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ciclo XXIV
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Technological Innovation in Korean Manufacturing Firms: Determinants and Effects

Tesi di Dottorato di Kim Kyung Surk
Matricola: 3710202

Anno Accademico 2010/11

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Contents

The Role of Innovation in the Korean [1] Economy: An Introduction

Theoretical background on innovation models

The role of technological progress was first introduced in the growth literature by Solow (1956) within a theoretical framework characterized by perfect competition and decreasing productivity of factors. The prediction of the model is that economies follow a balanced growth path toward a steady-state per capita income level and, in the path toward the equilibrium, economies grow at a declining rate. The rate of technological progress is presented among the determinants of the equilibrium level of per-capita income and therefore the existence of disparities between countries is explained by differences in the rate of technological progress. Although the model proposed by Solow has proven to be powerful in explaining cross-country growth[2], it is limited in explaining the non-declining growth of certain countries. In general two hypotheses of the Solow model have been highlighted as too restrictive: the exogeneity of technological progress and the production under diminishing returns to factors.

The New Growth Theory (Romer, 1986; Lucas, 1988) attempts to formulate models that overcome the aforementioned limits. In particular it is assumed that technological change is not exogenous but, on the contrary, that it is the outcome of specific investments in knowledge made by firms. Knowledge thus becomes a factor of production, which - contrary to labour and capital - is not subject to the law of diminishing returns. By the opposite logic, knowledge externalities cause the productivity of knowledge capital to increase with the stock of knowledge. Accordingly economic growth is the result of technological progress, which in turn depends on the accumulation of knowledge.

In this context, expenditure in Research and Development (R&D) came to play a key role in the theory of economic growth (Romer, 1987 and 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). With the important implication that the long-term economic growth of a country might be influenced by government policy through measures like tax-reduction, market regulation, provision

[1] Hereinafter, “Korea” refers to “The Republic of Korea (or South Korea)”.
[2] See for instance Barro and Sala-i-Martin (1992)

of necessary infrastructures, protection of intellectual property and intervention in international trade and the financial market. Several empirical investigations have provided robust evidence concerning the contribution of knowledge and R&D to productivity. For instance Griliches (1979) reports that returns to R&D investments more than doubled when compared to returns to investments in physical capital and were even higher once knowledge externalities were taken into account. Jones (2002) has found that approximately 80 percent of U.S. productivity growth during the period 1950-1993 can be ascribed to improvements in educational attainments and research investments.

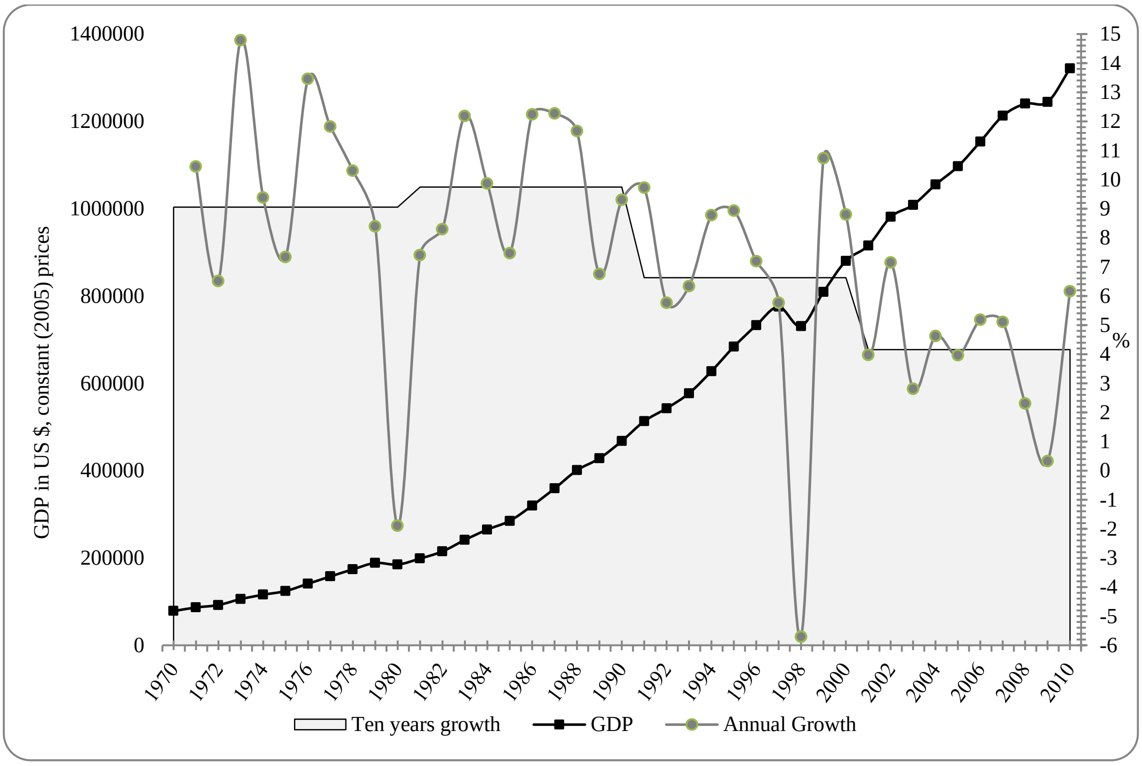
Although the importance of R&D is nowadays acknowledged worldwide, it has been noted that the effect of R&D on output and productivity growth largely varies across countries. Grossman and Helpman (1991) ascribe a major part of this variation to the degree of trade openness and list several channels through which trade affects R&D. First and foremost, in countries with large external trade, firms have access to a larger market and therefore may experience larger profit opportunities that stimulate investments in research. Secondly, firms in open countries face stronger, international competition and might use R&D investments as a strategy to maintain the position of technological leaders. Third, openness, especially in terms of import, lowers the price of R&D promoting investments. Fourth, with trade openness firms have access to external knowledge and might thus avoid costs related to the duplication of R&D investments. Fifth, trade offers access to a larger group of specialized suppliers and, finally, trade allows international R&D spillovers. With respect to this last hypothesis, Coe and Helpman (1995) provide evidence that open countries may benefit from externalities due to R&D spillovers, but also that these externalities increase with trade openness.

Innovation and economic growth in Korea

R&D and trade openness can shape the growth pattern of countries and to some extent can be considered responsible for the Korean miracle (Alam, 1989; SaKong, 1993). Korea was one of the poorest countries in the world at the beginning of 1960s, with an income per head on a par with the poorest parts of Africa. However, Korea has achieved unparalleled economic growth in the last five decades. During the period 1970-2010 the Korean economy registered a 7.4% rate of annual average growth (Figure I.1) with a more sustained growth in the first two decades. The only years for which a decline in production has been registered are the years 1980 and 1998[3]. Overall the level of GDP has increased to the standard of many other OECD countries and the catch-up process was boosted especially after the 80s. Nonetheless the growth rate of the economy has only slowly decreased from the 10% rate of the 80s to the 6.5% of the 90s and finally to 4% in the last ten years.

