds light on the impact of indirect R&D from both domestic and international sources upon productivity performance of Japanese companies from 1987 to 1994. Even if the results demonstrate a positive and statistical significance of firms' internal R&D capital and external knowledge flowing from abroad, the interesting finding is that the pool of domestic spillovers displays a negative and insignificant effect on growth rate of firm productivity. In conjunction with the analysis on American firms, Branstetter (2001) also examines the effects of national and foreign pools of spillover capital on output growth for a panel dataset comprising of firms from chemicals, machinery, electronics, transportation and precision producing industries. These findings directly conflict with Cincera (1998) as the pool of domestic spillovers contributes significantly to revenue growth of Japanese firms whereas there are no statistical inference that could be made for firms' internal knowledge

capital and foreign spillovers. Branstetter and Sakakibara (1998) consider the productivity effect of spillovers from participation in research consortium. As with internal R&D capital stock, their pool of domestic spillover variable is constructed by perpetual inventory methods whereas they also address the effects of cooperative research activities. Their evidence indicates a positive and significant impact of domestic R&D spillovers on the rates of firms' revenue growth throughout the period 1983-1989. Perhaps owing to considerable managerial burdens on R&D personnel over the course of research collaboration, the frequent participants in research consortia are found to have less revenue growth rates than those of nonparticipants.

O'Mahony and Vecchi (2009) consider both effects of internal R&D and spillovers on productivity growth. While following the concept of technological proximity, their specification of spillover variables is distinct from others in the literature that use either unweighted or weighted schemes on external R&D. They categorise companies into different groups by using dummies expressing the degree of R&D intensity and the level of skilled labour. Firm classifications of R&D and intermediate/high skill intensity are assumed to be the basis of spillover effects. With regards to the empirical analysis, they first estimate output growth in the extended production function to obtain residuals which are then measured as total factor productivity growth. In order to examine spillover effects, total factor productivity growth is subsequently regressed on dummies of factor intensity including those of R&D and skills. Using micro data of 2,096 Japanese companies for the period 1988-1997, the coefficient on firm R&D is insignificant, possibly due to the omission of explanatory variables reflecting the short-run adjustments in hours of work and capacity utilization. For an explanation of TFP growth, there is strong evidence on spillover effects as the results demonstrate that firms operating in R&D and skill intensive sectors would benefit from 5% rise in their productivity growth.

Ito (2004) investigates plant-level total factor productivity growth of firms and its determinants from 1981 to 1996. Focusing on intra-sectoral spillovers, she considers the spillovers of technical knowledge and distance effects in transaction relationships between automakers and auto-part suppliers. The results suggest R&D externalities' flow from automakers into suppliers. In addition, the geographical proximity with those of carmakers contributes a significant and positive effect on suppliers' TFP gain. In other words, part producers locating near assembly plants tend to achieve higher TFP growth. There is other productivity research which focuses specifically on the Japanese automotive industry,

however with different points of interest. Fuss and Waverman (1991) compare growth of average cost and total-factor productivity in the auto industry of Japan to those in the United States and Canada over the period 1970 to 1984. For each country, they decomposed growth rates in both cost and TFP to determine their sources. They distinguished their econometric models from others using Cobb-Douglas production function models, by using a Cost-function. Lieberman and Demeester (1999) evaluate linkages between labour productivity growth and the inventory-reduction strategy which have been implemented by both car-assemblers and component producers. Analysing data sample of 52 automobile firms from 1965 to 1991, they use correlation and causality methods and found that inventory reduction contributes to process improvement and productivity gains for a large number of Japanese automotive firms.

As shown in table 3.7, empirical analyses of R&D-profitability on both directions of the relationship have been reported in Japanese studies which generally provide evidence supporting the significant effect of R&D activity. However, two notable things are absent from their consideration are the effect of R&D externalities and absorptive capacity. Lee and Shim (1995) examine the impact of R&D on long-term firm performance and competitiveness within Japanese high-technology sectors. Focusing on the period from 1986 to 1990, they report a positive and significant relationship between R&D effort and rate of sales growth. Hundley et al. (1996) compared US and Japanese companies regarding the effects of profitability and liquidity on R&D intensity. For Japanese firms they found that the decline in profitability actually leads to higher degrees of intensification in research and development activities. Despite having fewer funds available for R&D activities, firms may increase their R&D efforts in response to a shortfall in profits owing to a concern of imminent organisational decline and to attempt to ensure long-term survival of the firm. This is in line with Tubbs (2007) who found that many firms have benefited from intensification of their R&D investment during a period of economic difficulty. Sales performance and market capitalisation tend to rise markedly after the economic climate improves. Comparing Japanese and American companies in automotive, chemicals, electronics and pharmaceutical sectors, Co and Chew (1997) finds that the source of divergence in R&D investment is either due to the country of origin of the firm or the firm's own capability to effectively use resources. Thus, they examined the dependence of the rate of change of R&D in the following year on the rate of change of the current year's sales performance by using correlation analysis.

Table 3.7: Econometric studies estimating the effects of Research and Development on profitability within Japanese context						
Study	Time period	Individual data	Model specification	Dependent variable	Independent variables	Estimation methods
Lee and Shim (1995)	1986-1990	143 firms	Linear regression	Operating revenue growth	R&D intensity, labour productivity, debt ratio, capital intensity	OLS
Hundley et al. (1996)	1986-1992	177 firms	Linear regression	R&D intensity	Lagged profitability and lagged liquidity	OLS
Co and Chew (1997)	1985-1994	164 firms	Linear regression	Operating revenue	R&D expenses	DEA
Archarungroj and Hoshino (1999)	1992-1996	170 firms	Linear regression	Profit margin, ROA, ROE	Lagged R&D intensity, lagged assets	OLS
Yasuda (2005)	1992	13688 firms	Linear regression	Operating revenue growth	Firm age, size, R&D intensity	FIML

Notes: OLS denotes ordinary least square; FIML denotes full-information maximum likelihood; DEA denotes data envelopment analysis
e indicates the estimation of elasticity of R&D
ROA denotes return on assets; ROE denotes return on equity

Archarungroj and Hoshino (1999) examined the influence of R&D upon profitability while taking into account firm size. In a cross-sectional investigation of 170 Japanese firms in the chemical and pharmaceutical industry, the results showed that both lagged R&D expenditures and the lagged ratio to sales revenues are positive and significantly related to a set of profitability measures, including return on assets, return on equity, gross profit margin, operating income margin and ordinary income margin. Further, larger firms are also found to be more efficient in managing R&D. This study is at the firm level and aims at one sector since these firms are assumed to possess similar characteristics, sell products in the same market and thus behave in a similar way, unlike firms from different industries. Since firm data for both sectors was pooled, no comparison between the two industries was made. Despite both being technologically intensive and dependent on R&D, the chemical and pharmaceutical industries are not classified as the same industrial sector since they are not manufacturing the same finished products. Yasuda (2005) uses a large sample of 13,688 firms in analysing the relationship between firm growth, size, age and R&D activity. To proxy R&D activity, two variants of R&D intensity is used: R&D investment per employee and R&D investment per sales. In separate regressions, both R&D variables are positive and statistically significant, suggesting that R&D enhances firm growth rates.

3.8 Existing gaps

Much of the preceding discussion of the micro-level literature on R&D-productivity highlights the effect of own R&D effort in the current period. But rather, R&D capital stock appears to reflect the cumulative effects of past R&D investment, as shown in the perpetual inventory methods of calculation. In contrast, R&D expenditures used in the rate of return to R&D estimation, is often incorporated into extended production functions without much clarification of its proper lag structure. With the exception of Maté-García and Rodríguez-Fernández (2008), either current or specified lagged R&D investment is shown in the model.

Whilst the investigation on productivity effects of spillovers is evident, it is apparent that only a small number of empirical papers have clarified the effects of R&D spillovers on profitability. In a number of earlier studies examining the relationship between R&D externalities and both performance measures, there is no clear segregation between the impact of spillovers within the same industry and the impact of spillover originated from other industries. As to literature signifying the type of spillover, these concentrate solely on either intra-sectoral spillover or inter-sectoral spillover, even if it is demonstrated in some

later studies, for example, Aiello and Cardamone (2005) that both types of spillovers explain changes in firm performance.

As mentioned above, the analysis on the impact of research externalities on both productivity and profitability is in the literature, even if such spillover effects are less frequently addressed with respect to profitability. However, few studies include any discussion of absorptive capacity or attempt to demonstrate the probable effect of absorptive capacity on not only firm performances, but also on the R&D effort of the firm. Furthermore, the concept of R&D absorptive capacity has been generally investigated empirically at an aggregate level. For example, Griffith et al. (2000) provide evidence at the industry level for OECD countries that transnational technology transfer is enhanced by intra-country R&D. Likewise, Guellec and Van Pottelsberghe de la Potterie (2001) use aggregate OECD data to demonstrate that R&D conducted locally helps increase the positive effect of foreign R&D upon productivity growth. Therefore, this thesis stresses that the issue of absorptive capacity is crucial as at the micro-level. Similar to the aggregate level studies, a firm's internal R&D could facilitate the firm to comprehend technologies or new technical know-how originated externally and embodied within new products and processes (Parisi et al., 2006).

Turning to empirical studies of Japanese industries and firms, research on both own R&D effort and R&D externalities are still relatively scarce. The biggest gap is that previous empirical evidence on absorptive capacity is not documented. In particular, the effects of spillovers are relatively rare in the literatures on the R&D-profitability relationship, especially in the management rather economics areas of study. With regards to studies of research externalities and productivity performance, the main focus is generally along the lines of non-Japanese specific counterparts and they consider predominantly either intra-industry or inter-industry spillovers. Previous studies on both performance measures tend to concentrate on the manufacturing sector as a whole. Thus, all firms in sub-sectors, for example, electronics, chemical and motor-vehicles are combined together into the research sample and simply distinguished by sectoral dummies. In fact, studies concentrating exclusively on the automobile or electronics industry are characterised by small samples. Goto and Suzuki (1989) provide empirical analysis on 3 automobile firms and 5 electronics firms while Suzuki (1993) applies a cost function on about 9-17 electrical machinery firms. The use of a relatively small samples can be problematical as it gives rise to questionable statistical results. Additionally, a great deal of the Japanese literature emphasise the time period from 1970s to late 1980s when Japan underwent dramatic economic development in

manufacturing, consistently overtaking those in other major industrialised nations. Only some studies focus on the 1990's when the Japanese economy was in recession. This thesis is concerned with the re-emergence of Japan as a force in automotive and electrical production and considers the effects of a reduction of R&D during the previous period. Now there is a global recession and internationally there is a crisis in the automobile industry with the growth of competition from newly industrialising countries.

3.9 Conclusion

This chapter has reviewed the extensive literature on R&D and the impact on firm performance. It has noted the diverse issues addressed, including studies that have demonstrated that R&D, both from internal efforts and from external sources, does contribute significant effects on productivity. In contrast, there is still a debate about the impact of R&D on the profitability of firms, particularly the effect of their own R&D effort. Interestingly, the reverse is also not conclusive as profitability does not always lead to more technological effort. The empirical evidence of R&D externalities' shows a positive effect on firm performance with much of the research taking a production or cost function approach. Several studies do confirm a greater impact on productivity than profitability of spillovers. Furthermore, preceding studies considering spillovers effects discuss absorptive capacity. Given its interconnection with R&D externalities, absorptive capacity can contribute to firm performance. However, few empirical studies on both productivity and profitability incorporate absorptive capacity into their investigation.

Both sectoral and micro-level data for Japanese manufacturing firms have been used in empirical studies which provide evidence supporting the significance of R&D but these are limited to the period of rapid growth prior to the 1990s Japanese economic downturn. Few have addressed the later period in Japanese history that has been largely focused on recovery. Even though the manufacturing sectors in Japan are typically regarded as technological-intensive and interrelated through networks of close relationship and production chains, it remains surprising that spillovers and complementary absorptive capacity effects are absent in the literature.

In summary, commonly recognisable gaps from the mainstream literature exist particularly there are unresolved issues related to the segregation of spillover effects and of absorptive capacity. This thesis provides a broader investigate of the effects on both production efficiency and financial performance of firm own R&D, R&D externalities and

their internal capability to absorb such external R&D. It also seeks to consider the likely reverse effect of profitability upon technological activities. Apart from the analysis on the links between R&D and the two performance measures, this investigation seeks to provide further empirical evidence of probable circular relationships between the three variables of interest.

Chapter 4: Data, Sample, Measurement Issues and Preliminary Data Analysis

Introduction

This chapter reviews approaches to measuring R&D, productivity and profitability at the firm level. The theoretical foundations of measurement are presented within each of the following sections, in particular, the difficulties in obtaining a true valuation for labour productivity and for capital. The data used in the empirical estimation are described, including the choice of industries, the firms in those industries, the variables selected and the transformations performed. The deflators used to adjust data to constant values are also explained. Finally, the preliminary data analysis tests the properties of the sample, compares the values for each industry and presents descriptive statistics and the coherence between each variable is examined using Pearson correlation analysis.

4.1 Data Sources and Sample Selection

This section addresses how the quantitative data was collected. All data are from secondary sources and the study uses solely unconsolidated firm data in the analysis. The primary source of the data for these firms listed on the Japanese Stock Exchange in the automotive and electronics industries is the OSIRIS database (Bureau van Dijk, 2011).

4.1.1 Unconsolidated data

Unconsolidated data is the direct opposite to consolidated data, which comprises of financial accounts of the parent company and its domestic and overseas subsidiaries. Within the context of Japanese automobile and electronics firms, this means that the consolidated accounts of the firm includes data combining all of its business operations both domestically and internationally. For an example from the electronics sector, the Sony Corporation is headquartered in Japan while it operates not only in the Japanese domestic market but also in other world regions. Its North American operations are mandated by one of its international subsidiaries; Sony Corporation of America (SCA). Thus, consolidated sales in a specific year will not only consist of sales generated by Sony Corporation itself, but also sales of SCA and other Sony affiliates. On the other hand, the unconsolidated accounts means that for any variable shown on reports such as the balance sheet and income statement, the is confined solely to the parent company's operations both in the home market and abroad. If subsidiaries of the firm are entirely in charge of international operations, the unconsolidated accounts reflect activities related to the domestic operations of the parent firm alone. Using

R&D expenses as an example, unconsolidated R&D expenses covers the amount of investment that the Japanese parent firm itself spends for R&D activities. Nonetheless, it could be noted that the vast majority of Japanese firms assign the running of overseas operations to its transnational subsidiaries. Hence, it could be generally assumed that unconsolidated R&D expenditures implies R&D spending conducted locally in Japan by the Japanese parent firm. Referring to the case of the Sony Corporation, research and development made by its Japanese and overseas affiliates would not be counted in Sony Corporation's unconsolidated R&D expenses. As an example from the automobile sector, the Honda motor company has among their subsidiaries; three Honda research institutes in Germany, the US and Japan. Consolidated R&D expenses of the Honda Motor Corporation will include research expenditures of Honda Motor Corporation as well as the research institutes discussed above whereas the unconsolidated R&D accounts represent only R&D investment conducted by the Honda Motor Corporation itself.

Within the context of this research, there are two main reasons to use unconsolidated data, rather than consolidated data. The principal reason is to avoid problems in productivity measurement using consolidated data. Japanese manufacturing firms largely operate on an international level and consolidated data on employment for example, included all personnel employed by any of their global affiliates. This can cause considerable measurement errors as concepts of labour productivity is locational specific. Even in the same manufacturing company, the productivity of a worker in one country will be different from worker productivity of a production plant located in another country. Also, using consolidated firm data could result in the overlap and duplication of data between firms. It is found that a number of producers or suppliers of parts and components are subsidiaries of Japanese automobile and electronics conglomerates. In the automobile sample, there are about 15 auto part producers that are identified by Osiris as subsidiaries to the Honda Motor Company alone. Thus, consolidated data of the Honda Motor Company will contain data of these 15 automobile firms. In particular, sales and R&D expenses of those subsidiaries are already a subset in the consolidated sales and R&D investment of the Honda Motor Company.

4.1.2 The Automotive industry

The sample of automotive firms includes all publicly listed-firms involved in manufacturing and assembling vehicles. This includes car-producers, auto-components producers, accessories manufacturers and performance tuning companies. This corresponds

to industrial classifications: NAICS 2007 code 3361 (Motor vehicle manufacturing), code 3362 (Motor vehicle body and trailer manufacturing) and code 3363 (Motor vehicle parts manufacturing). Lung (2001; 2004) notes that any analysis of the automotive industry should cover the system as a whole, rather than simply carmakers. This is because the coordination of competencies and knowledge in design, manufacturing and assembly between automakers and their suppliers has become a critical issue for the automotive industry.

4.1.3 The Electronics Industry

The sample of electronics firms differs slightly as these are less well distinguishable and comprises of various sub-sections grouped together. This much more diverse group includes firms categorised as producers of electrical machinery and apparatus, radio, television and communication equipment, as well as medical, precision and optical instruments. The industrial classification is NAICS 2007 code 334 (Computer and electronic product manufacturing).

4.1.4 Sample Size

Initially the sample included 104 automotive firms and 281 electronics firms, all of which had reported unconsolidated accounts for the fiscal years 2000 to 2009. From each firm's unconsolidated financial information, net sales, R&D expenditures, value of net tangible fixed assets, number of employees, total debts, total assets, year of incorporation and market capitalisation was collected. The sample was later reduced due to missing or erroneous values, as described below.

4.2 Recovering missing data

After reviewing the financial data for each of firm, the OSIRIS database was found to be incomplete for some firms, particularly in relation to R&D expenses, the number of employees and market capitalisation. To fill these gaps financial data disclosed annually by firms either from their websites or the Stock Exchange were reviewed closely. For some firms, similar amounts of R&D expenses were found in consolidated and unconsolidated financial reports and this it was straightforward to fill in missing values of unconsolidated R&D expenses with those of firm' consolidated data, although this required some careful manipulation. Useful domestic company databases are also available, although these tend to be in Japanese. For example, the Electronic Disclosure Investor's Network (EDINET), administrated by the Japanese government agency, provides securities report for listed

Japanese firms back to fiscal year 2000. Language constraints were overcome by translating only key words that referred to financial data on R&D expenses and number of employees. After finding Japanese words meaning R&D expenses and number of employees, these data in the unconsolidated report were located and used to fill in missing observations of firms in the dataset. Additional sources allowed the examination of each of the firms' public relation documents, particularly annual reports and financial statements. These documents were acquired from the firms' website as well as from enquiries to their public relation departments. As the analysis required a panel dataset, the compilation of this firm level data by fiscal year was very time consuming. However, in some cases no R&D expenditures were found and these firms were assumed to have none and thus these were dropped from the sample as this was a major objective of the research.

Other missing data were market capitalisation, which was also problematic. OSIRIS reports the amount of market capitalisation at the end of each firm's fiscal year although this starts only in 2002 for the majority of firms. Even if some firms have data on market capitalisation as early as fiscal year 2000, a handful of firms also have missing data in years between. Data on market capitalisation is difficult to find on firms' data at EDINET and company financial statements, thus constraining the chance to fill in missing values. Whilst both consolidated and unconsolidated market capitalisation data of a firm in OSIRIS encounter the same problem of unavailability of data in fiscal year 2000 and 2001, market capitalisation in both accounts are found to be the same. Thus, in this study market capitalisation data from consolidated accounts are used to fill in missing years between 2000 and 2009. Although the use of consolidated market capitalisation to fill absent unconsolidated values helps to solve the problem of missing observations in market capitalisation data, such data for year 2000 and 2001 is still non-existent. The study is thus forced to proceed by using market capitalisation data with generally missing observations for fiscal year 2000 and 2001.

Following attempt to tackle missing data, further efforts were made to identify and cope with outliers in each series. An outlying observation has a value markedly distinctive from others in the sample (Grubbs, 1969). The presence of outliers in panel data could result in inaccurate results in the subsequent regression models owing to bias in the estimation (Bramati and Croux, 2007). To detect outliers in the data for each individual company, values are examined carefully to spot signs of dramatic deviation from the rest of observations. Plots were used to observe nonconformity in trends over the period. The number of employees is noted for being the variable where outliers are noticeable. The amount of

employees of some firms displayed large variations, either increases or decreases, in a matter of years. In particular, the outlying observations appear to occur in the electronics industry more than automobile industry.

For example, one electronics firm had unrealistically only 2 employees for a couple of years and suddenly the amount surges to about 200 towards year 2009. Another electronics firm had around 200 employees throughout the first 5 years of the 2000s, but the amount declined to only about 7 by 2009. Additional areas in electronics firms' data that outliers are revealed are sales and tangible fixed assets, even though the amount of outlying observations are somewhat lower than in number of employees. The initial handling of outliers is to recheck on EDINET for data of the same fiscal years as those of outliers. This is to ratify whether those outliers could be owing to possible Osiris's errors in gathering and reporting firm data. In a number of firms, numerical values in outlying observations are similar for both Osiris and EDINET sources. As it might not be viable to substitute some outliers with non-deviated data, the likely solution is to drop these firms from the study. Having addressed issues of missing data and outliers, the eventual sample is a balanced panel of 325 firms, comprising 89 listed automotive firms and 236 listed computer and electronics firms. Thus, the total number of firm-years is 3,250.

4.3 The justification for panel data models

The secondary data collected in this research has two dimensions; it has cross-sectional units represented in term of firms and a time element is presented by fiscal year. In this respect, it holds the capability of amalgamating both cross-section and time-dimension together as panel or longitudinal data, which consists of multiple entities having repeated measurement over a defined time frame (Park, 2005). Yaffee (2003) states that analysis using panel data allows models with both a spatial and temporal dimension. Studying panel data can provide advantages over solely cross-sectional or time-series data. Since panel data are the combination of both dimensions, the sample size is improved and increases the degrees of freedom. This then provides a richer dataset with more variability and reduced linear-relations between predictor variables. Panel data estimation takes into account firm effects by incorporating firm specific variables into the regression. By examining the recurring observations of cross-sections, panel data could provide better analysis on dynamics of change and complex behavior over time (Gujarati, 2003).

4.4 Variables: Discussion, Definitions and Descriptions

4.4.1 Output

Output is defined either by sales or value added, as clearly this is an aggregate representation of production. Melitz (2000) notes that empirical studies on firm level productivity tend to use sales, deflated by a common industry price index, as a proxy for output. Nonetheless, they also argue that deflated sales are only appropriate when the industry produces homogeneous goods. It is clear that firms in most industries normally produced more than one type of goods, and that firm level prices would then fluctuate relative to a price index, undermining the link between firms' deflated sales and output. An alternative is to use number of goods sold as a measure of output, as described by OECD (2001). However, this is even more problematic as data on the quantity and quality of goods manufactured by firms are not available and only revenue from sales across those products can be found in annual reports or financial statements. Thus, solutions to the output proxy problem include the use of either total value of products produced by the firm or total revenue sales as a direct measure of output that is then homogenous across firms within the sector (Paul, 1999, Melitz, 2000). In the aspect of aggregated values of multi-products, Coelli et al. (2005) add that it is essential to ensure that the aggregates are formed across different type of products that share similar movements in relative prices or quantities. Besides, the firm's commodities must meet the separability condition with respect to the production function, which means that the relationship between two goods measured by their ratio of marginal products does not change with a change in relative prices.

So, a reasonable level of pragmatism is necessary to conduct the estimation. In this thesis, automotive firms can be generally categorized into two groups; vehicle producers and auto-components producers. Furthermore, multiple and non-related products are also manufactured within a single automotive company. For example, auto-tuning firms may produce various types of goods, range from air-induction system, oil filters, to aero-parts and interior accessories. The information regarding physical amounts of each commodity produced is largely unobservable, for example, only the number of vehicles produced is available for car-makers. In fact, the physical amount of component parts is not comparable with the completed vehicles as they are not the same type of products but rather complementary products. Electronics firms in the dataset are also different in the characteristics of products they are manufacturing. Some produces video and television

equipment while telecommunication equipment is an end-product for others. Therefore, products offered by electronic firms are not homogeneous.

In summary, the output data commonly available for all firms is total value of sales, taken from the firm financial data for each fiscal year. Hence, the choice of output variable is the real value of sales.

4.4.2 Labour

For empirical analysis at the firm level, the number of persons employed, number of hours worked, total wages and the cost of labour are the most commonly used measures of labour (Coelli et al., 2003). Schreyer (2005) notes that the total number of hours worked is the proper measure. This number should comprise the hours of employees, the hours of self-employed and the hours of unpaid workers such as for those of family business workers. Hours actually worked, however, also has drawbacks. OECD (2001) note that different countries may have different practices for calculating hours worked and full-time equivalents. In addition, an hour worked by one employee does not essentially add up to the same amount of labour input as one hour worked by another. This is because there may be differences in skills, education, health and professional experience, leading to large differences in the contribution of different types of labour (OECD, 2001). Another preferred measure of labour input is head count of employees, if working hours are unavailable (CBO, 2005). Although it is simple and generally available in commercial databases and annual reports, the number of employed persons in an organisation or within the industry can generate biased measures of productivity if there is a high turnover of employees or if employees hold multiple jobs (Schreyer, 2005). In other words, the amount of labour does not reflect changes in average hours worked, which can be caused by the changes in part-time work or the effect of variations in overtime, absence from work or shift in normal hours (OECD, 2001).

The firm level data from OSIRIS, financial reports and domestic databases, does not provide information on the number of hours worked by employees. Likewise, there are no data regarding wages or costs of employees. Also, the number of each type of employee is not reported in detail. To be precise, unskilled, skilled and R&D personnel are all included in total number of employees and this seems to be the practice for firms in both industries. To generate annual total hours actually worked for each firm, the physical amount of labour is multiplied by the annual number of hours worked per person in the Japanese manufacturing sector. The annual hours worked is computed from the sum of actual monthly number of

scheduled hours and actual monthly number of overtime hours worked in the manufacturing industry, multiplied by 12 to get an annual value. These two data are reported in the Basic Survey on Wage Structure, provided by Japan's Ministry of Health, Labour and Welfare.

4.4.3 Capital

This is another measure for which there is a huge literature. As OECD (2001) noted, the quantity of capital input can be measured by capital services, defined as a flow of productive services from the cumulative stock of past investments in any assets owned by the firm. Such flows of capital services are not directly observable, but can be estimated on the assumption that their flows are in a fixed proportion to the stock of assets. Thus, approximating flows of capital services would require the physical amount of capital or assets. In other words, capital goods that are purchased or rented by a firm are seen as carriers of capital services that constitute the actual input in the production process (OECD, 2001). According to CBO (2005), the stock of physical capital is defined as an estimate of the total amount of productive assets such as building structures and equipment available to the unit of analysis; a firm or an industry or an economy. Converting the stock of assets into standard efficiency units generate the so-called productive stock of traditional capital by each type of assets, and thus it is crucial to measure the flow of capital services used in the production process within each firm (Coelli et al., 2005).

To estimate traditional capital stock, researchers use the perpetual inventory method (PIM). Data required to measure capital stock includes the investment history of the physical capital and price indices (Paul, 1999). In the event that investment history data in traditional capital is unavailable, alternative measures of physical capital input, as suggested by Coelli et al. (2003), are replacement value, sale price and physical measures. In this respect, undepreciated replacement value held by the company is theoretically equal to the undepreciated value of the capital stock in constant prices. The sale price is the market price obtained from the sale of an enterprise. To use physical measures or proxies, researchers have to classify capital into broad categories and identify some simple measures. The use of physical measures would be subjected to variation in quality of the physical indicators; however. Taking for example, machineries owned by the firm may differ in types and usages; hence, it would be difficult to aggregate physical amount of various items under a category of capital. Other measures of traditional capital stock include the undepreciated and depreciated nominal capital stock, with the latter the preferred measure, and this is commonly reported in

annual accounting records. Nonetheless, these measures should only be used when data are limited and it is necessary to resort to company reports to acquire estimates of physical capital stock for purposes of productivity analysis.

Regarding raw data collected, there is lack of investment history in traditional capital. In financial reports, Japanese firms do disclose their investment expenditures related to some capital such as property, machinery and equipment. Nevertheless, longitudinal investment data are unavailable and not all Japanese firms show their detailed information on each type of asset. These limitations rule out the possibility for using the perpetual inventory method to calculate traditional capital stock for each firm in both industries. In company accounting reports, it appears that firms generally separate assets into current and fixed. The annual value of fixed assets is shown in the firm's annual reports and OSIRIS, particularly in the balance sheet. In OSIRIS, fixed assets are categorized into three sub-categories; tangible, intangible and other fixed. Tangible fixed assets are net fixed assets after the historical cost and revaluation of properties, the accumulated depreciation, amortization and depletion are taken into account. More specifically, it takes into account depreciated value of land, buildings, plant & machinery and transportation equipment. Given its definition, the value of tangible fixed assets is thus closely related to traditional or physical capital. In fact, some empirical literature appears to use either fixed assets or tangible fixed assets as the proxy for capital input in the framework of production function. In a study of UK manufacturing firms, Wakelin (2001) used total fixed gross assets, which were then deflated by the national investment deflator to generate real value of fixed assets. Fixed assets was selected as the proxy for capital stock in the study of Fu et al. (2008) and Oh et al. (2008), for their productivity analysis for Chinese and South Korean firms respectively. Kim (2009) and Kozo (2010) constructed capital input variable from deflated tangible fixed assets in their productivity studies on Korean and Japanese firms respectively. Likewise, Lieberman and Demeester (1999) included tangible fixed assets per employee at the end of each fiscal year in their regressions. Therefore, the nominal value of tangible fixed assets is adjusted for inflation and divided by the firm's total number of employee to generate an estimate of total physical capital investment per employee.

Given the constraints of access to investment history in each type of asset and physical capital and the obtainability of annual hours worked in each firm, this study uses real net tangible fixed assets per hour used as the proxy for capital input in the production function model as well as the analysis in the other two empirical chapters. The net value of

tangible capital assets is available in the firms' balance sheets while depreciation values in each fiscal year is also shown in the income statement.

4.4.4 Research and Development

In the literature, empirical studies use either R&D capital stock or R&D intensity as the proxy for R&D expenditure. The choice of R&D variable results in different estimates in the production function and its translog derivative. To calculate R&D capital, R&D expenditures with a substantial time period are necessary as lags are always found between the investment in R&D and any resulting change in firm performance. In this study, the raw company R&D expenses are insufficient in term of time length since the focus of the analysis started from only fiscal year 2000 and thus the lag structure is limited. Johansson and Loof (2008), when constructing the knowledge capital stock variable, note it is desirable to have a long history of firm level R&D expenditure. Also, a further constraint in this case is that the R&D depreciation rate is unknown for both Japanese industries under review. With R&D capital and R&D obsolescence rates difficult to compute, the estimate of R&D capital is thus highly impractical for the analysis.

On the other hand, R&D expenditures in each fiscal year are shown in firm annual reports. Real expenditure on R&D divided by total real value of sales will generate another R&D proxy; R&D intensity. To Scherer (1984) and Wilson (1977), R&D intensity is related to technological opportunity, which is the degree to which R&D activity will yield marketable innovation. Leonard (1971) notes three benefits of R&D intensity in a production function. First, R&D intensity comprises costs and expenditures relating to scientific and technical manpower, equipment and facilities. Second, R&D intensity takes account of the processes by which the expertise and knowledge of R&D personnel can be spread within the firm or industry, the viewpoint of management toward the output of the firm's R&D division and other intangibles. Third by converting the actual value of R&D expenditure into relative terms, a better comparison among units of analysis can be made. Within the context of profitability studies, an alternative to R&D intensity is R&D expenses per employee, which is described by House et al. (1994) as being a relatively better R&D activity measure as the number of employees appears to have less short term variability than the level of sales. Another possible measure is R&D expenses as a proportion of total assets, which Xu and Zhang (2004) argue is preferred as the use of total assets as the denominator better reflects innovation. However, the use of different measures of R&D spending can lead to different

analytical outcomes regarding the effect of R&D on productivity and on profitability as shown by Morbey and Reithner (1990).

Even so, the primary focus of this research is the relationship between research and development and two firm performance measures; labour productivity and profitability. Labour productivity, as will be discussed, is represented by the ratio of sales revenue-based output to hours worked. In addition, the computation of firm profitability is typically associated with sales revenue and costs incurred throughout the process of production and administration. The R&D intensity variant, the ratio of R&D expenses to sales, could be hence more viable in the analysis since this R&D intensity relates directly to the recognizable effects of research and development that are reflected in higher sales performance and profit generation. Chao and Kavadias (2009) stress the ratio of a firm's R&D investment to its revenue as a key metric for the assessment of inventive activity at the firm level because an increase in R&D spending is typically associated with an increase in sales revenue. To construct R&D expenditures as a fraction of sales, the study uses real R&D expenses as the numerator while real net sales is used as the denominator.

4.4.5 Productivity

It must be stated at the outset that a single factor productivity measure is used, that of labour. This is important as rather than a direct focus on productivity, this thesis is concerned with the role of R&D in the performance of the firm. The construction of total factor productivity indices would include a number of factors of production, including labour, capital and an estimate of technological change that is frequently captured by the level of research expenditures, usually with an imposed lag structure. Thus, in a study that seeks to examine the role of R&D as a separate factor of production it is necessary to disaggregate the model by single factor inputs.

Thus, this study uses output per worker as a measure of labour productivity, where both value added or sales could represent output. For each firm, total added value is calculated as the difference between the value of sales and the sum of the cost of raw materials and the value of depreciation. The annual value of depreciation is available from OSIRIS but there is not consistent data for material costs for all automotive firms in the sample. Therefore the value of sales divided by the annual total hours worked is used to proxy labour productivity (output per labour/worker input). This approach is similar to Hokkanen (2006), where labour productivity was computed as the ratio between earnings

before interests and tax (EBIT) and the number of employees. However, this differs in the present study in that operating turnover or net sales was used as the numerator and annual hours worked was used as denominator instead of number of employees. Labour productivity for each fiscal year is transformed into growth rates for estimation of the production function. To assess performance in the two Japanese industries, labour productivity indices were constructed. These used data primarily from OSIRIS. Labour productivity was calculated at 2005 constant prices using the real value of sales per hours worked.

4.4.6 Profitability

The empirical literature uses a range of possible measures to account for firm profitability. One is Net profit margin or return on sales (ROS), which is defined as net profit as a proportion of sales. This reflects from normal trading activities before tax and interest payments divided by sales and is the difference between sales and cost of goods sold as a percentage of firm sales (Arkali et al., 2008). This measure is well established in the literature, for example, Geroski et al. (1993); Leiponen (2000); Hanel and St-Pierre (2002); Bottazzi et al. (2008). A similar measure, suggested by Nås and Leppälähti (1997) is operating profit, which is the percentage of the net difference between sales and ordinary operating costs excluding financial items and depreciation. In case, the numerator, operating profit, captures the performance of ordinary production in firms. Also, it encompasses the technological aspects of operations, in particular, the manufacturing division within firms. Nevertheless, it has shortcomings as it does not take into account elements in costs and earnings compared to conventional profit margin metrics. In particular, it ignores costs related to dividends paid to shareholders, financial costs and depreciation or the expenses incurred in using machinery and buildings. In addition, elements omitted include earnings that are net gains from financial settlements or income generated from selling or renting out part of the firm or its own property. Nås and Leppälähti (1997) concede that firms with a positive operating profit may have a negative or remarkably low taxable income.

Another frequently used measure is return on total assets (ROTA), measured as the ratio of profit exclusive of extraordinary items but taking into account net financial items and asset depreciation. This is usually expressed as a percentage of total assets or capital in the firm. Some studies have argued for the impact of R&D investment on shareholder value (Mank and Nystrom, 2001; Yang et al., 2010) to be considered and therefore return on investment (ROI) has also occasionally been used. This takes into account the role of capital

and is commonly used for the assessment of firm's earnings per unit of overall investment. Finally, in a study of Norwegian manufacturing firms, the trend of sales valuation is used another profitability measure (Bottazzi et al., 2008). This variable is constructed by either using total sales or market share. Despite not directly related to profitability, this variable indicates the level of achievement by the firm in enlarging its activities, in particular, success in the market place and of the scale of operation.

There is an issue of whether to use profit before tax or profit after tax as the numerator in computing profit margin and return on total assets. To proxy firm profitability, Branch (1974) and Yang et al. (2010) selected profit after taxes plus interest paid and dividends by assets, which is essentially an index of the return on firm resources. However, using profit after taxation may lead to problems associated with tax-motivated sales. As Nås and Leppälahti (1997) suggest, firms are likely to report economic or financial outcomes as low as possible every year since these results are taxed on an annual basis. Further, the actual economic results may differ from those of disclosed financial accounting data and the performance results may be retained in the internal records of the firms. To avoid problems originating from tax-motivated sales, simple measures of profit should be used.

This thesis adopts the practice in existing studies with respect to the selection of profit margin. In computing profit-margin, the OSIRIS firm accounting data reports gross profits and profit/loss before tax. Gross profit is defined in OSIRIS as operating turnovers/sales net of cost of goods sold and is similar to Nås and Leppälahti's termed operating profit. In order to avoid problems with gross profit, the research used the profit/loss before tax to replace operating profit (gross profit as in OSIRIS) to construct the profit/sales ratio. Profit/loss before tax is labelled as income before corporate tax and unusual/exceptional tax items, but after depreciation and amortization, interest expenses and income. Neither OSIRIS nor company reports have information on the level of market share. Finally, it was judged that the trend in sales over time, proxied by total sales, is too closely associated with the productivity measure and it is important that profitability and productivity are differentiated, particularly in the third empirical chapter.

4.4.7 Technological spillovers and absorptive capacity

Detailed construction of research extramural and absorptive capacity measures are shown in section 5.2.1. In brief, both intra-industry and inter-industry research externalities are formulated with other firms' R&D divided by the recipient firm's sales. Even so, the

numerator of intra-industry spillovers construct is defined as the total amount of R&D spent by all other companies within the same industry that a particular company is operating in. The numerator of inter-industry spillovers is measured differently regarding automobile and electronics sector. The numerator of inter-industry spillovers for each automobile firm is defined as gross value of R&D expenditures made by all electronics firms whilst the electronics counterpart's is the sum of automobile R&D. The variable of a firm's absorptive capacity is herein constructed by multiplying internal R&D expenditures to the summation of available intra-sectoral and inter-sectoral externalities.

4.4.8 Controls: Firm size, age and debt ratio

Firm size, age and debt ratio are introduced as control variables in this study. According to Hall et al. (2010), the proper measure of market capitalisation is the market value of all claims on the firm's assets, which includes debt and any preferred or convertible stock, although the product of the number of shares outstanding and the share price is most common in the literature. The number of years since the year of incorporation up to each fiscal year (2000 to 2009) is taken as a measure of firm age. For each individual firm across automobile and electronics industries, each fiscal year is subtracted from the year that the firm was established. Clearly, the firm is getting older as time proceeds from 2000 to 2009.

The study also uses the firm debt to equity ratio in the R&D-profitability analysis since capital structure was found to be highly correlated with profitability (Yang et al., 2010). The debt to equity ratio is computed from total long term debts divided by the sum of total long term debts and shareholder equity (Natasha and Hutagaol, 2009). Total long term debt is equivalent to total liabilities and debt whereas the sum of long term debt and equity is essentially total assets. Both the value of total debts and total assets are available from Osiris company reports and these were used to calculate the debt ratio for each firm, for each year.

4.5 Transforming Nominal into Real Values

Deflators were collected and used to convert nominal into real values for all the financial data. To generate real sales, the gross output price index was used, obtained from the Bank of Japan. This input-output price index for the manufacturing industry is available by sector. These indices can be also manually computed from nominal gross output divided by sectoral real gross output in all manufacturing sectors (base year 2005). Automotive firm value of sales was deflated by the transportation equipment output price indices. Three output

price indices for sub-electronic sectors, electronic components, information and communication electronics equipment and precision instruments, were used to deflate the nominal sales of each firm, depended on their sector classification. R&D expenses, net tangible fixed assets and market capitalisation were deflated by Japanese consumer price indices (base year 2005), obtained from the World Bank World Development Indicators. Finally, all data except the number of employees and firm age were converted into US dollars at 2005 constant prices using purchasing power parity indices obtained from IMF International Financial Statistics (IFS).

4.6 Summary

Table 4.1 states the definition and units of measurement for each variable, including those taken from secondary sources and those constructed.

Table 4.1: Variable Definitions		
Variables	Unit	Description
Sales	Thousands of 2005 US\$	Net sales or operating turnover
R&D expenditures	Thousands of 2005 US\$	Research and development expenses
Number of Employees	Persons employed	Total number of employees
Profit or loss before taxation	Thousands of 2005 US\$	Income net of financial expenses, depreciation
Market capitalisation	Thousands of 2005 US\$	Share price*number of share outstanding
R&D intensity	Ratio	R&D/sales
Capital intensity	Ratio	Capital/labour's hour worked
Labour - hours worked	Hours	Mean annual hours worked*number of employees
Labour productivity	Ratio	Value of net sales/labour's hour worked
Profit margin	Ratio	Profit or loss before taxation/value of net sales
Debt ratio	Ratio	Total debt/total assets
Intra-industry spillover	Ratio	Other firms in the same industry's R&D/sales
Inter-industry spillover	Ratio	Another industry's gross R&D/ sales
Absorptive capacity	Ratio	(intra-industry spillover + inter-industry spillover) * R&D expenditures
Firm Age	Year	The difference between each fiscal year (2000-2009) to the year of firm establishment

Variables	Mean	Standard deviation	Minimum	Maximum	Number of Observation
Sales	3,036,967	8,923,325	20,032	99,348,544.3	890
R&D	180,686	731,611	8.98	6,791,298	890
Number of Employees	4,300	9,266.85	105	71,567	890
Profit or loss before taxation	126,757	868,266	-3,916,661	13,114,701.9	890
Market capitalisation	3,344,236	15,549,914.24	4,484	218,187,713	715
R&D intensity	0.025	0.026	0.00006	0.174	890
Capital intensity	0.062	0.053	0.009	0.491	890
Labour's hour worked	9,340,521	20,126,554	221,760	151,149,504	890
Labour productivity	0.213	0.118	0.061	0.79	890
Profit margin	0.024	0.057	-0.452	0.174	890
Debt ratio	0.534	0.160	0.132	0.989	890
Firm Age	57	21.52	10	127	890
Intra-industry spillovers	76.349	113.24	0.139	800.71	890
Inter-industry spillovers	52.145	76.07	0.133	492.77	890
Absorptive capacity	2.922	9.256	0.00014	119.36	890
Number of Firm	89				

Variables	Mean	Standard deviation	Minimum	Maximum	Number of Observation
Sales	923,324	3,456,071	859.269	42,988,539.7	2,360
R&D	47,301.77	195,157.84	8.005	2,078,517	2,360
Number of Employees	1,574.32	4,500.04	20	53,202	2,360
Profit or loss before taxation	9,474	222,302.74	-3,911,351	4,434,681	2,360
Market capitalisation	1,018,726	3,227,635	1,004.96	48,081,519.23	1,903
R&D intensity	0.05	0.057	0.000123	0.627	2,360
Capital intensity	0.043	0.037	0.00024	0.478	2,360
Labour's hour worked	3,421,909	9,793,783	43,680	116,831,592	2,360
Labour productivity	0.21	0.22	0.006	3.606	2,360
Profit margin	0.025	0.132	-0.937	0.648	2,360
Debt ratio	0.454	0.223	0.017	1.262	2,360
Firm Age	45	22.62	10	128	2,360
Intra-industry spillovers	249.58	626.84	0.222	11,488	2,360
Inter-industry spillovers	340.36	808.56	0.421	16,048	2,360
Absorptive capacity	62.188	410.83	0.005	9,604.5	2,360
Number of Firm	236				

4.7 Preliminary Data Analysis

4.7.1 Descriptive statistics

Descriptive statistics for all data are in table 4.2 and 4.3, and this allows the analysis of comparative values by the period of 10 years and by industry. In each industry, the mean, standard deviation, minimum and maximum values are shown for the period (2000-2009). Sales, R&D, Profit or loss before taxation and market capitalisation is measured in thousands of 2005 U.S. Dollar. The number of employees is presented in the actual physical amount. Labour's hourly worked unit of measurement is the actual amount of hours. R&D intensity, capital intensity, labour productivity, profit margin and debt ratio are presented. The series of market capitalisation has missing observations. The earliest observation in the majority of firms in both industries is in year 2002 whilst a handful of firms has complete ten-years series from 2000 to 2009. Firm age descriptive statistics are computed with reference to year 2009. To this end, the age of each firm in both industries; as of 2009, is analysed including mean, standard deviation, minimum and maximum values.

With the exception of R&D intensity, labour productivity and profit margin, it is apparent that firms in the automotive industry have higher mean values for each variable relative to firms in the electronics industry. One possible explanation is the relative size of the two samples. The electronics industry has a far larger number of firms than the automotive industry, with nearly three times the total firm-year observations. As a consequence, this results in a higher variance for variable for each firm. For example, the range between the maximum and minimum value of R&D expenditures and number of employees are very high in the electronics industry. At the minimum level there are also interesting values. Especially on the lowest side, there are a handful of electronics firms that had about 20 personnel and some that committed only roughly 8,005 U.S. Dollars to research and development activities. The median value is more meaningful for the majority of variables. On the other hand, automobile firms generated higher operating turnover and profit than electronics firms in term of median. Likewise, the largest sales and profit in the automotive industry exceed the equivalent in the electronics industry by two and three times respectively.

In term of mean and maximum values, automotive companies are found to invest more in R&D activities, although in terms of research intensity, electronics firms are ahead. In the dataset, the comparison of R&D intensity exhibits a similar pattern to two industrial aggregated R&D intensities, previously shown in figure 2.8 and 2.9, where the electronics

industry has clearly higher level of R&D intensification. To this end, those of electronics firms had larger mean R&D as a fraction of sales revenues, at 5% compared to 2.5% of automotive firms. Likewise, the largest research intensity in electronics data exceeds the highest equivalent in automobile data by a considerable margin, shown as 62.7% and 17.4% in electronics and automobile respectively. With regards to the age of firm, both industries have relatively comparable oldest and youngest age whereas the mean automobile firm is somewhat older than that of electronics counterpart. Generally, the essence of development in both industries started merely during the post-war economic development. Whilst a handful of large conglomerates were formed in either late 19th century or early 20th century, a bulk of automobile and electronics companies came to existence by the second-half of 20th century, particularly during the period of economic miracle from 1960s to 1980s.