[3] This negative growth rates should be respectively, to crop failure and political instability (in 1980) and to the Asian financial crisis of 1997 (for 1998).

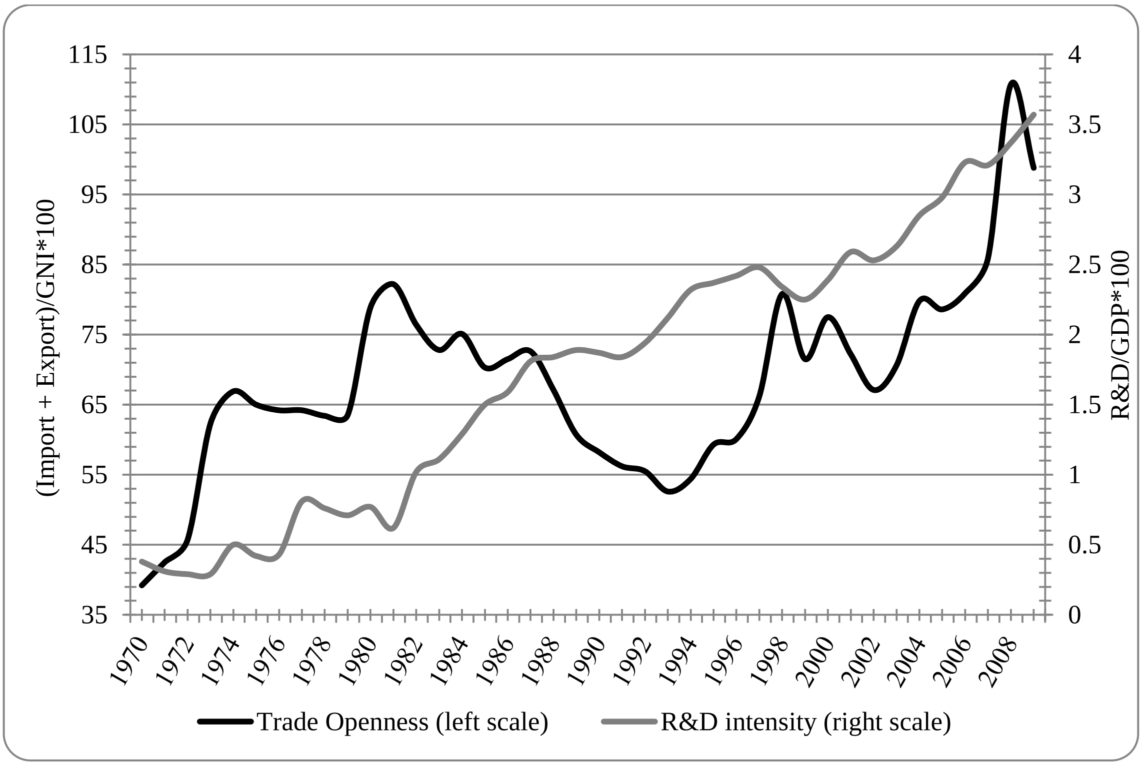
Figure I.1: Gross Domestic Product (real, 2005 prices) Level and Evolution (Source: OECD)



The change in both the level of GDP and in the growth rate can be traced back to several stages that have characterized the development of Korea. The development was initially based on the accumulation of traditional factors, especially labour, during the decades of 1960s and 1970s and gradually shifted to the accumulation of capital during the decades 1970s and 1980s. The objective of strong capital investments has been reached by focusing the policy attention on heavy and chemical industries (HCIs). The openness-to-trade policy orientation, jointly with the increasing investments in R&D in heavy industries, has undoubtedly accelerated the transition from an industrial base made by light industry to a production system oriented toward HCIs and the emerging industry of information technology (IT).

Korea achieved a sustained economic development in the late 1990s, when it became an OECD member nation and changed its economic development strategy from a factor input production system to a technological innovation-oriented strategy. This change in strategy led to a rapid increase in R&D expenditures reaching 3.74% of its ratio to GDP in 2010 (KISTEP, 2011) and setting 5% as target to be reached by 2012[4]. In the meantime the trade-to-GNI ratio has increased from the level of 57.7% in the 1970s to a level of 80% in the 2000s[5]. Figure I.2 shows the trends in trade openness, as measured by the ratio between the volume of trade and the GNI compared to R&D intensity, as measured by the aggregate expenditure in R&D over GDP. The change in Korean research policy is reflected in the change of the time trend in R&D intensity after 1990, when the threshold of 2% has been passed.

Figure I.2: Trends in Trade and R&D in Korea (Source: Statistics Korea)



Nowadays Korea is among the top R&D investors in the OECD counties. According to official statistics[6] Korea ranks third in the share of investments relative to GDP close to Japan (3.4%), and after Finland (3.7%) and Sweden (3.7%). Nonetheless, since Korea is a newly industrialized country, the levels of expenditure, both in overall terms and per-capita expenditure, remain low. In 2008 Korea invested €21,479 millions in R&D, which is quite low compared to the expenditure of the U.S. (270,732) and Japan (113,986). Also in per-capita terms Korean investments are relatively low (441.9 Euros) compared to the U.S. (888.5) and Japan (892.7). Furthermore, such a high R&D intensity in Korea is the result of strong specialization in R&D-intensive industries, which is different from other countries where R&D investments are made by firms in several manufacturing industries. This is the consequence of a strong policy orientation toward technology-intensive industries, such as computers

[4] Source: MEST (2011).
[5] Source: Statistics Korea.
[6] Source: Eurostat, Science and Technology Statistic Database, year 2008.

and electronics. it is worth noting that R&D activities are concentrated within a small number of large firms, and hence a few large corporations play a locomotive role in R&D.

R&D investments and the resulting consequences in the Korean economy: open issues analyzed in the Ph.D. thesis

Acknowledging the non-negligible role that R&D has played and continues to play in characterizing the economic development of Korea, it would seem that Korean development is somewhat unbalanced in favor of R&D. And this has cast some doubts on the overall effectiveness of such a policy orientation. First of all, Korea is facing the problem of youth unemployment and the lack of job opportunities is partly ascribed to the labour saving effect of investments in research. Secondly, the high concentration of R&D investments in only some industries might be related to the existence of returns to R&D in these industries. In other words it is possible that investments in R&D are considered unattractive by firms in traditional industries. Finally, innovation is not only made through R&D. On the contrary, firms might prefer to buy technology externally. This might especially be the case for young firms, which do not have the necessary experience and resources to engage in R&D.

The analysis of these three topics represents the structure of this work which aims at contributing to the existing literature on the effect of R&D for economic development in Korea by providing firm-level empirical evidence. The analysis that will be presented in the following chapters is empirical in nature and uses standard theoretical models from the literature on the economics of innovation.