There is higher median amount of employees in the automotive industry, indicating the comparatively higher level of total employment and workforce in the entire automobile industry than in the electronics industry. The lowest amount of employees is also clearly greater in the automobile industry than in the electronics industry. In this respect, minimum number of employees is found in component manufacturers in both industries. The electronics dataset comprises of part producers which employed remarkably small number of personnel, particularly lower than 40 employees over the course of 2000s. These electronics firms engage in designing, developing and manufacturing of rather specific parts such as fingerprint verification equipment and testing instrument for electricity and electric signals. In fact, those electronics firms with somewhat small size of employment are also shown to have also lower operating turnover and tangible fixed assets. It could be noted that such a small number of employees appears to be consistent with the scale of their business operation. Since the number of employees is related mathematically to total labour hours worked in this research, it is unsurprised that total hours worked by employees would be significantly higher in automobile industry. Automotive firms appear to have technically higher labour input than electronic manufacturing firms on average and the former also has relatively more capital intensity than the latter as the automotive industry has higher intensification by approximately 1.9%. When comparing the maximum value, it is worth mentioning that the highest amount for both sectors is not very dissimilar. Electronics's highest capital intensity is at 4.78%, in comparison with 4.91% in the automobile industry.

On average, the level of market capitalisation in the automotive industry is about three times larger than in the electronics industry. Besides, the largest amount of market capitalisation in the automobile industry also exceeds that of the electronics industry by a considerable margin. This points toward the possibility that automotive firms have been a more established presence in the capital market than electronics firms since the higher market capitalisation could imply either higher share price or a higher amount of share issued on the stock exchange. In addition, the gap in terms of market capitalisation between the two sectors can be due to the fact that the electronics sector in the aspect of information-communication technologies that had enjoyed significant progress in the capital market up until the year 2000. However it suffered contraction from the dot com crisis and the price slump in telecommunication and electronics equipment in the early years of the 2000s. The debt to equity ratio for the automotive sector is marginally higher than that of the electronics sector. This suggests that firms in the automotive industry relied more on borrowing to support their operations such as investing in new machineries and production plants.

Despite having different amounts of R&D spending and intensification level, the two industries show similar performance measures. Both median values of labour productivity and profit margin are almost similar for both industries. 21.3% and 21% of output values are generated by the use of a unit in labour input, for the automotive and electronics firms respectively. The difference in profit margin is merely slight. Electronics firms manage to generate net income of about 2.5% out their operating revenue whereas those of automotive companies attain the level of 2.4%. Likewise, the least value of profit in both industries demonstrates negative signs and comparable amounts of loss. One electronics firm that is identified as experiencing the largest annual loss of 3,911,351 thousands of U.S. Dollars was NEC Corporation during year 2008. NEC Corporation was affected by weakened demand for electronics devices amidst the global economic downturn as well as its business restructuring costs (SydneyMorningHerald, 2009).

In the automobile industry, Mitsubishi Motors Corporation shows a loss of about 3,916,661 thousand U.S. Dollars in year 2004. As a matter of fact, this carmaker encountered a catastrophic loss in consumer confidence and public image, stemming from the publicity about its corporate scandals in 2000 and 2004. Mitsubishi Motors was twice exposed as systematically hiding faults in vehicles manufactured in Japan since 1977 (BBC news, 2000; Russell, 2005). Because of the effect on both passenger and commercial trucks, it had to recall 156,433 vehicles previously sold in Japan for free repairs whereas at least 40

prefectures and local governments banned the purchase of Mitsubishi-made vehicles (Autosafety.org, 2004; Faiola, 2004). As a consequence, sales revenues of Mitsubishi motor company fell substantially and this added to the financial difficulties that the carmaker had already experienced since 1990s.

The means, minimum and maximum values of both extramural knowledge constructs, and technology absorption capacity in electronics sector are higher than those in automobile. Statistically, the electronics dataset has relatively larger sample size where small and component manufacturers compose a bulk of the research sample. Their sales value is less than those of major consumer electronics producers which have considerably lower presence in the electronics dataset. As the denominator in the formulas of technological spillovers and absorptive capacity, small amount of sale automatically implies that the ratio of research externalities and absorptive capacity constructs would be high.

4.7.2 Correlation analysis

The study uses Pearson pairwise correlation to examine relationships between variable pairs. Separate results for the automotive and electronics industry are in table 4.4 and 4.5 accordingly. Although correlation does not infer causality between variables, it does give some insight into the strength of the relationship between them (Gujarati, 1999). Since the number of employee is strongly related to hours worked, shown by a near perfect correlation coefficient of 0.999 and the use of the former in computing the latter, it is not surprising that hour worked is also highly correlated with sales.

In both industries, sales are positively correlated with R&D expenses, number of employees, market capitalisation, hour worked and labour productivity at the 1% level. There is a high correlation coefficient for sales and R&D investment, to acquire targeted level of sales, particularly in R&D intensive sectors, and this may motivate management to spend on R&D activities. Reversely, R&D is considered as the critical factor that sharpens a firm's competitiveness, and so an emphasis on R&D spending is presumed to result in a sustainable sales performance. Association between sales and both number of employees and hours also exists. This may be due to the fact that employees are hired for processes leading up to sales of finished goods in the marketplace. Processes may include manufacture of goods, quality and control and eventually marketing of products.

Likewise, the correlation between sales and labour productivity can also be explained in terms of variable construction. Since labour productivity is proxied by value of sales per hour in this study, labour productivity and R&D are likely to be interdependence. Market capitalisation is found to show a large degree of association with sales, possibly explained by the fact that market capitalisation not only represents the total market value of a firm's outstanding shares, but also is used to categorise a firm's size. To this end, a large value of market capitalisation may imply the substantial size of a firm which in turn suggests the ample value of sales that a large firm would acquire. As well, sales are positively correlated with firm age, even though with marginal correlation coefficients for both industries. The age of firm could relate to years of listing and experience in the industry and market environments and steady relationship with clients or consumers. Long established firms may be better able to foster awareness of their products ahead of new entrants. As for debt ratio, it correlates with sales, however, not with a strong relationship. Correlation coefficients are different between the industries, negative for automotive and positive for electronics sector respectively. This may reflect different capital structure among two sectors and is an important factor in profitability.

R&D positively correlates with number of employees and hours worked. More specifically, investment in research and development directly includes the recruitment and training of skilled employees. Market capitalisation may be linked to R&D via influences from external investors. According to Chan et al. (1990), stockholders tends to encourage high-technology firms to engage in research and development by willingly paying high prices for stocks of firms that do so. R&D and productivity are probably linked by the correlation between R&D and those of sales and hours worked. In both the automobile and electronics sectors, the amount of firm R&D expenses tends to be positively associated with variables controlling for size and age of firm. There is a positive correlation between R&D spending and labour productivity, nevertheless the degrees of association are of moderate and minimal for both industries. In this respect, the results suggest that investment in R&D may benefit the production proficiency of firms investing in innovative activity. As for the correlation with profit margins, there are contrasting results between industries. Whilst there is weak positive interconnection between R&D expenses and profit margins of automobile firms, the equivalent correlation coefficient for electronics firms is negative and statistically insignificant. Paralleling the case of sales, the correlation between R&D expenditures and these variables appears to be robust with market capitalisation but slight with firm age.

Table 4.4: Pearson correlations results of automobile industry

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1														
2	0.006	1													
3	0.145 ^a	0.1 ^a	1												
4	0.335 ^a	-0.089 ^a	-0.084 ^b	1											
5	0.394 ^a	0.114 ^a	-0.06 ^c	-0.109 ^a	1										
6	0.412 ^a	0.131 ^a	-0.062 ^c	-0.121 ^a	0.977 ^a	1									
7	0.207 ^a	0.097 ^a	0.328 ^a	0.07 ^a	0.625 ^a	0.617 ^a	1								
8	0.382 ^a	0.163 ^a	0.399 ^a	0.05	0.141 ^a	0.141 ^a	-0.065	1							
9	0.159 ^a	-0.422 ^a	-0.216 ^a	0.243 ^a	-0.192 ^a	-0.184 ^a	-0.178 ^a	-0.161 ^a	1						
10	0.191 ^a	-0.038	0.0001	0.101 ^a	0.265 ^a	0.285 ^a	-0.011	0.097 ^a	0.125 ^a	1					
11	0.508 ^a	0.103 ^a	0.443 ^a	0.091 ^a	0.214 ^a	0.217 ^a	0.399 ^a	0.935 ^a	-0.113 ^a	0.151 ^a	1				
12	0.418 ^a	0.132 ^a	0.588 ^a	0.071 ^b	-0.162 ^a	-0.165 ^a	0.073 ^b	0.892 ^a	-0.173 ^a	0.124 ^a	0.932 ^a	1			
13	0.442 ^a	0.085 ^b	0.517 ^a	0.065 ^c	-0.271 ^a	-0.275 ^a	-0.126 ^a	0.851 ^a	-0.125 ^a	0.163 ^a	0.942 ^a	0.887 ^a	1		
14	0.306 ^a	0.294 ^a	0.294 ^a	0.029	0.095 ^a	0.096 ^a	0.25 ^a	0.874 ^a	-0.181 ^a	0.09 ^a	0.795 ^a	0.741 ^a	0.681 ^a	1	
15	0.441 ^a	0.087 ^a	0.516 ^a	0.064 ^c	0.271 ^a	0.275 ^a	0.126 ^a	0.854 ^a	-0.125 ^a	0.162 ^a	0.941 ^a	0.886 ^a	0.999 ^a	0.685 ^a	1

a 1% significant level; b significant level; c 10% significant level

Notes: Variables 1-12 represents 12 variables that are put into correlation analysis. 1 is labour productivity; 2 is profit margins; 3 is R&D intensity; 4 is capital intensity; 5 is intra-industry spillover; 6 is inter-industry spillover; 7 is absorptive capacity; 8 is market capitalisation; 9 is debt ratio; 10 is firm age; 11 is sales; 12 is R&D expenses; 13 is employees; 14 is profit or loss before taxation; 15 is hour worked

Table 4.5: Pearson correlations results of electronics industry

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1														
2	0.047 ^b	1													
3	-0.177 ^a	-0.131 ^a	1												
4	0.221 ^a	-0.059 ^a	-0.049 ^b	1											
5	0.201 ^a	0.118 ^a	0.401 ^a	-0.174 ^a	1										
6	0.204 ^a	0.144 ^a	0.407 ^a	-0.171 ^a	0.977 ^a	1									
7	0.145 ^a	0.142 ^a	0.563 ^a	0.102 ^a	0.752 ^a	0.763 ^a	1								
8	0.3 ^a	0.085 ^a	0.045	0.134 ^a	-0.132 ^a	-0.13 ^a	-0.048	1							
9	0.071 ^a	-0.265 ^a	-0.112 ^a	-0.021	-0.02	-0.04	0.001	-0.029	1						
10	-0.013	-0.094 ^a	-0.126 ^a	0.071 ^a	-0.296 ^a	-0.292 ^a	-0.143 ^a	0.184 ^a	0.13 ^a	1					
11	0.28 ^a	-0.03	0.008	0.101 ^a	0.101 ^a	0.107	0.04	0.756 ^a	0.115 ^a	0.258 ^a	1				
12	0.174 ^a	-0.054 ^b	0.131 ^a	0.057 ^a	-0.092 ^a	-0.097 ^a	0.035 ^c	0.67 ^a	0.115 ^a	0.237 ^a	0.869 ^a	1			
13	0.096 ^a	-0.041 ^b	0.035	0.057 ^a	-0.124 ^a	-0.13 ^a	-0.049 ^b	0.665 ^a	0.126 ^a	0.303 ^a	0.833 ^a	0.861 ^a	1		
14	0.097 ^a	0.24 ^a	-0.054 ^a	-0.004	0.016	0.017	0.046 ^a	0.306 ^a	-0.128 ^a	-0.023	0.003	-0.165 ^a	-0.095 ^a	1	
15	0.095 ^a	-0.04	0.035	0.056 ^a	-0.124 ^a	-0.13 ^a	-0.049 ^b	0.666 ^a	0.126 ^a	0.303 ^a	0.83 ^a	0.861 ^a	0.999 ^a	-0.092 ^a	1

a 1% significant level; b significant level; c significant level

Notes: Variables 1-12 represents 12 variables that are put into correlation analysis. 1 is labour productivity; 2 is profit margins; 3 is R&D intensity; 4 is capital intensity; 5 is intra-industry spillover; 6 is inter-industry spillover; 7 is absorptive capacity; 8 is market capitalisation; 9 is debt ratio; 10 is firm age; 11 is sales; 12 is R&D expenses; 13 is employees; 14 is profit or loss before taxation; 15 is hour worked

Generally, R&D intensity could be regarded as strongly related to R&D expenses because of the construction of the variable. Nonetheless, the correlation results of R&D intensity with other variables are found to be different to the case of R&D expenses shown earlier. For automobile firms, R&D intensity demonstrates results similar to that of R&D expenses, albeit with a moderate degree of correlation. Although there is strong positive interconnection between value of R&D investment and both number of employees and hours worked, R&D investment as a percentage of sales of electronics firms does not correlate with either labour-input variables. In addition, the two industries display contrasting directions of correlation between R&D intensity and control variables of size and age. For automobile industry, the ratio of R&D expenditures to sales is positive and moderately interrelated with market capitalisation. Automobile R&D intensity is not related to firm age, as this correlation result is insignificant at 5% level. Regarding the electronics industry, the correlation coefficient of R&D intensity and market capitalisation is positive but insignificant whereas R&D intensity is negatively weakly correlated with age. The correlation between R&D intensity and the debt ratio in both industries share similar results demonstrating a weak relationship. However given its statistically significant results for both industries, it may suggest that mounting level of debts is a disincentive to put effort into R&D activities or projects which may be uncertain and raise the risk of potential failure. There is a somewhat weak and negative correlation between R&D intensity and capital intensity, which may be due to the fact that higher capital intensity could be a consequence of employing additional tangible fixed capitals into the production processes. More tangible capitals lead to the reduction in the budget available for investment in other activities including R&D.

R&D intensity in both sectors appears to have a weak correlation with both firm performance measures, nevertheless the sign of the correlation coefficients are directly opposite. With correlation coefficients values of 0.145 and 0.1, R&D intensity positively relates to labour productivity and profit margin correspondingly. On the other hand, there are negative correlations between electronic firms' R&D intensity with labour productivity and profit margin with correlation coefficients of -0.177 and -0.131 respectively. A possible explanation for negative correlation coefficients in the electronics sector could be the lagged effects of R&D intensity on firm performance in the sector. Statistically, the proper lag structure of R&D as an independent variable in this thesis could be longer than for the automobile sample. This contributes to either no correlation or a negative correlation between current R&D intensity and the two firm performance measures. There might be time gap

before the efforts in research and development, as proxied by R&D as a fraction of sales, is apparent. Hence, it is likely that R&D intensity at the present period may demonstrate no relation to firm profit whereas the return on R&D intensity of previous periods could exist. In another aspect, it is determined that current R&D intensity could be perceived as one of the costs of business operations. In the presence of a probable time lag effect, R&D intensity could initially correlate with labour productivity and such an interconnection will become positive as the yield of R&D investment becomes visible in the subsequent periods.

Correlation between labour productivity and profit margin is another area that illustrates different results between the two industries. In this respect, automobile correlation results indicate a positive and insignificant coefficient meanwhile the electronics results exhibit a positive correlation at 5% significance. The insignificance of the relationship between labour productivity and profit margin in the automobile industry implies that efficiency and profitability has a lag in effect in relation to both performance measures. Representing tangible capital, capital intensity correlates with both firm performance measures. The direction of the relationships is identical across the two sectors. Despite the fact that labour productivity is positively related to capital intensity, the strength of the relationship is moderate and weak for automobile and electronics sectors accordingly. As the amount of plant or machinery available for workers to use in the process of manufacture increases, greater production efficiency is likely to be realised possibly in the form of less production time taken and the uniformity of product quality. Computed correlation coefficients of profit margin and capital intensity indicate a negative and rather weak relationship between two variables for both automobile and electronics firms. Higher amounts of tangible capital may originate from further investment or purchase of new machinery and plant, and thus this fixed capital spending constitutes costs to the firm.

In both industries, labour productivity and profit margin are shown to correlate with the debt ratio. Meanwhile, the debt ratio correlates positively with labour productivity but there is a negative correlation between the debt ratio and profit margin. The weak relationship between labour productivity and the debt ratio may be due to the reason for the borrowed funds from external sources. It is possible that enhancement in production facilities or technologies may be financed through debt. A negative correlation of moderate strength between profit margin and the debt ratio could arise when profits are lower due to high interest expenses. Additionally, the age of the firm also differs with respect to the two performance measures across the automobile and electronics industries. In the former, the age

of the firm is positively related to labour productivity whereas the correlation between age and profit margin is found to be statistically insignificant. In the electronics sector, firm age is shown to be unrelated to labour productivity. While the age of the electronics firms is correlated with profit margin, the direction of correlation between two variables is different. For both automobile and electronics firms, the size of firm is positively related to both labour productivity and profit margin, whereas that between market capitalisation and the two performance measures indicate either a weak or moderate relationship.

Reminiscent of internal R&D's findings discussed earlier, the empirical results suggest that there is modest strength of interrelation between technological externalities and both firm performance indicators. To this end, there is positive correlation matrixes with p-values lower than 5% alpha level. The correlation between external knowledge of both sources and internal R&D variables (both firm R&D investment and R&D intensity) exhibit negative coefficients for both industries. These spillovers findings may imply the disincentive effect of spillover upon the private technology investment. These findings are in conformity with negative traditional effect of spillovers, as pointed out by Grünfeld (2003). While the existence of extramural knowledge accelerates the overall technological advancement in the industry, it could as well reduce the level of effort firms put into innovative activities. To Nieto and Quevedo (2005), this disincentive effect is triggered by two diverse motives. Facing a decreased likelihood of being able to make exclusive use of the results of their own inventive effort, the innovating firms would limit their new investment in R&D (Spence, 1984). If the available external technology generated by competitors may be regarded as a substitute rather than a compliment to their internal one, the imitator or absorbers of know-hows would as well lessen any R&D activities of their own (Henderson and Cockburn, 1996; Levin and Reiss, 1988). When an external technology is substitute, Spence (1984) shows that the firm's R&D intensity will be a decreasing function of the extent of spillovers which is operationalised as the share of R&D expenditures that effectively reaches all competitors. This is because the recipient firms may receive valuable knowledge from their environment at a price that is lower than the cost of producing this knowledge internally or of acquiring it in the market (Harhoff, 2000). Similar finding is present in the correlation between both research externalities and capital intensity and labour input (hour worked) where there are weak and negative correlation coefficient. In accordance with the spillovers effect upon own R&D, it could be stated that incorporation of new extramural knowledge may lead to the change in manufacturing processes. If an acquired outside technology is a substitute to own

technology, there could be less amount of traditional production inputs that the recipient firm utilises.

While the significance of technological absorption encourages the firm to conduct R&D internally, the existence of research externalities at the same time dissuades others from doing their own R&D. To this end, the decline in others' innovative effort could imply that there is less external knowledge to learn from. In this research, there is positive and significant correlation between absorptive capacity and those of R&D intensity and R&D expenses. In similar vein to Kamien et al. (2000), it could be contended that the disincentive to engage in internal R&D activities; stem from the existence of externalities, may be partially offset by the rationale to engage in R&D activities in order to enhance the capability to absorb inflow of outside technologies. The positive correlation between absorptive capacity and intra-organisational innovative effort has been documented in empirical literatures (Veugelers, 1997; Becker and Peters, 2000). Nieto and Quevedo (2005) point out that firms which have successfully amassed a certain capacity for extramural knowledge absorption are likely to have a greater propensity to innovate at the present time since they will be well placed to take advantage of all sources of knowhow; whether internal and external. According to Mowery (1984), an organisation could be far better equipped to absorb outside knowledge if it is also performing some amount of R&D internally. The positive correlation between absorptive capacity and those of firm innovative effort measures signify the role of internal R&D as a potential determinant of absorptive capacity. In absorptive capacity studies, scholars verify and recognise the importance of intra-firm technological effort using different measures (Escribano et al., 2009; Kneller and Stevens, 2006; Mancusi, 2004; Rocha, 1999).

There is also the possibility that purchased absorptive capacity may increase the organisation's own in-house R&D investment, although the effectiveness of such options may be mediocre. To Murovec and Prodan (2009), those of bought components of absorptive capacity are often associated with product and process innovation attained from external sources. In this respect, empirical studies argue that the acquisition of extramural knowledge; which concurrently brings along some degree of absorptive capacity, may stimulate rather than replace in-house R&D activities (Braga and Willmore, 1991; Hung and Tang, 2008; Siddharthan, 1992), given the condition that the recipient organisation already possess its own absorptive capacity (Veugelers, 1997). For both industries, both intra-sectoral and inter-sectoral spillovers exhibit direct and positive relationship to absorptive capacity. In

automobile case, the relationship between intra-sectoral externalities and absorptive capacity, and between inter-sectoral externalities and absorptive capacity have correlations of 62.5% and 61.7% respectively. As for electronics industry, observed correlations with absorptive capacity are 75.2% for intra-industry spillovers and 76.3% for inter-industry spillovers. The implication of these findings is of the fundamental role of absorptive capacity in the internalisation of external knowledge. Technological externalities and absorptive capacity are proven to be compliment. While the pool of extramural technologies is available and accessible to all firms, the variation in the efficacy and aptitude of the firm to exploit such non-inhouse technologies are likely to exist as firms have dissimilar level of absorptive capacity. The rise in amount of research externalities substantiates the necessity to invest in technological absorption capabilities whose growth conversely enables the firm to apply broader range of external knowledge.

4.7.3 Data Trend

Figure 4.1 to 4.10 demonstrate the trend of variables for the automobile whereas figure 4.11 to 4.20 illustrates the pattern for those of electronics. For each variable, mean value (vertical axis) is plotted against year (horizontal axis).

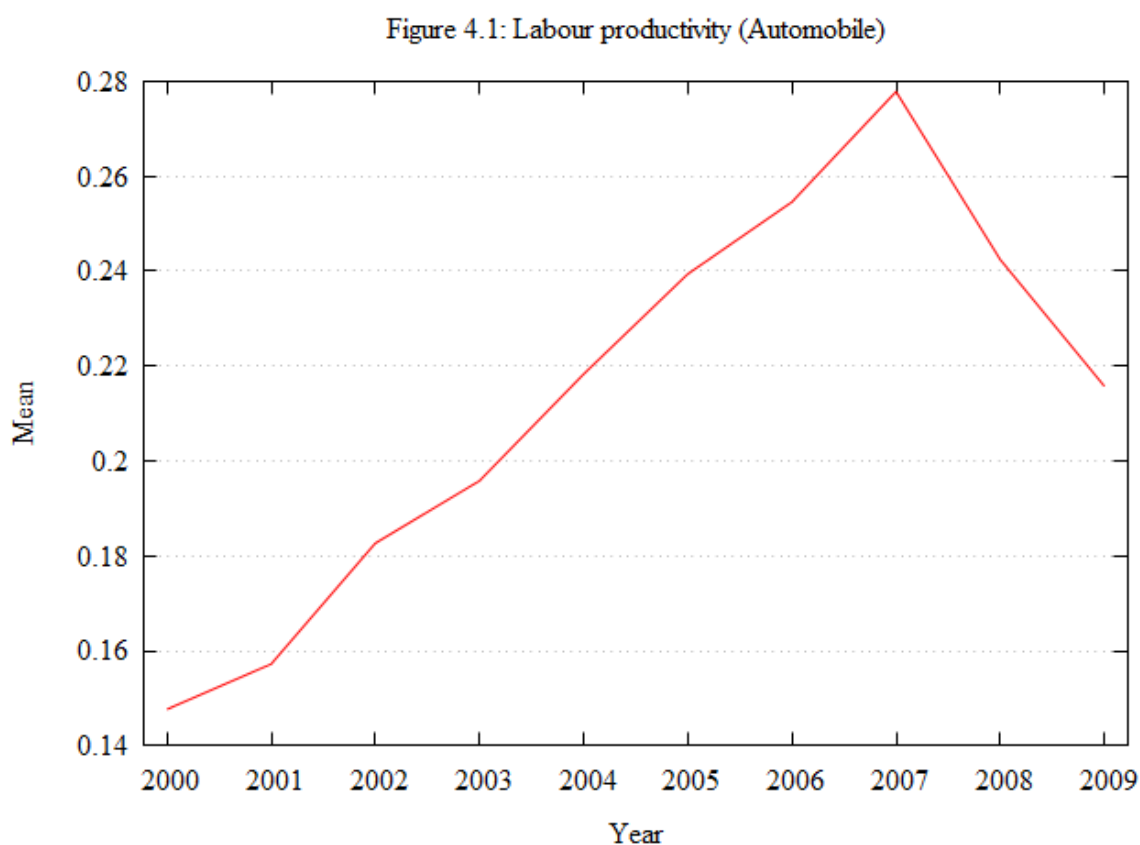


Figure 4.2: Profit margin (Automobile)



Figure 4.3: R&D intensity (Automobile)

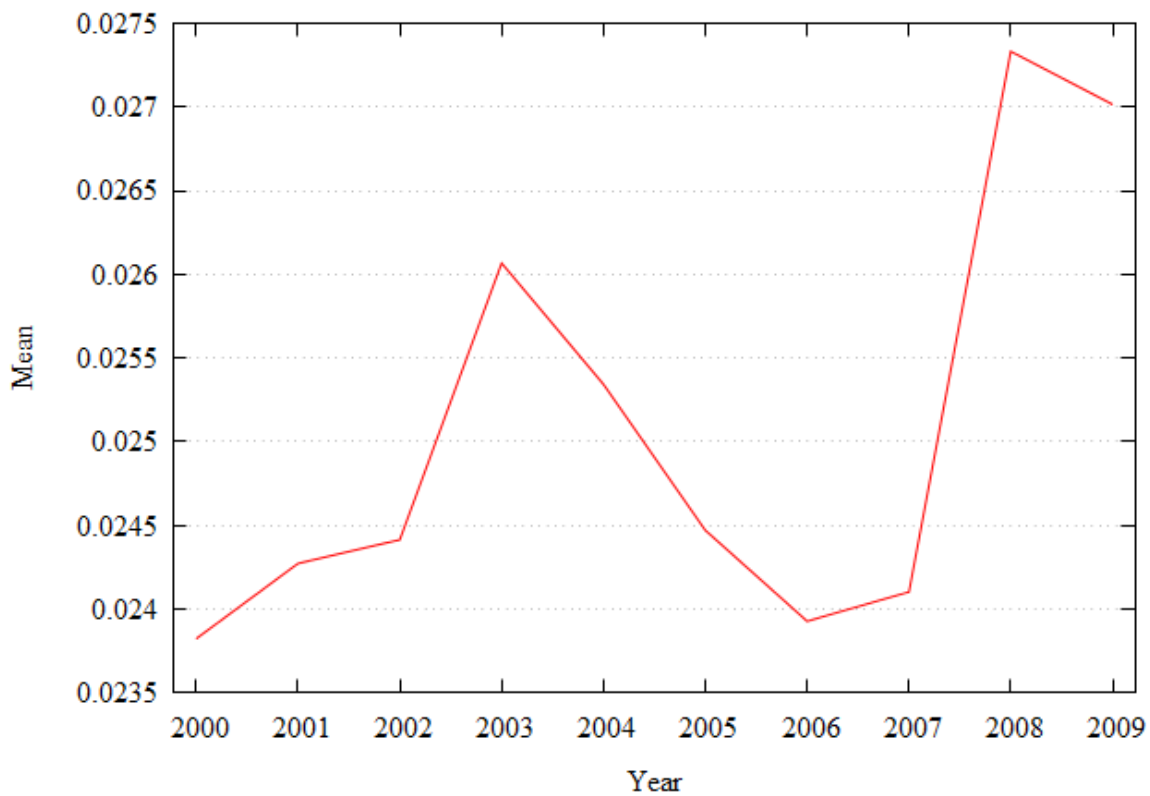


Figure 4.4: Capital intensity (Automobile)

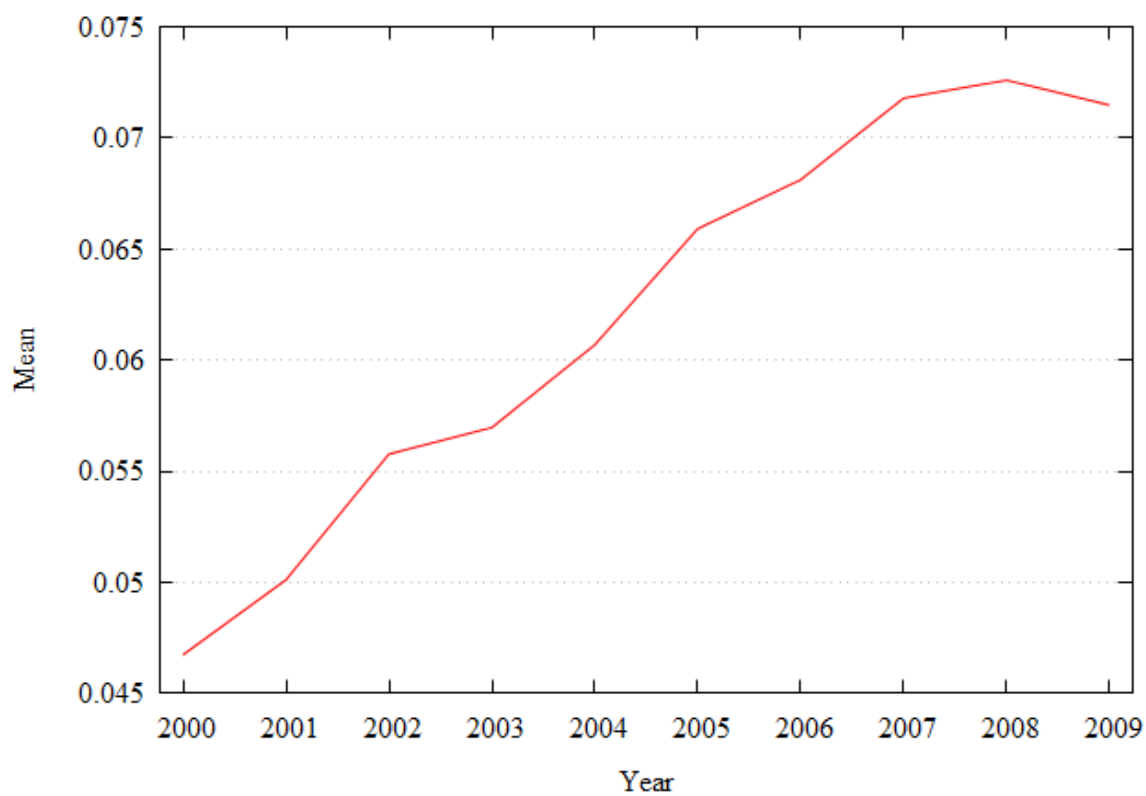


Figure 4.5: Intra-industry spillovers (Automobile)

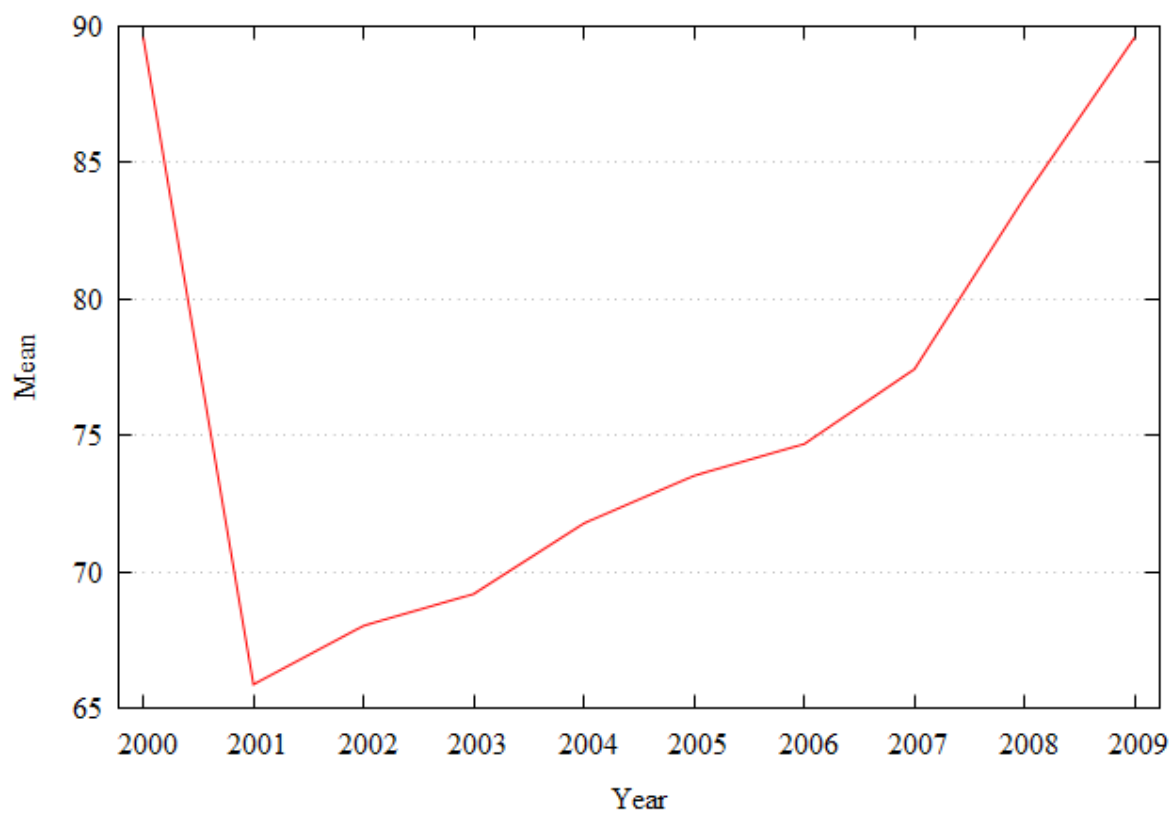


Figure 4.6: Inter-industry Spillovers (Automobile)



Figure 4.7: Absorptive Capacity (Automobile industry)

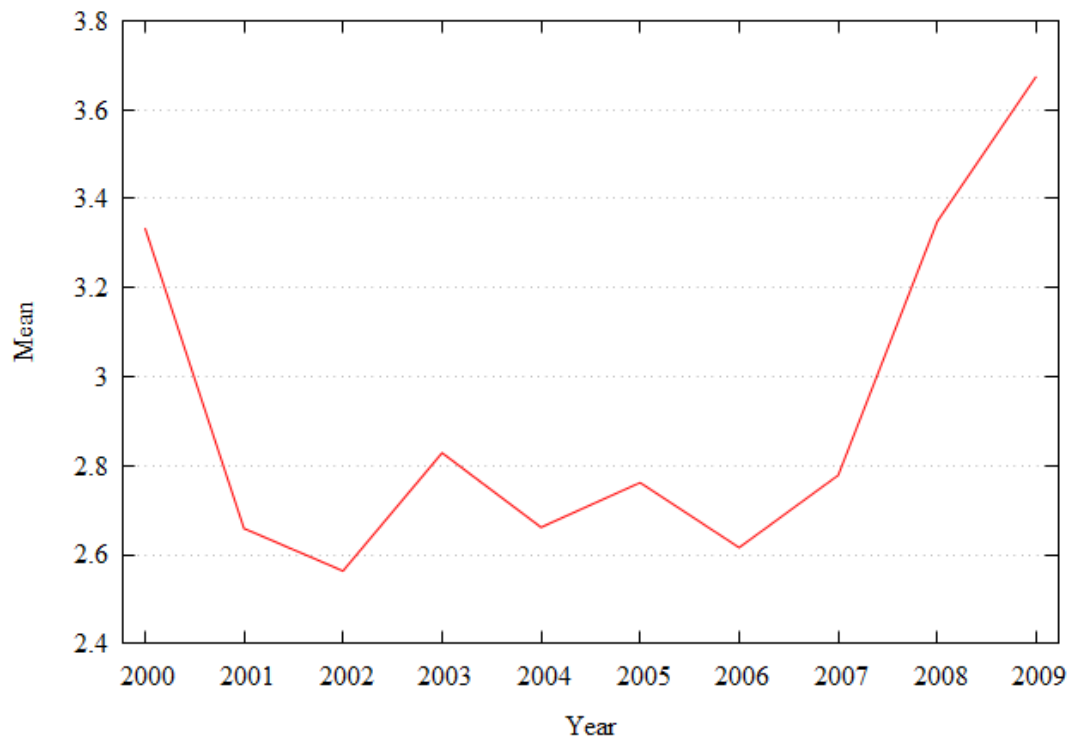


Figure 4.8: Market capitalisation (Automobile)



Note: e+006 is 10^6 ; 1e+006 is 1,000,000; 2e+006 is 2,000,000; 3e+006 is 3,000,000; 4e+006 is 4,000,000; 5e+006 is 5,000,000; 6e+006 is 6,000,000

Figure 4.9: Debt ratio (Automobile)

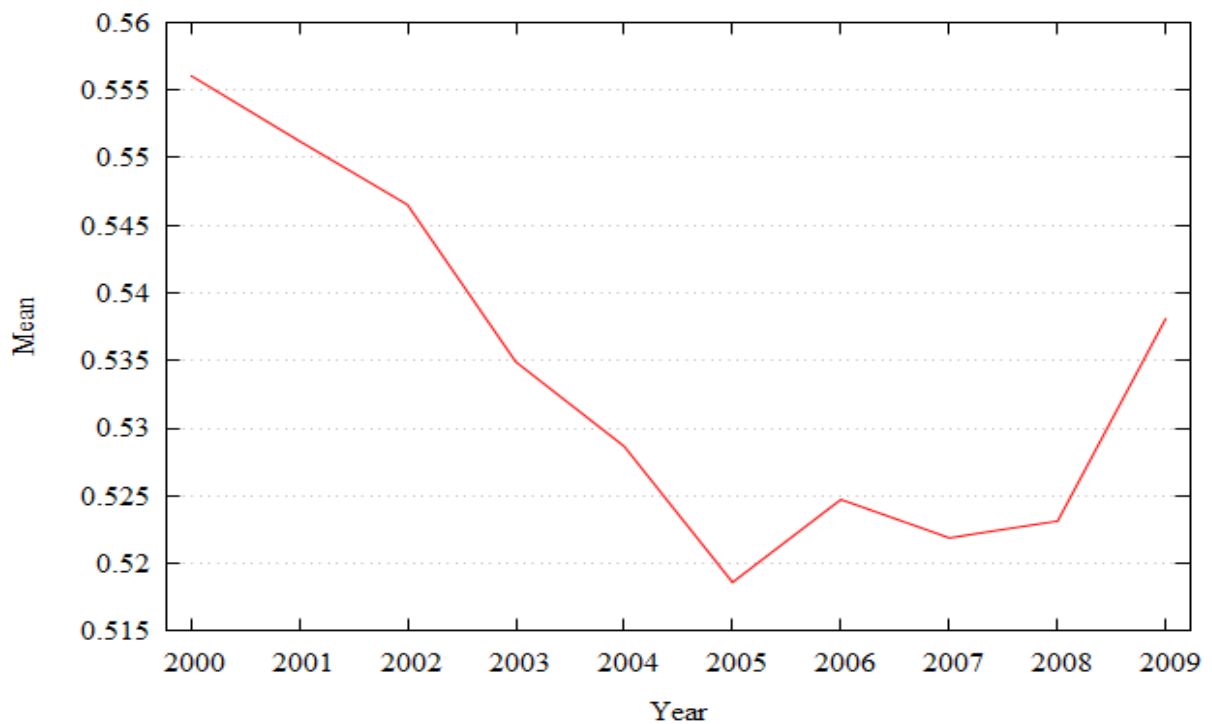


Figure 4.10: Firm age (Automobile)

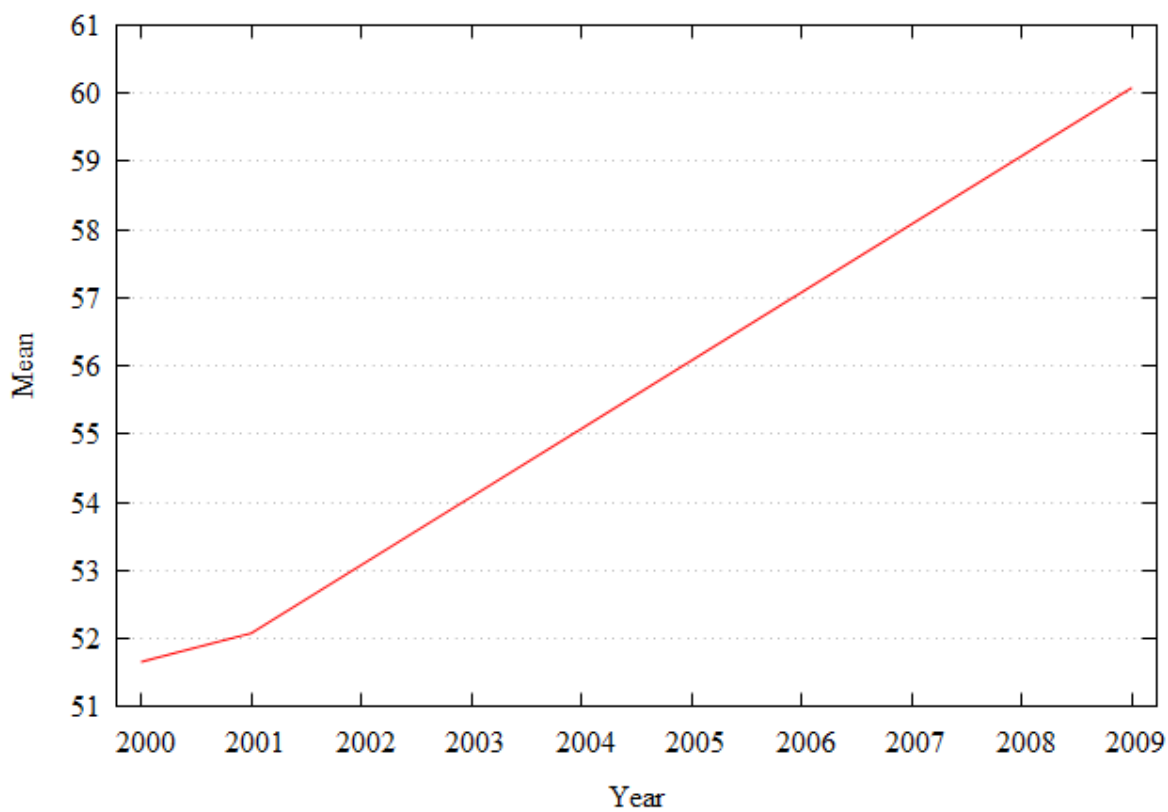


Figure 4.11: Labour productivity (Electronics)



Figure 4.12: Profit margin (Electronics)

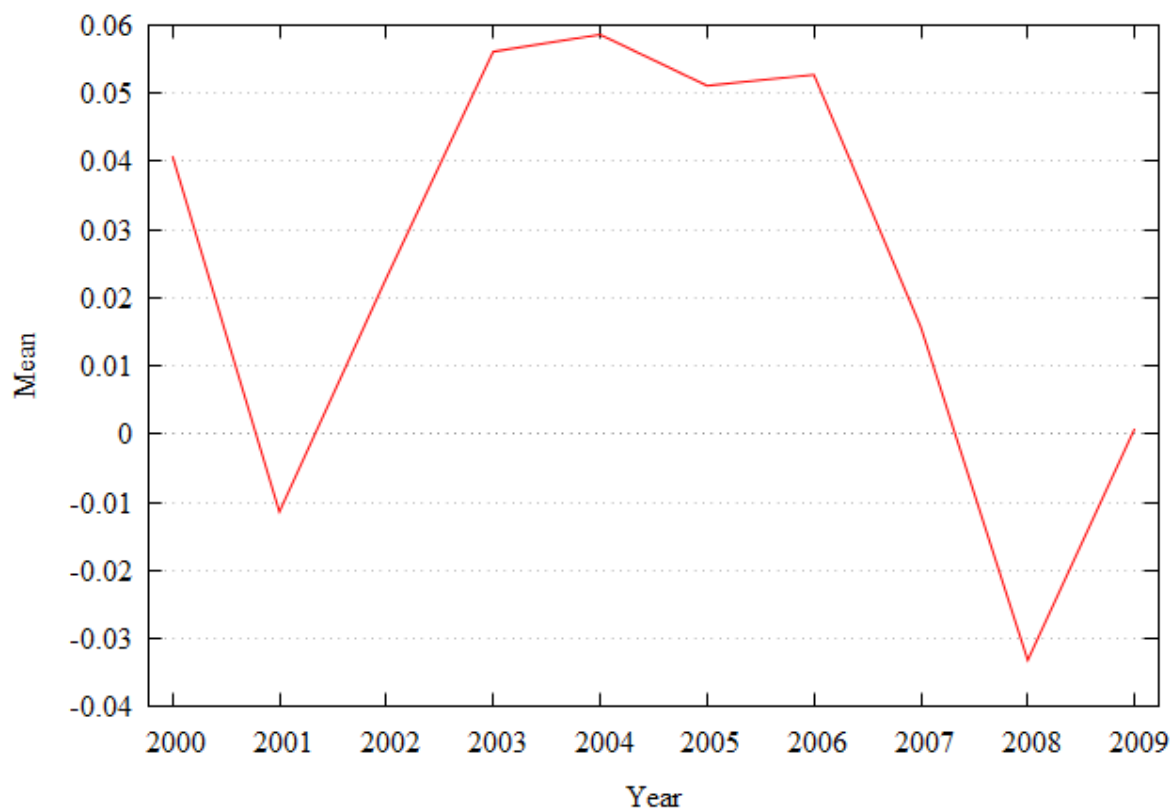


Figure 4.13: R&D intensity (Electronics)



Figure 4.14: Capital intensity (Electronics)

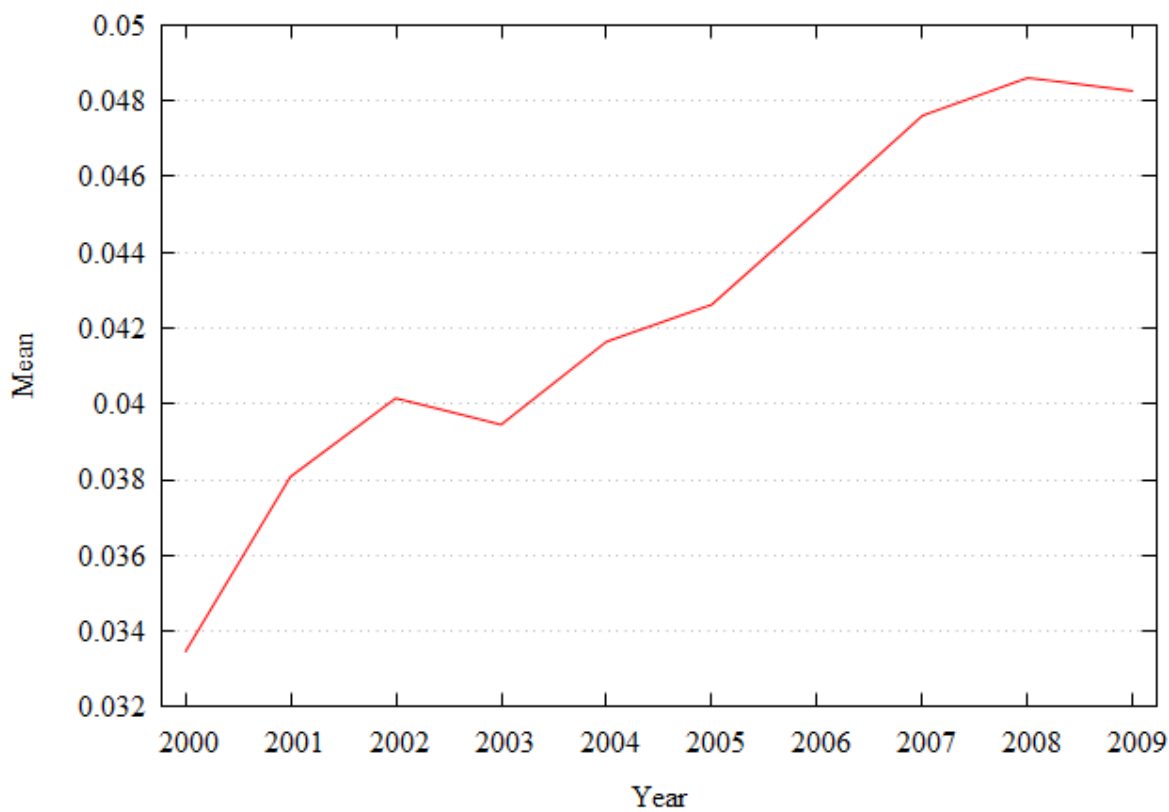


Figure 4.15: Intra-industry spillovers (Electronics)



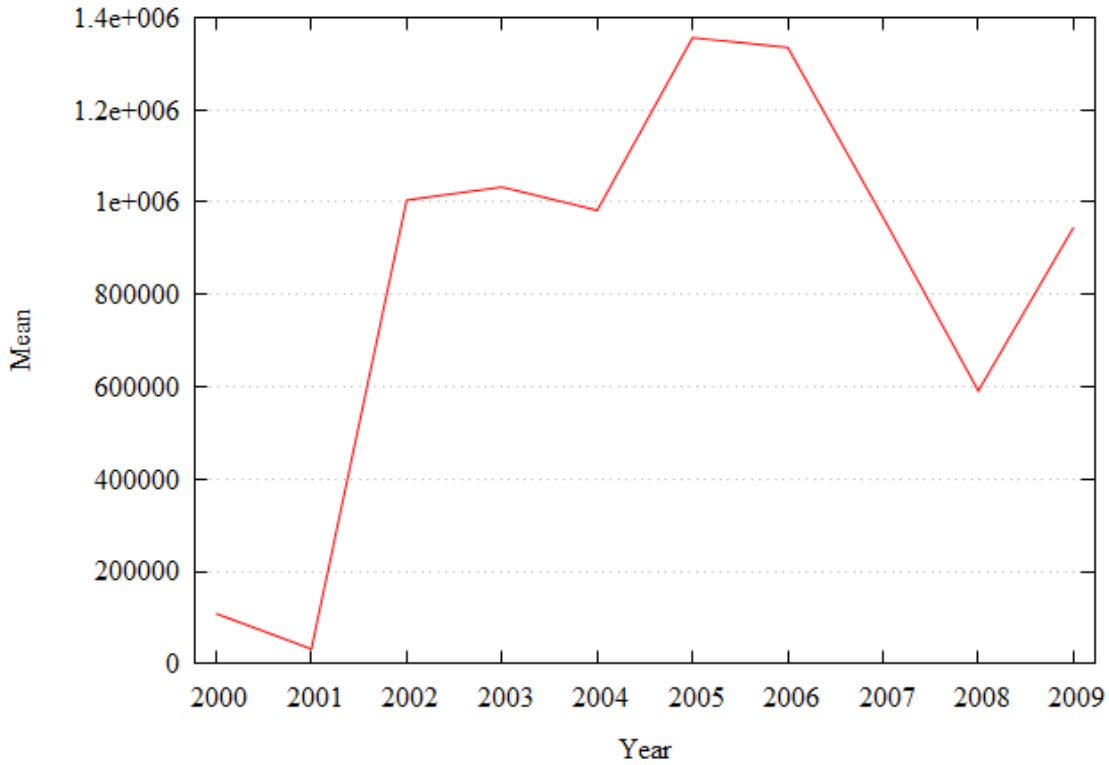
Figure 4.16: Inter-industry spillovers (Electronics)



Figure 4.17: Absorptive capacity (Electronics)



Figure 4.18: Market capitalisation (Electronics)



Note: e+006 is 10^6 ; 1e+006 is 1,000,000; 1.2e+006 is 1,200,000; 1.4e+006 is 1,400,000

Figure 4.19: Debt ratio (Electronics)



Figure 4.20: Firm age (Electronics)

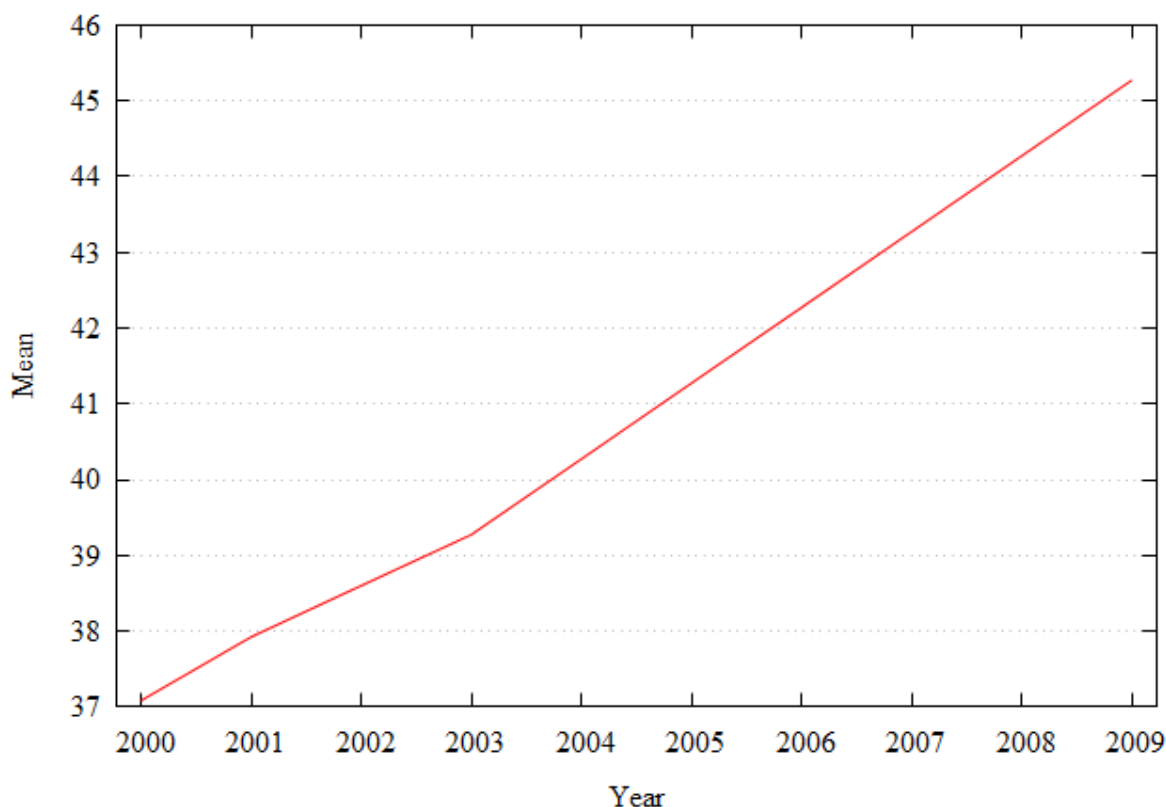


Figure 4.1 and 4.11 demonstrate that both industries underwent similar overall trend in labour productivity which had accelerated up until the economic difficulties of late 2000s. In particular, the electronics sector briefly encountered with downturn in productivity. This pattern appears to confirm the temporal setbacks stemming from the dot-com crisis and IT price slump in the early 2000s. The automobile's profitability (figure 4.2) had risen gradually but fell sharply in the wake of economic downturn in 2008. From figure 4.12, there is a clear fluctuation in electronics firms' profit margin. As in the case of labour productivity, the brief recession took place in the early 2000s, this decline was offset by consistent growth up to the middle of the 2000s. Afterwards, the electronics' profitability plummeted markedly to the level that is considerably less than those attained at the beginning of the decade. Automobile R&D intensity (figure 4.3) fluctuates throughout the decade but was on the growing trend. As illustrated in figure 4.13, on average, electronics R&D intensity had relatively higher degree of technological intensification than that of automotive. However, its overall trend indicates that internal innovative effort as a fraction of sales had been on steady decline. In this respect, there was roughly 20% decrease in electronics R&D intensity from 2000 to 2009. Capital

intensity, as shown in figure 4.4 and 4.14, display similar increase in trend for both automobile and electronics firms.

In figure 4.5, automobile intra-sectoral spillovers momentarily diminished during the beginning of the 2000s. This drop may be owing to the prolonged consequences of 1990s domestic economic contraction which generally dissuaded firms from investing extensively in technological development. The subsequent trend is characterised by the gradual upward. Reflecting the consistent reduction in individual firm's innovation effort, there was a continuing deterioration in the pool of knowledge available within the electronics industry (figure 4.15). This may be due to the continuing decline in the average R&D intensity of an electronics firm which implies that the amount of innovation output generated by electronics companies had been lessen over the course of the 2000s decade. Lower electronics' innovation effort might entail the fewer amount of electronics' technologies that could be accessible by automobile firms. This is evident in the decline in trend of the automobile's inter-sectoral spillovers variable (figure 4.6). The automotive absorptive capacity (figure 4.7) had first dropped and fluctuated over the course of 2000s but later exhibited the upward trend by the end of the decade. The average technological absorption capability of an electronics firm (figure 4.17) underwent significant volatility in trend while the general movement is in steady decline. Both automobile (figure 4.8) and electronics (figure 4.18) share the comparable trend in market capitalisation. In spite of the recession in 1990s, the level of market capitalisation showed continuous growth till the global economic downturn in late 2000s. Likewise, the average debt ratio of automobile (figure 4.9) and electronics (figure 4.19) gradually diminished over the first half of 2000s, the ratio began to pick up particularly in the light of global recession.

4.7.4 Distribution

Figure 4.21 to 4.30 demonstrate the frequency distribution of variables for the automobile whereas figure 4.31 to 4.40 illustrates the histograms for those of electronics.

Figure 4.21: Distribution of labour productivity (Automobile)

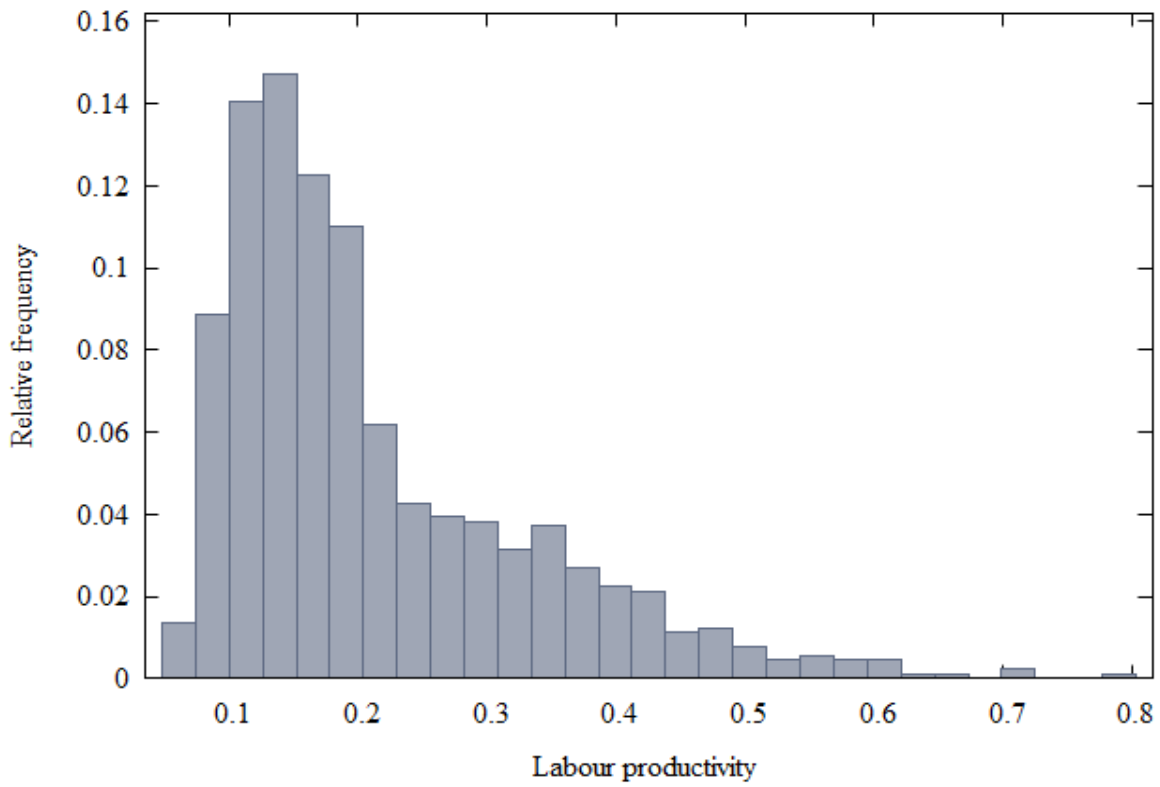


Figure 4.22: Distribution of profit margin (Automobile)

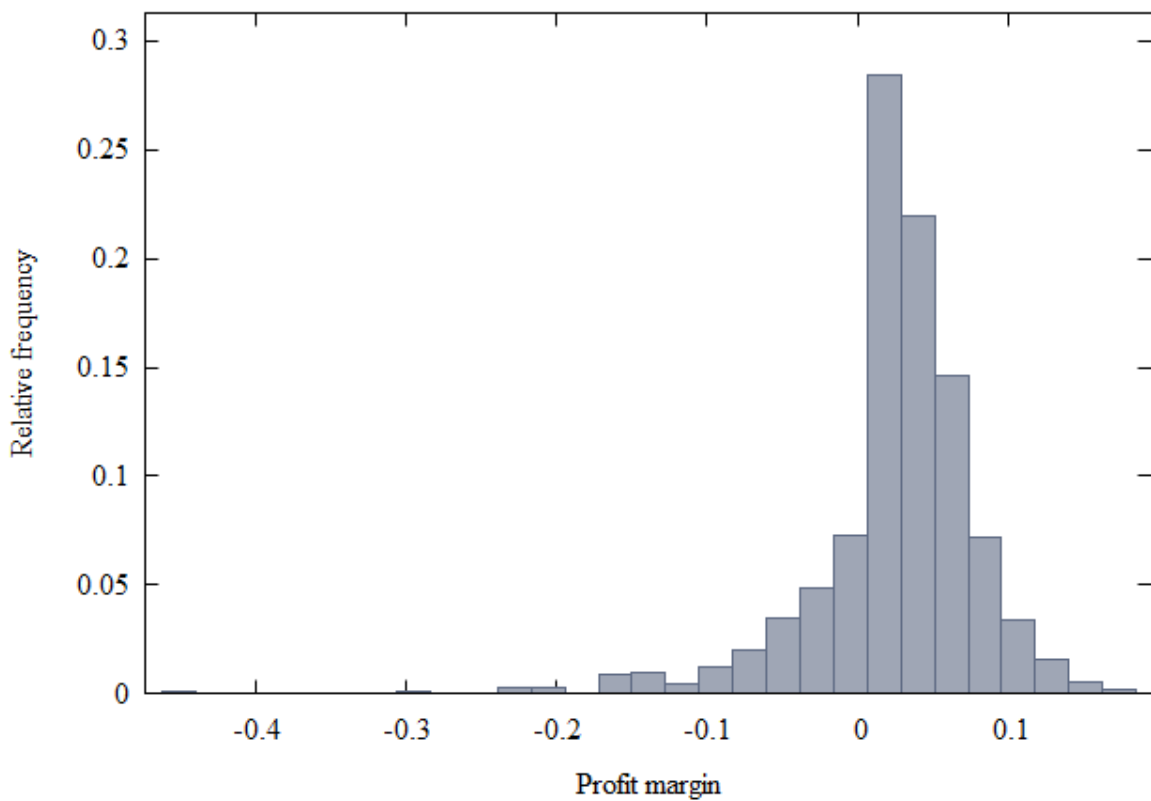


Figure 4.23: Distribution of R&D intensity (Automobile)

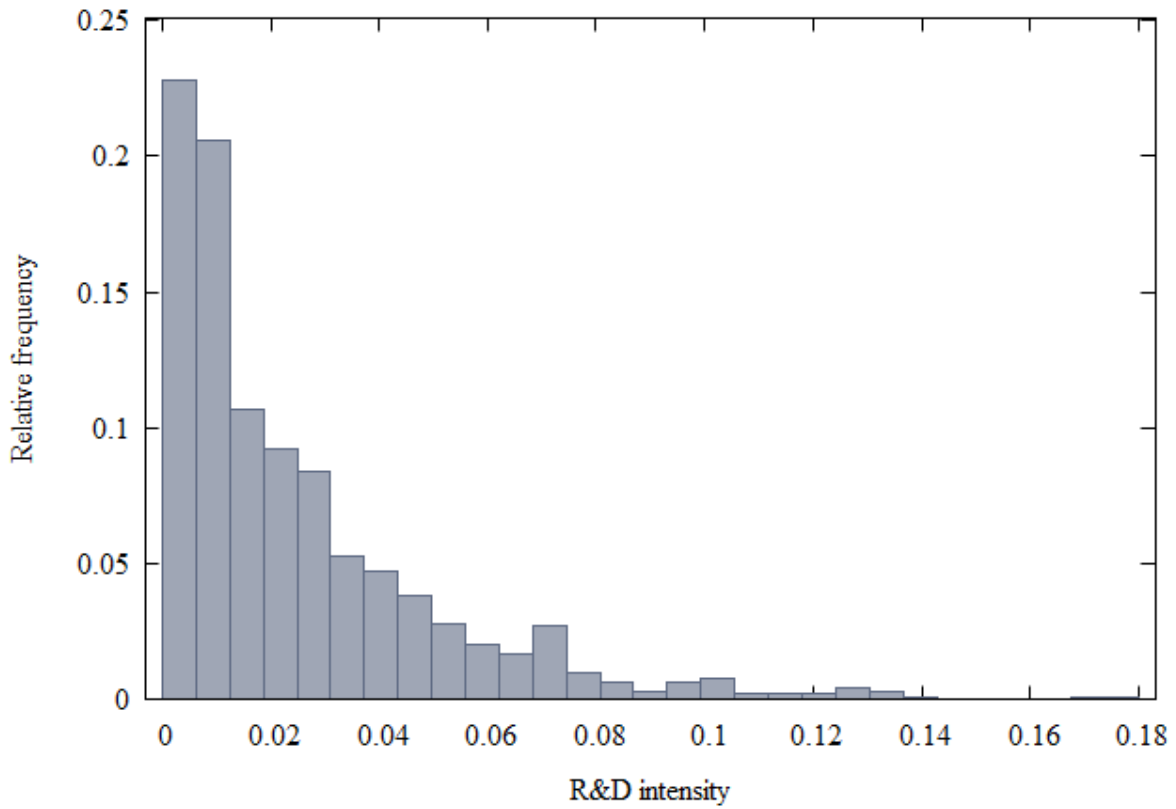


Figure 4.24: Distribution of capital intensity (Automobile)

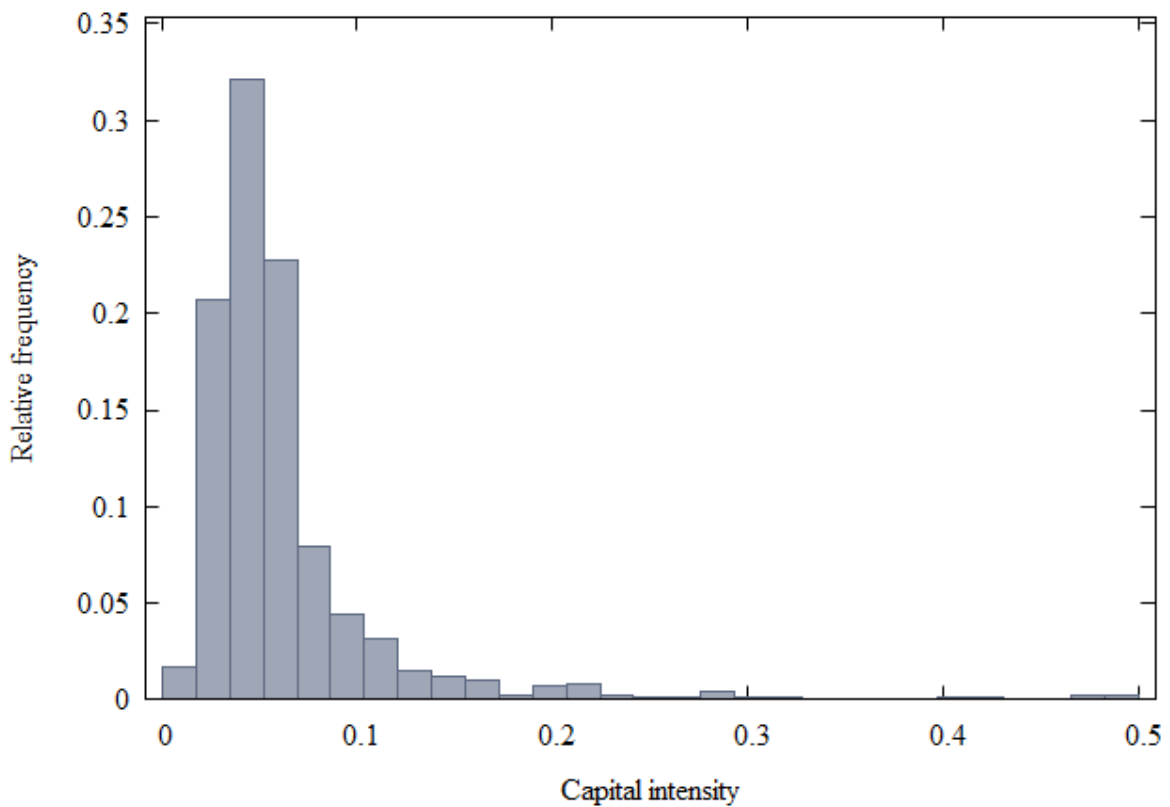


Figure 4.25: Distribution of intra-industry spillovers (Automobile)

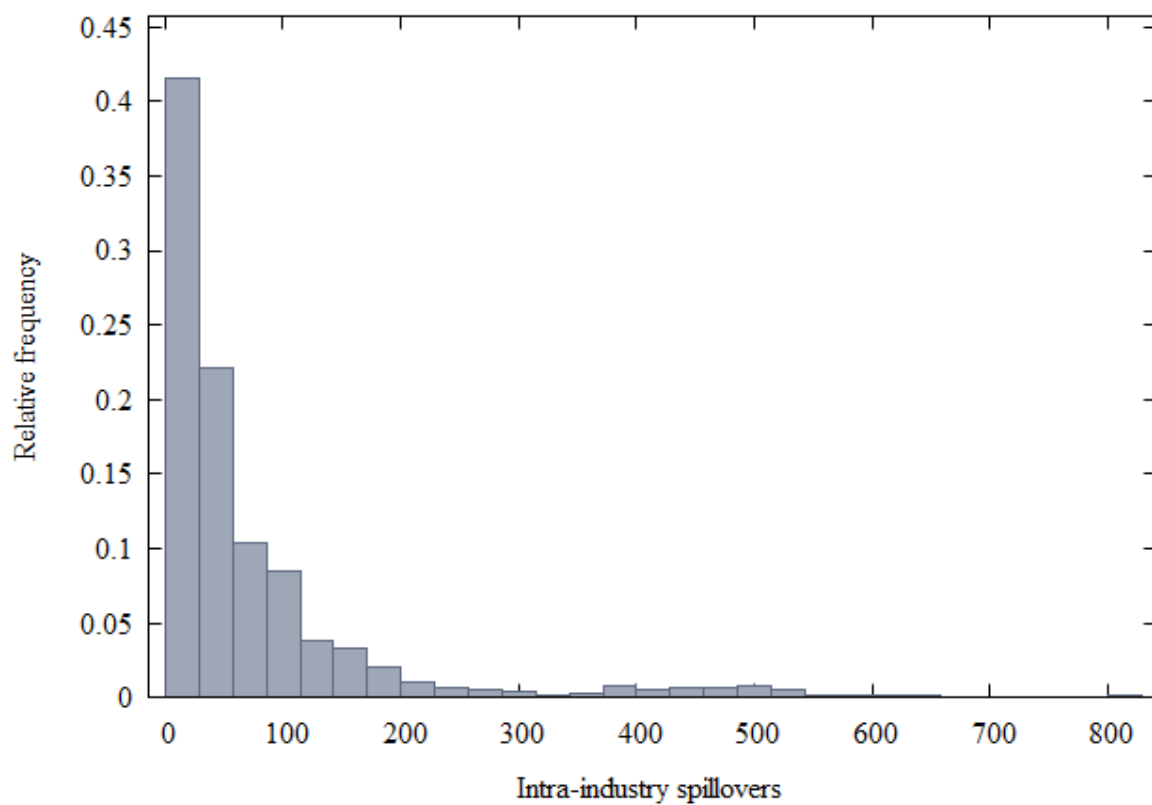


Figure 4.26: Distribution of Inter-industry spillovers (Automobile)

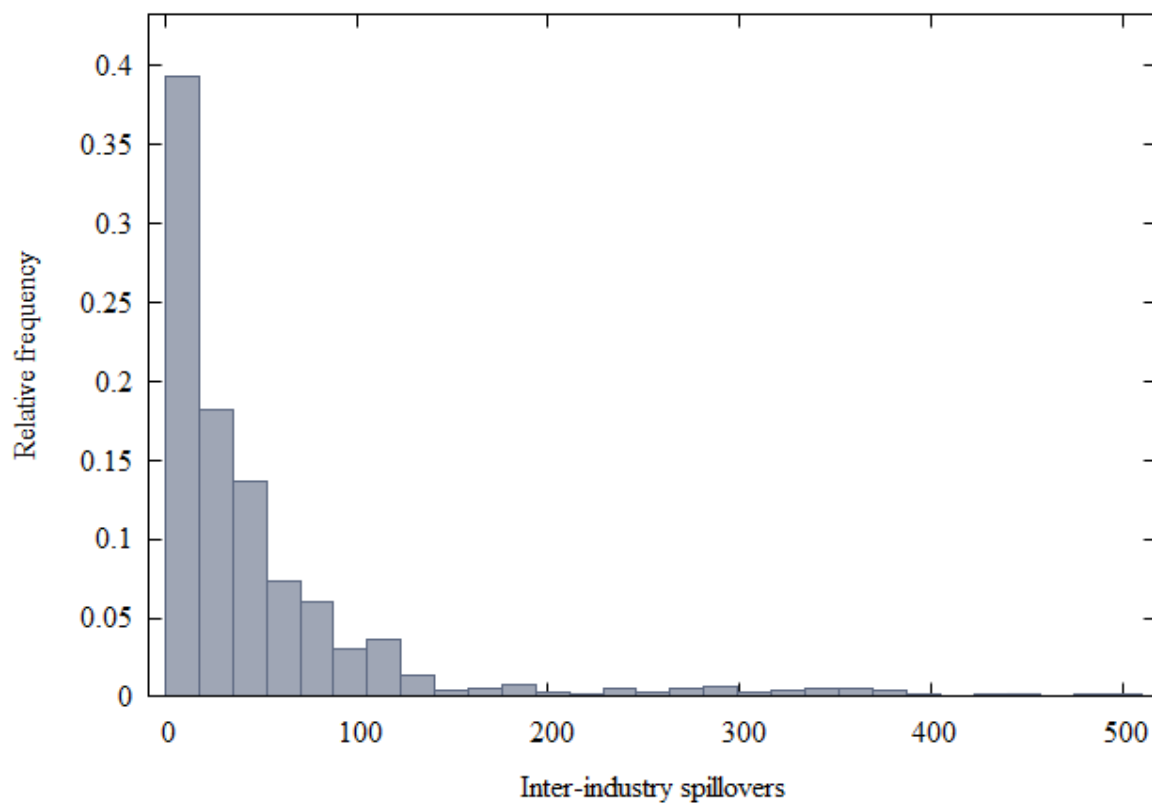


Figure 4.27: Distribution of absorptive capacity (Automobile)

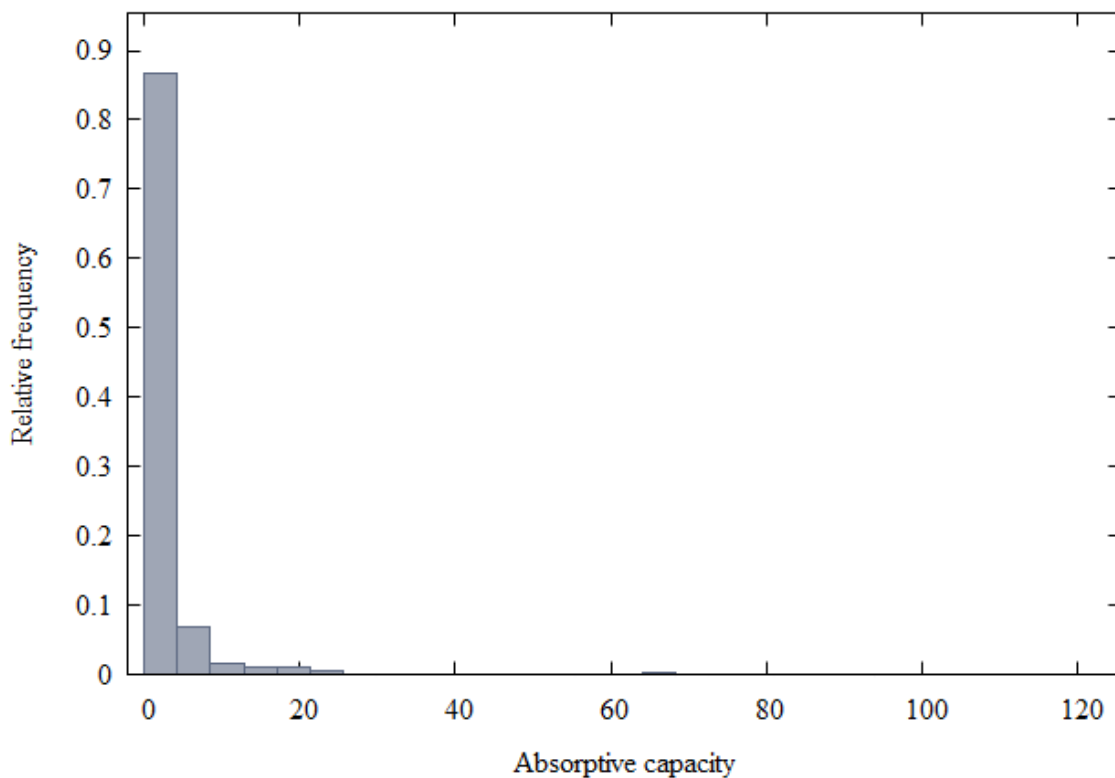
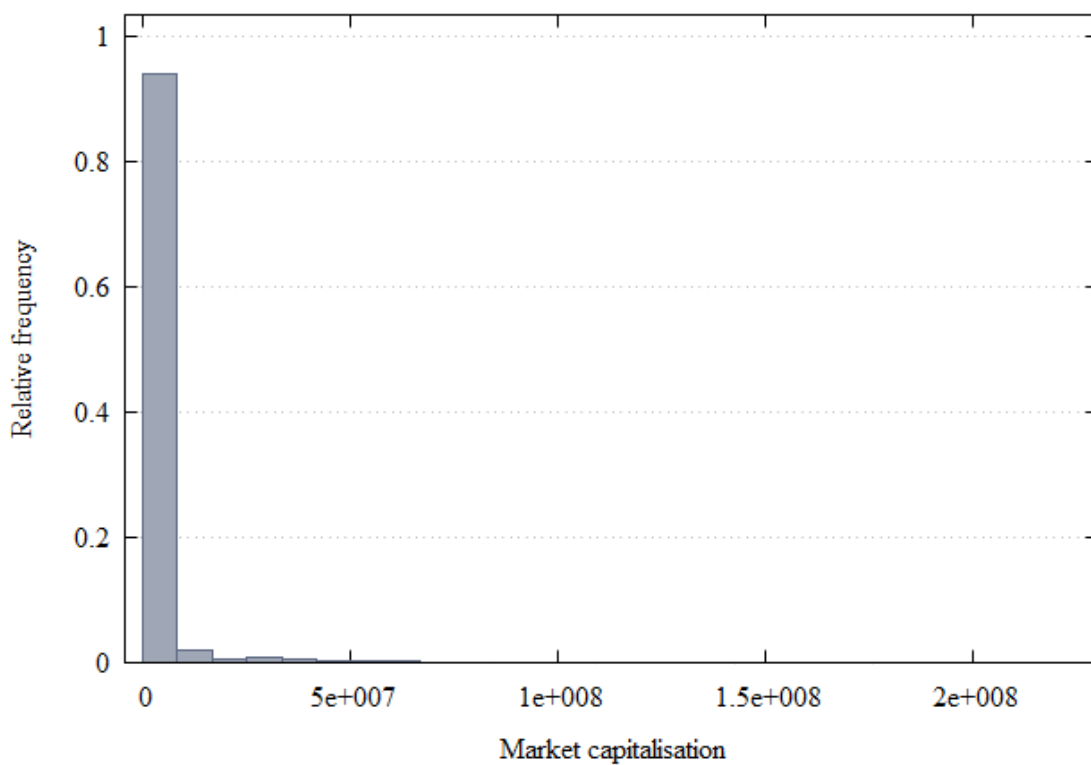


Figure 4.28: Distribution of market capitalisation (Automobile)



Note: e+007 is 10^7 , e+008 is 10^8

Figure 4.29: Distribution of debt ratio (Automobile)

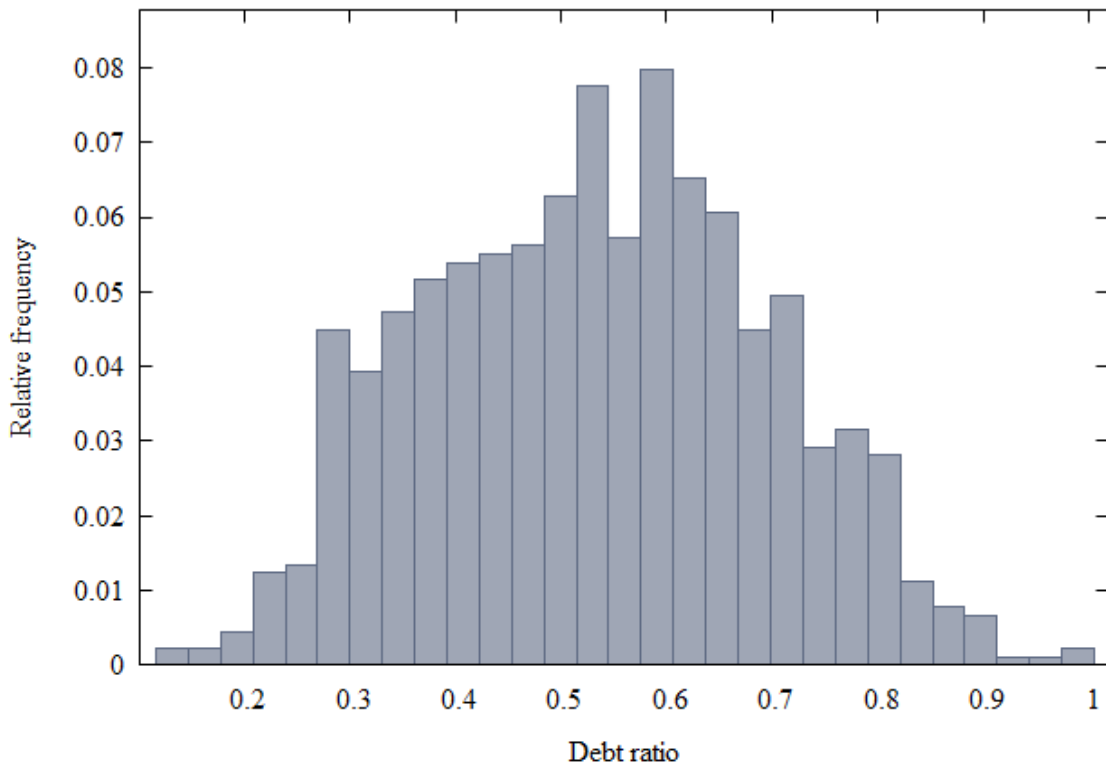


Figure 4.30: Distribution of firm age (Automobile)

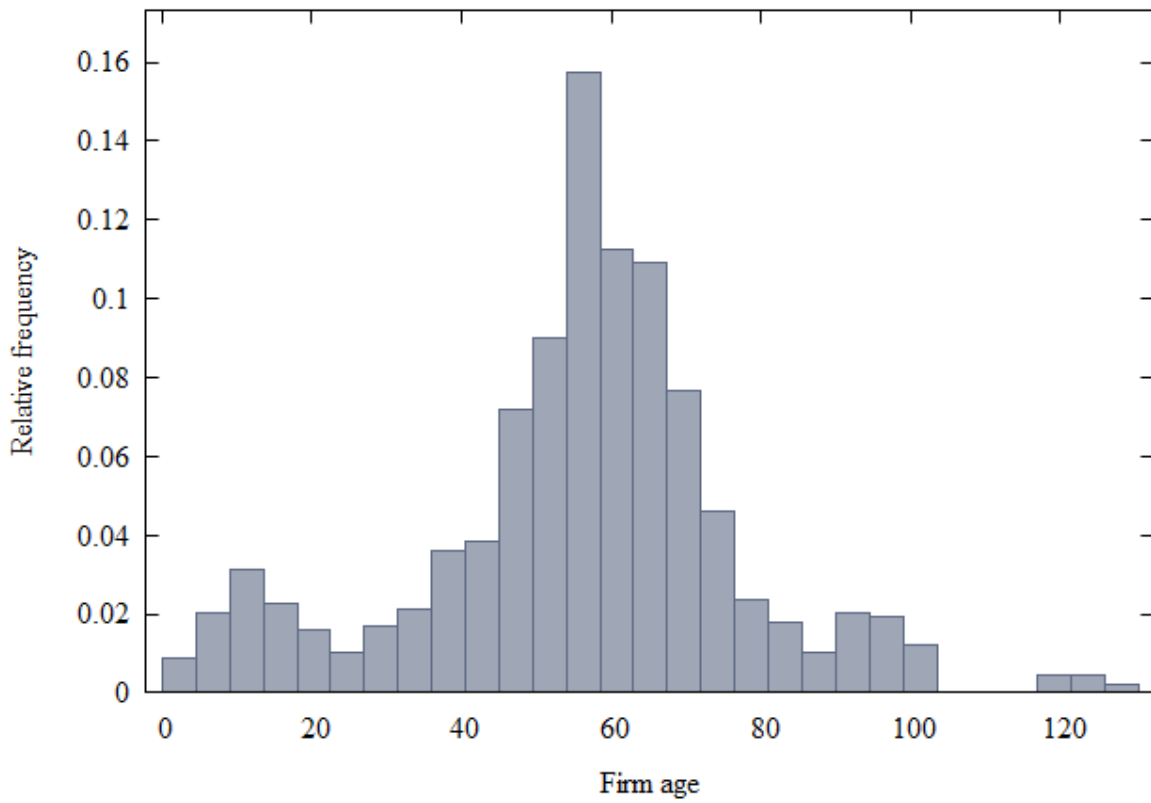


Figure 4.31: Distribution of labour productivity (Electronics)

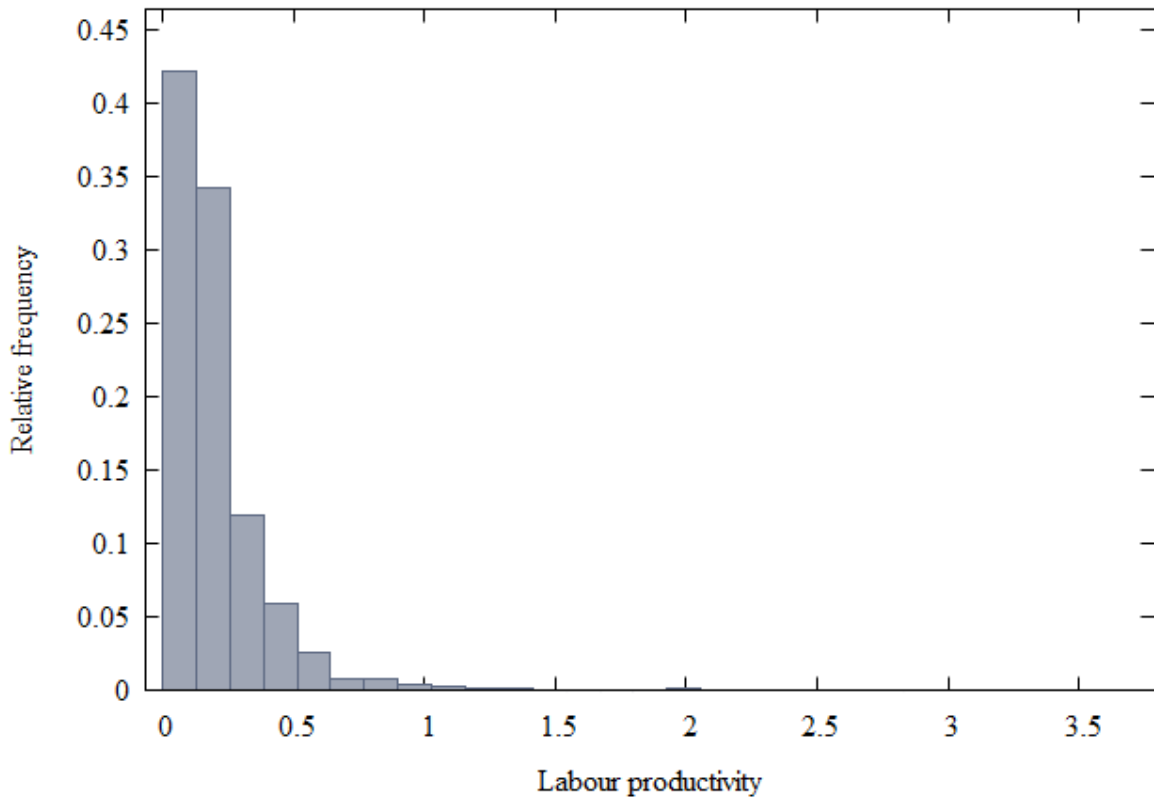


Figure 4.32: Distribution of profit margin (Electronics)