The first chapter analyses the way investments in research relate to the level of employment in firms. The empirical relationship is derived from a neo-classical labour demand in which the level of firm employment is expected to be influenced by sales, wage and technological innovation. This last should be negatively related to the level of firm's employment in order for innovation to be labour saving. In the second chapter the contribution of research investments to productivity is examined. Knowledge capital, accumulated by firms investing in research, is considered as an input in the production function and its contribution is directly estimated. The goal of the work is to show that investments in research positively contribute to the productivity of firms. Furthermore, the study is aimed at the investigation of the extent to which the positive contribution of these investments either characterizes only firms in high-tech industries or can be globally extended also to firms in more traditional, low-tech, industries. Finally, in the third chapter, the manner in which innovation is achieved by firms is explored with particular attention to the issue of innovation in young firms. A knowledge production function approach is used in which inputs other than internal R&D

expenditures are considered in an attempt to highlight the differences between young and mature firms in the use of different inputs.

Despite the fact that most of the issues discussed concern macro-policies and aggregate dynamics, in this work a firm-level perspective is used. The choice to ground the empirical analysis at the firm level has surely very important implications when it turns to interpret the results and to make inference in terms of policy. These points will be discussed in more detail in each chapter. Nonetheless, it is worth drawing attention to the fact that availability of structured firm-level dataset has permitted to shed light on certain aspects which were previously unexplored. Namely, this work has made use of two main sources of data available in Korea. One is the *R&D Survey* and the second is the *Korean Innovation Survey*.

The R&D survey following guidelines of the OECD Frascati Manual has been introduced in 1995 and was implemented by the Korean Science and Technology Policy Institute (STEPI). Since 1999 the survey has been conducted by the Korea Institute of Science & Technology Evaluation and Planning (KISTEP). The questionnaire has been circulated to a continuously increasing number of firms and public and private research institutes. The aim of the survey is to cover all the institutions in Korea that are involved actively in research projects. Table I.1 reports the number of surveyed institutions according to the classification by type of institution. Also, in bold, the number of institutions that reported to the questionnaire is indicated and, in parenthesis, the reporting rate.

The Table illustrates that the number of surveyed institutions has continuously increased over time and has doubled over the course of eight years, with a reporting rate always higher than 77%. The majority of surveyed institutions are obviously firms, for which reporting rates are usually the lowest amongst all other types of institutions. However, the reporting rate of firms has increased over time as has the number of firms involved in the survey.

By using the data in the survey it was possible to obtain precise information about the R&D activity of firms. In particular, the survey investigates not only the amount of the expenditure but also its composition allowing to distinguish, for instance, current from capital expenditure and, within the current expenditure, the expenditure for labour from other expenditures. This constitutes very valuable information as it reveals that almost one half of the expenditure classified as R&D by firms is used to pay the wage of researchers and research assistants. The implications of this are very important especially with regards to the effect of innovation on jobs. What at first glance may appear conducive of job-destruction might be revealed, on more careful scrutiny, to result in job-creation and even job-substitution, meaning with this the replacement of ordinary workers with more skilled workers. The issue will be further discussed in the first chapter. Furthermore, the survey reports information on the number and composition of research workers. This is also a very important piece of information as the definitions of labour and knowledge capital may overlap once almost one half of the expenditure for knowledge goes to labour. Consequently, the survey allows a definition of labour from which it is possible to exclude the knowledge capital. This in turn permits to better assess the real contribution of knowledge to labour productivity, which will be discussed in the second chapter.

Table I.1: Description of the R&D Survey

Year	2002	2003	2004	2005	2006	2007	2008	2009
Public Institutes	235	238	325	275	237	331	743	752
	233	**232**	**317**	**271**	**234**	**316**	**733**	**729**
	(98.5)	(97.5)	(97.5)	(98.5)	(98.7)	(95.5)	(98.7)	(96.9)
Universities	350	348	378	369	328	409	410	431
	347	**340**	**366**	**360**	**324**	**402**	**409**	**429**
	(99.1)	(97.7)	(96.6)	(97.6)	(98.8)	(98.3)	(99.8)	(99.5)
Medical Institutes	500	500	622	681	664	664	651	635
	485	**480**	**590**	**649**	**654**	**637**	**649**	**631**
	(97.0)	(96.0)	(94.9)	(95.3)	(98.5)	(95.9)	(99.7)	(99.4)
Firms	9735	9353	10908	12531	15075	18234	21506	23.874
	7178	**6991**	**8350**	**9837**	**12639**	**14966**	**17328**	**19762**
	(73.7)	(74.7)	(76.1)	(78.5)	(83.8)	(82.1)	(80.6)	(82.8)
Total	10823	10439	12233	13856	16304	19638	23310	25692
	8245	**8043**	**9573**	**11117**	**13851**	**16321**	**19119**	**21551**
	(96.2)	(77.0)	(78.3)	(80.2)	(85.0)	(83.1)	(82.0)	(83.9)

(Source : KISTEP, 2003-2010)

The second source of data is represented by the Korea Innovation Survey (KIS) 2010 (2007-2009) that, similarly to the Community Innovation Survey for European Countries, investigates all the aspects of innovation in manufacturing firms. Innovation is defined according to four categories, namely product, process, marketing, and organizational aspects. The expenditure for innovation is classified into four types: expenditure for R&D made internally to the firm, expenditure for R&D made externally to the firm, expenditure for the acquisition of machinery and expenditure for the acquisition of technology. According to the objective of the study the latter is the most important piece of information contained in the survey and it does not surprise that the availability of structured innovation surveys like the KIS have significantly contributed to the development of the literature on the determinants of innovation. This will be discussed in the third chapter.

The results found in this work shed new light on the academic and policy debates surrounding the role and effectiveness of R&D and R&D-related policies in Korea. More specifically, in the first chapter evidence is found that R&D investments have no direct labour saving effects and, on the contrary, high levels of investments in R&D positively affect firm employment. Furthermore, it is found that most of the contributions of R&D to employment manifest in the creation of new jobs in R&D departments and, therefore, that R&D expenditure is likely to increase job opportunities for highly skilled workers, with very important implications for young employment. The results in the second chapter indicate that investments in knowledge capital, as proxied by the cumulative R&D expenditure made by firms, boost firms' productivity. There is also clear evidence that the contribution of knowledge capital to productivity is sizable in all industries, although it is larger in high-tech industries in which R&D investments also concentrate. Finally, the evidence in the third chapter describes innovation in firms as a complex process driven not only by internal R&D investments. As expected, in fact, it is found that innovative investments different from internal R&D are also important in general and especially for young firms. Accordingly, it is found that in young firms innovation is driven by external R&D and by technological acquisition, more than by internal R&D. Although the centrality of the role of R&D for innovation in Korean firms is still acknowledged, the evidence suggests that a very important role is played by external, either public or private, institutes in collaboration with young firms.

As already mentioned, the rest of the work is organized in three chapters. The structure of each chapter is the following. First, the topic as well as the motivation of the study is presented, emphasizing the novel contributions of the empirical analysis as compared to the existing empirical literature. Secondly, a discussion of the theoretical approach to the topic is provided together with a detailed description of the dataset used to implement the empirical analysis. The empirical analysis, which is at the core of each chapter, is further presented and discussed and is followed by some concluding remarks.