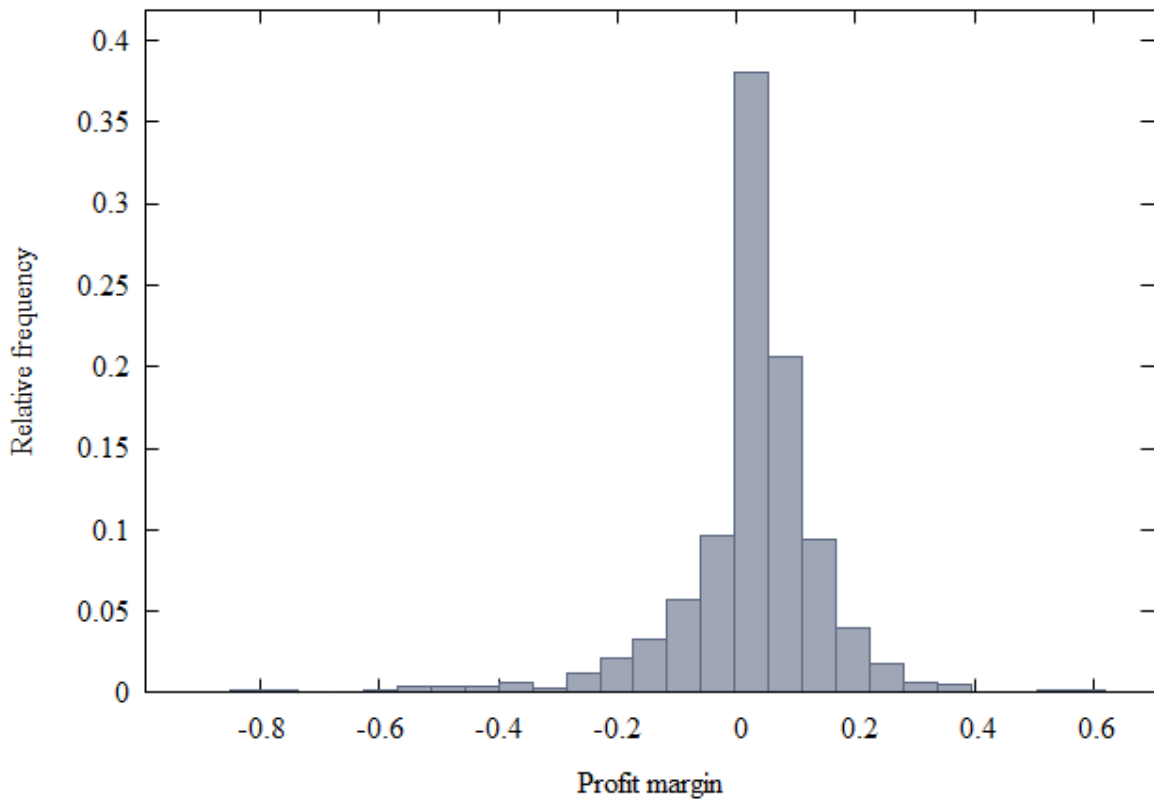


Figure 4.33: Distribution of R&D intensity (Electronics)

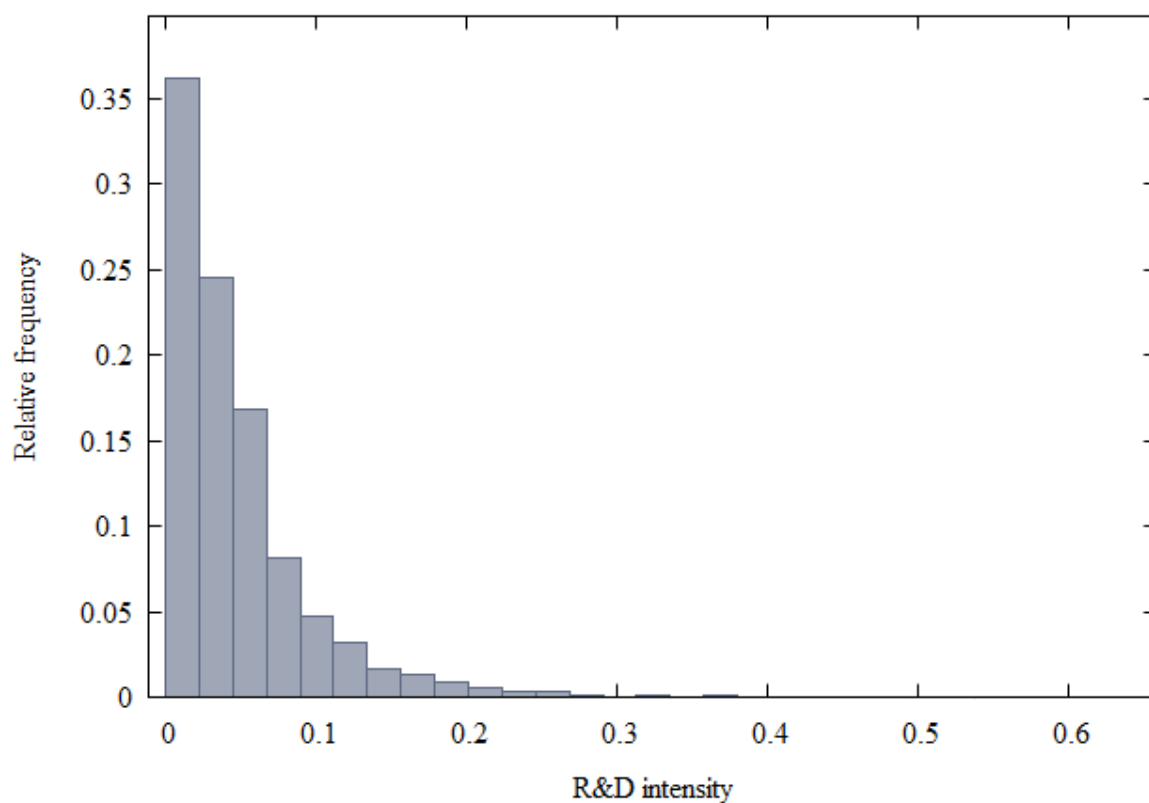


Figure 4.34: Distribution of capital intensity (Electronics)

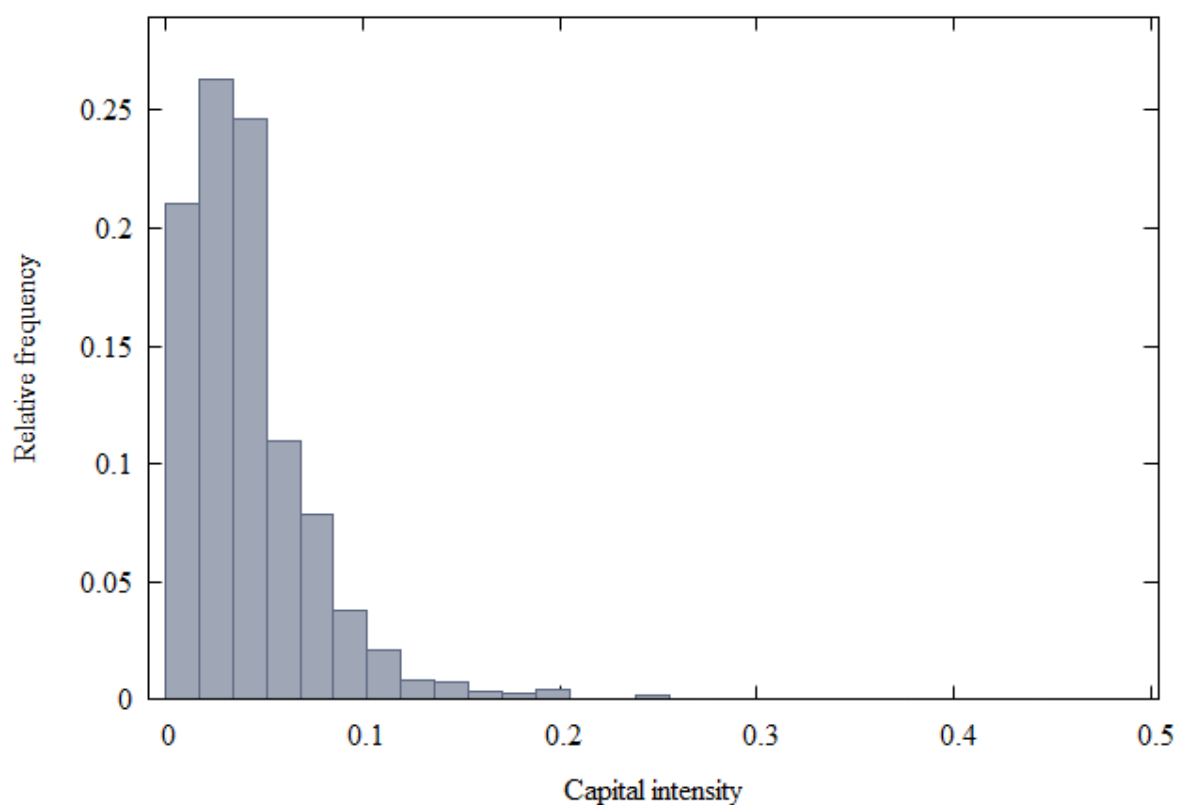


Figure 4.35: Distribution of intra-industry spillovers (Electronics)

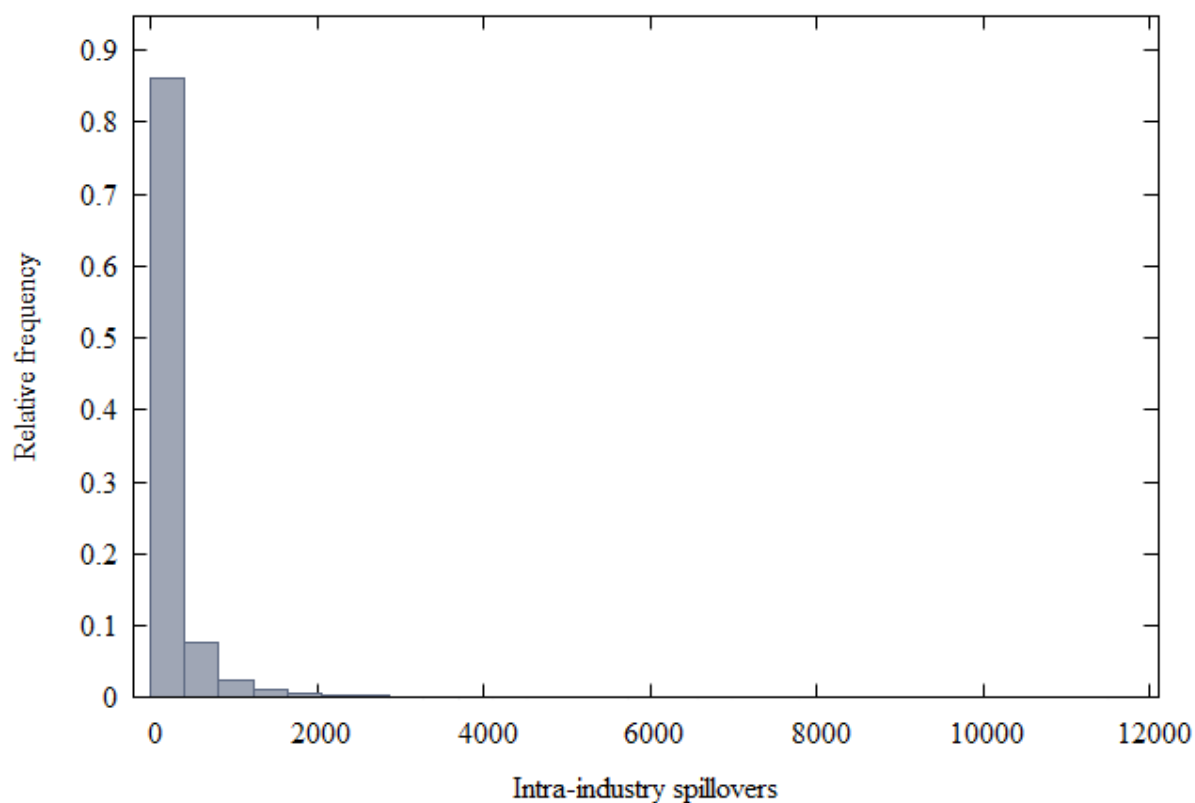


Figure 4.36: Distribution of inter-industry spillovers (Electronics)

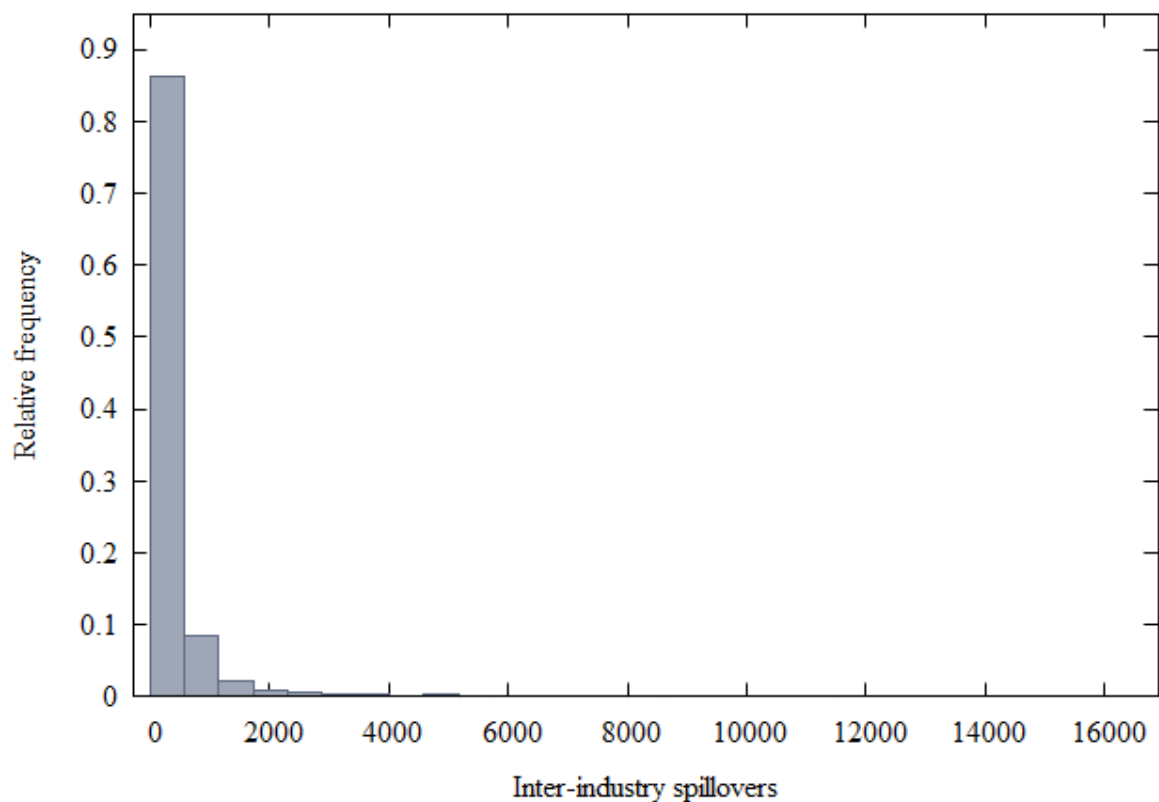


Figure 4.37: Distribution of absorptive capacity (Electronics)

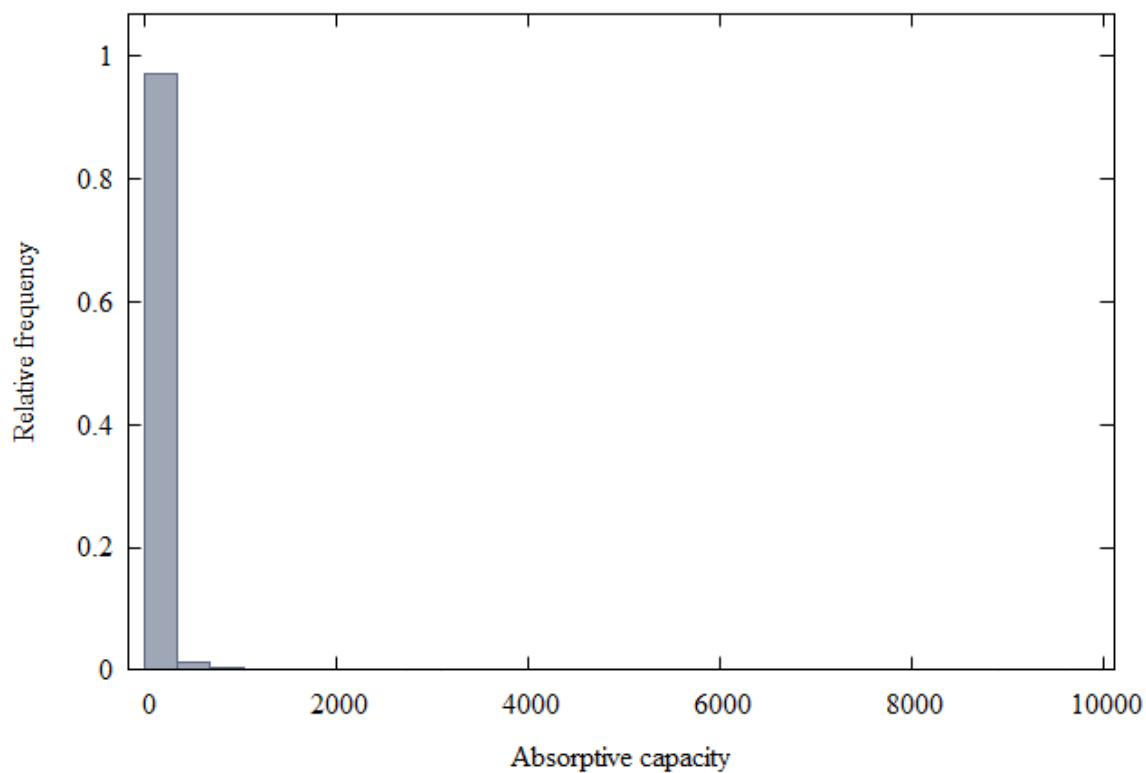
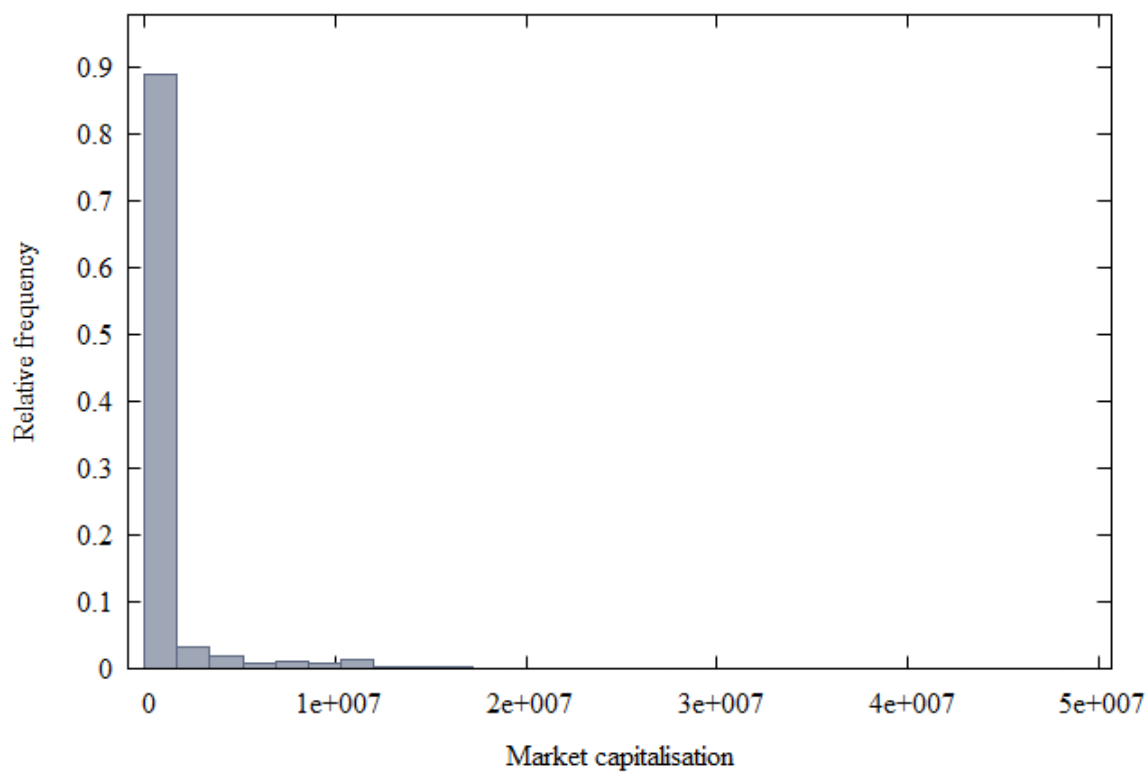


Figure 4.38: Distribution of market capitalisation (Electronics)



Note: e+007 is 10^7

Figure 4.39: Distribution of debt ratio (Electronics)

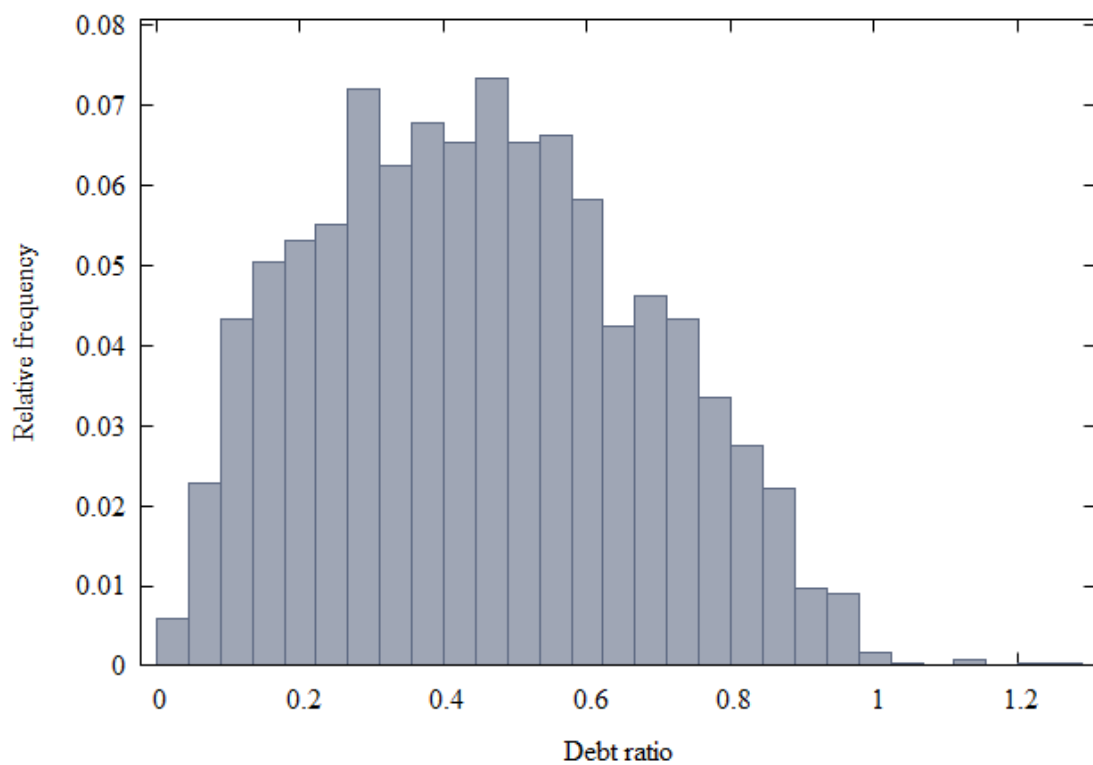
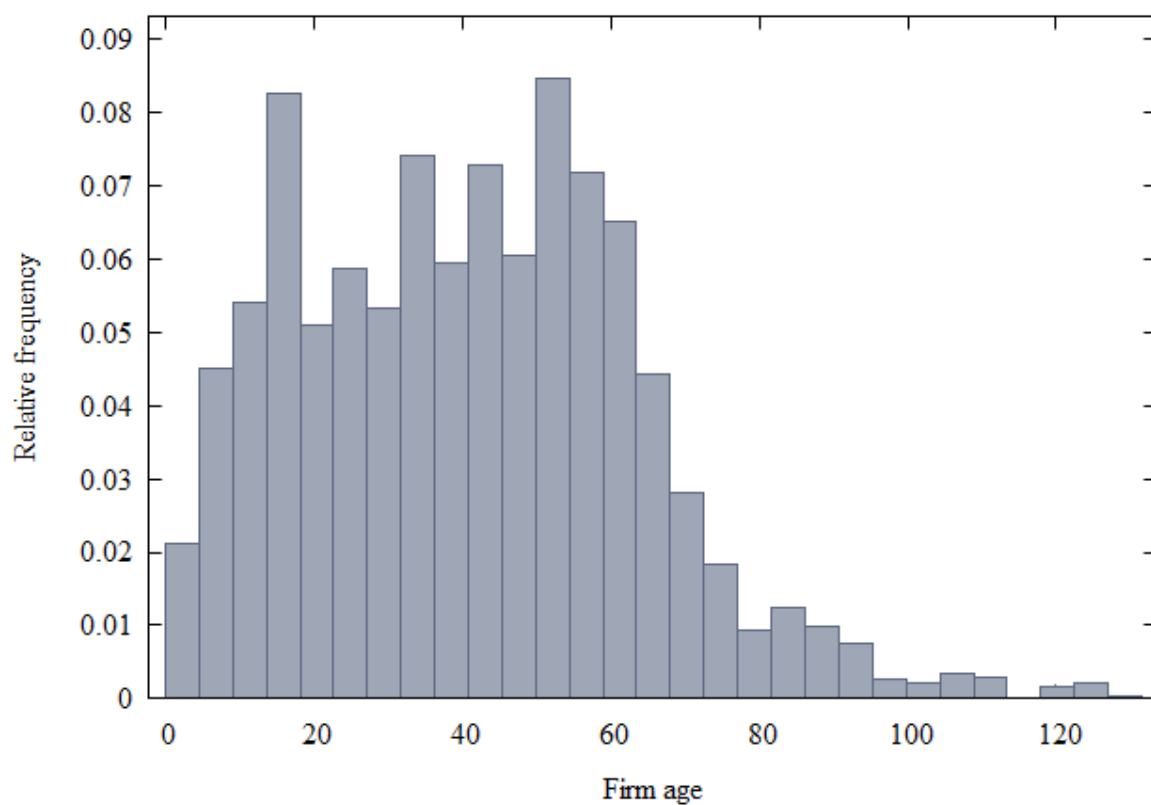


Figure 4.40: Distribution of firm age (Electronics)



Each histogram is displayed in grouped and relative term in which frequencies are categorised for data interval rather than for individual values. The horizontal axis represents relative frequency which indicates that each range of data is compared to the total number of items. With the exception of profit margin, debt ratio and firm age, the distributions of all variables in both sectors is clearly asymmetric, skewed so most of the mass is on the left. Profit margin of automobile (figure 4.22) and of electronics (figure 4.32) appear to have negatively skewed distribution as the tail of distribution extends to the left. Those of intra-industry spillovers (figure 4.25 and 4.35), inter-industry spillovers (figure 4.26 and 4.36), and absorptive capacity (figure 4.27 and 4.37) have distribution with very large positive skewness since it is shown that the tail in the positive direction clearly extends further than the tail in the negative direction. As for automobile, debt ratio (figure 4.29) and firm age (figure 4.30) differ in kurtosis. The histogram of automotive's debt ratio is platykurtic as it has relatively fewer score in its tail. On the other hand, its firm age is leptokurtic since it has comparatively more score in its tail.

Table 4.6: Normality tests for variables' distribution (Automobile)				
	Doornik-Hansen test	Shapiro-Wilk test	Lilliefors test	Jarque-Bera test
Labour productivity	525.949***	0.87***	0.157***	423.76***
Profit margin	256.244***	0.872***	0.159***	3467.24***
R&D intensity	858.64***	0.807***	0.172***	1305.64***
Capital intensity	3879.27***	0.615***	0.225***	24726.4***
Intra-industry spillover	3013.39***	0.633***	0.25***	4793.7***
Inter-industry spillover	3026.22***	0.641***	0.247***	4479.31***
Absorptive capacity	23682.4***	0.281***	0.376***	199768***
Market capitalisation	22478***	0.205***	0.415***	265549***
Debt ratio	16.66***	0.993***	0.033**	13.635***
Firm Age	25.058***	0.96***	0.105***	32.866***
5% significant level; *1% significant level				

	Doornik-Hansen test	Shapiro-Wilk test	Lilliefors test	Jarque-Bera test
Labour productivity	8565.37***	0.6***	0.195***	266996***
Profit margin	660.06***	0.838***	0.173***	9612.48***
R&D intensity	4735.49***	0.702***	0.192***	38340***
Capital intensity	2000.49***	0.779***	0.135***	57095.3***
Intra-industry spillover	39506.4***	0.351***	0.345***	1052130***
Inter-industry spillover	29215***	0.376***	0.337***	1048380***
Absorptive capacity	269499***	0.113***	0.44***	9806730***
Market capitalisation	19825.3***	0.328***	0.376***	311655***
Debt ratio	104.732***	0.983***	0.043***	63.151***
Firm Age	108.576***	0.974***	0.054***	93.431***
***1% significant level				

This study further conduct frequentist tests on variables of each industry in order to determine if the dataset is well-represented by a normal distribution and to compute the likeliness of a random variable underlying such dataset to be symmetrically distributed. To this end, there are four normality tests used; Doornik-Hansen test (Doornik and Hansen, 2008), Shapiro-Wilk test (Shapiro and Wilk, 1965), Lilliefors test (Lilliefors, 1967; 1969) and Jarque-Bera test (Jarque, 1980; 1981; 1987).

H_0 : The data of the variable come from a normally distributed population. Thus the data has skewness and kurtosis matching a Gaussian distribution.

H_1 : The data of the variable does not come from a normally distributed population. Its skewness and kurtosis corresponds with asymmetric distribution.

Table 4.6 and 4.7 provides the results of normality tests for automobile and electronics respectively. In all four tests, it is shown that the p-values of all variables are less than 5% alpha level. Hence, one rejects the null hypothesis and concludes that data of variables used in this study are not from a normally distributed population. For linear regression, it is idyllic to make certain that explanatory variables are just about normal in their distribution. When some variables are skewed, they would not meet the assumptions of parametric tests which require that the populations one is comparing are of Gaussian-type. Using those of parametric statistical tests such as t-tests, ANOVA or linear regression on such non-normal data could generate misleading results. In order to improve the normality of

these data, this research applies the natural logarithmic transformation of all variables before making further conversions; namely first-order difference, on some of those variables in the following empirical chapters. Log transformation on the data showing outliers at the high end could make such data fits with parametric tests' assumption better as the logarithm function tends to squeeze together the larger values in the dataset and stretches out the smaller values (MedCalc, 2014). To Zumel and Mount (2013), it is also rational to log transform data with values that range over several orders of magnitude. This is because data often comes from multiplicative processes, so log units are in some sense more natural.

4.8 Conclusion

This chapter has described the process of data collection, stratification of raw data, computation and measurement issues of variables in detail and provided the results of a series of preliminary analyses. For the period of 10 years between 2000 and 2009, secondary data and firm level data is collected primarily from Osiris database which provides annual company financial information. It is remarked that unconsolidated accounts of each company is the pivotal source where raw data is collected, as opposed to consolidated accounts that integrates all information of the firm itself and those of its subsidiaries across the world. Initially, data of net sales, profit before taxation, R&D expenditures, market capitalisation, number of employees, tangible fixed assets, total liabilities and debts, total assets, year of establishment are gathered from Osiris. To fill in missing observations, further investigation on company disclosed investor relation documents and Japanese domestic database so-called EDINET were carried out. The dataset was subsequently examined for outlying and unrealistic observations by individual firm and by series, this process results in the reduction in amount of firms in the dataset down to 89 automobile firms and 236 electronics firms. Companies that are ruled out from the dataset are characterised mainly for their lack of information in R&D expenses throughout ten years period. Another reason for dropping some firms from the dataset arises from the presence of outliers, particularly in number of employees. Firms displaying successive outliers that could not be interpolated or filled in with authentic values are hence excluded from the research dataset.

As data collected from Osiris is not yet adjusted for inflation, nominal data are then deflated by using the price of year 2005 as the base or reference year. Nominal values of sales are deflated using output price indices by industry meanwhile consumer price indices are deflators utilized in converting those of R&D expenditures, profit before taxation, tangible

fixed assets, market capitalisation, total liabilities and debts and total assets into real values. Also, as Japanese firm from Osiris is also reported in Japanese yen, all real data are converted into U.S. Dollars (year 2005 price). From then on, supplementary variables are constructed from the original dataset. Labour input of production is the total amount of hours worked in each year, computed from multiplying number of employees to annual hours worked by a worker in the manufacturing sector. Labour productivity and capital intensity are generated from the ratio of sales to hours worked and tangible fixed assets to hours worked respectively. R&D intensity is R&D expenses as a fraction in sales, and designated as the research and development variable. Dividing profit before taxation with sales creates profit margins which is use to proxy firm profitability. The debt ratio is calculated from total liabilities and debts divided by total assets and finally market capitalisation and firm age are also used as additional control variables.

Two preliminary analyses on the dataset are conducted. Comparing between two industries, descriptive statistics reveals that the average automobile firm employs a larger amount of employees and fixed capital per labour. Typically, automobile firms have a higher amount of R&D spending, sales values, profit as well as level of market capitalisation. Nevertheless mean values of profit margin and labour productivity of two sectors are similar and the average electronics firm commits larger R&D spending as a fraction of sales. Pearson correlations provide the strength and direction of the relationship between each variable. The tests of correlation among R&D intensity, labour productivity and profit margin show varying results. Although R&D intensity correlates with both labour productivity and profit margin, the direction of the relationship in the two industries differs although the statistical significance is similarly weak. In addition, the relationship between labour productivity and profit margin is either weak or nonexistent in the two industries. Even so, it should be noted that correlation analysis takes account of the current values and lagged effects may be present. All variables are analysed in their non-logged form although this transformation is used in the modelling that follows. In addition, dynamic effects are also incorporated into the models in subsequent chapters.

Chapter 5: The relationship between R&D and firm productivity

Introduction

This chapter presents an econometric analysis of the impact of research and development upon firm-level productivity in two Japanese manufacturing sectors; the automotive and consumer electronics industry. The chapter consists of two main sections which concentrates on the Cobb-Douglas production function model augmented with R&D inputs, which is applied to panel data at firm-level. The first section (the extended production function) uses a conventional regression model drawing on the estimation of the rate of return on R&D. Estimation, and pre and post estimation tests are presented alongside the empirical results. The chapter then presents the empirical results from a panel-data regression of random effects, fixed effects and pooled data models. The second section focuses on the effects of technological externalities and absorptive capacity. In this section, variables representing intra-sectoral spillovers, inter-sectoral spillovers and absorptive capacity are incorporated into the Cobb-Douglas production function. This chapter makes two main contributions to the existing literature. First, it adds to studies of the R&D-productivity relationship by taking into account the productivity effects of both the technological efforts of the firm and of outside knowledge. Second, it examines the significance of absorptive capacity for productivity at the firm level. By measuring performance in term of labour productivity and firm R&D, technological externalities and absorptive capacity, this chapter addresses the 1st, 2nd and 3rd research questions. In addition, the 5th research question is addressed by comparing the findings of the two industries under review.

5.1 Extended production function

5.1.1 Construction of Model

To investigate the R&D-productivity relationship, this study uses a production function as the analytical framework. In addition, the study complements the conventional production function with a vector of other explanatory factors that can affect output and productivity. Two new independent variables are added to the fundamental production function; market capitalisation and past R&D intensities. First, market capitalisation (MKTC) is included to control for the scale of the firm's operations. The influence of firm size on R&D is discussed in Archarungroj and Hoshino (1999), who find that larger firms incur

higher R&D expenditure as a share of total sales, and thus a larger degree of research intensification than smaller firms.

The study also incorporates lagged R&D intensities, in addition to current R&D intensity, following Gujarati (2003) and Hall et al. (2010). It is reasonable to expect that there is time gap for the return on R&D investment to take effect in terms of increased productivity. It is unlikely that the addition to R&D capital stock becomes immediately productive at the time of its investment but rather that a time lag exists between the investment and returns to that investment. In particular, there will be a lag between the development of an innovation and the time it is ready to be marketed as a new product or process. The commercially applicable phase and the lag which is introduced by the process of diffusion, plus the time before all the old machines are replaced by the better and newer ones, will vary by industry. R&D normally takes considerably more than a fiscal year to complete. In fact, there is also time lag associated with the decision on innovation usage and the effects of innovation on the firm's revenue or profits (Grilliches, 1979). Hence, the effects of R&D investment on firm performance may not result in an immediate return after it appears as an operating expense. Approaches to determining the lag structure for R&D differ in the existing literature. As reported by Mansfield et al. (1971), the average lag from R&D activities to innovation is three years. From R&D to growth in performance, the effect normally takes place in the second year after conducting investment. Further, the influence of R&D on company growth can rise steadily and last for up to nine years (Leonard, 1971). The length of time in these data is ten fiscal years; from 2000 to 2009, which is a limitation although a similar time period has been found. For example, with reference to studies within the Japanese context, such as Odagiri and Iwata (1986), eight or nine years are sufficient to capture the lagged effect of R&D.

The base model originates from a production function with the estimation of R&D capital's output elasticity approach. It is built on the foundation of equation 3.1 which is augmented with market capitalisation.

$$\text{Equation 5.1 } Q_{it} = A e^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} MKTC_{it}^{\infty}$$

Then taking natural logarithms,

$$\text{Equation 5.2 } \ln Q_{it} = \ln A + \lambda t + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln R_{it} + \infty \ln MKTC_{it} + \varepsilon_{it}$$

Since the study aims to use labour productivity as a performance measure then subtracting $\ln L_{it}$ from both sides of the equation, the following model is estimated:

$$\text{Equation 5.3 } \ln Q_{it} - \ln L_{it} = \ln A + \lambda t + \alpha \ln K_{it} + \beta \ln L_{it} - \ln L_{it} + \gamma \ln R_{it} + \infty \text{MKTC}_{it} + \varepsilon_{it}$$

As with many previous studies, constant return to scale (CRS) is assumed for labour and capital input, ruling out the coefficient and vector of labour input in the process. In the presence of constant returns to scale for the production function, the coefficients can be interpreted as factor shares, which, in the absence of price information, allow some inferences to be made about the relative importance of the individual factors (Piesse, 1999). The production function is estimated in first differenced form to reduce the problem of downward bias in the coefficient on R&D. For Hall et al. (2010), this problem can also be mitigated by imposing constant return to scale. Then the rearranged equation has labour productivity growth as the dependent variable and the growth rate of capital per labour input, R&D capital and market capitalization growth as explanatory variables.

$$\text{Equation 5.4 } (q-l)_{it} = \lambda + \alpha(k-l)_{it} + \gamma r_{it} + \infty \text{MKTCG}_{it} + \varepsilon_{it}$$

As a consequence of the limited information on R&D capital depreciation rate and the relatively short period of annual R&D data, the rate of return on R&D capital is the alternative estimation of the R&D effect on productivity, in place of an output elasticity of R&D capital. In other words, the R&D-intensity approach to productivity analysis is preferred, rather than the perpetual inventory method of R&D capital stock. Transforming the model based on the estimation of the output elasticity with respect to R&D capital, to the model based on the estimation of the rate of return to R&D capital was conducted in line with Wakelin (2001), as described in the literature review chapter. As such, the parameter of R&D capital stock growth was entirely replaced with that of R&D expenditure and its marginal product of R&D capital coefficient. Additionally, a logarithmic transformation is used for R&D intensity so that the rate of return on R&D investment in form of labour productivity increase could be seen more clearly. This further transformation of the R&D variable is in line with Antonelli (1994). Another rationale behind natural logarithms of R&D intensity arises from the attempt to enable the compatibility of R&D related variables in the other two empirical chapters. In this respect, natural logarithm of R&D intensity is also present in the model specifications in chapters 6 and 7.

$$\text{Equation 5.5 } (q-l)_{it} = \lambda + \alpha(k-l)_{it} + \rho \ln(RD/Q)_{it} + \infty \text{MKTCG}_{it} + \varepsilon_{it}$$

Therefore, the model further incorporates R&D expenditures in the previous fiscal year as lagged R&D variables. Thus, the vector of R&D variables was rewritten into a summation form and can be expressed as follows:

$$\text{Equation 5.6 } (q-l)_{it} = \lambda + \alpha(k-l)_{it} + \sum_{k=0}^n \rho_{t-k} \ln(RD/Q)_{i(t-k)} + \infty MKTCG_{it} + \varepsilon_{it}$$

For clarity, the analysis continues the notation as follows: $q-l$ is labour productivity growth; $k-l$ is capital intensity growth; RD/Q is R&D intensity; and $MKTCG$ is market capitalisation growth.

5.1.2 Methodology

This study conducts regression analysis using both random and fixed effect (within) estimators (details shown in Appendix A). After that, a post estimation test in accordance with Hausman (1978) will help in deciding the exact group effect model out of the two and the set of regression results to be adopted. Both panel data estimators are tested on firm-level data for the automotive industry and the electronics industry individually, as well as on pooled data merging both industries together. Regarding the fixed effect model, the LSDV model may be inappropriate for this study since the amount of group effect dummies would be large. Yaffee (2003) states that the problem of multicollinearity may also occur in a fixed effect model with too many dummy variables for cross-sectional units' specification by increasing the size of the standard errors and thus depleting the model of statistical power. This sample includes 325 firms; 89 firms from the automotive sector and 236 from the electronics sector. With 10 times periods from 2000 to 2009, the study in all has total observation of 3,250 for pooled data, 890 for automotive firms and 2,360 for electronics firms. Thus, the LSDV is clearly infeasible. To deal with fixed group effects, this research uses the fixed effect model with within transformation. The problem does not arise in the random effect model and the generalised least squares (GLS) estimator is used.

5.1.3. Determining the length of the lag

The intention to include lagged values of R&D intensity (RDI) gives rise to the issue of the exact amount of lagged RDI that should be present in the model. Having too many lagged RDI in the model could lead to multicollinearity as RDI in each time period is likely to be serially correlated. Ramanathan (1995) states that multicollinearity may result in unexpected signs on the regression coefficients and make it difficult to interpret the results. The different number of lagged periods gives rise to a set of possible models and therefore

model selection can be done by using information criterion. The lagged effects of R&D on productivity can vary among industries, companies within the industry and different R&D projects within a company boundary (Morbey, 1988). The determination of a proper lag length has a great impact on inferences (Gonzalo and Pitarakis, 2002). Following Thornton and Batten (1985) one should adopt a variety of model selection criteria in order to identify the appropriate lag structure. This study uses two types of information criterion; Akaike information criterion (AIC) and Schwarz information criterion (SIC). The models under consideration are different only in the R&D intensity's parameters ($\sum_{k=0}^n \rho_{t-k} \ln(\text{RDI})_{i(t-k)}$). Using ordinary least squares, five equations were estimated using STATA and the AIC and SIC values calculated following the fixed effects regression.

R&D intensity lag	Automotive industry		Electronics industry		Pooled data	
	Akaike criterion	Schwarz criterion	Akaike criterion	Schwarz criterion	Akaike criterion	Schwarz criterion
0	-797.028	-783.691	-21.922	-5.274	-501.489	-483.983
1	-806.657	-788.875	-363.133	-340.941	-886.454	-863.115
2	-796.722	-774.525	-395.155	-367.455	-918.633	-889.497
3	-680.848	-654.977	-462.598	-430.161	-930.754	-896.585
4	-591.462	-562.246	-439.951	-403.192	-859.579	-820.769
5	-503.567	-471.615	-318.063	-277.517	-664.306	-621.41

In table 5.1, the results confirm Morbey's findings (1989) on the time-lag difference between industries. Not only individual industries' regression should be incorporated with different lagged structure of R&D intensity, but pooled data regression also exhibits lagged R&D configuration as well. The lowest absolute value of AIC and SIC specify the best fitting model. For automotive firms, it was shown that the model with one lagged period had the highest absolute value for the AIC and SIC simultaneously. Tests for electronics firms signified time periods of lagged R&D intensity up to t-3 periods generated the lowest AIC and SIC. Finally the pooled data model including R&D intensity at period t, t-1, t-2 and t-3 parameters are shown to be the preferred specification. For automobile, electronics and pooled data, Equation 5.6 can now be specified. As shown below, equation 5.7 represents a

regression model with a distributed lag structure of R&D intensity for automobile firms while both electronics firms and pooled data would be analysed by using equation 5.8.

$$\text{Equation 5.7 } (q-l)_{it} = \lambda + \alpha(k-l)_{it} + \rho_t \ln(\text{RD}/Q)_{it} + \rho_{t-1} \ln(\text{RD}/Q)_{it-1} + \infty \text{MKTTCG}_{it} + \varepsilon_{it}$$

$$\text{Equation 5.8 } (q-l)_{it} = \lambda + \alpha(k-l)_{it} + \rho_t \ln(\text{RD}/Q)_{it} + \rho_{t-1} \ln(\text{RD}/Q)_{it-1} + \rho_{t-2} \ln(\text{RD}/Q)_{it-2} + \rho_{t-3} \ln(\text{RD}/Q)_{it-3} + \infty \text{MKTTCG}_{it} + \varepsilon_{it}$$

5.1.4 Stationarity tests

Before proceeding to the regression analysis, it is important to address the possible existence of stationarity in the panel data. Stationary data is characterised by a constant mean and variance over time. This is because non-stationary data have either an upward or downward trend (Gujarati, 1999). Asteriou and Hall (2007) state that the foremost consequence of nonstationary data in regression analysis is spurious regression, where the results show a significant relationship, although this may not be the case. Thus, nonstationarity in data could render the regression estimates and subsequent statistical inference inconsistent and inaccurate. In spurious regression that results from non-stationarity in the data, it is likely to report a high value of R-squared and t-ratios. Indeed, the overall fit of the regression and t-scores are in fact exaggerated and unreliable (Studenmund, 2001).

Table 5.2: Pre-estimation test of time series data's stationarity						
Variables	Automotive industry		Electronics industry		Pooled data	
	ADF	Phillips-Perron	ADF	Phillips-Perron	ADF	Phillips-Perron
Labour productivity growth	347.846***	266.792***	1913.365***	1347.76***	2261.21***	1614.56***
Ln(R&D intensity)	156.867	167.473	657.687***	673.134***	814.555***	840.607***
Ln(R&D intensity) at t-1 period	224.741**	325.478***	663.976***	701.024***	842.769***	877.156***
Ln(R&D intensity) at t-2 period	-	-	645.539***	661.657***	870.28***	883.766***
Ln(R&D intensity) at t-3 period	-	-	740.384***	678.881***	1071.64***	925.757***
Capital intensity growth	450.262***	322.465***	2076.224***	1506.36***	2526.486***	1838.83***
Market capitalisation growth	6085.413***	1649.05***	16700***	4429.32***	22800***	6078.37***
* 10% significant level; **5% significant level; ; ***1% significant level						

To examine and detect stationarity in panel data, unit root tests were conducted on each variable in the model. The study used two Fisher-type tests; Augmented Dickey- fuller (ADF) test (Dickey and Fuller, 1979) and Phillips-Perron (PP) test (Phillips and Perron, 1988) on labour productivity growth, capital intensity growth, logarithms of R&D intensity and its lagged values and market capitalisation growth. The difference between the former and latter tests is the assumption regarding the error terms. The ADF test is based on the assumption that the error terms are statistically independent from each other and have a constant variance whereas the PP test takes account of possible serial-correlation in the error terms (Asteriou and Hall, 2007). The two unit-root tests were conducted on both industries separately and on the pooled data, using the variables on both sides of equation 5.7 and 5.8. The hypothesis in testing each variable is as follows:

H_0 : There is a unit-root in cross-sectional time series data, thus data are non-stationary.

H_1 : The data are stationary

Table 5.2 presents the results of unit-root tests on each variable. For time series data in both individual industries, the ADF test showed that all computed tau values are far larger than the critical value and each variables' p-value is also less than 1%. Results from the Phillips-Perron test is in line with the ADF test, as it yields similar stationarity results variable to variable. Results from both unit-root tests suggest that the null hypothesis of unit roots existing should be rejected, thereby the time-series data of individual industries and pooled data were stationary. This is largely due to the fact that time series variables, with the exception of Ln(R&D intensity) and its lagged values, are in growth-form. Nonetheless, the only exceptions are for the case of automotive's Ln(R&D intensity) at t period, which have a p-value of 0.8712 that far exceeded the 10% significance level. Although, it is shown that automotive firms' data of Ln(R&D intensity) is non-stationary, the likelihood of spurious regression for the automotive case is lessened by two factors. The use of panel data, as Kao (1999) and Phillips and Moon (1999) mentioned, can avoid spurious regression since the panel estimators average across individuals for the estimated value of the parameter and the information in the independent cross-sectional dimension in the panel results in a stronger overall signal than the pure time-series dimension. For the second factor, this analysis does not conduct regression of non-stationary explanatory variables on also non-stationary explained variable. If the dependent variable and at least one independent variable are both non-stationary, then the regression is likely to be spurious (Studenmund, 2001). With

reference to equation 5.7, automotive firms' labour productivity growth is found to be stationary and the only nonstationary independent variable is current Ln(R&D intensity).

5.1.5. Model specification tests

As the study expanded the production function framework to incorporate market capitalisation to control for firm size, the Ramsey's Reset Test was used in the model with and without growth of market capitalisation to determine whether the variable improves the model fit. The RESET test was computed manually and the results reported in table 5.3.

For the automobile industry, the RESET test on the model without market capitalisation growth produces a significant F-statistic which implies possible specification error. The result from the model with market capitalisation growth shows the computed F-statistic to be insignificant at the 1% level. For electronics firms, comparing two subsequent RESET test, the model with market capitalisation growth appeared to have marginally lower F-statistic value which means that the model is improved by the inclusion of this variable and suggested that market capitalisation growth somewhat reduced specification errors. Regarding the pooled data model, the RESET test showed that including market capitalisation growth resulted in a larger F-statistic value than the model without market capitalisation growth. Nevertheless, the model specification can be also based on R-squared, where a relatively higher level of R^2 was observed for models with market capitalisation growth in the automotive industry, electronics industry and the pooled data. Assessment of R-squared indicated that the model with market capitalisation growth has a better fit than the one without it, not only for the regression on pooled firm data but also at the individual industry level.

Table 5.3: Pre-estimation test for comparing regression model with and without market capitalisation growth						
	Automotive industry		Electronics industry		Pooled data	
	With MKTCG	Without MKTCG	With MKTCG	Without MKTCG	With MKTCG	Without MKTCG
Ramsey RESET test	2.49 (0.059)	4.75***(0.002)	18.00*** (0.000)	18.42***(0.000)	22.53***(0.000)	21.13***(0.000)
R-square	0.2618	0.1873	0.1911	0.1796	0.1676	0.1585
*** 1% significant level; p-value in parentheses						

5.1.6 Tests for heteroscedasticity and autocorrelation

Cross-section and time series data encounter different kinds of problems; heteroskedasticity and serial correlation respectively. Because panel data combines both cross-sectional and time-series dimensions, it is likely to inherit both of the two problems. Baltagi (2005) notes that panel data may consist of cross sectional units that vary in terms of size, as a result it could demonstrate different variation in disturbances across individuals and years. In other words, the dispersion of the residuals around their means of zero or equivalently the distribution of observed value of the dependent variable around the regression line will not be the same across all observations or firms (Ramanathan, 1995). Moreover, the wide disparity in the largest and smallest observed values in panel data tends to aggravate the likelihood that the error term associated with them will have unequal variances (Studenmund, 2001). Gujarati (2003) notes that serial correlation is present as the error terms of consecutive time periods are correlated with each other. This phenomenon is referred to as first-order autocorrelation which is possibly a consequence of dependency of the value of a variable in a particular period upon its own value in previous periods. In a similar way, the current observation of the error term would be the function of the previous observations of the error term and the correlation coefficient between any two observations of the error term is not equal to zero (Studenmund, 2001).

The presence of heteroscedasticity and autocorrelation leads to analogous circumstances, OLS estimators become inefficient but maintain their consistent and un-biased estimates. Nonetheless, estimated standard errors will be smaller than the actual values meanwhile the goodness of fit measure for the regression is overvalued (Johnston and DiNardo, 1997). In addition, the statistical inference from regression results may be misleading because t-ratios are overestimated. As a consequence, a regression coefficient that appears to be statistically significant may not be so in reality (Ramanathan, 1995). To detect probable heteroscedasticity in panel-data regression, the study uses the likelihood ratio (LR) test and Wald test to examine the distribution of variances in the dataset. The likelihood ratio test generates the results in term of likelihood ratio chi-square values while the Wald test provides its results in ordinary chi-square values. Within the context of panel data analysis, the Wald test is essentially modified to test for heteroscedasticity in fixed effect regression models. The null hypothesis for all three tests of heteroscedasticity is that there is constant variance across firm units, thus the panel data is of homoskedastic.

Table 5.4: Pre-estimation tests for Heteroscedasticity in panel data			
Test	Automotive Industry	Electronics industry	Pooled data
Likelihood ratio test	228.71***	1223.03***	1513.82***
Modified Wald test for groupwise heteroskedasticity	2089.34***	37425.9***	53319.80***
* 10% significant level; **5% significant level; ; ***1% significant level			

The test results shown in table 5.4 demonstrate that the panel data of both industries and pooled data has a heteroskedastic variance since the null hypothesis of a constant variance is strongly rejected in both tests at 1% significance level. This is unsurprising because the panel dataset of both sectors consist of firms with different scales of operation. Taking the automotive industry as an example, carmakers incur larger values in variables such as operating turnovers and net fixed capital assets than those of component producers. The variation could be also present within the group of carmakers and part manufacturers themselves. For the electronics sector, the distinction in observation may be even more obvious than in automobile firms because the electronics panel dataset makes up of more diversified sub-industrial classification in which firms vary in term of their products and the scope of their business. Even those classified as major consumer electronics manufacturers in Japan can be further segregated into small and big firms owing to their disparity in incomes and amount of investment.

To identify serial-correlation, the study follows Wooldridge (2002) and Drukker (2003) that suggest the Wooldridge test for autocorrelation specifically in panel data. The null hypothesis is no first-order serial-correlation among error terms. It is apparent from table 5.5 that F-statistics in both industries and the pooled data exceed the critical F-values at the 0.05 level. The null hypothesis is thus rejected and it can be concluded that error terms in regression of all three cases are significantly serially correlated.

Table 5.5: Pre-estimation test for Autocorrelation in panel data			
Test	Automotive Industry	Electronics industry	Pooled data
F-statistics	6.031**	4.115**	5.467**
P-values	0.016	0.044	0.02
** means 5% significant level			

Thus, to conclude, it is clear the panel dataset and the regression model have evidence of heteroskedasticity and serial correlation. However, the modified Wald test; as shown in table 5.4, indicates that one of the panel data regression models used in this analysis, the fixed effect model may still encounter heteroskedasticity in the variance terms. The re-estimation of the model in a way which fully recognises the presence of heteroskedasticity and autocorrelation will help remedying both problems (Asteriou and Hall, 2007). Studenmund (2001) suggests that generalised least square (GLS) estimation can resolve this and generate coefficients that are more efficient and with corrected t-ratios and variances. GLS is used to estimate the random effect model, as shown in 5.1.2. In the spirit of Baltagi (2005) and Wooldridge (2002), combining methods of clustering at the panel level and robustness of standard errors correct the estimated values of standard errors for those of regressors. Clustered robust standard error estimators are generally consistent in a sample with a high number of cross-sectional units (Arellano, 1987 and Kezdi, 2004) and this panel dataset does have a sufficiently large number of firms in both industries. Therefore, clustered robust standard error estimators are applied in both the random and fixed effect regression models.

Independent variables below	Automotive industry		Electronics industry		Pooled data	
Dependent variable: Labour productivity growth	Random effects GLS model	Fixed effects (Within) model	Random effects GLS model	Fixed effects (Within) model	Random effects GLS model	Fixed effects (Within) model
Constant	-0.0007 (0.957)	-0.082 (0.468)	0.046 (0.005)***	0.122 (0.21)	0.061 (0.000)***	0.088 (0.328)
Ln(R&D intensity)	-0.078 (0.041)**	-0.082 (0.000)***	-0.216 (0.000)***	-0.222 (0.000)***	-0.195 (0.000)***	-0.202 (0.000)***
Ln(R&D intensity)at t-1 period	0.077 (0.044)**	0.063 (0.002)***	0.152 (0.000)***	0.156 (0.000)***	0.139 (0.000)***	0.139 (0.000)***
Ln(R&D intensity)at t-2 period	-	-	0.058 (0.003)***	0.067 (0.000)***	0.058 (0.001)***	0.066 (0.000)***
Ln(R&D intensity)at t-3 period	-	-	0.002 (0.917)	0.016 (0.397)	0.002 (0.873)	0.009 (0.592)
Capital intensity growth	0.494 (0.000)***	0.512 (0.000)***	0.068 (0.065)*	0.059 (0.007)***	0.087 (0.017)**	0.084 (0.04)**
Market capitalisation growth	0.009 (0.000)***	0.009 (0.000)***	0.052 (0.000)***	0.049 (0.000)***	0.032 (0.000)***	0.035 (0.000)***
R-square	0.2692	0.2708	0.1976	0.1989	0.1749	0.1754
No. of observations	630	630	1646	1646	2197	2197
No. of firms	89	89	236	236	325	325
No. of parameters	5	5	7	7	7	7
Akaike criterion	-	-806.657	-	-462.598	-	-930.754
Schwarz criterion	-	-788.874	-	-430.161	-	-896.585
Log likelihood	-	407.329	-	237.299	-	471.377
Robust Hausmann test	2.74 (0.6027)		1.6 (0.1465)		1.14 (0.3397)	

* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses

5.1.7 Empirical results

This section presents the principal empirical findings. Automobile firm data are investigated using equation 5.7 and equation 5.8 is used for the electronics firms and pooled data. In each of the three models, labour productivity growth is regressed on R&D intensity, lagged R&D intensities, capital intensity growth and market capitalisation growth. The effect of firm size is taken into account by market capitalisation which is in its growth-form in equations 5.7 and 5.8. Table 5.6 presents the regression results. For pooled data, and separately by the automotive and electronics industry, Table 5.6 compares the statistical results of the random and fixed effects models. By conducting a Chow test of poolability, the study determines whether the model and regression results of the two industries should be pooled.

With regards to capital intensity and market capitalisation growth, the pooled data results from random and fixed effect estimations are comparable. At a 5% significance level, capital intensity growth is positively related to labour productivity growth. For the random effects and fixed effects models, the coefficient values of capital intensity growth are 0.087 and 0.084 respectively. Market capitalisation growth is also significant at the level of 5%. The positive effect on labour productivity growth was more or less the same for both the random and fixed effects models, as the coefficient on market capitalisation growth is 0.032 and 0.035 in both models. Current R&D intensity is significant at 1% significance level with coefficient values of -0.195 in the random effects model and -0.202 in the fixed effects model. R&D intensity in preceding periods explains variation in labour productivity growth. In particular, both R&D intensities from t-1 and t-2 periods are shown to have a positive and significant impact on productivity growth. However, R&D intensity at t-1 period shows a relatively stronger effect on labour productivity growth, with a larger coefficient value of 0.139 in both panel-data regression models. At t-2 period, R&D intensity also has a positive effect on productivity growth, although with lower coefficients of 0.058 and 0.066 for the random effects and fixed effects model respectively. R&D intensity at t-3 period is positive but statistically insignificant in both models.

The regressions then focus on the industries individually. Real fixed assets per labour hour does impact production efficiency, that is, the firm is effective in its asset utilisation. In the random effects model, capital intensity growth is significant at the 1% level for the automotive and the 10% level for the electronics industries. When compared, capital intensity

growth appeared to contribute to labour productivity growth for automotive firms but has a stronger effect for electronics firms. This is shown by the value of 0.426 for the difference in coefficient value between the two sectors. In terms of market capitalisation growth, its effect on labour productivity growth in the electronics industry had a comparatively higher effect on labour productivity growth in the automotive industry.

In respect to the fixed effect models, capital intensity growth has an effect on the labour productivity of firms across both industries. However, the strength of the effect is found to be higher for the automotive industry. The automotive firms' capital intensity parameter has a coefficient of 0.512 in comparison with 0.059 for electronics companies. As with the random effects model, capital intensity for both sectors is significant at the 1% level. For firm size; the growth rate of market capitalisation, is significant at the 1% level, with larger levels of market capitalisation suggesting higher productivity. Again, market capitalisation growth effect on labour productivity growth is slightly greater in the electronics industry than in the automotive industry, with coefficients of 0.049 and 0.009 respectively.

As for the random effects models, the automotive industry clearly experienced a smaller and negative effect for present-period research intensity upon labour productivity growth. The coefficient on R&D intensity at the current period for the automotive industry is -0.078 and -0.216 for the electronics industry. The lag-structure for R&D intensity, examined earlier in the information criterion, was up to t-1 period for the automotive sector and up to t-3 periods for the electronics sector. Regarding the t-1 period, the lagged R&D intensity of both sectors, with p-values of 0.041 and 0.000, was found to be significant at 5% and 1% significance levels respectively. Similar to the current t period, the strength of the effect is again more substantial for electronics firms than for automobile firms, as evidenced by the difference in the value of the coefficient of about 0.075. Focusing on the electronics industry, R&D intensity at t-2 is significant at the 1% level. Coefficients for lagged R&D intensity leads to positive and significant effects on labour productivity growth for the period of t-1 and t-2, from then on the coefficient for R&D intensity becomes insignificant by t-3 period. Although R&D intensity at t-3 also exhibits a positive effect (a coefficient of 0.002), it is not statistically significant, with a p-value of 0.917.

Fixed effects models appear to mirror that of random effects models as both panel data regression models share identical coefficient signs and statistical significance for each independent variable. Current R&D intensity in both sectors is significant at the 1%

significance level. As such, the degree of the negative effect is obviously larger for electronics firms, the coefficient is -0.222 compared with -0.082 for automobile companies. Another difference is the extent of the effect of lagged R&D intensity upon productivity growth. Since the lag structure of R&D intensity in the regressions of automotive and electronics firms are different, and different lagged periods before the R&D intensity shows positive effects on labour productivity growth for firms in the two industries. As with the current period, the automobile R&D intensity at t-1 period is significant with a p-value of 0.000 and a coefficient at 0.063. The effect of R&D intensity at t-1 period is also large in the electronics sector. With an estimated value of 0.156, the electronics coefficient is more than twice that of the automobile one. Moreover, R&D intensity at a subsequent lagged period (t-2 period) is also relevant to electronics firms' labour productivity growth, as evidenced by a significant coefficient at the 1% level. Again, R&D intensity at t-3 period demonstrates results in line with the random effect model. While there is a positive coefficient for R&D intensity at t-3 period, it is not statistically significant. With p-value of 0.397 and a positive coefficient of 0.016, R&D intensity at t-3 period is thus far from being significant at the 10% level.

5.1.8 Test of poolability

From the regression results in table 5.6, it is obvious that the coefficient values of the independent variables for the separated industries are different. This is not surprising as insights from the information criteria also suggested that automotive and electronics industries have a dissimilar lagged structure for the R&D intensity variable. To confirm this, a poolability test on each of independent variables in the pooled model was performed. A Chow test utilising pooled OLS regression was used to test the poolability of R&D intensity, lag R&D intensities at t-1, t-2 and t-3 periods, capital intensity growth and market capitalisation growth in pooled data's regression function (equation 5.8). Null and alternative hypotheses are as follows;

H_0 : Automotive and electronics firms have equal coefficients for individual variables

H_1 : Automotive and electronics firms have different coefficients for individual variables
(thus, the panel data for the two industries are not poolable)

Table 5.7: Test of poolability	
F-statistics	P-values
11.31***	0.000
***1% significant level	

In table 5.7, results from the Chow tests of poolability for the independent variables shows that the F-statistic is larger than the critical value of F since the p-value is lower than the standard 0.05 significant level. In fact, the computed p-value is indeed less than the 0.01 significant level. Therefore, the study concludes that the null hypothesis of the poolability of two industries was rejected. This leads to the acceptance of the hypothesis that two sectors did not share the same coefficient values for each of independent variables. In the subsequent investigation of technological externalities and absorptive capacity, the study conducts the regression analysis for each of two industries separately.

5.2 Technological spillovers and absorptive capacity

The preceding empirical analysis in this chapter is based on first differencing that eradicates firm fixed effects from the production function. However, an interesting questions is whether firms differ in their ability to translate R&D effort, both own R&D and spillovers from other firms, into actual products or processes (Clark and Griliches, 1984). As an extension to the analysis in section 5.1, this section incorporates technological externalities and absorptive capacity into the models. There are two technological externalities to be included; intra-sectoral and inter-sectoral spillovers. Intra-sectoral spillovers refer to the potential pool of technical knowledge and technologies that are accessible to firms within the automobile sector or electronics sector respectively. While a number of empirical literatures tend to represent inter-sectoral spillover as technological diffusion from broader sectors in the same two-digit classification into a particular sector, the essence of inter-sectoral spillovers concentrates on available flows of spillovers between the automobile industry and the electronics industry. The narrow scope on inter-industry technology flows among the two industries reflects that of Goto and Suzuki (1989) who examine the effect of technologies originating in the electronics industry upon productivity growth of the manufacturing sector as a whole. In this respect, this study builds on the literature regarding the consideration of electronics technology as one of the sources of externalities. Yet, this study also considers the effect of technology diffused from the automobile sector into the electronics sector.

The previous section showed the poolability test that found that it is appropriate to use a common single regression model to represent both industries. Regressions on pooled data, combining both sectors' micro-level data, can be problematic due to the measures of intra-sectoral and inter-sectoral spillovers. The concept of intra-sectoral spillover is essentially an industry-specific variable in the sense that such flows of technology diffusion takes place within a particular industry. With the use of pooled data and the blurred industry boundaries, this spillover measure might be unclear as it could become a pool of other firms' technologies. To the extent of inter-sectoral spillovers, this type of spillover variable is likely to be dissimilar between the two industries. An inter-industry spillover variable in the automobile firms' regression model is defined as spillovers of electronics' technology while the same spillover variable for that of electronics is the direct opposite. Therefore, this section proceeds to add spillovers and absorptive capacity in the subsequent regression analyses as well as further unit root tests and post-estimation tests on the automobile and electronics firms.

5.2.1 Construction and measurement of intra-industry spillover, inter-industry spillover and absorptive capacity

This study is limited by the unavailability of information on both input-output tables and patent classifications. It is therefore not possible to apply either of those weighting schemes to the intra-sectoral and inter-sectoral spillover variables. As an alternative, unweighted measures are used for the spillover variables. The construction follows Antonelli (1994) and Raut (1995) which approximate their spillover variable as the sum of others' R&D effort. By representing technological effort by the amount of R&D investments, both spillover variables can be expressed as:

$$\text{Equation 5.9 IntraS}_{it} = (\sum_{j \neq i}^n \text{RD}_{jt}) / \text{Q}_{it}$$

For firm i at t period, equation 5.9 illustrates intra-industry spillovers as the sum of other firm (j^{th} to n^{th})'s R&D spending as a fraction of firm i 's net sales. This model reflects that of Goto and Suzuki (1989), Wolff and Nadiri (1993) and Wieser (2005), which use the output of the recipient firm or industry as the denominator. Equation 5.9 is applied to both the automobile and electronics industries.

While the inter-industry spillover variable is similar to the intra-industry spillovers, the definition is of different across two sectors. The distinction is in the numerator and is as follows:

$$\text{Equation 5.10 } \text{InterS}_{ait} = (\sum_i^n \text{RD}_{eit}) / \text{Q}_{ait}$$

Equation 5.10 represents inter-industry spillover in the automotive industry. Firm i operates in the automobile sector (a) during t period, and the available pool of inter-industry spillovers is the ratio between the sum of R&D investment made by all firms in the electronics sector to net sales of the firm in the automobile sector. Conversely, the numerator of this variable in the electronics case is the direct opposite to the numerator in equation 5.10.

$$\text{Equation 5.11 } \text{InterS}_{eit} = (\sum_i^n \text{RD}_{ait}) / \text{Q}_{eit}$$

In equation 5.11, InterS_{eit} is inter-sectoral spillovers potentially received by a electronics firm. This variable is the sum of all automobile R&D ($\sum_i^n \text{RD}_{ait}$) divided by the net sales of firm i in the electronics sector (Q_{eit}). For absorptive capacity, Griffith et al. (2000)'s measure based on the concept of the technological frontier is beyond the scope of this study as such a measure is particularly implemented at the macro-level. Rather, this study follows Jaffe (1986, 1989) and represents absorptive capacity by the interaction terms between internal and others' technological effort. Thus, the interaction term is defined as the a firm's own R&D investment and the combined pool of both intra-industry and inter-industry spillovers. Since the two industries diverge in term of inter-industry spillovers, their respective absorptive capacity would be different, and expressed as:

$$\text{Equation 5.12 } \text{Absorp}_{ait} = \text{RD}_{it} * (\text{IntraS}_{it} + \text{InterS}_{ait})$$

Therefore, for each time period and for each individual automotive firm, absorptive capacity (Absorp_{ait}) can be computed as shown in equation 5.12:

$$\text{Equation 5.13 } \text{Absorp}_{eit} = \text{RD}_{it} * (\text{IntraS}_{it} + \text{InterS}_{eit})$$

In a similar vein, the absorptive capacity of an electronics company (Absorp_{eit}) is derived by multiplying each firm's R&D investment by the gross amount of spillover. The only difference is that inter-industry spillover is presented by the term InterS_{eit} which is obtained from equation 5.11. Taking natural logarithms of these new variables and incorporating them into equation 5.7 and 5.8, two new models are estimated:

$$\text{Equation 5.14 } (q-1)_{it} = \lambda + \alpha(k-1)_{it} + \rho_t \ln(\text{RD}/Q)_{it} + \rho_{t-1} \ln(\text{RD}/Q)_{it-1} + \omega \text{MKT}CG_{it} + \nu \ln(\text{IntraS})_{it} + \tau \ln(\text{InterS})_{ait} + \omega \ln(\text{Absorp})_{ait} + \varepsilon_{it}$$

$$\text{Equation 5.15 } (q-1)_{it} = \lambda + \alpha(k-1)_{it} + \rho_t \ln(\text{RD}/Q)_{it} + \rho_{t-1} \ln(\text{RD}/Q)_{it-1} + \rho_{t-2} \ln(\text{RD}/Q)_{it-2} + \rho_{t-3} \ln(\text{RD}/Q)_{it-3} + \omega \text{MKT}CG_{it} + \nu \ln(\text{IntraS})_{it} + \tau \ln(\text{InterS})_{eit} + \omega \ln(\text{Absorp})_{eit} + \varepsilon_{it}$$

5.2.2 Stationarity test on additional independent variables

Variables	Automotive industry		Electronics industry	
	ADF	Phillips-Perron	ADF	Phillips-Perron
Ln(Intra-industry spillover)	347.846***	273.127***	1913.365***	514.946***
Ln(Inter-industry spillover)	285.898***	245.192***	657.687***	855.574***
Ln(Absorptive capacity)	224.741**	236.573***	663.976***	726.025***

***5% significant level; **1% significant level

The intra-industry spillover, inter-industry spillover and absorptive capacity have not been tested for stationarity. Thereafter, supplementary unit-root tests are performed with the results shown in table 5.8. For both industries, the results from both unit root tests indicate that the new three variables are stationary series (statistical significance at 0.01 and 0.05 level).

Table 5.9: Results of regression analysis: impact of intra-industry spillover, inter-industry spillover and absorptive capacity on labour productivity

Independent variables below	Automotive industry		Electronics industry	
Dependent variable: Labour productivity growth	Random effects GLS model	Fixed effects (Within) model	Random effects GLS model	Fixed effects (Within) model
Constant	-0.809 (0.425)	0.415 (0.465)	0.278 (0.772)	1.301 (0.206)
Ln (R&D intensity)	-0.142 (0.039)**	-0.183 (0.004)***	-0.219 (0.000)***	-0.209 (0.002)***
Ln (R&D intensity) at t-1 period	0.079 (0.028)**	0.069 (0.039)**	0.157 (0.000)***	0.17 (0.000)***
Ln (R&D intensity) at t-2 period	-	-	0.045 (0.015)**	0.053 (0.004)***
Ln (R&D intensity) at t-3 period	-	-	0.002 (0.869)	0.003 (0.883)
Capital intensity growth	0.453 (0.000)***	0.443 (0.000)***	0.065 (0.053)*	0.051 (0.01)***
Market capitalisation growth	0.002 (0.358)	0.001 (0.088)*	0.043 (0.001)***	0.042 (0.001)***
Ln(Intra-industry spillover)	-0.517 (0.001)***	-1.012 (0.000)***	0.849 (0.000)***	0.829 (0.000)***
Ln(Inter-industry spillover)	0.519 (0.001)***	0.629 (0.000)***	-0.868 (0.000)***	-1.143 (0.000)***
Ln(Absorptive capacity)	0.058 (0.348)	0.113 (0.033)**	0.014 (0.003)***	0.046 (0.018)**
R-square	0.3632	0.4752	0.2594	0.3489
No. of observations	630	630	1646	1646
No. of firms	89	89	236	236
No. of parameters	8	8	10	10
Akaike criterion	-	-1007.853	-	-797.882
Schwarz criterion	-	-976.733	-	-749.227
Log likelihood	-	510.927	-	407.941
Robust Hausmann test	14.05 (0.000)***		21.01 (0.000)***	

* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses

5.2.3 Empirical results

Table 5.9 provides the revised regression results after the integration of the spillover variables and absorptive capacity. Random effects GLS and within groups fixed effects methods are again used to obtain estimating coefficients for each independent variable. With regard to statistical significance, these are similar to those in the previous section 5.1.7.2. In addition to the elements noticed earlier comparison between two industries are carried over into these new empirical results. The magnitudes of the electronics' R&D intensities and market capitalisation growth remain relatively higher than those in the automobile industries. However, the reverse is true for the capital intensity coefficient where for automobile firms it is comparatively bigger than that in the electronics firms.

For the automobile industry, capital intensity growth is statistically significant at the 0.01 level in both random and fixed effects models. Likewise, capital intensity is also positively related to growth rate of electronics firms' labour productivity; at the 10% level in random effects model and the 1% level in the case of the fixed effects model. Further, market capitalisation growth is found to be significant in the fixed effects model whereas the same variable in the random effects model is positive yet insignificant. In electronics firms, market capitalisation in both panel-data models is similar in terms of coefficient value and statistical significance at the 1% level.

For both panel regression models in the automobile sector, present period R&D intensity is negative and significant. In absolute term, the fixed effects estimated rate of return is higher at 0.183 with 1% significant level whilst the equivalent estimate is significant at 5% level in the random effects model. R&D intensity at t-1 period is positive and significant at 5% level with a coefficient values of 0.079 in the random effects models and 0.069 in the fixed effects model. For the electronics firms R&D intensity at t period has a negative effect on labour productivity growth and is statistically significant at 1% level in both the random and fix effects models. At t-1 and t-2 periods, R&D intensity explains a positive variation in growth rate of labour productivity. Both lagged variables are significant at 0.01 level in fixed effects, and individually at 0.01 level and 0.05 level in random effects. R&D intensity at t-3 period is insignificant at any level for both panel models.

As shown from both the random and fixed effects models, the spillover variables in both sectors are statistically significant at the 0.01 level, although with opposite signs. In the automotive sector, intra-industry spillovers negatively affect labour productivity growth,

whereas the inter-industry spillovers exert a positive influence. For the electronics industry, spillovers generated within the sector contribute positively to the productivity of a firm, but technological externalities from the automobile industry exhibit a negative coefficient (values of -0.868 and -1.143) in the random effects and fixed effects models respectively.

Absorptive capacity has a positive coefficient in both panel regression models for the automobile and electronics sectors. Whilst absorptive capacity is significant at the 5% level in the fixed effects model, it is not statistically significant in the random effects model (p-value of 0.348). With p-values of 0.003 and 0.018, electronics' absorptive capacity is significant at 0.01 level in random effect model and at 0.05 level in fixed effects model.

5.3 Post-estimation tests

5.3.1 Comparison of random effects and fixed effects estimators to pooled OLS estimators

The random effects and fixed effects regressions results shown in table 5.9 take into account time invariant individual specific effects. Reviewing the related literature in chapter 3, it was found that a number of panel-data studies use conventional ordinary least squares (OLS) estimators in their regression analysis. In contrast, OLS does not highlight such firm effects. In particular, pooled OLS assumes a common coefficient for all cross-sections or firms, thus implying no difference between the estimated cross-section as a homogeneous dataset (Asteriou and Hall, 2007). The issue has risen regarding which method is better for this study and thus tests are conducted to compare the random effects and fixed effects models with pooled OLS regression. Breusch and Pagan (1980) point out that random effects can be examined by the Lagrange Multiplier test (LM) while fixed effects is tested by the incremental F-test.

Null and alternative hypothesis for LM test are as follows;

H_0 : Variances across individual firms are zero. That is, there is no random group effect. Hence, pooled OLS regression model is more appropriate.

H_1 : Variances across individual firms differ from zero. This means that firm-specific effects exist, thus the random effect model is preferable.

Table 5.10: Breusch-Pagan Lagrange multiplier (LM) test for random effects		
	Automotive industry	Electronics industry
Chi-squared	9.69***	20.74***
P-values	0.002	0.000
* 10% significant level; **5% significant level; ; ***1% significant level		

From table 5.10, the high chi-squared values are demonstrated in all cases of both industries and pooled data, with statistical significance at 0.01 level. LM tests on the automotive industry, the electronics industry and combined data result in a chi-square of 9.69 and 20.74 respectively. This leads to rejection of the null hypothesis in favor of the random effect model. Subsequently, F-tests are conducted to examine the presence of significant fixed effects across separated data, in order to compare the fixed effect model with pooled OLS regression. Two hypotheses are shown below;

H_0 : Parameter of firm specific effect's dummies are zero. Since firm effects are nonexistent, pooled OLS regression is robust.

H_1 : Parameter of firm specific effect's dummies are not zero, fixed effect model is then more pertinent for the analysis.

Table 5.11: Incremental F-test for fixed effects		
	Automotive industry	Electronics industry
F-statistics	50.84***	48.51***
P-values	0.000	0.000
* 10% significant level; **5% significant level; ; ***1% significant level		

From table 5.11, the automotive industry and the electronics industry illustrate large F-statistics at 50.84 and 48.51 correspondingly. All computed F-statistics are significant at the 0.01 level, thus rejecting the null hypothesis that there is no individual effect. As a consequence, the fixed effect model is preferred to the pooled OLS model. Overall, LM test and F-test provide the conclusion that both random and fixed group effect models significantly fit the panel-data of automotive and electronics industries better than pooled OLS without individual firm effect.

5.3.2 Robust Hausman test to compare Random effects and fixed effects model

As LM and Incremental F-tests signify that both random and fixed effects models are more consistent than OLS, a further test could be applied to identify the better model among those two panel data regression models. For the automotive sector, regression of random effects and fixed effects model tended to yield similar results where R&D intensity, lag R&D intensity at t-1 period, capital intensity growth and both spillover variables are significant to firm's labour productivity growth, although there was difference in terms of coefficient values in each of parameters. However, statistical significance of market capitalisation growth and absorptive capacity tend to markedly differ among those two panel data regression models. For the electronics sector, it is also apparent that the regression on fixed effects and random effects model generated comparable results for the significance of lagged R&D intensity on labour productivity growth. Both random and fixed effects models suggest that the R&D intensity parameter of t-3 period is insignificant. To examine whether the model is appropriate with random effects or fixed effects, Hausman test (Hausman, 1978) has been generally used. However, given the use of clustered robust standard errors in the regression, the conventional Hausman test may not be applicable and the robust version of Hausman Test, proposed by Wooldridge (2002) was conducted. Two hypotheses were drawn;

H₀: Both fixed effects and random effects estimators are consistent (in other words, there is no difference in coefficients of fixed effects and random effects model)

H₁: Either or both fixed effects and random effects estimators are inconsistent (this implies that fixed effects model is more favorable)

The acceptance of the null hypothesis implies that not only the random effect model is valid, but also that the fixed effect model still generates consistent estimates of the identifiable parameters (Johnson and Dinardo, 1997). The study runs robust Hausman tests for pooled-data and separated industries regression and the results are shown in the last column of table 5.9. F-statistics values for automotive industry and electronics industry are 14.05 and 21.01 whereas their p-values are 0.000 respectively. Computed p-values of the tests on both industries are less than the standard 0.05 level. The results suggest that the coefficients yielded by both models are not similar, for cases of both sectors and error are associated with the coefficient. Thus, the null hypothesis that the random effects and fixed effects model are both consistent was subsequently rejected. This implies that the fixed

effects model is more suitable and better than the random effect model in the analysis of both samples. Also, time-invariant factors are not independent of other regressors in the equation. Thus, the regression results of the fixed-effects model (FEM) are used to interpret the empirical findings.

To a lesser extent, results of similar robust Hausman test displayed in earlier table 5.7 appear to be markedly different. The p-values of tests on both automobile and electronics are not statistically significant even at 10% level. The null hypothesis is accepted, and both the random and fixed effects regression model are appropriate for the earlier analysis that did not take into consideration research externalities and absorptive capacity. It could be noted that the presence of such technological related variables accentuate divergence between the results of the two panel data regression models. In fact, an increase in consistency of fixed effects model could be also noted from another indicator. That is, in table 5.9, the fixed effects models in both the automobile and electronics firms exhibit higher R-square values than the random effects models. This implies a better fit in the former regression model to the latter.

In general, the Lagrange multiplier (LM) test and incremental f-test first informs that models with group effect should be chosen, rather than ordinary least squares method. Thus, the final selection is left to comparison between random effect and fixed effect models. Tests of poolability and Hausman specification gave rise to two indications. First, firm-level data of automotive and electronics industries could not be pooled and examined together. Thus, regression results of pooled model shall be dropped from the R&D-labour productivity analysis for these data. And secondly, only regression results of fixed effects model should be considered and interpreted.

5.4 Discussion

In accordance with the existing literature, this chapter demonstrates the extent to which firm own R&D effort impacts on productivity growth. Yet, the current level of R&D was found to have negative effects for both sectors. This can be explained by the fact that R&D is a cost to the firm investing and the return on such an investment may not materialise in the present period. Firm performance might thus be influenced by R&D after a lagged period of time (Cooper and Schendel, 1976).

It is apparent that both sectors experience the positive effect of R&D investment on their efficiency in no more than a fiscal year after spent investment in R&D activities. Accelerated product life cycle and customer perspectives favouring consistently developed technologies may explain the relatively short period time that return on R&D is evident. Clark et al. (1987) pointed out that the auto industry is an example of a manufacturing sector where product development constitutes a large bulk of total R&D investment and represents a considerable commitment of resources. Product development in the aspect of product design could affect yields and costs in production, and productivity in process. Likewise, R&D investments in the Japanese electronics sector are also mainly in product development and applied research (Florida and Kenney, 1994). The change in design may alter the selection and use of materials and parts. With intense competition in the Japanese domestic market, the life of the product's designs and engineering has been shortening as the pace of development cycles becomes faster (Cusumano, 1985). To Florida and Kenney (1994), as new generations of products are introduced to the market at an ever-increasing pace, seamless innovation has become a pivotal component of the production process. The concentration on substantial R&D investment is noted by Yang et al. (2010), especially for such high-technological industries that competition is based significantly upon the technology offered by firms.

In addition, the modern enhancements to an existing model, especially in the middle of a product's lifespan, incurs with additional product development. Updating present models could also result in gains in sales volumes and market share. Product innovation may involve a time lag as it may take time for consumers to find out about it and to accept it (Grilliches, 1979). In the words of Tubbs (2007), product development times could be very long so that firm performance in the present period may be affected by R&D investment in preceding years. In the context of both automotive and electronic products, potential consumers appear to have awareness of upcoming technologies and products. This is bolstered by the fact that rumours and news about new products are released officially by the firm or perhaps leaked to the public. Automobile examples include secret shots featuring future vehicles during road and track tests and pre-production debuts, whereas electronic firms often regularly update their progress in developing as well as disclosing possible advanced specification of their forthcoming merchandise.

While the positive and significant R&D intensity variables in both industries are found at t-1 periods, their respective rate of return coefficients could be viewed in percentages as 6.9% in automobile industry and 17% in electronics industry. Although the

estimated rate of return on the R&D variable support previous finding regarding the presence of R&D investment's productivity effect, it becomes clear that the rate of return on R&D over the 2000s period dwindled remarkably from the level achieved during the 1970s and 1980s. Estimated automotive and electronics' rates of return on R&D are compared with previous studies' estimated values shown in table 3.6. In specific, an industry-level study of Goto and Suzuki (1989) report higher rates of return at 33% for automobile firms and 22% for electronics firms. Despite the different scope of the study and the construction of the proxy variables, a number of empirical studies of the overall manufacturing sector during the 1970s and 1980s report figures about 20-30% and as high as 56% in Griliches and Mairesse (1991). Even so, the estimation results on firm R&D intensities in this chapter diverge from those focusing on the economic stagnation period. With the exception of Kwon and Inui (2003), prior studies investigating R&D-productivity links during the 1990s period point towards either a negative or no effect of R&D spending.

In absolute terms, R&D intensity and its lag variables are found to show higher coefficient values in the electronics sector than in automobile industry. As mentioned earlier, in 5.1.1, the coefficient of R&D intensity in the model represents the marginal product or rate of return on knowledge capital, and a higher coefficient value could thus imply the greater benefit that the firm can gain from an increase in its investment in research and development. To some degree, a probable explanation may arise from the notion that the automotive sector undertakes a lot of technologies for its own use. In the product or component development and production processes, the automobile industry is clearly applying technological innovations and inventions originated in multiple industries. Advancement in material usage is one example. The introduction of ran-flat tyres leads to the better fuel economy and lower vehicle weight due to the unnecessary spare-tyre. Vehicle body and parts made of carbon-fibre reinforced polymer has substantially greater strength, rigidity and lighter weight and this results in new innovations in automotive engineering and design.

These arguments for lower coefficients in the automobile case might be substantiated by findings on the automobile inter-industry spillovers variable whose size is much greater than own R&D effort variables. As automobile firms' inter-industry spillover variable proximate the implication of electronics' technology, it could be the case that the impact of outside technologies upon labour productivity growth is even more substantial than the R&D carried out by automobile firms themselves. In fact, the electronics sector itself contributes to the significance of automotive R&D. Owing to integration of telecommunication and audio

equipment technologies in automobiles, carmakers appear to continuously develop vehicle related components and design layouts compatible with these. Despite being originated in the semiconductor industry, light emitting diode (LED) has been increasingly applied and further modified for use in automobile lighting, such as head and rear lamp, brake lamp and more recently daytime running lamps. This evidence seems to concur with Griliches (1979) that technical knowledge in one sector does not only originate from within-firm or industrial research and developments, but also is affected by the knowledge borrowed from other firms or industries.

A negative externality is established in the inter-sectoral spillover of electronics model. As a direct contrast to the automotive case, flows of automobile's technology is shown to be negative to electronics firm's productivity. This is expected owing to the considerably higher R&D intensive efforts made by the electronics sector itself. From figure 2.6 to 2.9, it has been clearly established that the electronics sector is well ahead of the automobile and other sectors in the intensification of R&D activities. Goto and Suzuki (1989) note that the electronics sector might be already situated at the apex of manufacturing's technological linkages. It is likely that the electronics sector obtain few or hardly any viable R&D externalities from other industries. Transactions between these two sectors unquestionably take place in reverse direction. Electronics firms would rather draw on their own R&D effort, than make use of others' discoveries that could be in lower levels of technological advancement. In this respect, the attempt to make the most of automobile technologies for their own use could be detrimental to electronics productivity as less significant technologies are unlikely to eventually result in improved product quality.

The negative automobile spillover might be explained in reference to adjustment costs. Given the growing status of electronics industry as the pivotal supplier of component to automobile manufacturers, the surge of automobile's innovative activities contributes to new technological discoveries in that sector which in turn lead to the change in components. In this research's dataset, majority of electronics companies are classified as part manufacturers. It could be argued that the advancement in the automobile technology accentuate the adjustment cost to those of electronics firms as they have to acclimatise their production to suit with the criteria of new automotive innovation.

A possible factor with respect to intra-sectoral spillovers might be strong ties in supplier-end user relationships. Odagiri (1994) and Branstetter and Sakakibara (2002)

consider the presence of business groups and research consortia as crucial sources of spillovers. In fact, the electronics sector is noted for close linkages by the development of integrated production complexes in which component suppliers extensively conduct R&D, both individually and collaboratively with electronics makers (Florida and Kenney, 1992; Ikeda 1979; Sako, 1992). Cooperative R&D activity appears to emerge between companies that are interrelated through the production network (Rokuhara, 1985). Examples of such collaboration include those between materials and intermediate goods manufacturers and between users and assembly firms (Goto, 1997). Another characteristic that possibly fosters the flow of technological diffusion could be the long-term relationship among business group affiliates as a number of firms in the electronics panel dataset are part of vertically integrated production networks (Suzuki, 1993). In fact, business affiliates often engage in the exchange of key research and engineering personnel with the objective of ensuring the effective transfer of process technology innovations across firm boundaries (Branstetter, 2000). As affiliates also share the results of their innovative efforts, this allows them to internalise the positive externality of technical knowledge generated by the business group. By sharing complementary technologies, suppliers and downstream firms within the same production network can enhance the efficiency of their manufacturing process (Caves and Torii, 1992).

With regard to supplier-user relationship, the Japanese automobile sector is said to be similar to the electronics sector and a number of component manufacturers are subsidiaries or business partners of notable automobile producers. Hence, this implies technological cooperation between counterparties. Clark et al. (1987) note that the supply network in the Japanese automobile industry was characterised as being the source of product development. Car-makers draw extensively on the capability of their part suppliers to design and engineer new components and proprietary parts. Thus, automotive components part suppliers are a crucial source of innovation and continuous product improvement (Florida and Kenney, 1994). Extensive networks of alliances and partnerships among car manufacturers currently exist not only within Japan boundaries but also between Japanese carmakers with their overseas counterparts (JAMA, 2010). In this respect, Japanese auto firms appear to forge capital and technical links and joint R&D and production operations with their American and European counterparts. Close linkages between foreign R&D facilities and Japanese domestic R&D and manufacturing are noted by Imai, Nonaka and Takeuchi (1985), particularly with the high level of interaction between R&D and production facilities in the automotive sector (Angel and Savage, 1996). However, the empirical results are proven to be counterintuitive

as it is demonstrated that intra-industry spillovers have a negative impact upon productivity growth for automotive companies. An appealing argument for negative intra-sectoral spillovers among automobile companies might be in conformity with the conjectures of creative destruction and patent race. The creative destruction arising from the new technologies discovered outside the firm boundary provides the implication for the presence of a market stealing effect (Anon Higon, 2007). As rivals manage to offer a product that is superior in terms of either technology or quality, such competitive pressure might force a firm in the same industry to lessen its output (Branstetter, 2001). More specifically, the firm would encounter a downward sloping demand curve, which shifts inward due to a price reduction or product improvement achieved by competitors (Jaffe, 1984). At the same time, this could also drive a firm further up its cost curve, particularly in the presence of sizable fixed costs, and therefore lower the productivity of this firm (Aitken and Harrison, 1999). This negative competition effect might compensate or even dominate positive spillover effects generated from intra-industry research collaboration and production chains.

As discussed above, some of lagged firm's own R&D efforts are positive and statistically significant, as is the interaction term between firm's own R&D and the gross externality pool. The inclusion of such interaction term reveals that marginal productivity of external knowledge is significantly affected by the internal R&D. This points to the fact that the important role of internal firm R&D in promoting the absorptive capacity. Such findings might confirm presumptions in the absorptive capacity literatures on the two roles of internal innovative efforts. Internal R&D might directly increase the technology level by adding more innovation meanwhile it also indirectly induces the incidence of technology spillovers by bolstering the firm's absorptive capacity (Kinoshita, 2001). In this study, absorptive capacity clearly affects labour productivity. From the empirical results, it has been shown that 11.3% and 4.6% additional growth rates of labour productivity for firms operating in automobile and electronics industries. Table 5.9 indicates that the absorptive capacity coefficient in automobile estimations is larger than lagged R&D intensity variables, suggesting the relatively greater role of R&D in fostering absorptive capacity than its conventional role. This evidence accentuates the interdependence of the automobile industry upon the extensive use of external knowledge originated in other manufacturing sectors. The estimated coefficient of the electronics' absorptive capacity is relatively lower than the lagged R&D intensity (t-1 and t-2 periods), supporting the findings of Jaffe (1989).