References I

Aghion, P. and Howitt, P. (1992). *A Model of Growth through Creative Destruction*. Econometrica. 60: 323-351.

Alam, S.M. (1989). *The South Korean 'Miracle': Examining the Mix of Government and Markets*. The Journal of Developing Areas. 23: 233-258.

Barro, R.J. and Sala-i-Martin, X. (1992). *Convergence*. Journal of Political Economy. 100: 223-251.

Coe, D.T. and Helpman, E. (1995). *International R&D Spillovers*. European Economic Review. 39: 859-887.

Griliches, Z. (1979). *Issues in Assessing the Contribution of Research and Development to Productivity Growth.* The Bell Journal of Economics. 10: 92-116.

Grossman, G. M. and Helpman, E. (1991). *Innovation and Growth in the Global Economy*. Cambridge, MA: MIT Press.

Jones, C. I. (2002). *Sources of U.S. Economic Growth in a World of Ideas.* American Economic Review. 92: 220-239.

KISTEP (Korean Institute of Science and Technology Evaluation and Planning). (2003-2011). *Survey of R&D in Korea, 2003-2011.*

Lucas, R.E. Jr. (1988). *On the Mechanics of Economic Development*. Journal of Monetary Economics. 22: 3-42.

MEST (Ministry of Education, Science and Technology). (2011). *Year 2011 Plan Report.* (http://www.mest.go.kr/main.do).

Romer, P.M. (1986). *Increasing Returns and Long-Run Growth*. Journal of Political Economy. 94: 1002-37.

Romer, P.M. (1987). *Growth Based on Increasing Returns due to Specialization*. American Economic Review. 77: 56-62.

Romer, P.M. (1990). *Endogenous Technological Change*. Journal of Political Economy. 98: S71-S102.

SaKong, Il. (1993). *Korea in the World Economy*. Peterson Institute Press. All Books.

Solow, R.M. (1956). *A Contribution to the Theory of Economic Growth*. Quarterly Journal of Economics. 70: 65-94.

Statistics Korea. *Korea Statistical Information Service*. (http://www.kosis.kr)

CHAPTER 1

The Effect of R&D Expenditures on Employment: A Panel Analysis of Korean R&D Micro-data

1.1 Introduction

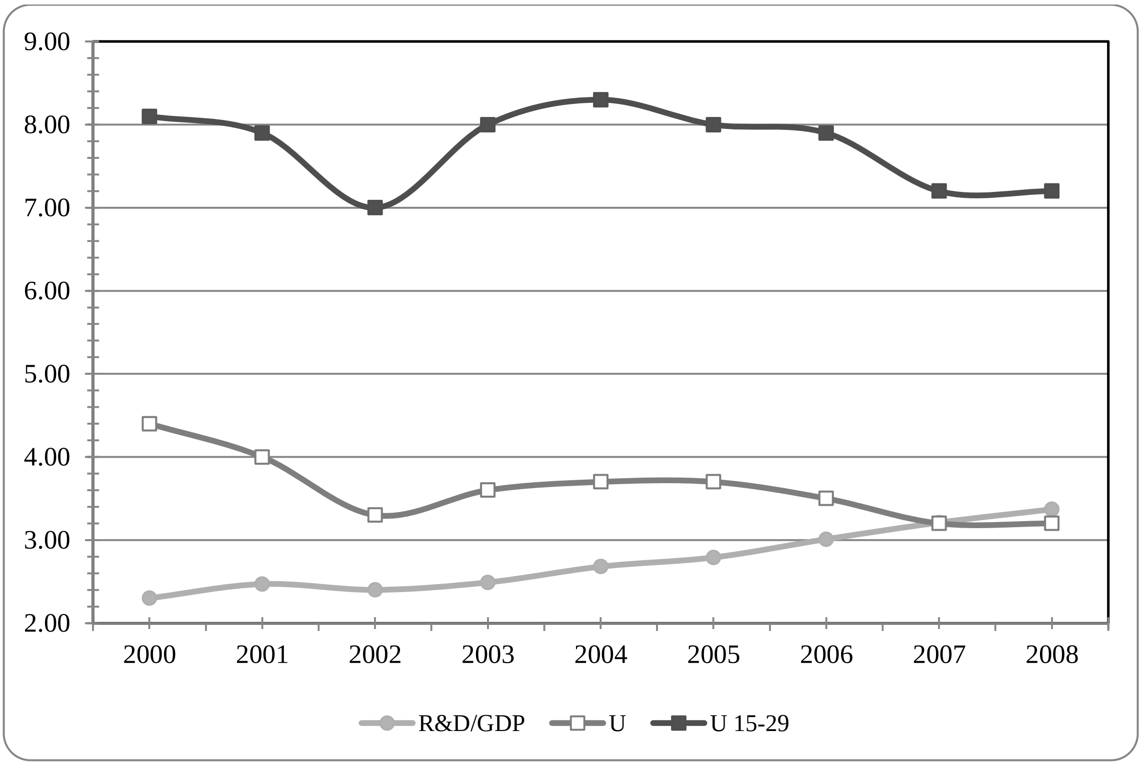
The way technological innovation relates to change in employment is a complex issue in the Economics of Innovation literature[1]. Along with the widespread viewpoint that technical change destroys jobs, it is generally understood that innovation also has the effect of creating jobs. The distinction between product and process innovation has been issued as a fundamental aspect from past research experiences[2] for the comprehension of whether innovations' effects on employment are negative or positive. At the same time, the variety of data used, methodologies and analysis levels, have led to such a heterogeneous set of results that it would be difficult to definitively conclude on the issue. As a result, the ongoing academic debate of the job creation/destruction effect of innovation seems un-ending.

At least at the firm level, however, there is general agreement on the point that technological innovations rather have positive effects on employment (Piva and Vivarelli, 2005). In addition, the literature discussing the determinants of company growth emphasizes the important contribution of innovation to a firm's growth (Coad and Rao, 2011) with direct and indirect effects on employment growth[3]. Accordingly, one might expect that investments in R&D, boosting innovation, positively

[1] Regarding innovation-employment concerned literature Pianta (2004) summarized a variety of perspectives in terms of economic system, methodologies and levels of empirical analysis.
[2] See, for instance, Stoneman (1983), Katsoulacos (1984) or Blechinger et al. (1998).
[3] Actually the literature on company growth relates innovation to different measures of company performance, amongst others employment growth. See, for instance, Coad and Rao (2008). There are thus noticeable differences with respect to the literature on innovation and employment, the latter focusing on employment, not employment growth.

impact employment[4]. Korea, which achieved a high level of economic development in the late 1990s, when it became an OECD member nation, changed its economic development strategy from a factor input production system to a technological innovation-oriented strategy. This change in strategy led to a rapid increase[5] in the rate of R&D expenditures reaching 3.74% of its ratio to GDP in 2010 (KISTEP, 2011). Moreover, this figure is expected to rise as the Korean government has set a target of 5%, to be achieved by 2012[6]. However, in recent years, unemployment, particularly youth unemployment, has become a pressing political and social issue. Compared to the generally low level of Korean unemployment, youth unemployment is considerably high (see Figure 1.1) and, not surprisingly, as the R&D to GDP ratio continues to increase, there is a concern that Korea may experience so-called "jobless growth", a state of affairs which countries such as the U.S. and other developed nations are often said to be facing (Ha and Moon, 2010; Kim, 2010). Consequently, there surfaces the argument that enhancing technological innovation has been responsible for Korea's unemployment problem (Choi, 2008).

Figure 1.1: R&D and Unemployment in Korea



Source: Statistics Korea and KISTEP

Nonetheless the two can be considered, to some extent, as overlapping, especially concerning the hypothesis about the effects of innovation at the firm level.

[4] A recent study by Bogliaccino and Vivarelli (2010) has shown that, at least at the industry level, employment growth is more related with product innovations, which are in turn driven by R&D expenditures.

[5] The average annual increase rate of R&D during 1990-2009 was 9.6% in real terms, which is calculated by using Shin (2002) and KISTEP's Surveys of R&D in Korea (see Appendix A).

[6] Source: MEST (2011).

Being aware that the evaluation of the “jobless growth” question requires a macroeconomic point of view, at which level the direct (either positive or negative) effect is counterbalanced by different compensation mechanisms, the firm level analysis permits, nonetheless, to better understand the most important and direct effects. As argued by Piva and Vivarelli (2005), results of microeconometric analysis cannot be generalized for policy purposes; however, the great advantage of a microeconometric study is that it provides a direct way of testing whether a labour saving effect of technological innovation exists. This study is thus aimed at understanding the way innovation determines employment in Korea, a country with a different economic environment from that of the EU and the USA, to which most of the literature refers.

More specifically the hypothesis of a labour saving effect of R&D investments on employment is tested, and several specification issues are addressed in order to assess the robustness of emerging evidence. In general terms, alongside the empirical analysis, the standard product/process differentiation is adopted, expecting a positive effect of innovation to be a characteristic of the former rather than the latter. Other specification problems are also discussed in this work. First and foremost, given that more than 40% of total R&D expenditure is used to pay the salaries of researchers[7], it is possible that a strong positive relation between R&D and employment emerges as a consequence of the higher level of expenditure by firms employing a larger number of researchers and, consequently, of employees. The hypothesis of labour saving effect of R&D is therefore tested considering both the total employment and the sole amount of non-research workers. Secondly, industry specific characteristics, known to influence both firms' size and the decision of the amount to be invested, may also play a role in determining the firm's employment response to R&D investments. In particular a labour augmenting effect of innovation is expected to characterize firms whose main activity is in high-tech industries while, on the contrary, innovation is more likely to be labour saving if the firm works in a low-tech industry. As a consequence, evidence of a positive effect of innovation obtained using the whole sample of firms could hide different behaviuors of firms in different industries. And for this reason the labour saving effect of innovation is tested across different groups of firms classified according to their technological levels. Finally, recent *streams* of empirical literature have highlighted the appropriateness of a dynamic model when considering a model of firm level labour demand (Piva and Vivarelli, 2005; Lachenmaier and Rootmann, 2011), given the high persistence of a firm's employment level over time. Therefore the main model we investigate is also specified in a dynamic framework and estimated making use of GMM-SYS methodologies for dynamic panels.

Starting from a neoclassical labour demand augmented including technological innovation, this paper builds a link between innovative activity, measured by R&D expenditures, and employment at

[7] See section 1.3.

the firm level. Using a new and completely balanced dataset composed of a panel of 732 private Korean manufacturing firms over the period 2002-2008, it is found that there is an overall positive relationship between R&D expenditures and employment, thus rejecting the hypothesis that innovative investments have a labour saving effect. The result proved to be robust to changes in the specification of the econometric model. Nevertheless, measuring innovation with R&D expenditure has two consequences that are worth noting. The first is that most of the R&D expenditure, as already mentioned, serves to pay the wages of researchers and thus the exclusion of the number of researchers from employment weakens the evidence of a positive effect of innovation. The second is that firms use internal R&D mainly for product innovation and consequently results tend to be biased toward a larger effect of R&D expenditure for product innovation than for the process counterpart.

The rest of the work is organized as follows. The next section discusses the theoretical relationship between innovation and employment including a survey of the existing empirical literature regarding the case of Korea. Section three presents the empirical model used for estimation, and briefly describes the dataset. Results are summarized in the fourth section, and the conclusion follows.

1.2 Literature

The distinction of innovative activities based on product/process division has led the theoretical discussion on the innovation-employment relationship. For both, however, the main effect might be weakened by secondary effects, yielding unclear theoretical predictions (Lachenmaier and Rottmann 2006, 2011).

In the competition framework, for example, product innovation is likely to increase the market share of a single, innovative firm. This may eventually increase labour demand as a consequence of sales increase. The same innovation may, on the contrary, bring about a fall in sales if the firm decides to exploit its monopolistic power gained through the introduction of a new product. Process innovations, likewise, are usually considered labour-saving, as long as the same amount of output can be produced using less labour. However, an increase in labour may follow the job creation effects of some compensation mechanisms; for instance, price and income effects described by Vivarelli (1995) and Vivarelli et al. (1996).

Empirical models are used in order to discriminate among these several theoretical hypotheses. However, previous studies about the effect of innovation on employment show very heterogeneous results. Limiting the field only to the firm level, studies can be classified, at least based on the results, according to the following five macro-categories, more carefully described in the next paragraphs: (1)

studies in which a positive effect of technological change has been found, without distinction between product and process innovations; (2) studies showing evidence of a positive effect of both product and process innovations; (3) studies in which the positive impact of product innovations is contrasted with a weak or negative effect of process innovation; (4) studies in which a positive effect of process innovations and a weak or negative effect product innovations are found; (5) studies indicating negative or null effect of both product and process innovation on employment.

Innovation positively influences employment - evidence of a positive effect of innovation was initially provided by Doms et al. (1997). Using data of the U.S. companies for the period 1987 and 1991, the authors find a positive relation between technology change and employment without distinction of product/process innovation. Also Piva and Vivarelli (2005) make use of a global measure of innovation that does not distinguish process from product innovation. Their results, applying GMM-SYS methods on a longitudinal dataset of 575 Italian manufacturing firms over the period 1992-1997, also indicate a positive relation between innovation and employment.

Both product and process innovations positively influence employment – Smonly (1998) uses different indicators for product and process innovations in his analysis of a panel of German firms for the period 1980-1992. Using Pooled OLS regression, the study reveals robust evidence of a positive effect of both product innovation and process innovation. Based on a different sample of German firms, the study by Lachenmeier and Rottmann (2011) analyzes the innovation-employment relation with GMM-SYS methods. Their result confirms previous evidence.