5.5 Conclusion

This chapter has reported comparisons of performance between two R&D intensive industries based on the effect of R&D investment upon labour productivity. Using a production function framework, this chapter examined the importance of the firm's R&D, technology diffusion and absorptive capacity in explaining productivity growth. Using random and fixed effects estimators, the empirical model is first analysed in the absence of technological externalities and absorptive capacity. For both sectors, capital intensity and firm size were found to affect firm productivity growth, but particularly at a relatively lower contribution than research and development activities in the electronics industry. In line with existing studies, the results suggest R&D investments effect worker productivity growth. The current-period R&D investment made by firms is associated with cost. And, the return on R&D investment has a lagged effect on productivity.

The significance of R&D investments is in relation to new products making their way to the market. Intense competition has driven perpetual R&D investments which results in the new products or innovations at different periods of time. However, not all past R&D efforts by electronics firms constitute impacts on firm productivity whereas previous R&D of automobile companies is proven to be significant. To some extent, this may reflect the different time-period of the statistical significance of lagged R&D, particularly for the electronics industry. It is noticeable that in electronics firms past R&D in two fiscal years earlier did statistically influence firm's productivity growth in that sector, although there is an exception of R&D investment in $t-3$. Thus, the length of a product's life span and the introduction of its successors to the market may be different between the electronics and automotive industry. Overall, the electronics industry tends to introduce new and replacement products more frequently than the automotive sector where it takes no less than a year to present new or refined vehicles. In contrast, electronic equipment, especially telecommunication and personal computers, tend to be rapidly replaced with more advanced ones in a couple of months after their release. In general, positive rates of return on R&D are found to be lower than the levels during 1970s and 1980s which are reported by previous literatures. Estimated rates of return are also similar to levels achieved during 1990s. This insight may signify the prolonged consequences of economic stagnation well into 2000s in Japan, which is the time period covered in this study. In addition, the decline in the rate of return may be the result of technological catch up and rapid development by international competitors, particularly other East-Asian producers.

Another insight observable from the empirical results is the level of R&D intensity and its lag variables. The electronics industry shows relatively larger coefficients on the R&D intensity variables than that of automobile industry. The possible explanation is the spillovers of knowledge and technical know-how, both from other sectors into the automotive sector and within the sector itself. This leads to the subsequent introduction of technological spillover variables and their related absorptive capacity into the model. In line with expectations, inter-sectoral spillovers exert positive and strong effects on the automotive industry's productivity growth. Technological spillovers from others industries, in particular from those also classified as R&D intensive ones, could better clarify the comparatively lower degree of R&D impact on automotive industry's productivity growth. From the stages of developing future models to manufacturing vehicles and related components, this involves the combined uses of innovations, technological products derived from various branches of scientific fields and technology-intensive industries. In contrast, automotive technologies diffused into electronics industry are confirmed to be disadvantageous for firms attempting to incorporate such technologies.

The effect of intra-sectoral spillover may contribute less to the gap in R&D intensity effects among two industries, close collaboration between producers of finished goods and their suppliers in the aspect of research and development are found in both industries. This kind of research collaboration might be regarded as the basis for the benefits of technological diffusion within the electronics industry. Even so, the probable benefit from intra-sectoral spillover in the automobile case is seemingly counterbalanced by the stiff competition which yields the negative market stealing effect. While automobile firms engage in business cooperation, they are also manufacturing and competing in similar product categories. This competition not only exists among major car assemblers but also within component makers. Technological superiority achieved by one firm could potentially undermine performance of others in the same sector. The other crucial finding is that only when the company vigorously engages in R&D activities is there adequate capability to absorb and adopt external technologies. With regards to absorptive capacity, this chapter appears to draw conclusions consistent with the literature that the company's own R&D effort contributes both direct and indirect effect upon productivity. The indirect effect, regarded as a key to building up absorptive capacity, is relatively more significant than that of the direct effect in accelerating labour productivity growth of the company. Additionally, both internal R&D and technological externalities exist simultaneously.

Chapter 6: The relationship between R&D and firm profitability

Introduction

This chapter examines the impact of internal R&D, technological externalities and absorptive capacity on firm profitability. Whilst research questions addressed in this chapter are similar to chapter 4, firm performance is measured by profit margin. This chapter also augments the previously investigated firm performance indicator, labour productivity, into the analysis of profitability determinants. With the presence of lagged dependent variable and a distributed lag structure of one of the independent variables, the regression model is dynamic panel data model characterised by an autoregressive distributed lag (ADL). Rather than focusing on traditional panel data estimators, the method of estimation is general moment method (GMM). In this regard, the results of differenced GMM and the system GMM are demonstrated whilst ordinary least square (OLS) and within-group (fixed) effect estimations are still provided as a reference point.

While there is a selection of pre-estimation tests of unit roots, heteroscedasticity and autocorrelation identical to the previous chapter, applied tests for lag structure of R&D intensity are additionally presented in both industries and pooled data. Both this chapter and the previous one demonstrate the presence of a distributed lag structure for the R&D variable in their respective regression models. It could be noted that the lag structure of the independent variable is confined to R&D intensity as it is the variable of particular interests in the analysis. The purpose of adding lagged R&D intensity is to tackle the estimation issues arising from invalid instruments. As the outcomes of R&D intensity lag selection reveal differences between the separate sectors and pooled data regarding amounts of lagged R&D intensity parameters, the chapter provides the results individually. In addition, incremental F-tests are employed to test for the existence of individual firm specific effects which further justify the use of dynamic regression model.

The analysis is divided into two parts. The first part constitutes the fundamental model in which profit margin is regressed on lagged profit margin, R&D intensity, lagged R&D intensities, labour productivity, market capitalisation, debt ratio and firm age. This section ends with poolability test which indicates infeasibility of using pooled data model for further analysis and interference. The second section addresses the evidence on spillovers and absorptive capacity with respect to profitability. Intra-industry spillovers, inter-industry spillovers and absorptive capacity variables are included in the empirical model. Follow that,

post estimation tests on instruments and autocorrelation make no evident of estimation inconsistency. As the comparison between two GMM estimates reveals System GMM variant as the superlative estimator, its parameter estimations of automobile and electronics are considered as key results of this chapter.

6.1 Analytical model

6.1.1 Model specification

The lagged dependent variable is incorporated into the regression model, this is justification for two reasons. Previous firm performance may exert an impact on future output decisions (McDonald, 1999). As a further point, the existence of a lagged profit rate takes into account partial adjustment to shocks in the persistence of profits (Levy, 1986 and Geroski and Jacquemin, 1988). In other words, lagged profit might account for the dynamic component in firm profitability (Machin and Van Reenen, 1993 and Stierwald, 2009). The independent variable of particular interest is R&D intensity. Thus, the study incorporates current value as well as lagged values in the equation. Therefore, it is likely that the regression model for each of industries is different regarding lag structure of R&D intensity. As a further point, the proper lag structure for pooled data regression may also be unlike that of the two separated industries.

Market capitalisation is in the model as a proxy for firm size. Firm size often relates to scale economies where large firms are expected to possess a higher degree than those of small counterparts. The possible impact of firm size on profit may also have a root in the size advantage; the market power and access to capital markets of large firm may give them investment opportunities that are not available to smaller firms (Baumol, 1967 and Steindl, 1945). Degryse and Ongena (2000) note that a greater level of market power and efficiency may lead to higher profitability for the firm. The debt ratio is included to control for firm leverage which is the likely effect of capital structure on firm profitability. The rise in the debt to equity ratio could entail higher risk to the firm undertaking investment since it incurs interest expenses. A certain amount of profit may be subsequently used to cover for interest expenses of borrowed capital (Eriotis et al., 2011). Reflecting tangible assets, capital intensity can also be considered to have effect on profit. McDonald (1999) points out that high capital intensity implies the large sum of sunk costs that firms in the industry have to face. Thus, such a capital requirement could form a barrier to entry that consequently gives rise to monopoly profits. The age of the firm enters the model as a control variable.

According to Stierwald (2009), firm age may be an approximation of intangible capital such as market reputation and business experience which older firms can attain relatively more easily than younger counterparts. The estimating equation is expressed:

$$\text{Equation 6.1 } (P/Q)_{it} = (P/Q)_{it-1} + \sum_{k=0}^n \rho(RD/Q)_{i(t-k)} + (Q/L)_{it} + (K/L)_{it} + MKTC_{it} + DEBTR_{it} + AGE_{it} + \varepsilon_{it}$$

Then taking natural logarithms,

$$\text{Equation 6.2 } \ln(P/Q)_{it} = \ln(P/Q)_{it-1} + \sum_{k=0}^n \ln(RD/Q)_{i(t-k)} + \ln(Q/L)_{it} + \ln(K/L)_{it} + \ln(MKTC)_{it} + \ln(DEBTR)_{it} + \ln(AGE)_{it} + \varepsilon_{it}$$

With the exception of R&D intensities, it is worth mentioning that the variables in this equation are different from those in the previous chapter.

6.1.2 Methodology

The autoregressive model outlined in equation 6.2 can be effectively investigated by using panel dataset owing to its advantages over those of cross-sectional and time series data. Bond (2002) points out that the estimation of dynamic relationships from observations in a single point in time is highly improbable since cross-sectional data tends to provide insufficient information about preceding periods. Therefore panel data also offers the possibility to examine heterogeneity in adjustment dynamics among different firms which is obscured in time-series data.

Nevertheless, there are likely endogeneity problems stemming from the specification of the empirical model. The definite endogenous variable in the model is the dependent variable, current profit margin, which is modeled as being systematically affected by the changes in the other variables on right-hand side of the equation. Typical regression models posit that all independent variables are exogenous. Each of those variables must not be determined by other independent variables in the same model whereas it could possibly be determined by factors external to the model. Endogeneity is particularly relevant in the context of time-series analysis of causal processes, as it is common for some variables within a causal system to be dependent for their value in period t on the values of other variables in the same causal system (Pearl, 2000). In this respect, the presence of lagged dependent variable and the distributed lag structure of R&D intensity as explanatory variables provide evidences of endogeneity issues in the model. One could consider the lagged dependent

variable, profit margin in $t-1$ period, as endogenous because it is correlated with the error term in the model. Similarly, the level of present R&D intensity could be regarded as endogenous as it will vary according to the previous R&D intensities owing to its correlation with disturbance terms. Besides, some explanatory variables could have causal relations. In other words, there might be simultaneity or interdependence between variables. Taking for instance, labour productivity may be endogenous to R&D intensity, capital intensity since the changes in the latter two might constitute effect upon labour productivity. Such causal relations among labour productivity and those of R&D intensity and capital intensity may have their roots in the earlier model specification and empirical results in chapter 5 where there is the functional form relationship representing the composition of labour productivity growth as a function of R&D intensity and capital intensity growth. Therein, it is established that the variation in labour productivity growth rate is explained by those two independent variables. Likewise, research externalities and absorptive capacity which are as well present in the labour productivity's function and exert significant influence upon productivity growth. According to Woodward (1995), If x_j is exogenous to a matrix of independent variables X (excluding x_j), then if we perform a regression of x_j against X (excluding x_j), we should expect coefficients of zero for each variable in X (excluding x_j). However, the empirical results of a regression of labour productivity growth against an assortment of aforementioned variables (shown in table 5.9) demonstrate that each factor's parameter estimate is not equal to zero in both industries. Therefore, it could be remarked that labour productivity is not exogenous as any increase in some other independent variables would have discernable effect upon it.

The existence of endogeneity in explanatory variables would result in the biasness of conventional OLS estimator. The estimated coefficient values are likely to be upwardly biased (Hsiao, 1986). Particularly, the coefficient on the lagged dependent variable would be inflated given the fact that predictive power is associated with the individual firm effect, and this is very common in lagged dependent variables (Roodman, 2006). The use of conventional fixed (within group) effect estimators does not solve endogeneity problems and Nickell (1981) and Beck (2004) state that the fixed effect will bias the estimated coefficient values downwards. Given the drawbacks of conventional panel estimators, a solution is to use proxy variables (instruments) in the estimation to control for endogeneity in a regression relationship. Instruments are variables that could be used to explain a variable that is suspicious for being endogenous meanwhile they are exogenous with regard to the equation

(Reichstein, 2011). They are variables that correlate with endogenous variables while uncorrelated with the error term. A typical instrument correlates with independent variables but not with the dependent variable in the model. Nevertheless, IV estimator might become inefficient by the presence of heteroscedasticity. Baum and Schaffer (2003) argue that even though the consistency of the IV coefficient estimates is unaffected, the conventional IV estimates of the standard errors would be inconsistent and this could prevent valid inference in process. Owing to the drawback of conventional IV estimator with respect to heteroscedasticity, this study intends to use Generalised method of moments (GMM), introduced by Hansen (1982). GMM estimators is an estimation tool that also utilises instrumental variables in the regression. It has an advantage over standard IV estimator as it allows for heteroscedasticity of unknown form. In addition, there is no prerequisite for any distributional assumption, particularly the normal or Gaussian type. Differenced GMM and system GMM (detail shown in Appendix B) would be used for the following analyses in this empirical chapter.

In order to confirm the assertion that system GMM should be preferred over difference GMM, this study utilises both difference and system GMM on dynamic panel data model. Although regarded as inconsistent and biased for dynamic panel data model, OLS and within group estimations are also conducted and used as benchmark to examine the possible ineffectiveness of difference GMM estimators as well as to ratify the consistency of system GMM estimates. By using both difference and system GMM, the study takes two-step estimation rather than one-step approach. The main reason behind this arises from Roodman (2006) who suggests that one-step estimator may not be robust to heteroscedasticity and serial correlation in the error terms. The two-step estimator however might suffer from seriously downward biasness in the standard errors, especially in small samples. While not resulting in biased coefficient estimates, this phenomenon can generate spurious precision in the form of small standard errors, hence subsequently leading poor statistical inferences (Arellano and Bond, 1991). To effectually cope with this flaw in two-step GMM estimation, the study uses corrected standard errors, which illustrates that the two-step estimator with corrected standard errors is quite accurate and superior to the one- step with robust standard errors, see Windmeijer (2005).

6.1.3 Lag selection of R&D

The model represented in equation 6.2 is characterised by the existence of possible lagged R&D intensity values, apart from R&D intensity at the current period. In contrast to traditional OLS and fixed effect estimators, there is no lag selection method such as the information criterion that is compatible for both GMM variants. In order to determine the lag structure of labour productivity, the study alternatively experiments utilising two tests; the Hansen test and autoregression (AR) test. The rationale for these tests that are used as post estimation tests is to observe the validity of the instrumental variables and the pattern of serial correlation of the regression models with different lag structures for R&D intensity. Since each model could have different test results between sectors and pooled data, it is plausible to determine the model having two settings; valid instruments and no second order autocorrelation. Being the preferred method of estimations, results from system GMM is used for the tests. In this respect, combined tests are used on models starting from that comprising R&D intensity at the current period only. From then on, tests are conducted on models with a lagged R&D intensity structure backward as early as t-5 period.

For the automotive, electronics and pooled data cases, Table 6.1 presents the joint results for each different lag structures. Regarding the automobile sector, the model with no lagged R&D intensity is shown to have the highest p-value in the Hansen test than those with four period lags. The computed P-value of 0.739 is above the 0.05 significant level; suggesting that instruments in the model are adequate and effective. It is clear that the p-values of the Hansen test decline as the number of lagged labour productivity rises. Also, autocorrelation tests reveal no second-order autocorrelation problem on all five lag-structure cases. Although showing no indication of second-order serial-correlation, the electronics sector models consisting of no lag and distributed lag of R&D intensity up to t-1 period suggest the presence of weak instruments in the estimation.

Table 6.1: Pre-estimation tests for determining Ln(R&D intensity)'s lag structure			
Ln(R&D intensity)'s lag	Automotive industry		
	Hansen J test	AR(1) test	AR(2) test
0	31.15 (0.739)	-2.07 (0.04)**	1.29 (0.195)
1	31.37 (0.688)	-2.676 (0.007)***	0.575 (0.565)
2	30.08 (0.66)	-2.687 (0.007)***	0.567 (0.57)
3	26.83 (0.632)	-2.667 (0.008)***	0.315 (0.752)
4	25.66 (0.426)	-2.72 (0.007)***	-0.021 (0.984)
5	18.7 (0.476)	-2.112 (0.035)**	0.482 (0.63)
Ln(R&D intensity)'s lag	Electronics industry		
	Hansen J test	AR(1) test	AR(2) test
0	54.56 (0.031)**	-4.704 (0.000)***	1.12 (0.263)
1	54.88 (0.023)**	-4.707 (0.000)***	0.963 (0.335)
2	46.17 (0.08)	-4.704 (0.000)***	1.161 (0.246)
3	42.71 (0.074)	-4.563 (0.000)***	0.997 (0.319)
4	36.54 (0.064)	-3.909 (0.000)***	0.69 (0.49)
5	39.966 (0.07)	-2.631 (0.008)***	0.754 (0.451)
Ln(R&D intensity)'s lag	Pooled data		
	Hansen J test	AR(1) test	AR(2) test
0	52.95 (0.043)**	-5.151 (0.000)***	1.066 (0.287)
1	42.34 (0.216)	-5.081 (0.000)***	0.937 (0.349)
2	29.47 (0.689)	-5.176 (0.000)***	1.104 (0.27)
3	28.44 (0.547)	-5.153 (0.000)***	0.759 (0.448)
4	24.32 (0.501)	-4.581 (0.000)***	0.269 (0.788)
5	19.05 (0.454)	-3.721 (0.000)***	0.827 (0.408)
***1% Significant level **5% significant level			

As computed by Hansen test, p-values for those two lag structures are 0.031 and 0.023 respectively. With all P-values lower than the 5% significant level, this leads to the acceptance of the hypothesis of invalid instruments. In this chapter, the likelihood of weak instruments may more or less hinder the use of appropriate dynamic model with no lag and a distributed lag up to t-1 period in the analysis. Further tests on the model with lagged labour productivity appear to show a variety of results for each of four cases. With lagged labour productivity (t-2) as an additional explanatory variable, the validity of instruments is improved. Other lag structures display different outcomes with respect to the validity of instruments. Models with lagged variables up to t-3, t-4 and t-5 also point to the presence of valid instruments. The p-value of models with lagged variables up to t-2 period are characterised by the Hansen test being narrowly accepted, that is, the null hypothesis of valid

instruments is accepted. Specifically, their p-values of 0.074, 0.064 and 0.07 are close to 0.05 significant level.

Even though second-order autocorrelation is not present, the pooled data model without lagged R&D intensity is found to have invalid instrumental variables, with the p-value of 0.043 clearly within 5% significant level. In fact, the model with two additional lags of R&D intensity displays not only valid instruments but also no second-order autocorrelation. Then, the further extension of distributed lag R&D intensities result in lower Hansen test's p-values, compared with p-values of 0.689 in the model with lagged R&D intensity backward to t-2 period.

Consequently the suitable regression model for the automotive industry should be the model with no lagged labour productivity. Applying a distributed lag structure of R&D intensity in the earlier equation 6.2, the following equation 6.4 states the regression model for automobile industry:

$$\text{Equation 6.4 } \ln(P/Q)_{it} = \ln(P/Q)_{it-1} + \ln(RD/Q)_{it} + \ln(Q/L)_{it} + \ln(K/L)_{it} + \ln(MKTC)_{it} + \ln(DEBTR)_{it} + \ln(AGE)_{it} + \varepsilon_{it}$$

Likewise, the regression model designated for the electronics and pooled data is as follows:

$$\text{Equation 6.5 } \ln(P/Q)_{it} = \ln(P/Q)_{it-1} + \ln(RD/Q)_{it} + \ln(RD/Q)_{it-1} + \ln(RD/Q)_{it-2} + \ln(Q/L)_{it} + \ln(K/L)_{it} + \ln(MKTC)_{it} + \ln(DEBTR)_{it} + \ln(AGE)_{it} + \varepsilon_{it}$$

6.1.4 Stationarity test

This chapter follows the previous one regarding unit root tests on panel data set. Even so, it is apparent that the variables in the model are different. All are in natural logarithm variables. Given $\ln(\text{R\&D intensity})$, and $\ln(\text{R\&D intensity})$ at t-1 period and t-2 periods, were already tested for stationarity and reported in table 5.2. Hence, the investigation on unit root proceeds with the new variables in equations 6.4 and 6.5. The unit-root test results are presented in table 6.2. For the electronics and pooled data, the results indicate that all variables in equation 6.5 are of stationary series as their computed t-statistics are larger than critical t-values and significance at 1% level. Thus, it is noted that non-stationarity is absence from the panel dataset of the electronics sector and the pooled data. As for the automotive sector, all variables in equation 6.4 excluding the explained variable, $\ln(\text{R\&D intensity})$, are found to be stationary. As earlier stated in the subsection 5.1.4, the problem of spurious

regression is again remedied by the use of panel data in the analysis of automotive firms. This is combined with the fact that Ln(R&D intensity) is the only independent variable in equation 6.4 that is identified as non-stationary whereas the dependent variable and the rest of independent variables are not.

6.1.5 Tests for heteroscedasticity and autocorrelation

This chapter also tests for heteroscedasticity and serialcorrelation in panel data by using the likelihood ratio (LR) and Wooldridge tests (2002) respectively. Table 6.3 presents the likelihood-ratio tests and indicates the clear presence of heteroscedasticity in the electronics and automotive sectors separately and pooled. Since all likelihood ratio chi-square values are greater than their critical values, this leads to the significance at 1% level. To the extent of serial-correlation, tests shown in table 6.4, F-statistics and p-values obtained from Wooldridge test (2002) display the statistical significance at 1% level. This consequently results in the rejection of the null hypothesis of no autocorrelation in the error terms. The successive interrelation of error terms can be explained by the appearance of lagged variables, lagged dependent variable (profit margin at t-1 period) and lagged R&D intensities (t-2 period), on the right-hand side of the equation.

Table 6.2: Pre-estimation test of time series data's stationarity

Variables	Automotive industry		Electronics industry		Pooled data	
	ADF	Phillips-Perron	ADF	Phillips-Perron	ADF	Phillips-Perron
Ln(Profit margin)	467.249***	333.091***	1136.377***	731.318***	1136.377***	1064.41***
Ln(Profit margin) at t-1 period	449.71***	317.055***	1102.559***	685.96***	1102.559***	1003.02***
Ln(Labour Productivity)	205.984***	253.916***	717.211***	770.153***	717.211***	1024.07***
Ln(Capital intensity)	314.726***	287.374***	1065.922***	773.601***	1065.922***	1060.97***
Ln(Market capitalisation)	288.938***	314.548***	582.444***	552.23***	1009.76***	761.233***
Ln(Debt ratio)	479.812***	205.959***	661.564***	670.28***	661.564***	870.057***
Ln(Firm age)	801.841***	1652.67***	17000***	4404.05***	17000***	6054.07***

* 10% significant level; **5% significant level; ***1% significant level;

Table 6.3: Pre estimation test for heteroscedasticity in panel data			
	Automotive Industry	Electronics industry	Pooled data
Likelihood ratio test	238.91***	723.12***	974.09***
***1% significant level			

Table 6.4: Pre-estimation test for autocorrelation in panel data			
	Automotive Industry	Electronics industry	Pooled data
F-statistics	32.04***	62.106***	79.382***
P-values	0.000	0.000	0.000
*** 1% significant level			

6.1.6 Detection of individual-specific effect

Table 6.5: Pre-estimation test - Incremental F-test for fixed effects			
	Automotive industry	Electronics industry	Pooled data
F-statistics	11.89***	11.21***	16.89***
P-values	0.000	0.000	0.000
***1% significant level			

As Roodman (2009) suggests, both difference GMM and system GMM are intended for the estimation of dynamic linear models with a lagged dependent variable, additional explanatory variables and individual fixed effects. The existence of time-invariant fixed effects can be investigated to rationalise the use of two dynamic panel data estimators in this chapter. The study employs the incremental F-test which was previously used to compare within group estimators against pooled OLS estimators in subsection 5.3.1. According to table 6.5, F-statistics for the automotive, electronics and pooled data are all significant at 1% level with values of 11.89, 11.21 and 16.89 respectively. Thus, it is clear that firm specific effects do exist in this chapter's dynamic regression model.

Table 6.6: Estimation of autoregressive distributed lag model of determinants of profitability (Automotive industry)				
Dependent variable: Ln(Profit Margin)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	-2.233 (0.000)***	-6.258 (0.018)**	0.465 (0.87)	-3.42 (0.279)
Ln(Profit Margin) at t-1 period	0.513 (0.000)***	0.139 (0.047)**	0.111 (0.064)*	0.218 (0.025)**
Ln(R&D intensity)	0.033 (0.195)	0.022 (0.834)	0.068 (0.115)	-0.021 (0.637)
Ln(Labour Productivity)	-0.243 (0.001)***	-0.076 (0.789)	0.904 (0.005)***	0.502 (0.000)***
Ln(Capital intensity)	0.013 (0.794)	-0.409 (0.086)*	-0.527 (0.131)	-0.857 (0.145)
Ln(Market Capitalisation)	0.045 (0.025)**	0.44 (0.000)***	0.417 (0.000)***	0.159 (0.05)**
Ln(Debt Ratio)	-0.105 (0.354)	0.25 (0.553)	-0.452 (0.365)	-1.373 (0.285)
Ln(Firm Age)	-0.058 (0.165)	-0.819 (0.206)	-2.301 (0.072)*	0.533 (0.338)
R-Square	0.3694	0.146	-	-
No. of observations	516	516	423	516
No. of firms	89	87	86	87
Test for first order autocorrelation in first-differenced errors	-	-	-2.277 (0.023)**	-2.07 (0.04)**
Test for second order autocorrelation in first-differenced errors	-	-	-0.233 (0.816)	1.29 (0.195)
Hansen J. Statistics	-	-	20.59 (0.546)	31.15 (0.739)
* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses				

Dependent variable: Ln(Profit Margin)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	-1.585 (0.000)***	-4.822 (0.007)***	-1.491 (0.66)	-4.17 (0.027)**
Ln(Profit Margin) at t-1 period	0.61 (0.000)***	0.233 (0.000)***	0.195 (0.095)*	0.383 (0.000)***
Ln(R&D intensity)	-0.17 (0.002)***	-0.043 (0.454)	-0.062 (0.492)	-0.074 (0.436)
Ln(R&D intensity) at t-1 period	0.197 (0.003)***	0.166 (0.006)***	0.155 (0.044)**	0.214 (0.016)**
Ln(R&D intensity) at t-2 period	-0.003 (0.943)	0.023 (0.642)	0.024 (0.792)	0.055 (0.62)
Ln(Labour Productivity)	-0.101 (0.024)**	0.101 (0.513)	0.436 (0.023)**	0.067 (0.681)
Ln(Capital intensity)	0.005 (0.865)	-0.017 (0.872)	-0.204 (0.152)	-0.158 (0.282)
Ln(Market Capitalisation)	0.055 (0.002)***	0.403 (0.000)***	0.336 (0.000)***	0.264 (0.002)***
Ln(Debt Ratio)	-0.126 (0.013)**	0.151 (0.287)	-0.337 (0.119)	-0.638 (0.157)
Ln(Firm Age)	-0.13 (0.000)***	-0.428 (0.321)	-1.157 (0.157)	0.044 (0.905)
R-Square	0.456	0.1432	-	-
No. of observations	1200	1200	938	1200
No. of firms	230	230	215	230
Test for first order autocorrelation in first-differenced errors	-	-	-3.494 (0.001)***	-4.704 (0.000)***
Test for second order autocorrelation in first-differenced errors	-	-	1.145 (0.252)	1.161 (0.246)
Hansen J. Statistics	-	-	46.18 (0.098)	46.17 (0.08)

* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses

Table 6.8: Estimation of autoregressive distributed lag model of determinants of profitability (Pooled data)				
Dependent variable: Ln(Profit Margin)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	-1.625 (0.000)***	-4.514 (0.003)***	0.1 (0.976)	-3.211 (0.127)
Ln(Profit Margin) at t-1 period	0.592 (0.000)***	0.206 (0.000)***	0.144 (0.14)	0.304 (0.001)***
Ln(R&D intensity)	-0.14 (0.004)***	-0.037 (0.476)	-0.053 (0.457)	-0.071 (0.393)
Ln(R&D intensity) at t-1 period	0.183 (0.002)***	0.154 (0.004)***	0.129 (0.036)**	0.157 (0.035)**
Ln(R&D intensity) at t-2 period	-0.015 (0.689)	0.024 (0.562)	0.033 (0.642)	0.017 (0.84)
Ln(Labour Productivity)	-0.109 (0.005)***	0.081 (0.564)	0.458 (0.008)***	0.098 (0.552)
Ln(Capital intensity)	-0.001 (0.975)	-0.09 (0.347)	-0.225 (0.112)	-0.027 (0.075)*
Ln(Market Capitalisation)	0.046 (0.001)***	0.378 (0.000)***	0.321 (0.000)***	0.257 (0.000)***
Ln(Debt Ratio)	-0.138 (0.002)***	0.137 (0.305)	-0.196 (0.341)	-0.467 (0.039)**
Ln(Firm Age)	-0.114 (0.000)***	-0.561 (0.159)	-1.634 (0.048)**	-0.52 (0.286)
R-Square	0.4484	0.1368	-	-
No. of observations	1713	1713	1358	1713
No. of firms	317	317	301	317
Test for first order autocorrelation in first-differenced errors	-	-	-4.212 (0.000)***	-5.176 (0.000)***
Test for second order autocorrelation in first-differenced errors	-	-	1.005 (0.314)	1.104 (0.27)
Hansen J. Statistics	-	-	35.42 (0.448)	29.47 (0.689)
* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses				

6.1.7 Empirical results

Based on equations 6.4 and 6.5, the study regresses profit margin on lagged profit margin, R&D intensity and/or lagged R&D intensities, labour productivity, capital intensity, market capitalisation, debt ratio and firm age. For the automotive, electronics and pooled data, Table 6.6, 6.7 and 6.8 present the regression results of panel data analysis on the factor affecting profitability with particular attention given to the element of R&D and labour productivity. Coefficient values from all estimation are essentially the elasticity of profit margin with respect to each of independent variable. Estimators used comprise ordinary least square (OLS), fixed (within) effect, differenced GMM and system GMM. Each table provides a comparison of results of differenced GMM and system GMM estimators. While the results from the first two estimators are not described in detail, they are used as points of reference for the consistent estimators which would be selected out of those two GMM estimators.

For automotive firms, coefficients on lagged profit margin dated t-1 is shown having consistencies in the sign and statistical inference between the two GMM estimates, albeit at different significance levels. From differenced GMM estimates, the value is relevant to the present profit margin at 10% level. Likewise, the same lagged dependent variable has a positive impact on profit margin at 5% level in the system GMM estimates. Similarly, labour productivity is statistically significant for both GMM estimates. With p-values of 0.005 and 0.000, labour productivity is significant at the 1% level in the differenced GMM and system GMM accordingly. Both GMM estimates are the same regarding the significance of market capitalisation to profit margin at 1% and 5% level, displaying coefficient values of 0.417 and 0.159 correspondingly. Given p values of 0.115 and 0.637 in both GMM estimates, R&D intensity is clearly insignificant to profit margin. Also, its sign is shown to vary; positive in differenced GMM and negative in system GMM. Capital intensity and the debt ratio appears to show a negative coefficient sign. Even so, they both are inconsequential to profit margin since their respective p-values considerably exceed the 10% significant level in both GMM estimates. A discrepancy between the two GMM estimates appears in the firm age variable. From differenced GMM estimation, the age of firm contributes a negative effect on profit margin, with a p-value of 0.072 denoting statistical significance at the 10% level. Conversely, firm age is found to have no effect on firm profit margin at the 10% level given its p-value of 0.338.

With regards to lagged profit margin, current R&D intensity, lagged R&D intensities, capital intensity and market capitalisation, there are similarities between the electronics sector GMM estimates in terms of statistical significance and coefficient sign. Aside from current R&D intensity, capital intensity and the debt ratio, the rest of the variables have positive coefficient signs. The lagged dependent variable (profit margin dated t-1) is positive and significant at the 10% level for differenced GMM and at the 1% level for system GMM. Market capitalisation in both GMM estimates exhibits a positive impact on profit margin at the 1% significant level. The estimated results on R&D intensities are more varied. There is a negative coefficient on present-period R&D but it is statistically insignificant as its p-values of 0.492 and 0.436 are beyond 10% level of significance. R&D intensity at t-1 period is significant at the 5% level in both the differenced and system GMM estimates. Although the lagged value at t-2 is also positive, its p-values reported by both GMM estimates clearly suggest insignificance at any level. Results from both GMMs currently show the non-existence of effects of capital intensity, debt ratio and firm age upon profit margin. This is evidenced by p-value that are clearly greater than the 10% significant level critical value. Whereas firm age displays a negative coefficient in differenced GMM case, its system GMM equivalent is positive. This difference between the two GMM estimates lies in the labour productivity estimates. System GMM's estimated labour productivity has p-value of 0.687. As it is not significant at the 10% level, labour productivity could be considered as extraneous to profit margin. Conversely, labour productivity in differenced GMM estimation shows a positive significant effect at the 5% level, with a coefficient of 0.436.

Comparing the individual industry's results, estimation results on pooled data exhibit even more dissimilarity between the two GMM estimates. At the 1% significant level, system GMM's lagged profit margin has a positive effect on profit margins in the current period. On the contrary, the differenced GMM is shown to be statistically insignificant as its p-value of 0.14 is higher than the 10% significant level. Likewise, capital intensity and the debt ratio in system GMM are significant whilst the same explanatory variables are insignificant at any acceptable level in both GMM estimates. Despite both GMM estimates having similar signs on labour productivity and firm age, these variables are only statistically significant in the differenced GMM estimates at 1% and 5% respectively. For R&D intensities and market capitalisation, estimation results from differenced and system GMM are alike in terms of coefficient sign and statistical significance. R&D intensities dated t and t-2 has a negative and positive sign, yet they are shown to have an insignificant effect on profit margin. Lagged

R&D intensities at t-1 period and market capitalisation exhibit a positive and significant impact on firm profit at the 5% and 1% level.

6.1.8 Poolability test

Table 6.9: Poolability test	
F-statistics	P-values
2.29***	0.009
***1% significant level	

Given the difference in distributed lag structure of R&D intensity, it is clear that the automobile and electronics industries are not sufficiently similar to use the same model. In both panel dynamic regression models, estimated coefficients and their statistical significance are also different between the two sectors. For example, a divergence arises from labour productivity estimates. While differenced and system GMM estimates in the automobile sector show a positive impact of labour productivity on profit margin, both GMM estimates are not the same regarding the statistical significance of labour productivity. With regards to the pooled data, this is analysed by using a model with same lag structure of R&D intensity as the electronics industry. With the exclusion of the debt ratio in system GMM, other explanatory variables that have an effect in the pooled data are also statistically significant in the case of the electronics industry. To further uphold the view that both industries may not be combined and have the same estimated coefficients, a Chow test is conducted to test the hypothesis that estimates are the same for the two industries. From table 6.9, it is clear that the p-value of 0.009 within the 0.01 significant level and this hence results in the rejection of the null hypothesis that the sectors are poolable in this chapter.

Table 6.10: Results of regression analysis: impact of intra-industry spillover, inter-industry spillover and absorptive capacity on profitability (Automobile)

Dependent variable: Ln(Profit Margin)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	-2.469 (0.614)	0.472 (0.942)	-1.751 (0.858)	2.793 (0.776)
Ln(Profit Margin) at t-1 period	0.399 (0.000)***	0.119 (0.086)*	0.107 (0.699)	0.166 (0.008)***
Ln(R&D intensity)	0.285 (0.327)	0.659 (0.089)*	-0.043 (0.945)	0.532 (0.022)**
Ln(Labour Productivity)	0.018 (0.826)	0.854 (0.05)**	0.595 (0.017)**	1.413 (0.009)***
Ln(Capital intensity)	0.019 (0.726)	-0.233 (0.288)	-0.246 (0.528)	-0.611 (0.109)
Ln(Market Capitalisation)	0.356 (0.000)***	0.551 (0.000)***	0.458 (0.000)***	0.462 (0.000)***
Ln(Debt Ratio)	-0.059 (0.578)	-0.126 (0.781)	-0.318 (0.504)	-0.635 (0.286)
Ln(Firm Age)	-0.031 (0.384)	0.303 (0.482)	-1.64 (0.294)	-0.857 (0.289)
Ln(Intra-industry spillover)	-1.182 (0.017)**	-2.072 (0.007)***	-2.086 (0.000)***	-1.109 (0.07)*
Ln(Inter-industry spillover)	1.63 (0.002)***	2.524 (0.002)***	1.341 (0.041)**	1.842 (0.006)***
Ln(Absorptive capacity)	0.269 (0.355)	0.673 (0.092)*	0.195 (0.06)*	0.52 (0.03)**
R-Square	0.3694	0.218	-	-
No. of observations	516	516	423	516
No. of firms	89	87	86	87
Test for first order autocorrelation in first-differenced errors	-	-	-2.324 (0.02)**	-2.886 (0.004)***
Test for second order autocorrelation in first-differenced errors	-	-	-0.033 (0.974)	0.352 (0.725)
Hansen J. Statistics	-	-	44.698 (0.126)	39.58 (0.235)

* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses

Table 6.11: Results of regression analysis: impact of intra-industry spillover, inter-industry spillover and absorptive capacity on profitability (Electronics)

Dependent variable: Ln(Profit Margin)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	1.307 (0.779)	5.276 (0.363)	5.61 (0.475)	9.922 (0.112)
Ln(Profit Margin) at t-1 period	0.548 (0.000)***	0.236 (0.000)***	0.375 (0.001)***	0.417 (0.000)***
Ln(R&D intensity)	0.256 (0.369)	0.715 (0.067)*	0.504 (0.368)	0.993 (0.01)***
Ln(R&D intensity) at t-1 period	0.15 (0.011)**	0.147 (0.007)***	0.185 (0.02)**	0.188 (0.019)**
Ln(R&D intensity) at t-2 period	0.002 (0.965)	0.014 (0.777)	0.01 (0.916)	0.061 (0.508)
Ln(Labour Productivity)	0.099 (0.041)**	0.818 (0.007)***	0.663 (0.168)	0.993 (0.000)***
Ln(Capital intensity)	-0.001 (0.971)	0.028 (0.785)	-0.191 (0.168)	-0.092 (0.504)
Ln(Market Capitalisation)	0.272 (0.000)***	0.376 (0.000)***	0.327 (0.000)***	0.288 (0.000)***
Ln(Debt Ratio)	-0.038 (0.438)	-0.037 (0.765)	-0.393 (0.069)*	-0.438 (0.494)
Ln(Firm Age)	0.033 (0.337)	0.26 (0.59)	-0.126 (0.864)	0.733 (0.408)
Ln(Intra-industry spillover)	0.95 (0.064)*	1.978 (0.000)***	1.122 (0.064)*	1.358 (0.023)**
Ln(Inter-industry spillover)	-0.609 (0.23)	-1.597 (0.001)***	-1.07 (0.067)*	-0.641 (0.099)*
Ln(Absorptive capacity)	0.415 (0.129)	0.684 (0.064)*	0.539 (0.291)	1.036 (0.003)***
R-Square	0.5138	0.1756	-	-
No. of observations	1200	1200	938	1200
No. of firms	230	30	215	230
Test for first order autocorrelation in first-differenced errors	-	-	-4.304 (0.000)***	-5.035 (0.000)***
Test for second order autocorrelation in first-differenced errors	-	-	1.437 (0.151)	1.487 (0.137)
Hansen J. Statistics	-	-	28.1 (0.459)	30.85 (0.474)

* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses

6.2 Technological spillovers and absorptive capacity

This section of the chapter follows chapter 5 in taking into consideration the effects of R&D externalities and absorptive capacity. Thus, as before, these variables are incorporated into the models as demonstrated following section 6.1. The investigation on pooled data does not continue into this section owing to the results of poolability test in section 6.1.6. Also, pooled data are not appropriate in this regression. Such limitations are analogous to ones discussed previously in section 5.2. In this section, the models are augmented with the additional independent variables, followed by the new results on both the automobile and electronics industries.

6.2.1 Additional model specification

The construction of intra-industry spillovers, inter-industry spillovers and absorptive capacity are identical to those in section 5.2.1. The three variables enter the existing empirical models in the form of natural logarithms. Introducing two spillovers variables and absorptive capacity developed in equation 5.9, 5.10 and 5.12 into equation 6.4 generates an amended model for automobile firms as follows:

$$\text{Equation 6.6 } \ln(\text{PM}/\text{Q})_{it} = \ln(\text{PM}/\text{Q})_{it-1} + \ln(\text{RD}/\text{Q})_{it} + \ln(\text{Q}/\text{L})_{it} + \ln(\text{K}/\text{L})_{it} + \ln(\text{MKTC})_{it} + \ln(\text{DEBTR})_{it} + \ln(\text{AGE})_{it} + \ln(\text{IntraS})_{it} + \ln(\text{InterS})_{ait} + \ln(\text{Absorp})_{ait} + \varepsilon_{it}$$

Similarly, three more explanatory variables are added into equation 6.5 by using equation 5.9, 5.11 and 5.13. This modification yields equation 6.7; the revised model for the electronics sector:

$$\text{Equation 6.7 } \ln(\text{PM}/\text{Q})_{it} = \ln(\text{PM}/\text{Q})_{it-1} + \ln(\text{RD}/\text{Q})_{it} + \ln(\text{RD}/\text{Q})_{it-1} + \ln(\text{RD}/\text{Q})_{it-2} + \ln(\text{Q}/\text{L})_{it} + \ln(\text{K}/\text{L})_{it} + \ln(\text{MKTC})_{it} + \ln(\text{DEBTR})_{it} + \ln(\text{AGE})_{it} + \ln(\text{IntraS})_{it} + \ln(\text{InterS})_{eit} + \ln(\text{Absorp})_{eit} + \varepsilon_{it}$$

With reference to sections 5.1.4 and 6.1.4, all variables appearing on both sides of equation 6.6 and 6.7 have already been tested for stationarity. Since equation 6.6 is clearly a direct extension of equation 6.4, $\ln(\text{R\&D intensity})$ is again found as the only non-stationary variable in the model of the automobile sector. Bearing in mind arguments stressed in foregoing stationarity tests, this would not undermine consistency of estimation results.

6.2.2 Empirical results

Regression analyses are conducted on modified empirical models of automobile and electronics sectors; equation 6.6 and 6.7 accordingly. Estimation methods are similar to those discussed and used in section 6.1. New empirical results are shown in table 6.10 and 6.11. In line with earlier analysis in this chapter, ordinary least square and within group effects are presented and used to compare with the two GMM estimation results. Overall, estimation results on most of the independent variables remain unchanged from those in section 6.1.5. The exception is R&D intensity in the current period as the sign on this coefficient changes. Additionally, the appearance of spillovers and absorptive capacity in the model leads to adjustments in the statistical significance of the variable in the two GMM estimation models.

Regarding automotive firms, the foremost change in the results is that for current period R&D intensity. System GMM's R&D intensity at the present period becomes positive and significant at the 5% level with a coefficient value of 0.532. In contrast, the same variable in differenced GMM estimation exhibits negative but still statistical insignificance given its p-value of 0.945. Likewise, lagged profit margin is significant at the 1% level in system GMM estimation whereas it is not in the case of differenced GMM. Labour productivity is found to explain variation in profit margin since its p-value is within 5% and 1% significant level in the differenced GMM and system GMM respectively. Market capitalisation remains with a positive coefficient sign and is significant at the 0.01 level. There is no change in the regression results of capital intensity, firm age and debt ratio. All three variables have negative coefficient signs. However, their respective p-values exceed 10% level of significance, and thus no statistical inference could be claimed for these variables. Both GMM estimations generally share similar results on spillovers and absorptive capacity variables, albeit at different levels of statistical significance. Intra-sectoral spillover is negative and significant at the 1% level for differenced GMM and at the 10% level for system GMM. Differenced GMM inter-sectoral spillovers are positive and significant at the 0.05% level meanwhile in the system GMM this variable is statistically shown to contribute a change in profit margin at the 0.01% level. And last, there is a positive and significant effect of absorptive capacity on profit margin. This is because its estimated p-values of 0.06 and 0.03 are within the 10% level and 5% level correspondingly.

Turning attention towards electronics firms, there are a number of peculiarities among differenced and system GMM estimations. Even though their coefficient signs are positive,

present-period R&D intensity, labour productivity and absorptive capacity are shown to be statistically significant only in the system GMM estimation. Conversely, the differenced GMM estimated debt ratio is shown to exert a negative and significant effect on profit margin whereas the system GMM estimate is not statistically significant at any level. Even so, the two GMM estimations are alike regarding lagged R&D intensities, capital intensity and debt ratio. R&D intensity at t-1 period is significant at 5% level whereas the statistical insignificance of R&D intensity at t-2 period, capital intensity and debt ratio remains unaltered from their prior estimation results. Despite being noted for the difference in coefficient sign across the two GMM estimations, the control variable for age is found to be not relevance to profit margin. Market capitalisation retains its positive coefficient and significance at the 0.01% level. There is a positive coefficient on intra-industry spillover which is significant at the 0.1% level in differenced GMM and at the 0.05% level in system GMM. Inter-industry spillovers contribute to contribute to the variation in profit margin as well, yet its coefficient sign is negative. It is statistically significant at the 0.1% level in both GMM estimations.

6.3 Post-estimation tests

6.3.1 Validity test of instrument variables

One fundamental assumption in GMM estimation is the exogeneity of the instrumental variables, specifically that the instruments are independent of the error term at the past periods, present period and forthcoming periods. The correlation between instrumental variables and the error term can lead to the inadequacy of the estimates (Baum, 2009). In order to investigate this association, the Sargan test (1958) or Hansen test (1982) could be used. This study prefers to use the Hansen test for two reasons. Firstly, the Sargan test can result in as over-rejection of the the null hypothesis in the presence of heteroscedasticity (Arellano and Bond, 1991). In this respect, the earlier pre-estimation test on panel heteroscedasticity in section 6.1.5 appears to clarify that heteroscedasticity is clearly present. Secondly, the Sargan test may not be feasible. Arellano and Bond (1998) point out that the Sargan test based on two-step estimator is heteroscedasticity consistent. However, it is not appropriate under the assumption of robust standard errors. The null hypothesis for the Hansen test is that all instrumental variables used in the estimation are uncorrelated with the disturbance term. To Baum (2009), the rejection of the null hypothesis implies that some

instruments are inappropriately excluded from the model since it may exert a direct influence on the dependent variable.

For differenced and system GMM estimations, the last columns of table 6.10 and 6.11 provide Hansen test results for the automotive, electronics and pooled data respectively. In the automotive and electronics cases, all p-values of both GMM variants' Hansen test exceed the standard 0.05% significance level. This indicates that instrumental variables used in the estimation are adequately effective. In fact, test results on earlier models for electronics sector used in section 6.1 indicate lower p-values in both differenced and system GMMs estimation. From table 6.7, the p-value of the Hansen J test in differenced GMM is 0.098 whereas it is 0.08 for system GMM. The introductions of spillover variables and absorptive capacity essentially lead to more instruments used in the estimation.

As to automobile industry, it can be noted that p-values obtained from the Hansen J test of GMM estimations of the new model (equation 6.4) are lower than those shown in the Hansen test of table 6.6. This suggests that some of additional instruments may be not effectual. However, the decline in p-values in the Hansen J test does not lead to eventual rejection of the null hypothesis of valid instruments. Given the Hansen test's p-values of 0.126 and 0.235 from table 6.10, the null hypothesis of valid instrumental variables is accepted in both GMM estimations. The revised regression model of automobile industry is still reasonably robust.

6.3.2 First-order and second order autocorrelation

Previously, in the pre-estimation test, it was noted that serial correlation exists in the error terms. The detection of such correlation subsequently leads to the use of GMM to estimate the dynamic panel model in this chapter. Lagged values of profit margin, particularly from t-2 period backwards are employed as instrument variables. If the errors from t to t-2 are actually correlated in sequence, the GMM estimator would no longer be consistent. In order to scrutinise the characteristics of autocorrelation in depth, the study conducts autoregression (AR) tests for first-order AR(1) and second order AR(2) serial correlation, proposed by Arellano and Bond (1991). The particular consideration would be the second-order autocorrelation.

Results of AR tests are shown in the second and third to last column of table 6.10 and 6.11. For the automotive industry, the AR(1) test in differenced GMM and system GMM

estimations yield similar outcomes confirming the occurrence of first-order serial correlation. Thereafter, second order serial correlation is proven to be nonexistent because computed p-values of 0.974 and 0.725 are greater than 0.05% significant level. Likewise, the electronics sector results are also noted for the presence of first-order autocorrelation and the absence of subsequent second-order correlation. As a further point, these insights are not different across the two GMM variants. To this end, AR(1) test results are significant at the 1% level meanwhile AR(2) tests denotes p-values that generally exceeding the 5% level.

6.3.3 Comparison between differenced and system GMM

With respect to the estimates of differenced GMM and system GMM across the sectors, it is important to mention that there is divergence in terms of statistical significance and coefficients, particularly in the automotive industry. This sector exhibits apparent dissimilarity in estimated values and signs of the coefficients, in particular, the lagged dependent variable and R&D intensity. Whereas parameter estimates in the electronics sector are also different, the significance of the bulk of independent variables with the exception of current R&D intensity, labour productivity absorptive capacity are similar for the two GMM estimations. Given the variance in results between the two estimators, it is necessary to select a preferred set of estimates from the two presented GMMs. The criterion for such a selection relies upon the estimates of the lagged dependent variable. In the presence of firm-specific effects, OLS tends to provide upwardly biased estimates of the lagged dependent variable, whilst the fixed (within) group effect gives downwardly biased estimates (Blundell et al., 2000). Given these two estimates appear to be biased in different directions, Blundell and Bond (1998) points out that a plausible estimate lies somewhere between them. For Bond (2002), the consistent estimate could also be at least not higher than OLS or lower than the within group estimate. If the differenced GMM estimate on the lagged dependent variable lies close to or below the within group estimate, it could indicate that the differenced GMM suffers downward bias caused by weak instruments (Bond et al., 2001).

In the automotive sector (table 6.10), the coefficient on the lagged profit margin estimated by system GMM is between the within group estimate and OLS, meanwhile the differenced GMM estimated coefficient of 0.107 lies below the within group estimate. Thus, it could be concluded that the system GMM estimate is more effective than differenced GMM. For the electronics sector (table 6.11), it is surprising that the differenced GMM estimate is not only between the within group and OLS estimates, but also somewhat closer

to those of the system GMM estimates. This implies that differenced GMM estimates here do not appear to be seriously biased. Compared to the system GMM estimate of the lagged dependent variable, the differenced GMM estimated coefficient value of 0.375 can still be regarded as nearer to the direction of the within group estimate. Further scrutiny of the Hansen test of instruments in the electronics sector, shown in 6.3.1, reveals that instruments used for differenced GMM estimation are valid, although at slightly lower p-values. Both of these points might contribute to confidence that the system GMM estimator effective in the empirical analysis.

6.4 Discussion

The earlier empirical results reveal that the automotive and electronics industries are in similar in effects of a number of variables on the profitability of the firm. In this context, lagged profit margin, R&D intensity, labour productivity, market capitalisation and absorptive capacity are found to contribute significantly to profit margins in the current period. In addition, the results indicate that capital intensity, the debt ratio or firm age are not relevant to firm profits. Further, spillovers constitute the difference between the two sectors, intra-sectoral spillover in particular. Whilst intra-sectoral spillover exert a weak and negative influence on profitability of automotive firms, its impact is positive to those in the electronics industry.

The significance of the lagged profit margin may require a link between firm profit in each period. In this respect, it suggests that the more profit the firm has accumulated in the past periods, the greater the current profit the firm could achieve. Past profits provide the opportunity to realise profits at current and perhaps future periods. This is due to the fact that previous earnings could be used to re-invest into research and development and these successful outcomes of product and process innovation can subsequently increase future firm profits. Proxied by market capitalisation, firm size shows it does enhance firm profitability. Thereby it is positive and significant, suggesting that bigger firms in both industries appear to be more profitable in comparison with smaller firms. Since the size of firm relates to economies of scope and scale economies, the findings illustrate that larger firms are able to reap benefits from two cost advantages. Firstly, that scale economies allows large firms in both sectors appears to enjoy relative advantage in terms of management, distribution, marketing as well as product development (Pomfret and Shapiro, 1993), and these benefits may result in greater profitability and increased market power. Secondly, according to

Scherer (1980) and Stierwald (2009) that large firm may also access capital at lower cost than their smaller counterparts.

In both industries, the sign of the coefficient on current labour productivity is important. These findings give support to the interpretation that more productive the firm is the more profitability it can achieve. This is most likely due to the high productivity discussed in the previous chapter. Ha et al. (2001) notes that productivity increases has an effects on the way inputs are converted into outputs. As the firm achieves higher productivity level, its average cost of production may be reduced. That is, a greater amount of outputs could be manufactured by using either fewer or the same amount of inputs. Thirdly, there is also higher improvement in the quality of products. The first two productivity gains are essentially related to efficiency in term of production costs which interconnects with profitability. When the productive firm is able to distinguish itself from other competitors by realizing cost related efficiency, it will possess competitive advantage that is reflected in higher profitability. Operation techniques such as just-in-time and total quality control, which have long been implemented in Japanese technology-intensive sectors, could be also considered as factors leading to significant gains in productivity (Lee and Shim, 1995).

Apart from direct investment in technologies, R&D effort also necessitates investment in complementary activities and materials, in order to reach and sustain new profitability levels. However, it should be noted R&D-associated spending will not instantaneously influence firm profits. In the case of electronics firms, the insignificant effect of lagged R&D intensity dated t-2 period may be based on the fact that the return to R&D spending is attainable via the accumulative process of R&D activities. As R&D investment in t-2 period may be at the early stage of new projects, the fruit of such innovative effort at the end of that fiscal year could be still in in the form of prototypes which are unlikely to be commercialized immediately, if at all. Despite being irrelevant to firm performance, the outcomes of R&D efforts during t-2 period would possibly serve as a foundation for further research and refinement of new products in subsequent periods. In fact, the positive and statistically significant R&D intensity dated t-1 and t periods might signify the periods during which the fruits of innovative efforts are gradually developed into new products. Particularly, experimental models pass through a series of trials and are developed into production models in the future. With the successful commercialisation of those new products, firm profitability could be enhanced. In addition, the time gap in the profitability effect of own R&D spending is clearly minimal, indeed, this may be explained by increasingly shorter product life cycles

and by firms' efforts to develop and make new products available to the market at a faster pace. In the spirit of Grabowski and Mueller (1978), the positive profitability effect of R&D intensity also implies that R&D may serve as a source of entry barriers in both industries. R&D gives rise to economies of scale type barriers as R&D investment tends to be costly, uncertain and reliant on particular specialisations in personnel and equipment (Mueller and Tilton, 1969). In agreement with empirical findings on firm size, large firms are able to reach a threshold level of investment critical for R&D to be done proficiently and successfully. In this regard, large firms are able to pursue numerous R&D projects at the same time, allowing them to diversify risk that is not available to small firms with only a small number of projects. These factors may contribute to dissuade entry of small scale operation in industries where variations in R&D expenses and product quality are vital to establish and retain market shares (Phillips, 1966).

The negative sign on the debt ratio coefficient is also reported by Lee and Shim (1995) who stress that high debt could prevent companies from raising additional funds for inventive projects and the company could be left less competitive in the long-run. Owing to the absence of a debt ratio effect, it is determined that the use of debt as a source of finance does not exert influence on the firm future earnings. Firms; profitable and loss-making alike, have access to debt financing with relative ease, although at different costs. Generally, it may also imply that equity capital has steadily become the second source of financing in Japan. Firms may prefer either internal funds or equity capital to finance investments such as production plant expansions and marketing campaigns. Years in business does not bring about the tendency to be more profitable. In other words, a firm's amassed experiences and reputation through time do not guarantee earning capability. In the same market environment, it may be that younger or fledging firms could profitably outperform their larger counterparts. A potential interpretation here has its root in products that firms offered. Age does not necessarily entail strengthening the attractiveness of a firm's product to be successfully sold in the marketplace. Indeed, high technologies or innovative products that are consistent with customer preferences may be also presented by younger firms in the market.

An upsurge in capital intensity is often termed capital deepening. Positive variations in capital deepening typically either lead to the creation of new products or cost reduction and increase profits above normal levels (Dompere and Ejaz, 1995). The presence of capital requirements could form an entry constraint, especially in the electronics industry. This is because the electronics industry is generally regarded as having high R&D expenditures and

the necessary capital intensity. Ernst and O'Connor (1992) state that these characteristics constitute entry barriers in terms of production related scale economies and intangible investments. For example, the semiconductor section would require substantial fixed outlays in both research and capital equipment before production can begin. These fixed investments are increasing as new generation products are consistently being introduced. Additionally, threshold barriers may also relate to the application of technological knowledge for product development within the firm. On the other hand, estimated capital intensity is not positive and extraneous for firm profitability in both industries. An interpretation of the negative coefficient could arise from the view that capital deepening undoubtedly heightens costs during the present period, suggesting that profitability is currently hindered. In addition, given the clear association between capital deepening and production activities, it is probable that the monetary return on such a rise in fixed capital per labour hour may not be realisable within the same time period.

The negative coefficient on capital intensity can also be explained from the framework of neo classical theory of demand for capital (Harris, 1978). According to Harris, the marginal product of capital and labour input are considered as respectively equal to the rate of profit and the wage rate. The ratio between those two marginal products generates capital intensity which could be expressed as a wage-profit ratio. With the assumption that full employment equilibrium under competitive conditions is maintained, any change in one ratio would be remunerated by the contemporaneous variation in one another ratio. Thus, an increase in the wage-profit ratio thus requires a comparable level of capital deepening. Given diminishing returns in production (Sullivan and Sheffrin, 2007), capital deepening would be a consequence of a rise in the marginal product of labour input and a reduction in the marginal product of capital. Simultaneously, such an enhancement in capital intensity would be met by a rise in the wage and falling profits. While the effect of capital intensity reduces profit in the automotive firms, this can be explained by long term intra-firm trade transactions within the automobile sector. In the light of yen appreciation and high corporate taxation, there has been transference of production activities to international subsidies where production costs are relatively lower. Vehicle and components manufactured abroad are frequently re-exported back to sell and distribute into the domestic market.

Findings regarding the profitability effects of spillovers and absorptive capacity clearly echo preceding findings in chapter 5. In fact, electronics firms could not entirely reap the benefits of their own inventions or technical knowledge owing to a certain degree of

inappropriability. It should be borne in mind that technological dissemination from the electronics sector into the automobile sector are likely take place via cross-sectoral research collaboration and purchase of electronics sector's intermediate goods to use in the automotive sector's finished products. In the case of the latter inter-sectoral spillovers channel, it is to the advantage of consumers in downstream industries such as those of automotive companies who are able to purchase inputs and components incorporating new electronics technology at a price typically less than the original costs of development of such new technologies. The availability of intra-sectoral externalities does not enhance profitability of automobile firms. However, on the contrary, the larger the presence of other automobile firms' discoveries, the lower the profitability of an individual automobile firm. This result supports those of Jaffe (1986) and Zantout and Tsetsekos (1994) that prospective profits from innovation could be competed away by rivals conducting research in closely related technological fields. Automobile firms' own R&D activity may to some extent benefit from available pools of quasi-public knowledge originated and circulated within that sector. Even so it is likely that the negative effect of rivalry overwhelms the positive effect of such intra-automobile sector externalities as the competition within the marketplace could give rise to the possibility of rivals imitating the results of inventive efforts and maximising their own profits at the expense of innovating firms and other rivals (Hanel and St. Pierre, 2002). Further, the degree of appropriability within the sector may determine the relationship between intra-sectoral externalities and firm profitability. As reported by Megna and Klock (1993), rivals' patents negatively affect profitability of an individual firm. Although this research differs from the existing literature regarding the primary interest on R&D investment, the negative coefficient on intra-sectoral spillovers may suggest that elements of research capital are appropriable in the automobile sector. When competitors are granted patents on designs of unique vehicle technologies, other companies are henceforth not permitted to access those technological discoveries without license agreements. In practice, those rivals would have a temporary advantage in the market to capture profits from their own discoveries until such inventions become outdated or other companies can response with comparable technologies of their own.

Similar to the findings in the previous chapter, the spillover effect in the electronics sector appears to be a contradictory to that in the automobile sector. Again, it could be stressed that automotive technologies might not be relevant and noteworthy to new products and inventions made by those in the electronics companies. To a degree, this argument could

be reinforced by the estimation results of inter-industry spillovers which reports somehow weak statistical significance with its respective p-value very close to the 10% level. For instance, it is expected that computer and electronics appliance makers would not apply technologies originally created in the automotive sector such as anti-lock braking systems (ABS) for the development of semiconductors, data storage and advanced instruments. As automobile indigenous technologies could be considered as distinct from electronics counterparts, electronics companies are unlikely to find feasible cross-sectoral technological discoveries in their processes to create innovative and improved goods. In the context of adjustment cost, using automotive technologies not only potentially results in futile research outcomes, but could as well substantiate a financial burden that undermines firm profitability. Further, the established role of electronics firms as manufacturers and supplier of components to automobile makers might imply another source of adjustment costs. Electronics firms have to adapt to new automobile technologies which their automobile firm customers aim to incorporate into their vehicles or parts. This process of adjustment and learning is subject to financial costs to the firm in short run.

The positive effect of intra-industry spillovers in electronics is significantly different from zero. As an elasticity, its coefficient implies that while all firms in the same electronics sector enhance their R&D by 10%, an electronics firm could attain 13.58% more profit with the same amount of fixed capital or hours worked. To some extent, there may be as well negative effects of the intra-sectoral pool of spillovers stemming from competition since a number of electronics companies tend to manufacture and compete in similar products. However, the positive coefficient on intra-sectoral spillovers can signify that such competitive elements are helped by the positive effect of being comparatively technologically intensive when others also engage in research activities. In an environment which characterises the electronics sector in general, firms with little awareness of R&D effort are likely to face a decline in profits whereas firms with either average or high R&D budgets would be able to reap the net positive effect of others' R&D (Jaffe, 1986).

Turning to the absorptive capacity effects, the interaction between the firm' own R&D effort and the total research externalities available to it constitutes important effects. Empirical results indicate that an extra percentage of absorptive capacity build-up is associated, on average, with a 0.52% rise in automobile firm profits and a 1.036% increase in the profitability of electronics firms. This finding could be interpreted that profitability of own R&D investment is determined by the potential pool of spillovers meanwhile the effect

of technological externalities upon profitability relies on the degree of R&D effort internally made by the firm itself. As the positive sign on absorptive capacity suggests the overall complementarity between internal R&D and external R&D, it could be noted that weak negative effects of intra-industry spillovers in automobile and of inter-industry spillovers in electronics discussed above are seemingly contradictory. Technologically intensive firms such as those in the automobile and electronics sectors might be able to garner net benefit from technological spillovers (Jaffe, 1989), particularly when such benefit is net of competitive disadvantages such as high R&D contemporaries in the case of automobile firms.

6.5 Conclusion

This chapter investigates the relationship between R&D and another firm performance measure; profitability. The specification of the dynamic model clearly set the analysis in this chapter apart from that in the previous chapter, including a different criteria regarding lag selection of R&D intensity. Nonetheless, this chapter is in accord with the preceding chapter for comprising of two consecutive parts where the second half notably highlights the effects of spillovers and technological absorptive capacity. As with the earlier empirical chapter, automobile, electronics and pooled data are given separate model specifications based on the distinction in their own R&D variable' lag structure. Whilst it has been shown that pooled data and the electronics sector should be examined by using a model having slightly more lagged R&D intensity variables than that of the automobile firms, the poolability test at the end of the first main section prove it is inappropriate to pool the data of both industries and empirically analyse by using common regression model. In this context, the ensuing interpretation and discussion of evidences are limited to the two individual industries.

As with the earlier empirical chapter, the control variable of size constitutes a positive impact on the profitability of the firm. Additional variables taking into account leverage and age are found to exert no influence on firm profitability as the data leads to the hypothesis that these two independent variables are zero in both industries' respective empirical models should be accepted. The current labour productivity variable clearly has a significant impact on profitability. It is apparent that the improvement in labour productivity shows hardly any lag in its positive impact upon the profitability of the firm. The evidence on firm own R&D effort in electronics firms affirm the notion that an upsurge in R&D investment does not constitute a straightforward and immediate effect on the monetary aspect of firm performance. In this regard, internal R&D variables are reported to be positive but not all are

statistically significant. While R&D activity necessitates successive processes, this does not mean that investment made in every period contributes to profit enhancement. While a firm undertakes R&D, it may have to successively invest in related assets and materials, both tangible and intangible, in order to enhance its research capability and reach its objective of inventive projects. This increased investment entailed during the process of R&D effort may be perceived as a cost or is irrelevant to profit of the firm in the following periods since cumulative investment may be lead to higher rates of return and individual investment.

Evidence regarding spillovers and absorptive capacity are similar to those reported in the previous chapter. Thus, spillover variables with negative coefficients exhibit rather weak statistical significance with their respective p-values close to exceeding the 10% level. It is expected that the findings on the impact of automotive technologies on profitability of electronics companies may not be clear. As to the automobile firm results, an argument on probable competitive or a negative effect of other auto firms' innovative activities could continue to surface. Findings on absorptive capacity suggest the positive interrelation between the amount of own R&D and the overall pool of research externalities. The effectiveness and profitability of others' R&D potentially applied by a firm is determined by the magnitude of its own R&D effort.

Chapter 7: The direction of the R&D-profitability relationship

Introduction

This chapter follows up on the insights gained from the earlier empirical chapters which find that innovative activity of the firm generally is constructed as a positive but lagged effect on production efficiency and profitability. In an effort to investigate the bi-directional relationship between own R&D and firm performance, the impact of profitability on a firm's R&D investment is examined. Similar to the previous chapter, the panel-data regression is a linear model with R&D intensity as the dependent variable. The chapter uses dynamic panel data regression models to test the hypothesis of possible reverse-causality from gains in profit to R&D activity. Thus, the linear model is designed with R&D as the dependent variable which is determined by a set of independent variables including profit margin. Then, methodology issues are explained in detail and followed by four pre-estimation tests. Similar to the preceding chapter, tests of unit-root, heteroscedasticity and serial-correlation are conducted. From then on, the chapter moves forward to present the empirical results divided into the two separate industries and combined using pooled data. Results of differenced GMM and system GMM are shown and compared by using results from ordinary least square and fixed effects models as benchmarks. Thus, the results of system GMM estimation is selected and discussed. Post estimation tests on the validity of the instrumental variables and types of autocorrelation prove that there is the instrumental variables are the presence of second order autocorrelation.

7.1 Analytical model

7.1.1 Specification of model

A variable that has been used as a prominent determinant of R&D investment in this and other studies is firm size. Despite reflecting capacity of a firm to undertake R&D, the role of firm size in influencing R&D has been established in various ways. In the assumption of Schumpeter (1934), large firms tend to possess advantages in R&D activities owing to their capability to spread costs on long production runs and the complementary between R&D and other firm activities. In other words, large firms can spread considerable fixed costs over large sales volume (Galbraith, 1952). Being better endowed, larger firms tend to undertake R&D activities and invest more on R&D (Schumpeter, 1950). Another factor is the imperfection in capital markets which render the possibility of getting external financial

sources to fund R&D activities difficult, especially for small firms. Large firms, in contrast, are more likely to be able to fund their R&D by using their own internal financial means. In this respect, large firms can use their resources to establish R&D laboratories as well as employing skilled researchers and engineering personnel (Mishra, 2007). A number of studies support Schumpeter's hypothesis of firm size and technological efforts (Horowitz, 1962; Scherer, 1965b; Rosenberg, 1974). A study by Doi (1994) on firm size and R&D activity in Japanese manufacturing industries demonstrates that generally R&D activity in Japanese firms is positively interrelated to firm size. Nonetheless, the literature focusing on the relationship between firm size and R&D outlay do not appear to confirm large firms' advantage hypothesis with respect to R&D and the share of industrial R&D over smaller firms. However, Acs and Audretsch (1990) and Gustavsson and Poldahl (2003) found that small firms tend to account for a disproportionately large share of innovations. In fact, it appears that a substantial number of small firms, particularly in high-technology sectors, engaged in innovative activity (Acs and Audretsch, 1993 and Kleinknecht, 1989). Mahlich and Roediger-Schluga (2006) find that a pivotal external source of finance available to small and young companies comes from venture capital. Extending the previous chapter, the study continues to use market capitalisation to proxy firm size. Although other studies used either value of sales or assets as a firm size variable, both variables appear to be mathematically close to other explanatory variables in this study such as profitability and capital intensity and are thus not suitable.

Financial-related variables are thought to affect not only a firm's R&D but also other capital investment because of asymmetric information in capital markets (Fazzari and Athey, 1987). In this regression analysis, two variables are incorporated as independent variables. The first financial variable is profit margin as a proxy for profitability which is of particular interest in this chapter. Thus, the profitability measure is regarded in the existing literature as being linked to R&D spending through its role as a source of internal funding. By virtue of this fact, research and development is associated with risk and uncertainty, particularly during the period when the outcome and time span of the innovation is unknown. As a result, technological investment tends to require extensive and long-standing financial support (Gilpin, 1975 and Nelson and Winter, 1977). Since an external funding source may be difficult to acquire, generated profit is crucial for maintaining R&D programmes conducted within the firm. To Grabowski (1968), this leads to the deliberation of profitability as an indicator of a firm's internal liquidity or cash flow. It could also be perceived as an indicator

of competition (Gustavsson and Poldahl, 2003). The second financial variable is the debt ratio, as included in the work of Natasha and Hutagaol (2009) and Yang et al. (2010) as an independent variable that also impacts firm profit through its effect on R&D activities. The high level of debt incurred by the firm could restrict funds available for supporting R&D projects and new product development in order to maintain the firm's competitiveness in the long run (Hokkanen, 2006).

Capital intensity interrelates with research and development effort since technological innovation is embodied in new machinery. As shown by Aghion and Howitt (1999), the introduction of capital assets in intermediate production leads to a positive correlation between capital intensity and innovation. Scherer (1980) and Van Dijk et al. (1997) note that capital intensity can also signify barriers to entry in the industry owing to the link between the scale of production and innovation. As an indicator of scale economies, capital intensity in certain parts of a firm's operation may influence innovation by providing scope economies for R&D (Galbraith, 1952). For an industry characterized by high capital requirements, it is probable that the share of intra-industry research and development would be higher for large firms than for small firms since new and small firms are hampered from entering the marketplace (Mansfield et al., 1977 and Rothwell and Dodgson, 1994). The age of the firm is another variable included in the model as an explanatory variable. It represents the stock of technological knowledge accumulated through a series of R&D expenses. In this respect, the firm that started earlier in their innovative activities may attain comparative advantage over others. In other words, a long established firm could have larger amounts of knowledge capital stocks, more experienced research personnel and better R&D facilities and infrastructure, compared to a new firm (Lee, 2003 and Mishra, 2007).

Owing to the nature of R&D activity that requires a long-term strategy, it is probable that there might be time lags between R&D investment and its determinants (Lee and Hwang, 2003). Similarly, short term profit alone may not be the only determinant of R&D investment. Following the approach of Ito and Pucik (1993) and Gomez –Mejia and Palich (1997), the cross-sectional study of Archarungroj and Hoshino (1999), preliminary tests for the lagged effects of profitability variables first defined R&D at a specific year as a basis for calculation. Then, they regress R&D in the year base year on profitability with different lagged periods in order to determine the regression that indicates the best fit (better R² value). This study includes lagged R&D intensity (t-1) as an independent variable, which allows for feedback from past R&D effort to the current value of the dependent variable;

R&D intensity at t period. The presence of lagged R&D intensity results in the dynamic econometric model in this chapter. Thus, the benefits of dynamic modeling in this regression model include accounting for autocorrelation in the residuals as well as remedying the potential spurious regression (Eigner, 2009).

The regression model is linear with an autoregressive distributed lag (ARDL) and R&D intensity at t-1 period enters the model as a lagged dependent variable as follows:

$$\text{Equation 7.1 } (RD/Q)_{it} = (RD/Q)_{it-1} + (P/Q)_{it} + (K/L)_{it} + MKTC_{it} + DEBTR_{it} + AGE_{it} + \varepsilon_{it}$$

Then taking natural logarithms,

$$\text{Equation 7.2 } \ln(RD/Q)_{it} = \ln(RD/Q)_{it-1} + \ln(P/Q)_{it} + \ln(K/L)_{it} + \ln MKTC_{it} + \ln DEBTR_{it} + \ln AGE_{it} + \varepsilon_{it}$$

7.1.2 Methodology

The model in the preceding sub-section is similar to the dynamic panel data model used in chapter 6, with both models featuring a lagged dependent variable. Likewise, lagged R&D intensity dated t-1 period is highly likely to correlate with error terms. The use of OLS and within group effect estimators would probably lead to biased and inconsistent estimates. Given the statistical issues raised in the previous chapter, this analysis uses a general moment methods (GMM) framework to investigate the effect of profit on R&D intensity. Again, the favored GMM variant is system GMM whose comparison would be made in relation with differenced GMM and two aforementioned traditional panel estimators.

7.1.3 Stationarity test

All variables in the regression model (equation 7.2) have been already examined regarding their stationarity in sections 5.1.4 and 6.1.4 of the earlier empirical chapters. For both separated industries and pooled data, it has been illustrated in table 6.2 that profit margin, market capitalisation, capital intensity, the debt ratio and firm age have no unit-root in their series. For the electronics firms and the pooled data, all variables are stationary since both ADF and PP tests variants indicate 1% statistical significance. In the automobile data, table 5.2 suggests that the null hypothesis of unit root in R&D intensity is accepted as its respective test results also show similar results as lesser t-statistics than critical t-value. Despite being the dependent variable in the regression, the automotive firms' R&D intensity dated t-period is the only variable that has a unit root in its data-series. As in the previous

chapters, it is noted that non-stationarity of present-period R&D intensity of automobile data does not contribute to likely spurious estimation results.

7.1.4 Tests for heteroscedasticity and autocorrelation

As in the two preceding chapters, heteroscedasticity and autocorrelation are investigated to determine and deal with econometric issues if required. The results in table 7.1 clearly indicate the existence of heteroscedasticity in the panel data of both sectors and of the pooled data as the likelihood ratio chi-square values exceed the critical values. Equally, the statistical significance at the 1% level leads to rejection of the null hypothesis of equal variance. In the autocorrelation test in table 7.2, the null hypothesis of no serial correlation in the error terms is not accepted for all cases since the F-statistics are shown to be larger than the critical F-values at the 1% level. This leads to the acceptance of the alternative hypothesis that error terms are consecutively interconnected, this may be explained by the occurrence of lagged dependent variable; $\ln(\text{RD}/\text{Q})$ at $t-1$ period on the right hand side of the equation.

7.1.5 Detection of individual specific effects

As in chapter 6, the use of GMM is justified because of the occurrence of firm fixed-effect in the dynamic panel data model. Thus, an incremental F-test was used as explained in Chapter 6. In table 7.3, data from both the automotive and electronics industries and the pooled data demonstrate F-statistics at 14.63, 15.6 and 22.05 on an individual basis, with all significant at the 1% level. Therefore, it is clearly established that the dynamic panel data model is similar to the fixed effects, which means that the traditional OLS estimator would be inappropriate as it omits the effect of individual-firm specific factors from the regression model.

Table 7.1: Pre estimation test for heteroscedasticity in panel data			
	Automotive Industry	Electronics industry	Pooled data
Likelihood ratio test	645.01***	1481.74***	2163.88***
***1% significant level			

Table 7.2: Pre-estimation test for autocorrelation in panel data			
	Automotive Industry	Electronics industry	Pooled data
F-statistics	63.856***	60.035***	81.254***
P-values	0.000	0.000	0.000
*** 1% significant level			

Table 7.3: Pre-estimation test - Incremental F-test for fixed effects			
	Automotive industry	Electronics industry	Pooled data
F-statistics	14.63***	15.6***	22.05***
P-values	0.000	0.000	0.000
***1% significant level			

Table 7.4: Estimation of autoregressive distributed lag model of determinants of R&D intensity (Automotive industry)				
Dependent variable: Ln(R&D intensity)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	-0.405 (0.069)*	-1.662 (0.077)*	-0.328 (0.717)	-0.442 (0.821)
Ln(R&D intensity) at t-1 period	0.982 (0.000)***	0.487 (0.000)***	0.488 (0.000)***	0.879 (0.000)***
Ln(Profit margin)	0.006 (0.724)	-0.021 (0.414)	-0.016 (0.602)	-0.033 (0.332)
Ln(Capital intensity)	-0.056 (0.156)	-0.012 (0.914)	0.053 (0.633)	0.011 (0.965)
Ln(Market Capitalisation)	0.012 (0.157)	-0.028 (0.39)	-0.034 (0.321)	-0.034 (0.547)
Ln(Debt Ratio)	-0.01 (0.826)	-0.315 (0.027)**	-0.364 (0.011)**	-0.437 (0.017)**
Ln(Firm Age)	0.001 (0.945)	-0.145 (0.419)	-0.38 (0.049)**	0.007 (0.975)
R-Square	0.953	0.2784	-	-
No. of observations	568	580	449	580
No. of firms	89	89	87	89
Test for first order autocorrelation in first-differenced errors	-	-	-3.22 (0.0013)***	-3.712 (0.0002)***
Test for second order autocorrelation in first-differenced errors	-	-	1.141 (0.2538)	1.251 (0.211)
Hansen J-Statistics	-	-	42.358 (0.183)	52.37 (0.181)
* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses				

Table 7.5: Estimation of autoregressive distributed lag model of determinants of R&D intensity (Electronics industry)

Dependent variable: Ln(R&D intensity)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	-0.621 (0.000)***	-1.448 (0.047)**	-1.659 (0.017)**	-1.378 (0.061)*
Ln(R&D intensity) at t-1 period	0.907 (0.000)***	0.442 (0.000)***	0.373 (0.000)***	0.574 (0.000)***
Ln(Profit margin)	0.014 (0.266)	-0.006 (0.688)	-0.056 (0.001)***	-0.05 (0.007)***
Ln(Capital intensity)	-0.006 (0.676)	-0.047 (0.538)	0.025 (0.727)	0.184 (0.426)
Ln(Market Capitalisation)	-0.0005 (0.94)	-0.015 (0.652)	-0.041 (0.176)	-0.041 (0.253)
Ln(Debt Ratio)	-0.086 (0.000)***	-0.099 (0.255)	-0.05 (0.04)**	-0.09 (0.082)*
Ln(Firm Age)	0.043 (0.018)**	-0.213 (0.091)*	-0.121 (0.354)	0.006 (0.961)
R-Square	0.8661	0.2231	-	-
No. of observations	1448	1448	1088	1448
No. of firms	235	235	230	235
Test for first order autocorrelation in first-differenced errors	-	-	-2.806 (0.005)***	-3.428 (0.000)***
Test for second order autocorrelation in first-differenced errors	-	-	1.29 (0.1972)	1.51 (0.132)
Hansen J-Statistics	-	-	36.115 (0.416)	49.58 (0.227)

* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses

Table 7.6: Estimation of autoregressive distributed lag model of determinants of R&D intensity (Pooled data)

Dependent variable: Ln(R&D intensity)	Ordinary least square model	Fixed effects (Within) model	Differenced GMM	System GMM
Constant	-0.582 (0.000)***	-1.54 (0.013)**	-1.702 (0.009)***	-1.252 (0.076)*
Ln(R&D intensity) at t-1 period	0.934 (0.000)***	0.45 (0.000)***	0.449 (0.000)***	0.701 (0.000)***
Ln(Profit margin)	0.012 (0.254)	-0.009 (0.478)	-0.05 (0.000)***	-0.049 (0.002)***
Ln(Capital intensity)	-0.015 (0.289)	-0.046 (0.508)	0.04 (0.54)	0.162 (0.395)
Ln(Market Capitalisation)	0.007 (0.199)	-0.015 (0.533)	-0.025 (0.278)	-0.03 (0.269)
Ln(Debt Ratio)	-0.072 (0.000)***	-0.118 (0.135)	-0.142 (0.062)*	-0.169 (0.092)*
Ln(Firm Age)	0.034 (0.018)**	-0.201 (0.067)*	-0.147 (0.227)	-0.001 (0.992)
R-Square	0.9027	0.2312	-	-
No. of observations	2028	2028	1537	2028
No. of firms	324	324	317	324
Test for first order autocorrelation in first-differenced errors	-	-	-3.427 (0.001)***	-4.192 (0.000)***
Test for second order autocorrelation in first-differenced errors	-	-	1.67 (0.095)	1.836 (0.066)
Hansen J-Statistics	-	-	35.673 (0.437)	44.38 (0.221)

* 10% significant level; **5% significant level; ***1% significant level; p-value in parentheses

7.2 Empirical results

With all variables in natural logarithm form, the study regresses lagged R&D intensity, profit margin, capital intensity, market capitalisation, debt ratio and firm age on current R&D intensity. For the automotive and electronics sectors, and the pooled data, Table 7.4, 7.5 and 7.6 correspondingly present the regression results to examine factors affecting R&D investment with particular attention given to productivity. Coefficient values from all estimation are essentially the elasticity of R&D intensity with respect to each of independent variables. Estimators used comprise ordinary least square (OLS), fixed (within) effect, differenced GMM and system GMM. Each table provides a comparison of the results of the differenced GMM and system GMM estimators. While the results from the first two estimators are not described in detail, they are used as points of reference for the consistent estimators which would be selected out of those two GMM estimators. In addition, post-estimation tests, namely Hansen test and Arellano-Bond test for serial-correlation, are also shown to further clarify the specification issues.

7.2.1 Automotive firms

At the 1% significance level, R&D intensity at the earlier t-1 period is found to be positive and significant to current R&D intensity. Its coefficient values are 0.488 and 0.879 for those of differenced GMM and system GMM estimation accordingly. In both differenced and system GMM estimations, coefficients are negative and nearly identical. However, current profit margin is not statistically significant with respect to R&D intensity. Specifically, its p-values of 0.602 and 0.332 in two respective GMM estimation clearly exceed the 10% significant level.

Capital intensity and market capitalisation have a positive and negative coefficient, respectively. However, both are not significantly different from zero and therefore were not found to have any impact on R&D intensity. As for the age of firms, there are contrasting results between the two GMM estimators. In differenced GMM, firm age is significant at the 5% level to R&D intensity with a negative effect. This implies that younger firms tend to spend a relatively higher fraction of R&D investment to operating turnover. On the other hand, system GMM also estimates a negative coefficient on firm age but is not significant.

The debt ratio has a negative and significant effect on R&D intensity in both GMM estimations, albeit at a different statistical significant level. With a coefficient of -0.364 and

p-value of 0.011, the debt ratio in differenced GMM is clearly significant within the 5% level. But, while showing having a higher coefficient of -0.437 and p-value of 0.017, system GMM results also indicate the significance of the debt ratio at the 5% level.

7.2.2 Electronics firms

In this subsample there is a convergence between the two GMM estimation results. Both GMM estimations indicate that lagged R&D intensity positively explains variation in the current level of research intensification of the firm with coefficient values of 0.373 and 0.574 respectively. The p-value of 0.000 is well below the 1% significant level. Both differenced and system GMM estimations results in a positive coefficient sign and significance of electronics on the profitability measure. For profit margin, both GMM estimators result in significant coefficients at the 1% level as respective p-values are 0.001 and 0.007 correspondingly. Furthermore, both GMM estimations report positive and similar coefficient values at -0.056 and -0.05.

The results for capital intensity are also similar between the two GMM estimators. With a p-value of 0.727, capital intensity is found to be a positive but insignificant influence on R&D intensity in the case of standard differenced GMM estimator and also in the system GMM estimation, where the p-value of 0.426 is beyond that required at the 10% significant level. Hence, it no influence is found for this variable. Further, the same is true for market capitalisation and firm age. Even though the signs and coefficients values are dissimilar between the two GMM estimation results, both are statistically insignificant. Finally, the debt ratio from differenced GMM is negative and significant at the 0.05% level it has a much weaker impact using system GMM estimates, where it is only significant at the 10% level. The GMM estimations, coefficient values of debt ratio are -0.05 and -0.09 respectively.

7.2.3 Pooled data

When considering the total sample the results are different. R&D intensity at t-1 period has a significant impact on current R&D intensity in both GMM estimations. With p-values of 0.000, lagged R&D intensity is statistically significant at the 1% level for both differenced and system GMM estimates. Lagged R&D intensity's coefficient of 0.701 is higher in system GMM estimation, compared with 0.449 in differenced GMM. Differenced and system GMM estimators both illustrate that current profit margin has a significant and negative impact on R&D intensity at the 0.01% level, with p-values of 0.000 and 0.002

respectively. Also, the estimated coefficient is slightly higher in differenced GMM than in system GMM.

There are different signs on the coefficients for capital intensity, also neither the system nor differenced GMM estimates result in a statistically significant relationship. Likewise, market capitalisation and firm age are clearly not a significant influence on R&D intensity since their corresponding p-values in both GMM estimations are greater than the 10% critical value. These results are in line with separate industries. The two GMM estimations provide similar coefficient value for the debt ratio with system GMM being slightly higher at -0.169.

7.3 Post-estimation tests

7.3.1 Validity test of instrument variables

For the two GMM estimations, Hansen test results are shown in the last column of tables 7.4, 7.5 and 7.6. In differenced GMM, p-values for automotive industry, electronics industry and pooled data are 0.183, 0.416 and 0.437 respectively and in system GMM, p-values are 0.181, 0.227 and 0.221. Results from both differenced and system GMM indicate that computed p-values exceed the standard 0.05% significant level. As a result, the null hypothesis is accepted and these instruments are jointly valid and thus the GMM estimates are meaningful.

7.3.2 First-order and second order autocorrelation

As in the previous chapter, autoregressive (AR) tests are conducted to ensure there is no second-order serial correlation in the error terms. For two separate industries and the pooled data the results of AR(1) and AR(2) tests are presented in tables 7.4, 7.5 and 7.6 with the critical value at the standard 0.05% significance level. Regarding differenced GMM, the automotive and electronics sectors and the pooled data show the existence of first-order autocorrelation in the disturbance terms as their respective p-values of 0.0013, 0.005 and 0.001 are less than the 0.05% level. Second order autocorrelation is found to be absent in all three cases. For system GMM, all three cases demonstrate no second order serial-correlation with p-values of 0.211, 0.132 and 0.066, all clearly above the standard 5% significant level.

7.3.3 Comparison between differenced and system GMM

As illustrated in each individual industry and the pooled data cases, differenced and system GMM appear to provide different estimation results in both parameter value and statistical significance for some variables. It is of important to determine which GMM estimates are preferred in the interpretation of results. Thus, the study follows the previous sub-section 6.3.3 on the criteria, which is based on the estimates of the lagged dependent variable across four estimators. In this respect, the consistent GMM estimate is supposed to have a coefficient value on R&D intensity at t-1 period between within group and OLS estimates. With the estimated coefficients on lagged R&D intensity (Ln(R&D intensity)) dated t-1 period) in table 7.4, 7.5 and 7.6, it is apparent that the system GMM estimates are between OLS and within estimates for both industries and pooled data. On the other hand, lagged R&D intensity estimated by differenced GMM of the electronics data is significantly lower than within group estimates. Likewise, the automotive and pooled data differenced GMM estimate for this coefficient is very close to that of the corresponding within group estimate. Thus, it could be noted that differenced GMM estimates encounter bias in the direction of within-group parameter estimates and are considered therefore less effective.

7.3.4 Poolability test

Table 7.7: Post-estimation test of poolability	
F-statistics	P-values
15.78***	0.000
***1% significant level	

Parallel regression results in table 7.4 and 7.5 show the estimated coefficients of the exogenous variables are dissimilar for the automotive and electronics sectors between estimators. Although the same dynamic panel regression model is used, the comparison reveals the differences between two industries. Some variables are found to be statistically significant in one industry whilst not in the other industry. Also, the sign of some coefficients differ. To some extent, these facts point towards the likelihood that the two industries used in this chapter should not be pooled. To test this further a Chow test was applied to investigate the poolability of the independent variables in the model. The null hypothesis is that coefficient parameters of all explanatory variables are identical across automotive and electronics industry, the results are shown in table 7.7. The F-statistics suggest that at the 1%

significance level this should be rejected and thus the panel data is not poolable with respect to these two industries.

In summary, the Hansen *j* test clarifies the rationality of instrumental variables used in both GMM estimations. Further tests to identify the pattern of autocorrelation shows the presence of first order autocorrelation in the error terms for both industries. Second-order serial correlation is not found in all cases, and this hence validates the instrumentation of lagged variables of *t*-2 period and more. Using OLS and within group estimations as points of reference, the study compares differenced and system GMM estimations and finds that differenced GMM estimation is shown to be biased and inconsistent since it bears a close resemblance to the within-group estimates. Therefore, results from system GMM are regarded as the parameter estimates of choice for ensuing discussions. Finally, poolability tests confirms that pooled data regression results does not represent the mutual results of both the automotive and electronics sub-samples.

7.4 Discussion

A negative effect of the debt ratio with respect to total assets suggests that debt outstanding exerts a constraint upon R&D activities of these firms. It also implies that firms in both industries rely substantially on borrowed funds to carry out their R&D investment. To Allen and Gale (2000), a major source of external finance is from relational debt loaned by banks. Japanese firms are characterised by the long-standing interoperate ties with banks with considerable emphasis on implicit contracts (Abegglen & Stalk, 1985; Gerlach, 1992). In fact, Hoshi et al. (2001) explain that firms with a close association with banks appear to be relatively less sensitive to liquidity. This external debt allows Japanese firms to access relatively cheap and long term external funds (Mahlich and Roediger-Schluga, 2006). Another funding source is transactional debt, defined as the issue of bonds and equities, and this type of debt became readily accessible owing to the financial deregulation during 1980s (Hoshi and Kashyap, 2001). Severe debt-deflation originally took place during the 1990s and damaged those manufacturing firms with stringent financial constraints. Ogawa (2004) states that the average debt-asset ratio in large manufacturing firms declined throughout the 1990s but there remained a considerable number of firms with substantial debt outstanding. The findings in this chapter complement Ogawa (2004) and it should be noted that the impact of these massive debt burden has still continued into the 2000s. The negative impact of debt on R&D intensity could result in two possible consequences, as pointed out by Long and

Ravenscraft (1993). Firstly, management may be discouraged from investing in further R&D, which incurs negative present-value of projects and secondly there is a tendency to shelve or cancel ongoing R&D projects.

The lagged dependent variable, R&D intensity t-1 period, positively affects the current R&D intensity. Echoing the previous findings in chapters, the impact of lagged R&D intensity appears to be larger for the automotive sector than the electronics sector. As with inferences made in the previous chapter, the greater effect of lagged R&D intensity could originate from the spillovers of knowledge and technological innovation, both within other automotive firms and from other manufacturing sectors including the electronics industry. The significance of R&D investment in the earlier periods upon the firm's current R&D effort might be due to the fact that an R&D project ordinarily requires consecutive efforts and flows of investment. Development of new-generation products or advanced technologies could not be accomplished within a single time period. The efforts in preceding R&D activities are thus vital for subsequent R&D to proceed.