Product innovations positively influence employment while process innovations do not – In the study by Entorf and Pohlmeier (1990), data collected from a cross section of 2,276 West German firms during the year 1984 is investigated. Results indicate that product innovations have a positive effect on employment, while the effect of process innovations is not significant in regression results. Cross-sectional regressions are also used by Peters (2004) to analyze German CIS3 (1998-2000) data. Estimates support the hypothesis that only product innovations positively affect firm employment.

Process innovations positively influence employment while product innovations do not – Evidence for this hypothesis is provided by Blanchflower and Burgess (1998), applying cross-section methods to innovation survey data of UK in 1990 and Australia in 1989/1990. The same evidence is, however, confirmed by the study of Greenan and Guellec (2000), who, on the contrary, apply panel data methodologies to study a sample of 15,186 French firms between 1984 and 1991. Their findings reveal only a weak effect of product innovations, as opposed to a sizable effect of process innovation.

Neither product nor process innovations positively influence employment – In this last category the study carried out by Brouwer et al. (1993) is observed, a study based on a cross-sectional dataset composed of 859 Dutch firms. Using R&D expenditures as a proxy for firm innovation, authors report evidence of an aggregate negative relation between R&D expenditures and employment. Also in the study by Klette and FØrre (1998), an analysis of 4,333 Norwegian plants over the period 1982-1992, there is no evidence of a positive relation between R&D intensity and employment.

Turning the attention to the empirical literature which examined the case of Korea, it can be observed that the innovation-employment relationship has been so far investigated at the macro, aggregate level (Kang, 2006; Bae et al. , 2006; Ha and Moon, 2010; Kim, 2010), while only a minority of studies have dealt with the issue at a micro, firm level. Moon et al. (2006) use Korea Innovation Survey (KIS) 2002 (2000-2001) data consisting of 2,149 firms, and applying multi-product model suggested by Jaumandreu (2003), report that the increase of new product sales made by product innovation brings about a larger job growth effect than the increase of old product sales, signifying that product innovation leads to a positive effect on employment. Lee et al. (2010) analyze KIS 2008 (2005-2007) data composed of 1,478 firms, and applying Van Reenen's labour demand model (1997), argue that a firm which implements product and process innovation together benefits of a job creation effect in Korea while implementing only one of two innovations does not.

1.3 Model and Data

The job creation (destruction) effect of technological innovation is investigated in this paper using a method that has become standard in the reference empirical literature and has been widely employed in the studies mentioned in previous sections. Innovation is here considered among the determinants of a firm labour demand (Van Reenen, 1997), which is directly derived from a CES production function [1.1] with firm output Q being produced using capital K, labour N and technologies (T, A, B) which are respectively neutral and labour and capital augmenting. σ is the elasticity of substitution between capital and labour.

[1.1] $$Q = T\left[(AN)^{\frac{\sigma-1}{\sigma}} + (BK)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Profit maximization requires equating marginal productivity of labour to wage w and from this first order condition the optimal labour demanded by each firm can be derived as

[1.2] $$N^{*} = Q\left(\frac{w}{p}\right)^{-\sigma} A^{(\sigma-1)}$$

with p being the output price. In order to obtain a valid empirical formulation, the model in [1.2] can be rewritten in log

$$[1.3] \qquad \log(N) = \log(Q) - \sigma \log\left(\frac{w}{p}\right) + (\sigma - 1)\log(A)$$

and can be estimated using the following formulation[8] (lower case indicates log)

$$[1.4] \qquad emp_{i,t} = \beta_1 sales_{i,t} + \beta_2 wage_{i,t} + \beta_3 inno_{i,t} + \left(a_i + \delta_t + \varepsilon_{i,t}\right).$$

$emp_{i,t}$ is the number of firm employees at time t, $sales_{i,t}$, $wage_{i,t}$ and $inno_{i,t}$ are respectively the amount of sales realized by the firm in the year, the wage per employee, and the amount of R&D expenditures. a_i and δ_t are respectively firm specific and time specific unobservable effects which are likely to influence firms' employment while $\varepsilon_{i,t}$ is the common vector of spherical disturbances. Although equation [1.4] should be considered the main model to empirically investigate the link between innovation and employment, a second formulation [1.5] is used, in which total R&D expenditures are replaced by those for product and process innovation.

$$[1.5] \qquad emp_{i,t} = \beta_1 sales_{i,t} + \beta_2 wage_{i,t} + \beta_{31} proc_{i,t} + \beta_{32} prod_{i,t} + \left(a_i + \delta_t + \varepsilon_{i,t}\right).$$

Models in equations [1.4] and [1.5] can be consistently estimated by using the within estimator in place of the standard Pooled OLS, biased by the impossibility to account for firms specific characteristics. However, the within estimator becomes inconsistent when a lagged dependent variable is included among the regressors. Such a dynamic specification, suggested by Van Reenen (1997) and applied, among others, by Piva and Vivarelli (2005) and Lachenmaier and Rottmann (2011), is useful to account for possible adjustment dynamics and persistence in the firm's demand for labour. In this case the GMM-SYS methodologies can be applied, with the clear advantage of a) controlling for unobservable and time-invariant characteristics, which are dropped since the model is specified in the first differences, b) ensuring consistent estimate of the lagged dependent variable parameter by using internal instruments, c) allowing to account for possible endogeneity of innovation variables.

For empirical test purposes, the labour demand will be estimated using the static specification ([1.4] and [1.5]) to answer the research questions posed in the previous section and the consistency of the main results will be checked using the dynamic specification described above. The data used is

[8] The formulation proposed in this paper is a simplified version of that presented in Van Reenen (1997). In the latter, profit optimization is solved by the firm simultaneously with respect to labour and capital. Accordingly, the value of output is substituted with that derived from the FOC with respect to capital. Such a formulation requires using a proxy for the firm's capital in the empirical estimation. The capital variable is, however, available for the only 68% of the firms in our dataset and its use would have implied the loss of an important piece of information. For this reason the simplified version already adopted by Piva and Vivarelli (2005) has been used.

part of a new database obtained by matching information from the R&D survey carried out by the Korean Institute of Science and Technology Evaluation and Planning (KISTEP) with firms' financial statements data from the Korea Information Service Co. (KISVALUE) [9]. The R&D survey, following guidelines of the OECD Frascati Manual has been introduced in 1995 and since 1999 it has been implemented by KISTEP. From that date the questionnaire has been delivered to a continuously increasing number of firms. Of the more than 4,500 firms for which survey data were collected for at least one year from 2002 to 2008, we selected the 2,638 belonging to the manufacturing and, within that group, the 732 for which data were available every year. This yielded a balanced panel of manufacturing firms made of 5,124 observations. The loss of information due to the choice to balance the dataset is minimal both in terms of the number of firms and of number of employees. Relevant statistics comparing the whole sample of manufacturing firms with the subsample of firms in the balanced dataset are provided in Table 1.1. From the survey, this study used data on employment, sales and R&D expenditures, both in the total amount and divided according to the product/process destination[10]. Also industrial classification was derived from the surveys. Wage was, on the contrary, obtained from firms' accounts as the total amount of expenditure in wages and salaries divided by the number of employees declared in the official balance. Descriptive statistics for the relevant variables are provided in the Appendix C.