Age and size of firm are not important to a firm's R&D effort in these data, shown by the lack of statistical significance of firm age and market capitalisation in the regression. These findings suggest that old and/or large companies do not possess advantages over smaller counterparts in conducting research and development activities. This does not support the assumption of Schumpeter (1950) on large firm advantage in these industries. Likewise, the results does do not suggest that small and newer firms have a tendency to invest in R&D at a relatively higher proportion. This is a contrast to the existing literature (Lee, 2003; Shefer and Frenkel, 2005) who demonstrate that smaller and newer firms engage in technological development more than larger and long established ones. Another insight gained from the results is that old firms which supposedly have more experience in R&D activities and a larger pool of knowledge and technical capital stocks are more or less on the par with smaller firms in the same sector, with respect to R&D intensity. An explanation could be drawn from the fact that there is growing tendency to outsource R&D activities in manufacturing sectors. In addition, joint research collaboration between big corporations and those of their affiliates is noted. Particularly, Japanese carmakers purchase a substantial amount of component parts from international partners to use in their production. Japanese domestic producers may have very low levels of individual involvement in R&D of such parts, as technologies and innovations are developed and conducted by suppliers and is thus already embedded in purchased parts.

As a further point, the independence of R&D intensity from firm size may require additional understanding. Lee (2003) notes that the size of firm does not affect either customer preferences over quality and price or the productivity of R&D in terms of technological output. Customer preference and production cost effects of product R&D may not face all firms in the same industry equally. The lack of a relationship between capital intensity and R&D investment suggests that the scale economies of operation does not exert influence on the intensification of R&D at the current period of time. In general, capital intensity can also be associated with the size of firm since big firms are thought to possess greater amounts of tangible fixed assets such as plant and machinery than smaller firms.

Divergence between two industries is shown in link between profit margin and R&D effort. Profit margin has a weak and negative impact upon R&D intensity of automotive firms. One possible explanation for this is that the local market is perceived as relatively less important than the global market. The Japanese domestic market accounts for less than half of total revenue generation, compared to large and strategic foreign markets such as North America and China where firms have a presence. In fact, the number of vehicles sold in the local market has been declining since the start of the financial crisis in early 1990s. Waning automotive sales is also as a consequence of the shift in consumption preferences toward consumer electronics products. The poor market conditions were recently further exacerbated by the global recession in 2008-09. Research and development, conducted both in Japan and in R&D facilities abroad, may therefore be aimed at developing technologies and new products designated to compete internationally. In addition, the insignificance of the profit margin may suggest a preference for financial funding of R&D activities among automotive firms. Thus, those firms might not prefer to use internally generated revenue as funding source for ongoing R&D.

On the other hand, this profitability measure is found to have negative effect on the current ratio of R&D investment to total sales in electronics firms. Within this context, the negative role of the profit margin suggests the following. Current R&D investment is perceived as and expenses incurred in the operations of the firm. The upward in profit margin could be as a consequence of reducing these operational costs, including R&D expenditures. Another insight also arises from the inverse relationship between profit margin and R&D intensity. This finding is consistent with the analysis of Mensch (1979), who attributed greater innovative activity during economic hardship to firm-level reactions to deteriorating profits in established markets. Further, empirical Japanese studies such as Thurow (1992) and

Hundley et al. (1996) have proposed that R&D investment by Japanese firms is not sensitive to profitability fluctuations. Profit in the present period could be regarded as an indicator of forthcoming profits. In this respect, firms encountering or predicting a decline in profits may be motivated to innovate (Elliott, 1971). In addition, an underperformance in profits may hint at impending organizational shortfall. Even though the funds available for R&D activities are lower, the firm might bolster R&D efforts in an attempt to ensure long-run survival (Hundley et al. (1996). Firms in the electronics industry are likely to face high levels of competition between each other. This is due to the entry of international competitors such as South-Korean producers of consumer electrics into the Japanese domestic market. This market rivalry might lead to the shortfall in profit generation. In order to reinforce their competitiveness and future profitability, firms increase their R&D expenditure (Chiao, 2002). A willingness to intensify R&D activities is linked to the efforts of firm to stay in the forefront of the technological frontier. In high-technology industries, the product life cycle appears to be getting shorter, maybe due to the fact that competition among firms is based on the progress of product innovation. With new products featuring advanced technologies introduced to the market at a consistent pace, the average price of technology based products can diminish more rapidly than those of non-technology based products. To Yang et al. (2010), continuous downward pressure on product margins might exert pressures on management to increase spending on R&D in order to signal the launch of a new product.

7.5 Conclusion

This chapter uses a similar model to the previous one, include the addition of a lag structure in the independent variables. Within the context of R&D determinants, an insight gained from the analysis in this chapter demonstrates the clear difference from the traditional literature that supports the large firm advantage based on access to financial resources, scale of operations and number of years established. As such, variables representing size, age and tangible fixed capital all are found to be unrelated to automotive and electronics firm's investment in R&D activities. This can be explained by the availability of financial resources from banks in Japan, which are willing to support R&D investment in both large and smaller firms. However, the findings on the debt ratio imply that the continuing high leverage is causing difficulties and are a sizable restraint to the firm's investment in technologies as well as expansion of traditional capital assets. Another inference is that R&D activities nowadays are being increasingly conducted outside the firm via outsourcing and joint-projects with business partners.

An interesting feature in this chapter is that profitability appears to exert a reverse impact on firm R&D only in the electronics industry where greater competition now exists. In this context of market rivalry, findings suggest that firms may foresee the shortfall in profit in future years and thus respond by increasing their efforts on technological development in order to sustain their market position. Although the domestic market for the automotive industry is also intensely competitive, it is characterised by deterioration in customer demand for new vehicles in the light of Japan's decades-long struggling macro-economy. This is in accordance with the fact that the domestic market is increasingly no longer a cornerstone of revenue generation and product R&D is being redirected towards developing vehicles and components to suit worldwide markets. These facts can explain the lack of a relationship between firm profit and R&D activity.

Chapter 8: Conclusion

Introduction

This concluding chapter reviews the key findings arising from three empirical chapters and discusses implications of the thesis. Some of the limitations relate to the adopted conceptual and methodological framework. Particularly, emphasis is put on the main drawbacks of the current formalisation of technological development, externalities and absorptive capacity in the empirical models. Finally, some issues deserving further consideration are discussed and some potentials areas of future study are suggested.

8.1 Summary of research findings

In this study, the performance effect of three aspects of technological activities are empirically analysed. The first topic concerns the measure of the impact of internal R&D carried out by the firm. The second investigates the effects of other firms' innovative discoveries on performance of the recipient firm. And, the third focus is on the significance of technological absorptive capacity which might be linked to the indirect role of intra-firm R&D effort. In addition, this work investigates the reverse effect of performance upon the firm's R&D investment. Performance is measured in term of labour productivity and profit margin. The empirical analysis is conducted on a firm-level database which consists of 325 Japanese listed firms operating in the automobile and electronics manufacturing industries. The time-period of the study is from year 2000 to 2009, which covers the period following the economic turbulence of the 1990s and the backdrop of global recession during the late 2000s. The empirical results of both industries are presented and compared in each empirical chapter.

The purpose of chapter 5 has been to quantify the impact of three technological factors, i.e. intra-firm R&D effort, technological externalities and absorptive capacity, on labour productivity at the firm level. To this end, it addresses the 1st, 2nd, and 3rd research questions by examining the productivity effects of the three technological factors. Fundamentally, the specification of the empirical framework relies on the production function, which is respectively augmented by a lagged structure of R&D intensity, intra- and inter-industry spillovers and the interaction between firm R&D investment and the pool of spillovers. A number of conclusions emerge from the estimations using within a group (fixed effects) model. The findings of R&D intensity underline the significance of internal R&D

activities on labour productivity. Thus, the assumption that investment in technological innovation affects productivity positively is clearly established in both the automobile and electronics sectors. It can be highlighted that R&D investments in the current period would not instantaneously lead to growth of productivity even if both industries are experiencing a short product life cycle. Despite this, the estimated lag structure of R&D intensity suggests that the major share of the positive productivity effect of the firm's technological effort occurs with relatively short time gap, that is, a year after the investment in technology. With a delayed effect of R&D effort taken into consideration, the current spending in R&D activities might be perceived as a cost to firm operation in the present period.

In general, the findings suggesting the importance of firm R&D supports previous studies on the relationship between R&D and productivity both at the firm and sector level. Yet, the divergence between this research and the existing literature is on the effect of research and development effort in the current period. The majority of focusing on the impact of R&D on productivity claim a positive influence in the short term. Thus, the difference in the structure of the R&D variables between this study and others is clear. Whilst other studies are shown to either a current period or single lag R&D variable in their empirical model, there are both current and lag values of R&D variable in this study. In this respect, the effects of research and development are distributed across all R&D variables in the model. It is worth noting that the distributed lag structure of R&D variables is excluded from the analysis of a number studies on R&D-productivity, particularly in the management literature, and where they do exist the results are inconclusive.

The estimates of technological spillovers provide evidence of opposite results between the two industries, suggesting that not all technological externalities are beneficial for the recipient firm. In fact, there could be negative feedback stemming from the occurrence of a different sort of external knowledge on productivity of firms in different industries. New innovations discovered by others in the automobile industry are not only disadvantageous for firms in the same sector but also are of limited importance for firms in the electronics sector. Electronics firms are mainly receptive to intra-sectoral knowledge stock and automobile firms take advantage from inter-sectoral knowledge stock. Overall, the coefficients on technological spillovers are clearly higher than the results obtained for the specific firm R&D and this may point towards the greater importance of the social return on R&D than the private one. The results on technological absorptive capacity are consistent with previous findings. In this regard, the positive and significant influence of the interaction term between

firm R&D and technological spillovers provides evidence supporting the concept that R&D internally carried out by the firm has a crucial role in encourage the absorption of new external technologies. Such improvement in absorptive capacity in turn contributes to the additional rise in productivity and performance.

The objective of chapter 6 is similar to that of chapter 5 as it also presents an analysis of the contribution of internal R&D, research externalities and absorptive capacity in the firm performance. Whilst it attempts to address the 1st, 2nd, and 3rd research questions, the focus is on the profitability effects of the three technological factors. Further, the econometric methodology is a dynamic regression in the context of panel data. In spite of methodological differences, the empirical findings obtained in chapter 6 are complementary to those in chapter 5. For own R&D effort, the estimation results show that it has an important beneficial impact on profitability of the firm and that this is more immediate than in the case of productivity. As with the earlier empirical chapter, the distributed lag structure of own R&D variable is present, particularly in the electronics industry model. In this respect, some internal R&D in the preceding period is not a significant influence on firm profit. This can be interpreted as the accumulation of knowledge capital stock or new technology development being important rather than the current period R&D. On one hand these findings on the role of firm R&D are consistent with a number of existing R&D-profitability studies reporting the significance of lagged firm R&D to profit. But on the other hand it should be noted that internal R&D at the present period is incorporated into the empirical model and also exerts positive feedback to profitability in the same time-period.

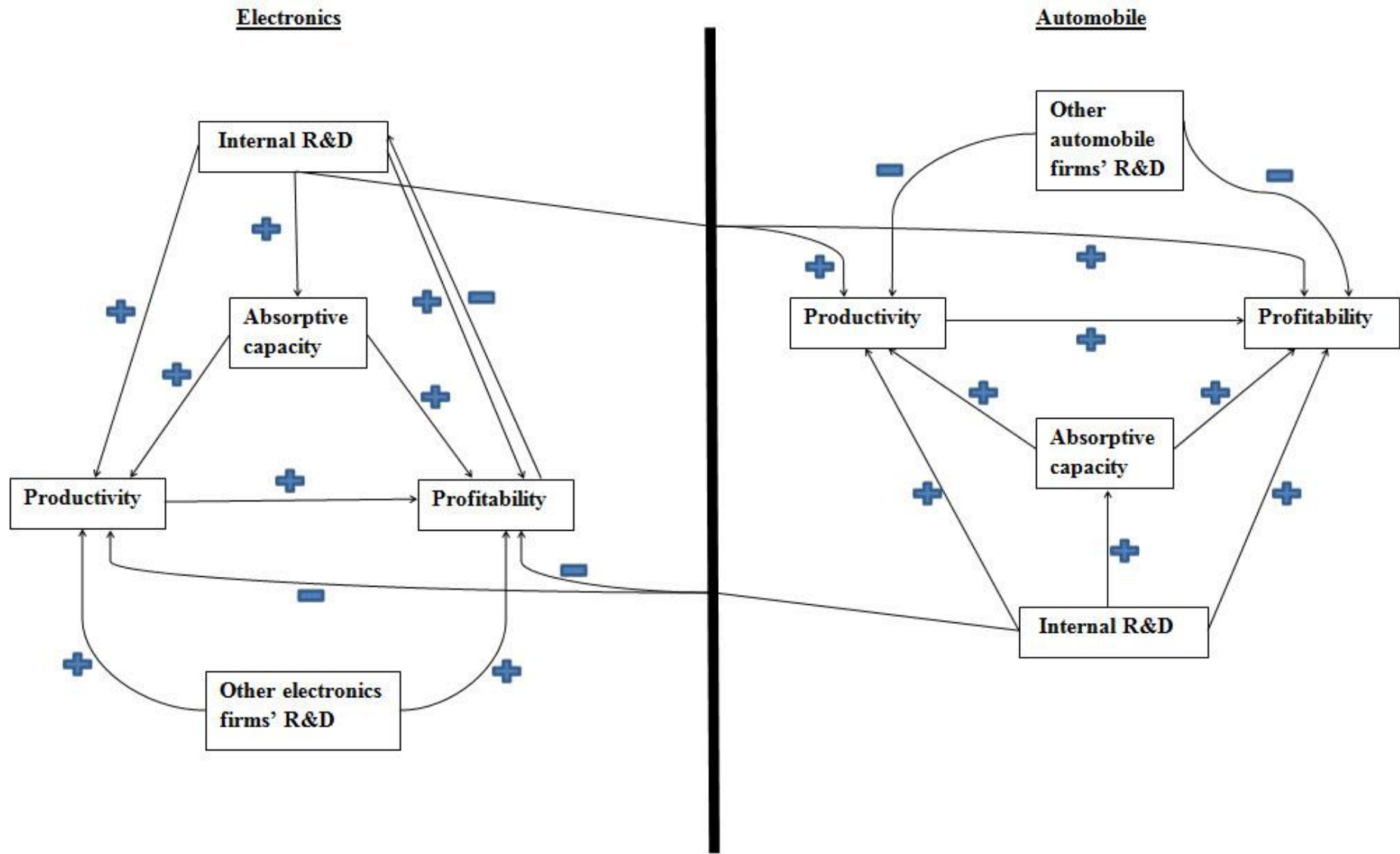
The increase in labour productivity is shown to exert influence on the firm's profitability, suggesting that an improvement in one aspect of performance could constitute one cause of the change in another. Results on the profitability effect of productivity support previous findings that R&D and productivity are potential determinants of profit. Ostensibly, findings on technological externalities and absorptive capacity mirrors those reported in chapter 5. Positive impacts on firm profitability are achieved from different technological externalities, that is, intra-industry components for the electronics sector and inter-industry innovations for the automotive sector. Automotive and electronics firms do not appear to benefit equally from the pool of quasi-public knowledge circulating inside the same industry and technologies generated across sector. The results obtained for absorptive capacity confirms the indirect contribution of own innovative efforts on firm profit through its association with the internalisation of the available pool of outside knowledge. These

findings are in accord with preceding firm-level studies of Jaffe (1986) and Hanel and St.Pierre (2002).

The purpose of the last empirical chapter is to explore the interconnection between profitability and R&D. Aiming to address the 4th research question, it takes into consideration profitability as one of the determinants of firm's technological effort. Findings in chapter 7 focus on the potentially reverse effect of profit increases upon R&D efforts of the firm, however, this assumption appears to be proven solely in the case of electronics firms. In this respect, the time gap regarding the impact of profit on R&D investment is marginal. The industry difference regarding this profit effect is likely to be due to conditions in the home market where automobile firms appear to continue to struggle to generate adequate sales revenues. Whereas R&D activities may not be under the influence of automobile companies' domestic business performance, it could be stimulated by competition abroad.

In general, the significance of firm profit on R&D investment conforms with preceding studies, particularly Branch (1974). Nevertheless, two issues appear to set these findings apart from others. Firstly, it is the current profit that exerts an effect on research spending, as opposed to past profit in the existing literature. Secondly, profit in the present period is shown in the model to have a negative and significant effect on R&D investment while profit in previous studies is positive although this can be significant or insignificant. Nonetheless, the finding of a negative and significant profit impact supports Scherer (2001), that the firm counters the anticipated loss in its profitability by increasing its efforts in R&D. Stiff competition in the home market is also further hastened by the entry of potential foreign competitors. These tough market environments may lead the incumbent electronics firms to expect contraction of future profits unless they invest more in R&D. Whereas Scherer considers expected profit to be a separated variable determining R&D investment, the present research perceives this factor as being embedded in current profitability of the firm.

Figure 8.1: Relationship between internal R&D, technological externalities, absorptive capacity, productivity and profitability



8.2 Final discussion

Findings on the positive feedbacks of own R&D on productivity and profitability gives prominence to both the direct and indirect role of such internal technological effort in enhancing firm performance. It should be stressed that direct role of own R&D is straightforward, as shown by the significance of the estimates over the course of the empirical analyses. Productivity increase is often considered as a typical consequence of process innovation, which could bring about a reduction in the average cost of manufacturing of existing products. Spending on innovative activity, especially for those firms operating in technology-intensive sectors, is associated with the introduction of a new product featuring better quality or technology. But the advance in production efficiency may be also regarded as a by-product of such product innovation. In fact, the introduction of a new product could entail a restructuring and simplification of the manufacturing process. The profitability effect of own R&D is largely related to the creation of new product-related technologies, the eventual outcomes may emerge in the form of improved product quality and the expansion of the spectrum of available goods.

An indirect role of own R&D clearly identified from the empirical results is its involvement in the enhancement of intra-firm capability to absorb and implement external knowledge. One of the causes of an increase in productivity levels may be advanced technology embodied in new fixed capital. The amount of spending and the introduction of these tangible assets alone do not guarantee a positive productivity change, as the implementation of an external process innovation is determined by the amount of own R&D activity. Besides being able to exploit their internal innovative effort, the firm may inadvertently contribute to the pool of technological externalities available to both firms within the same industry and those in other industries. This is shown in the significance of intra-industry and inter-industry spillovers in the results of this study. The feedback of the firm's generated knowledge on others' performance is mixed, but it could be dependent upon factors such as the technological level of the sector that other firms operations and the capability of others to internalise the firm's diffused innovations.

To some extent, another indirect function of internal R&D may arise from its direct role in enhancing productivity. With reference to growth in profitability (Aw et al.,2008), it should be noted that the internal technological activity indirectly contributes through its productivity effect. As mentioned in section 8.1, R&D investment undertaken by the firm

clearly constitutes a delayed positive impact on labour productivity growth. Although the magnitude of effect is not as great as that of external knowledge variables, it was shown that the variation in the productivity growth rate of intra-firm labour is partly explained by firm R&D. At the same time, labour productivity is statistically proven to be amongst the factors that influence firm profits. In this regard, an element in labour productivity change that eventually leads to higher profitability is technological innovation, which results from the intensification of innovative activities of the firm. Unlike the profitability impact resulting from the direct contribution of internal R&D, this indirect profitability effect might not be instantaneous owing to the fact that there is a lag before the effects of internal R&D translates into productivity increases in the present period.

The role of firm size in research and development, productivity and profitability is ambiguous. The size advantage, as advocated by Schumpeter (1934; 1950) exists in the firm-level performance of both R&D intensive sectors examined in this thesis. It is apparent that large corporates continue to dominate in productivity and profit generation although they may not invest higher amounts of R&D proportionally than smaller firms. As size tends to relate to scale and scope economies, large companies may realise the benefits of both manufacturing extensively and having a number of subdivisions and multiple product categories. Within the Japanese context, the automobile and electronics conglomerates are obviously able to maintain a relative advantage through their consolidation of market power and industrial organisation over a long period. Whilst large automobile makers maintain market share with vehicles of various types, smaller car producers can offer a comparatively narrower category of vehicles and thus able to reach specialist or niche markets. Likewise, big electronics companies have had a sizable presence in the home market for a long time. In fact, in Japan no new firm has been able to attain a high ranking among leading electronics conglomerates for over half a century.

The relation between firm R&D, technological externalities, absorptive capacity, productivity and profitability is illustrated in figure 8.1, which provides a comparison and depicts the externalities linkages between the electronics and automobile industries. It is established that internal R&D exerts a significant influence upon both firm performance measures. Firm R&D has a considerable impact on labour productivity although R&D activities initially constitute costs to the firm business operations. However, productivity responds positively to firm R&D over a lagged period and this lag is surprisingly short. A likely explanation arises from the fact that research and development in both technology-

intensive sectors is also geared towards improving current products and launching them promptly to compete in the market. This suggests that the portfolio of research projects include new products and enhancements to existing ones, something that is lost the aggregate research expenditures data. In this respect, such research outlays will be comparatively lower than research into a new product and the return on R&D investment could be realised earlier as well. Subsequently, the gain in productivity contributes to a rise in firm profitability in the same period of time. Because of the importance of productivity gains to profitability, R&D can have an impact on profitability through its delayed effect on productivity levels. Conversely, the upward trend in firm profit stimulates more spending on R&D activities, although this finding is demonstrated only for the electronics sector. In addition, ongoing technological efforts also stimulate further research activities. It is clear that the outcome of own technological efforts is not exclusively appropriable by the firm itself, rather such research output becomes external knowledge to other companies both within the same sector and in related sectors. At the same time, innovative discoveries by others become technological spillovers available to the firm. This outside knowledge may or may not be beneficial to the performance of the firm, depended on the industry in which it is operating. Lastly, the pivotal role of internal R&D in bolstering absorptive capacity is confirmed and these intra-firm capabilities result in an additional increase in both aspects of firm performance.

8.3 Implications of the research

Some of the conclusions from this thesis present valuable implications for both managers and policy makers. In general, the findings are supportive of the argument that there are significant linkages between technological development and performance. R&D activities, undertaken by the firm and by others, constitute significant impacts on firm performance in terms of productivity and profit generation.

Given the firm level evidence on the important role of internal R&D in stimulating performance, this leads to the conclusion that own technological investment is worthwhile despite the time and cost and in the light of associated uncertainties. Yet, it is also important to draw the attention to the conclusion that unsatisfactory profitability continues in both the domestic and international marketplace. This shortfall is a particular problem in the electronics firms in this sample. Throughout the 2000s, Japanese electronics manufacturers have been increasingly challenged and outperformed by other emerging East-Asian

producers, particularly South Korea, who secure cheap capital, abundant skilled labours and can thus lower the price of final goods. This phenomenon raises questions regarding the productivity of firms and the returns to R&D. More specifically, the deterioration in competitiveness may have its root in the failure to capitalise on R&D activities even though Japanese electronics firms have spent substantial amount of funds on innovative activities. In this respect, the potential explanation could arise from the choice of projects and quality of the research. The literature refers to this as the Red Queen effect, where innovative effort is increasingly made by companies to improve themselves in face of harsh competitive environments, and simply remain level rather than move towards the frontier (Senge and Carstedt, 2001). In this regard, the firm invests in technology simply to keep pace with other innovating competitors, rather than attempting to achieve a breakthrough with products or organisational practices.

Although overall, Japanese R&D has been increasing throughout the recent decade, it appears that the majority of firms have not distinguished themselves as they have in the past as original inventors and been able to command high prices and license fees. In order to rise to this challenge, both policymakers and business managers must take decisions that enhance the process of transforming knowledge capital stock into new products and processes. Within the companies themselves, Japanese electronics firms should aim to perform well against their competitors on the grounds of product innovation rather than cost-efficiency. In other words, the firm should utilise its existing technological proficiency by creating cutting-edged and revolutionary products. The networks and alliances amongst departments should be developed and nurtured, as this will create scale and scope economies with the range of R&D activities and later lead to technological innovation that can be applicable across divisions within a firm. At the same time, the firm should concentrate on competing in the product lines that are expected to reach the technological and manufacturing quality adequate to compete with their peers. In the overall industry, firms could realise the scale benefits via inter-firm partnerships, such as joint-venturing, to manufacture commodity components, as well as combining efforts into researching new technology for products and shared parts. On the macro level, there could still be bottlenecks in national innovation system. It is stressed that weak university-industry linkages in Japan limit technology transfer between two said groups and this may hinder growth in science-based industries (Goto, 2000 and Nagaoka, 2007). In addition, government may wish to tackle this constraint by promoting

fundamental research in universities and strengthening collaboration in research projects between universities and technology-intensive firms.

The consistent finding on the positive contribution of technological spillovers on firm performance signifies that the firm's R&D investments yield both private return and social return. The latter is strongly associated with the presence of spillovers. Owing to the substantial spillover effects observed from the empirical findings, the social return on R&D may be considerably higher than the private return. At the same time, the significance of technological externalities also implies that innovating firm could not appropriate the return to their own R&D activities exclusively. This may dissuade firms from engaging in inventive activities that are geared toward creating original products. Consequently, the overall industry may under-invest in technology and the private and social returns on R&D investment could decrease in the long-run. To mitigate this problem, the government can respond with policies to effectively bolster the level of private sectors' R&D. Policymakers may become involved by offering subsidies to firms that undertake R&D and facilitate joint projects with universities and by giving tax incentives. Alternate policies to improve the appropriability of innovation, such as anti-trust laws, are also essential since these allow innovating firms to internalise the results of their technological efforts.

In addition, scientific and technology policies that promote research co-operation between firms, and between the public and private sector, can reinforce the firm's enthusiasm for investment in technology. Despite that, implementing such policies in the industry with a highly competitive environment, clearly takes place in the automotive findings on intra-sectoral externalities, although it could be challenging. On one hand, the R&D collaboration between firms provides opportunities for them to share the outcomes of their mutual efforts. On the other hand, pressures from rivals could potentially affect the private return on joint R&D projects. Each of partner firms may be skeptical about its counterparty acquiring identical technologies since both of them are also operating and competing in the same market. In consequence, the public benefits yielded from inventive activities of both intra-firm and cross-firm collaboration would be undermined. It could be argued that the high levels of competition in the market partly stems from factors exogenous to the automobile industry such as prolonged economic stagnation, contracted domestic markets and low demand for new vehicles. In this respect, macro-economic policies that could effectively address these issues are still lacking and policymakers still have a responsibility to establish an industrial environment that stimulates inter-firm partnerships.

The findings on absorptive capacity also have important implications for firm managers. Absorptive capacity, amassed by the firm, is proven to be crucial for the internalisation of external knowledge. Through its association in the adaptation of other firms' innovations, intra-firm capability contributes significantly and positively to productivity and profitability. As internal R&D is an element in absorptive capacity, this can justify a steady stream of R&D investment even in the face of economic difficulties. Nevertheless, managers should be aware that the R&D investment intended to bolster absorptive capacity could weaken the ability of the firm to generate in-house innovations as the spillover receiving firm may gradually shift from creating original results to one of mimicking others' strategies. In this persists, a focus on improving absorptive capacity will erode productivity of own R&D, which is strategically important for firms in technology-intensive industries. In the allocation of funds regarding technological activities, managers should therefore carefully consider the choice between R&D projects aiming to yield own innovations and the investment related to absorptive capacity. There is also a policy implication at the macro-level. As there is a link between firms' absorptive capacity and country's absorptive capacity (George and Prabhu, 2003), a policy earmarked for reinforcing companies' absorptive capacity could be somewhat effectual in making the nation more pliable to the inflows of knowledge across the country boundaries. These inter-national externalities might end up stimulating local innovation as well (Escribano et al., 2009).

Finally, another aspect of importance gained from the finding in the empirical chapters is the role of firm size in the overall knowledge pool. Even though the findings from chapter 7 do not indicate that large firms are relatively more innovative than their smaller counterparts in both industries, long standing industrial consolidation among large conglomerates are superior in terms of productivity and profitability and the benefits of scale may hinder the innovation capability of smaller and fledging companies. The public policy support for nascent companies may come from both government and industrial association.

8.4 Limitations of the study

The study does have limitations, largely out of the control of the researcher. Most relate to data availability, including the quality as well and quantity of information. The period covered by the analysis is of short, ten years for each panel, due to a lack of relevant and critical data for both industries for earlier years. One of the constraints regarding data availability is evident in the choices of deflator. To adjust observations' value for inflation,

the thesis required industry-level indices. Similarly, the measure of labour input is partly computed by using sectoral-level yearly hours worked. Kozo (2011) explains in the case of Japanese studies that quantity-based measure is unavailable at the micro level unless one utilises historical data. A number of shortcomings in applying industry-level price-indices to firm-level data have been already pointed out in earlier empirical studies such as Griliches and Mairesse (1998) and Syverson (2011). This issue is yet a hindrance to be worked out in order to obtain relatively more precise observation values and subsequent estimates.

There are issues associating with accuracy and appropriateness of data. Particularly, data on R&D expenditures may be biased in measuring value of R&D activities, this is owing to the possibility of under-reporting by small firms (Kim et al., 2009). To this end, small firms tend to informally conduct research in the absence of R&D departments and specialist R&D personnel and this contributes to the likelihood of under-reported R&D investments (Kleinknecht, 1987 and Kleinknecht and Verspagen, 1989). Another R&D data issue that could also cause biasness is the criteria in reporting R&D expenses. In the financial reports, listed Japanese firms are not required to disclose the amount of investment in R&D activities, unlike many other countries. Moreover, those that do report these items have their R&D expenditures included either in selling, general and administrative expense or in cost of sales. Often, there are simultaneously different amounts of R&D expenditures shown in these categories. There is no detail on the exact source of OSIRIS's firm-level R&D expenses, that is, whether R&D expenses have been extracted from the amount included in cost of sales or not.

But perhaps even more important is that studies on R&D in the private sector are limited by the unwillingness of firms to bring their research programmes into the public domain. Thus there remains a lack of any comprehensive R&D data that allows the generation of more specific R&D variables. In this respect, R&D expenditures as used extensively in the research to construct R&D variable does not segregate such spending into different R&D related activities such as product development, process innovation and cost of hiring research personnel. This is acknowledged, for example, by the Australian Industry Commission (1995), who claim that research and development could be also categorised into three types, basic research, applied research and experimental development, and studies should be able to differentiate these in any study. Alternatively, R&D expenditure is often split between wages of scientific personnel and research materials and related equipment on the other (Hall and Van Reenen, 2000). Different types of R&D spending may be diverged

by their significance on labour productivity and profitability while the degree of their individual effects may vary across individual firms and industries. Incorporation of detailed R&D data into the empirical analysis might provide clearer insight on the exact sources of own technological effort that contribute to firm performance and to which separated effects they are determined by rise in profitability. But such detail remains unavailable to the researcher.

Likewise, the theoretical framework in this thesis takes no consideration of the differentiation between knowledge and rent types of spillovers. This is partly because of the difficulties in devising a weighting scheme for measuring the nature and extent of technological externalities. One possibility is to acquire patent data at the firm-level, which could have been used to approximate both technological space and an input-output matrix. But patent data is very long term, given the time between a patent application and its approval and implementation. This prevents the thesis from being able to disentangle the net effects of intra-industry and inter-industry technological externalities into the two main sorts of spillovers.

The measure of indirect role of firm R&D via absorptive capacity is another conceptual challenge. As in previous studies, this thesis simplifies the formalisation of absorptive capacity by assuming that internal R&D investment is homogeneous, that is, there is no difference between the technological effort to create new innovation and expenditure aim at the improvement of absorptive capacity. However, it is argued by Cassiman et al. (2002) that absorptive capacity is more likely to be associated with basic research and is a particular sort of R&D carried out to enrich the understanding of fundamental knowledge, rather than applied research whose objective is practical or commercial applications. A basic research capability is a requisite in order to monitor and evaluate inventive activities being conducted elsewhere (Rosenberg, 1990). Furthermore, investments in absorptive capacity not only take the form of pure basic research effort, but also the connectedness with sources of external knowledge (Lim, 2000). To draw a distinction between basic and applied research, internal R&D is distinguished into two components according to Hammerschmidt (2006); one that leads to in-house innovation and another that is particularly allocated to foster absorptive capacity. As already emphasised, a lack of detailed R&D spending data regarding the split between funds allocated to pure basic research and applied research rules out the possibility of obtaining a better approximation of absorptive capacity.

To a lesser extent, another limitation arises from the empirical framework. There is an absence of universal models that could be applicable across two sectors, as evident in a series of poolability tests in each empirical chapter. It is apparent that both industries have their own specific features such as quantitative models with different lag structures in some variables even though models used for each industry in chapter five and seven are identical. For example, in chapters 5 and 6, the distributed lag structure of firm's R&D variable is similar in both industries although the lag is longer in the electronics than the automotive sector. Thus, this study may be constrained from examining the impact of lagged R&D from earlier periods in the automobile case. Similarly, in chapters five, six and seven, the conventional panel data regression is used in the former whereas dynamic panel data regression is appropriate in the latter two. Owing to the dissimilarity in methods of estimation, the form of variables used during the course of three empirical chapters may not be the same.

8.5 Further avenues for research

In this thesis, R&D investment, through the form of R&D intensity, has been extensively used as a proxy for innovation and as a component in the measurement of technological externalities and absorptive capacity. Nonetheless, there may be biases associated with the use of a single variable to represent innovation and it could be argued that spending in R&D activities is not the only input that leads to advancement in technology level and eventually performance growth. More complete measures of innovativeness, particularly from the aspect of innovative output, could be used in future research in order to overcome this. Examples of alternative innovativeness could improve the models and new constructions that include an index measuring multiple characteristics of patents (Lanjouw and Schankermann, 2004), product and process innovation (Parisi et al., 2006), and patent intensity proposed by Coad and Rao (2008), which are not dependent on timely information but rather simulations.

Increasing R&D investment alone does not guarantee the improvement of firm's profit generation without the firm's capability to transform their technological creativity into a profitable operation (Archarunroj and Hoshino, 1999). Likewise, Koku (2011) argued that the firm's ability to successfully market its new or improved products after the process of commercialisation of generated innovations also determines the firm's success at the market place. Technology oriented firms could suffer setbacks from their high R&D intensification owing to the lack of complementary assets and competences such as marketing and financial

capabilities (Lin et al., 2006). This implies the possible importance of activities dealing with commoditisation, sales and marketing of products in shaping R&D-profitability performance of the firm. Apart from these activities, the return to R&D could also be determined by the interaction between the firm's own strategy, competitor's response and stochastic macro-economic surroundings which are not likely predictors at the time of investment decision regarding R&D (Hall et al., 2010). Thus, new data and new methods will enhance future research into R&D activity.

While the firm attains a new technology both as an outcome of its own innovative activities and through the internalisation of external knowledge, such technology may also necessitate adoption costs. These complementary investments involve learning new skills and implementing new organisational practices (Bessen, 2002). In this respect, additional resources on new technology may be even larger than amount of strictly R&D expenditures. Unless costs of adopting a new technology are taken into consideration, the rate of return to R&D investment could be relatively lower than estimated (Maté-García and Rodríguez-Fernández, 2008). Since technology adoption costs may potentially affect the rate of return to R&D investment and hence the output of the firm, future research should incorporate them into the empirical framework in order to obtain a more accurate rate of return to R&D.

A further area of interest concerns outgoing spillovers. It could be argued that the diffusion of know-how in the economy takes place through multifaceted transactions. While other firms cannot perfectly appropriate external benefits, the innovating firm can attempt to limit the outflow of internal knowledge. As in-house technology becomes more publicly accessible, it may be beneficial for other rivals who may imitate and adapt such technology to both maximise their profits and reduce their costs. Consequently, gains in performance of competitors would be achieved at the expense of the firm. It is thus worthwhile to empirically assess the potential effect of outbound externalities upon performance of the firm responsible for creating such original innovation. Measuring the magnitude of internal knowledge that is likely to spillover to outside users would be complex but very valuable. Clearly, not all of the firm's innovation outcomes or existing knowledge capital stock could be assumed to result in outgoing spillovers, and understanding the magnitude would be worth investigating.

Another promising issue closely linked to out-flowing technological externalities would be to determine the value of in-house technology to competitors during the programme of research. Such efforts would assist in curbing outgoing spillovers and relates to the

accumulation of absorptive capacity that encourages incoming research externalities. One of the conventional means for the firm to manage the flows of outgoing knowledge is to protect itself from appropriation of its innovations by other firms (Cassiman et al., 2002), largely through legislation and intellectual property protection. As the magnitude of restriction on knowledge appropriability imposed by the innovating firm may determine both the return on internal R&D for the firm itself and the spillovers effect for those of recipient firms, it is worthwhile to take into account strength of the protection of outgoing flows of in-house knowledge.

Finally, an international dimension is a valuable extension to the existing research. Where data are available, a better understanding of the link between technology and firm performance could be the comparison of these relationships across countries. It is clear that neighbouring far-eastern nations such as South Korea and Taiwan have also accumulated expertise in technological intensive industries, particularly the electronics sector where many firms are already capable of either rivaling or surpassing Japanese firms in aspects of quality and innovation. In the automotive industry, South Korean firm share similar characteristics to those in Japan regarding consolidation of the domestic market and national structure of highly-diversified business conglomerates. The Korean automobile industry is described as having huge investments in indigenous models of development and manufacturing facilities (Chu, 2002). As in Japan, linkages between automakers and parts producers also existed, with the former leading the latter in terms of capital accumulation and technical capabilities. Jung (2007) explains that car-manufacturers encourage and support the parts suppliers by training them on technologies and management skills. In conjunction with differentiated type of R&D, a cross-country assessment may reveal the divergence regarding innovation strategies, technological linkages and the ensuing effects on productivity and profitability of these firms.

Appendix A

In this section, the description of two panel data regression models are provided. Conventionally, regressing panel data can be done using two approaches; either a random effect model (REM) using generalised least square method or a fixed effect model (FEM) using ordinary least squares. Gujarati (2003) distinguishes the two models by the difference with respect to the intercept, error term and individual specific effects in the equation. For the fixed effects model, a firm's indigenous effect is part of the intercept. As a consequence, the intercept is fixed across time but varies across firm or cross sectional units. The key presumption is that unique attributes of individuals are not outcomes of unsystematic variation and do not vary across time (Mandala and Lahiri, 2009). Those individual specific effects are presumed to be correlated with the independent variables. With the assumption of the same slope coefficient and constant error variances across firm units, the fixed effects model is used for examining firm differences in intercepts. Fixed effects estimation evens out all effects that are firm-specific, as well as those of unobserved effects.

The use of dummy variables to proxy individual intercept component is predominant in a widely used fixed effect model variant; least squares dummy variable (LSDV). In LSDV model, a dummy variable is assigned for each individual firm unit. The main disadvantage of LSDV model lies on the extensive use of dummy variables to take into account the difference across cross-sectional units, especially in the event that there are many individual groups in the cross-sectional time series data. LSDV model is numerically, but not computationally, equivalent to the fixed effects model and only works the number of time observations per individual unit is considerably larger than the number of individuals in the panel (Wooldridge, 2012). The coefficient of dummy variables could not be consistent as the number of parameter grows with an increase in the number of cross-sectional units (Baltagi, 2005). If the number of firms is substantial, the degrees of freedom (df) would be considerably sacrificed and the model could be left with inadequately powerful statistical tests (Yaffee, 2003).

An alternative fixed effect model that has been used to avoid problem stemming from large amount of dummies is the within group transformation. To this end, the fixed effect model eliminates those of unobserved individual effects by demeaning the variables. According to Park (2005), the within group effect model transforms both dependent and independent variables in the model by using group means while sharing identical parameter

estimates of the regressors with that of LSDV. In other words, the within group estimator uses only the variation within an individual firm's set of observations (Johnson and DiNardo, 1997). More specifically, the within-group means for each variable are subtracted from the observed values of those variables, this basically discards all between-group variability and leaves only within-group variability to analyse (Allison, 2009).

In contrast, the random effect model assumes that the individual effect is not fixed specifically for each firm, but randomly drawn from a population. Such individual specific effects are independent of explanatory variables. A firm specific effect is considered as a component of errors which then diverges across firms. While the intercept and slope in the model are assumed to be constant across firms, the random effects model focuses on estimating the error component across firms. In comparison with conventional LSDV model, the random effects model may be more appropriate since it does not require the estimation of cross-sectional intercepts. There are unique, time constant attributes of individuals that are the results of random variation and do not correlate with individual regressors (Mandala and Lahiri, 2009). The random effect model is normally estimated by the technique of generalised least squares (GLS). Nevertheless, using the random group effect model in this study would require the consideration that there is virtually no relationship between the error component in the model and other regressors such as R&D intensity and market capitalisation growth.

Appendix B

This section presents the outlines of dynamic panel data regression and the two GMM estimators used in the empirical chapter 6 and 7. Dynamic panel data estimation is based on two main assumptions. First, all explanatory variables must not correlate with their past, present and future error terms, in other words, they are exogenous in the model. Second, the error term has a constant variance with a mean value of zero. Given these assumptions, the inclusion of the lagged dependent variable could lead to biasness and inconsistency in OLS estimators since lagged dependent variable are likely to be correlated with the disturbance term, in particular individual specific effect.

For the dynamic panel data model, the lack of exogeneity in lagged dependent variable and serial correlation in error terms could be tackled by the generalised method moment (GMM) framework (Nowak-Lehmann, 2006). GMM framework is noted by the extensive use of instrumental variables as predictors of endogenous regressors in the equation. To attain consistent estimation, instrumental variables are with critical assumptions that they does sufficiently correlate with the explanatory variables they instrumented meanwhile they must not associate with error terms in the equation. In this vein, instrumental variables are excluded the equation, nevertheless it shows only indirect influence on explained variable via its correlation with included explanatory variables (Baum, 2009). The use of instrumental variables enables parameters to be estimated consistently in the model which consists of one or more explanatory variables possibly related with error terms as well as in the presence of measurement error (Bond et al., 2001).

Two forms of the GMM estimator have been used in empirical studies of dynamic panel data; difference GMM (Holtz-Eakin, Newey, and Rosen, 1988 and Arellano and Bond, 1991) and system GMM (Arellano and Bover, 1995 and Blundell and Bond, 1998). Roodman (2006) notes that both GMM estimators are appropriate for situations where independent variables are not-strictly exogenous, meaning they may correlate with past and current error terms whereas heteroscedasticity and autocorrelation are present within individual firms but not across them. The procedure of difference GMM estimation is the transformation of variables by first-differencing both sides of the equation, which takes out time-invariant individual effects.

In chapter 6, the first-differencing of the original equation 6.2 leads to the transformation of variables on both sides of the equation into growth rate-form, thus creating a differenced equation, as follows:

$$\text{Equation 6.3 } (p-q)_{it} = (p-q)_{it-1} + \sum_{k=0}^n (rd-q)_{i(t-k)} + (q-l)_{it} + (k-l)_{it} + \text{MKTCCG}_{it} + \text{DEBTRG}_{it} + \text{AGEG}_{it} + \varepsilon_{it}$$

Thereafter, the estimation is done on first-differences (equation 6.3) while the lagged dependent variable is instrumented by using its lagged values at t-2 and earlier periods. The rest of independent variables are instrumented by their first differenced counterparts. To this end, other instruments are first-differences of R&D intensities, labour productivity, capital intensity, market capitalisation, debt ratio and firm age. In the latter part of the empirical analysis, additional instruments entering the model are first differences of intra-sectoral spillovers, inter-sectoral spillovers and absorptive capacity.

As for chapter 7, both differenced GMM and system GMM use the transformation of variables on both sides of equation 7.2 into first-differenced form during the estimation procedures, as follows:

$$\text{Equation 7.3 } (rd-q)_{it} = (rd-q)_{it-1} + (p-q)_{it} + (k-l)_{it} + \text{MKTCCG}_{it} + \text{DEBTRG}_{it} + \text{AGEG}_{it} + \varepsilon_{it}$$

The lagged dependent variable; R&D intensity at t-1 period, is instrumented by the values at t-2 and previous periods. Other instruments are first differences of profit margin, capital intensity, market capitalisation, debt ratio and firm age.

Nevertheless, there are criticisms of the difference GMM estimators as shown in the literature (Mairesse and Hall, 1996; Blundell and Bond, 2000). The drawback for difference GMM originates from the possible weakness of instruments in the first-differenced equation. In particular, the lagged level of the series could be inadequately correlated with those of the transformed regressors. This disadvantage is exacerbated and reflected in the situation that time series data are persistently autoregressive and the number of time series observation is small (Bond et al., 2001 and Kitazawa, 2001). Blundell and Bond (1998) demonstrate that the presence of weak instruments could then lead to large finite sample bias and imprecision of the difference GMM estimators. This biasness and inaccuracy are recognized in simulation studies of Ahn and Schmidt (1995) and Alonso-Borrego and Arellano (1999). On the contrary, system GMM is usually considered as generating more efficient and accurate

estimation due to additional instruments used in the levels equation. Using system GMM, Blundell et al. (2000) report an improvement in the estimates over difference GMM for a model which typically comprises of a lagged dependent variable and additional explanatory variables.

Roodman (2009) states that system GMM is built on the foundation of difference GMM but estimating simultaneously both difference and level equation being instrumented individually. In particular, system GMM augments difference GMM with an additional assumption that the individual effect is unrelated to the first observable first-differenced dependent variable (Drukker, 2008). Given this assumption, system GMM is able to instrument the levels equation with a lagged first differenced dependent variable, while also retaining lagged levels of the lagged dependent variable as instrumental variables for the difference equation (Arellano and Bover, 1995). As being transformed into first-differenced form, the lagged first difference of the explanatory variables is thus exogenous to individual fixed effects existing in the levels equation. To this end, further instruments used in System GMM estimation of chapter 6 and 7 are first-differenced profit margin at t-1 period and first-differenced R&D intensity at t-1 period respectively.

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