Table 1.1: Yearly Statistics of Firms and Employment in Survey and Sample

	Number of Firms		Mean Number of Employees		Total Number of Employees		
	Whole Sample	Balanced Sample	Whole Sample	Balanced Sample	Whole Sample (A)	Balanced Sample (B)	Share A/B
2002	1515	732	476	714	722080	522964	72.4%
2003	1594	732	504	788	781429	576988	73.8%
2004	1648	732	512	834	844217	610823	72.3%
2005	1889	732	468	858	884335	628381	71.0%
2006	2173	732	439	860	955046	629547	65.9%
2007	2068	732	458	875	948102	640501	67.5%
2008	2053	732	462	860	950269	629639	66.2%

To the author's knowledge this is the first time Korean R&D micro data has been used for the investigation of the innovation effect on employment. Moreover, some features of the data distinguish this study from existing ones. The first important thing is that the survey reports the detail of the composition of R&D expenditure, differentiating between current expenditures (Labour, Training and Materials) and capital expenditures (R&D machinery, R&D lands and buildings, Computers and

[9] See Appendix A.
[10] See related questionnaire in Appendix B.

Software)[11], and the R&D personnel as well. Given that, on average, more than 40% of expenditure (see Table 1.2) is intended for labour (i.e. researchers' wages), we doubt a positive association between R&D and employment to be the outcome of such a firm's behaviour and not the result of the positive effect of innovation described in the introduction. On the contrary, innovation might have negative effects on the firm's labour demand for non-research employment. For this reason the amount of researchers and research assistants is subtracted from the total employment. A positive and significant β_3 coefficient would clearly reject the hypothesis that R&D investments are made in a labor saving trajectory. The second thing is that control for price variations both in time and between industries is made, since monetary values are subject to variation due to changes in input and output prices. Such a variation typically holds over time and time dummy in panel models should correct coefficient estimates capturing the price effect, which varies over time but is constant across firms. We argue that time dummy may be insufficient to capture the inflation effect and also that a change in prices determine variations not only over time but also across industries. For this reason, the monetary variables we use are "real" variables, meaning that they are deflated using a synthetic price index for wage and an industry specific price index for sales and R&D expenditures[12].

Table 1.2: R&D by Type of Expenditure (% of Total)

Type of Expenditure	Average
Labour	43%
Training	4%
Materials	11%
Other	31%
Machinery and Equipment	9%
Land and Buildings	1%
Computers and Software	1%

1.4 Results and Discussion

The empirical analysis is organized in two steps. In the first, a static labour demand is estimated with some changes in the specification in an attempt to verify whether a labour saving effect exists. In particular, it is tested whether R&D expenditures have a labour saving effect on non-research workers, if the effect depends on the type of innovation R&D expenditure are intended for, and, finally if the effect varies across firms operating in different industries, classified according to the level of

[11] See related questionnaire in Appendix B.
[12] Source: Statistics Korea.

technology. In the second stage, once it is made clear that R&D expenditures do not have a labour saving effect, the model is estimated using the dynamic specification.

1.4.1 Static Model

We start by estimating the model in equation [1.4] with the Pooled OLS estimator with a battery of industry dummy and the fixed effects estimator, this second in order to wipe out the bias coming from the omission of firm-specific characteristics. The model is estimated using (a) the total amount of employees and (b) the amount of employees once research personnel has been excluded from the computation and the innovation coefficient is expected to be positive and significant in both cases. Results are presented in Table 1.3.

Table 1.3: Static Labour Demand with R&D Expenditures

	sales	*wage*	*inno*	*intercept*
		Pooled OLS		
(a)	0.633*** (0.008)	-0.278*** (0.013)	0.143*** (0.008)	1.319*** (0.243)
(b)	0.702*** (0.010)	-0.316*** (0.016)	0.082*** (0.009)	1.381*** (0.286)
		Fixed Effects		
(a)	0.353*** (0.028)	-0.184*** (0.029)	0.038*** (0.009)	4.117*** (0.481)
(b)	0.398*** (0.035)	-0.205*** (0.036)	0.021* (0.013)	3.932*** (0.590)

Notes to Table:
Robust SE in parenthesis
***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.
In model (a) the dependent variable is the total employment (in logs). In model (b) the dependent variable is constructed subtracting the number of researchers to the total employment (in logs).

The coefficients are always significant and of the expected sign (positive for output and innovation and negative for wage), with both dependent variables. When fixed effect estimation is used the magnitude of all coefficients is reduced, as usual. Paying particular attention to the effect of R&D, the fixed effects estimate indicates that the response of employment to a 1% increase in the R&D spending ranges from 0.02% to 0.04%, depending on the type of dependent variables used. This is very low compared to the estimates using POLS, according to which the response ranges from 0.08% to 0.14%. Finally, comparing models (a) and (b), the coefficient for R&D is always positive and significant. It is, however, worth noting how the significance of the innovation variable decreases in the specification which uses employees without research personnel as dependent variable. Nonetheless, the evidence does not support the hypothesis of a labour saving effect of R&D investments, for a further consistency check both specifications, with and without researchers, will continue to be employed in the remaining of the work.

The second model specification includes expenditures classified according to the product/process differentiation (equation [1.5]) in place of the overall R&D expenditure. Once again the model is estimated by using POLS and FE estimators. Two different batteries of dummies are included in the POLS specification, namely industry dummies and technology dummies, this last defined following the OECD classification of industrial manufacturing sectors[13]. Results are presented in Table 1.4.

Table 1.4: Static Labour Demand with Product and Process Innovation Expenditure

	Employment Including Researchers			Employment Excluding Researchers
	Pooled OLS Industry Dummy	Pooled OLS Technology Dummy	Fixed Effects	Fixed Effects
sales	0.672^{***}	0.652^{***}	0.365^{***}	0.403^{***}
	(0.007)	(0.008)	(0.027)	(0.035)
wage	-0.261^{***}	-0.253^{***}	-0.182^{***}	-0.204^{***}
	(0.013)	(0.012)	(0.029)	(0.036)
prod	0.073^{***}	0.083^{***}	0.008^{**}	0.007
	(0.006)	(0.007)	(0.004)	(0.007)
proc	0.023^{***}	0.028^{***}	0.003^{**}	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
intercept	1.003^{***}	1.689^{***}	4.149^{***}	3.948^{***}
	(0.244)	(0.201)	(0.482)	(0.589)

Notes to Table:
Robust SE in parenthesis
***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.

As expected, the two models estimated with POLS return almost identical estimates, correctly sloped and significant in both the cases. The third and fourth column reports fixed effects estimates, respectively using employment with and without researchers as dependent variable. Looking at the coefficients for sales and wage in column 3, they are very close to those in Table 1.3 (.365 and -.182 compared to .353 and -.184). Innovation coefficients are also correctly sloped and significant although lower in magnitude. Also the sum of the two (0.008+0.003) is lower than the estimate with the overall expenditure (.038). In general, estimates suggest that R&D expenditure for product innovation has a greater effect than that for process innovation and, in any case, the hypothesis of a labour saving effect of R&D expenditure is ruled out by empirical evidence. Less robust evidence is presented in the fourth column where the innovation coefficients, although still of the expected positive sign, are now not significant.

Finally equations [1.4] and [1.5] have been estimated for different technology groups in order to test the hypothesis that an overall positive effect of R&D investment hides labour saving effects in low-tech industry. The whole sample of firms has been divided in four technology groups according to

[13] See Hatzichronoglou (1997)

the OECD classification of industries in “High Tech”, “Medium/High Tech”, “Medium/Low Tech” and “Low Tech”. Parameters for the four different groups have been jointly estimated by including interaction terms in the regression[14]. In order to obtain useful SE estimates for all the coefficients the model was estimated avoiding the choice of a base category. Nonetheless, an additional model (not shown) was also estimated by choosing high-tech as a base category and adding interactions for all of the remaining categories. On the basis of these estimates the hypothesis of joint insignificance of category-related interactions has been empirically tested. Results, obtained by applying exclusively the unbiased and consistent FE estimator are summarized in Tables 1.5 (using total employment as dependent variable) and 1.6 (using employment without researchers as dependent variable).

Table 1.5: Static Labour Demand - Estimates by Technology Groups (Total Employment)

	HT		MHT		MLT		LT	
sales	0.300***	0.322***	0.408***	0.423***	0.332***	0.332***	0.424***	0.431***
	(0.039)	(0.038)	(0.035)	(0.034)	(0.076)	(0.073)	(0.090)	(0.090)
wage	-0.205***	-0.198***	-0.144***	-0.144***	-0.168*	-0.169*	-0.422***	-0.415***
	(0.054)	(0.055)	(0.032)	(0.032)	(0.089)	(0.089)	(0.082)	(0.081)
red	0.040**		0.058***		0.023*		0.049***	
	(0.018)		(0.015)		(0.014)		(0.017)	
prod		0.003		0.016**		0.010*		0.004
		(0.007)		(0.006)		(0.005)		(0.008)
proc		0.001		0.005**		0.006		0.004
		(0.003)		(0.002)		(0.005)		(0.004)
intercept	4.072**	4.125**						
	(0.455)	(0.462)						
F-stat			3.75	3.09	0.28	0.30	2.01	1.57
			[0.000]	[0.015]	[0.843]	[0.875]	[0.111]	[0.180]

Notes to Table:
Robust SE in parenthesis, p-values in brackets. ***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.
F-stat is the value of the test statistic for the null hypothesis that all the category-related interaction terms are jointly insignificant. Under the null the set of category coefficients is not statistically different from the HT set.

Using the total employment reveals that there are no big structural differences in coefficients of sales and wage, both when the overall expenditure is used and when the expenditure is split according to the product/process classification. The wage coefficient in low-tech industries represents a notable exception[15]. Turning to innovation, the R&D expenditure coefficient is the highest in the subsamples of firms in medium-high-tech industries. The R&D coefficient is surprisingly large also in the subsample of firms in low-tech industries and relatively lower (although still larger than the whole sample average value of 0.038) in the subsample of firms in high-tech industries. The estimate’s value

[14] Results obtained by separate estimation are available in appendix D.
[15] The reason for the above results seems to be attributable to the fact that low-tech industries are mostly composed of small and medium enterprises. The higher wage elasticity in these firms might thus be associated with the lower wages characterizing these types of firms.

falls down only in the subsample of firms in medium-low-tech industries for which it also appears to be significant only at a lower confidence level.

Concerning the hypothesis of differences across subsamples the statistical test provides evidence that such a difference exists only between high-tech and medium-high-tech industries while the difference is not statistically significant in all the other cases.

There are also evident structural differences between firms in different groups in the change in employment following a change in expenditures in product and process innovation. For both variables the estimate is positive in all groups but not necessarily always significant. The estimate of the coefficient for product innovation is significant only for firms in medium-high-tech and medium-low tech industries. Moreover, for these two groups the coefficient is also higher than the estimate using the whole sample of firms (.016 and .010 compared to .008). Coefficients are, conversely, lower than the value of .008 and not significant for firms in high-tech and low-tech groups. The estimate of the coefficient for process innovation is again higher than the whole sample estimate in the groups of firms in medium-high-tech and medium-low-tech (.005 and .006 compared to .003), nonetheless significantly different from zero only in the former case.

Table 1.6: Static Labour Demand - Estimates by Technology Groups (Employment without Researchers)

	HT		MHT		MLT		LT	
sales	0.336***	0.343***	0.479***	0.489***	0.376***	0.374***	0.415***	0.421***
	(0.057)	(0.055)	(0.048)	(0.046)	(0.088)	(0.084)	(0.083)	(0.083)
wage	-0.230***	-0.229***	-0.177***	-0.176***	-0.163	-0.163	-0.432***	-0.426***
	(0.063)	(0.063)	(0.046)	(0.046)	(0.104)	(0.103)	(0.089)	(0.089)
red	0.018		0.039**		0.016		0.041**	
	(0.031)		(0.017)		(0.015)		(0.017)	
prod		0.006		0.011*		0.008		0.000
		(0.019)		(0.007)		(0.006)		(0.009)
proc		-0.001		0.004*		0.006		0.003
		(0.004)		(0.003)		(0.006)		(0.004)
intercept	3.856***	3.896***						
	(0.543)	(0.545)						
F-stat			3.57	2.79	0.26	0.58	1.38	1.14
			[0.014]	[0.025]	[0.854]	[0.677]	[0.247]	[0.338]

Notes to Table:
Robust SE in parenthesis, p-values in brackets
***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.
F-stat is the value of the test statistic for the null hypothesis that all the category-related interaction terms are jointly insignificant. Under the null the set of category coefficients is not statistically different from the HT set.

Overall, Table 1.5 shows a positive effect of innovation on all the technology groups although, admittedly, the lack of significance of coefficient estimates seriously casts doubt on the effectiveness of R&D investments, at least based on the product/process differentiation. Thus, even if the hypothesis of labour saving effect of R&D investments can be strongly rejected, on the other side there is weak evidence of the contribution of R&D in promoting employment growth in different industries.

Weaker evidence is provided by the estimates in Table 1.6. Here the wage and sales related coefficients continue to be positive and significant. The R&D coefficient continues to be larger in the groups of medium-high-tech and low-tech industries. In addition, the R&D coefficient is also insignificant in the two remaining groups and the picture does not look better if the effect of innovation is estimated by dividing product from process innovation. In this last case, the coefficients are significant only in the subsample of firms in medium-high-tech industries, where the effect of product innovation still appears to be larger than that of process innovation.

1.4.2 Dynamic Approach

Results discussed so far have highlighted three most important facts. The first is that R&D investments have a positive effect on a firm's employment. The second is that investments directed to product innovation have larger employment effects than those directed to process innovation. The third is that R&D investments have large effects on research employment and only minor effects on non-research employment. In this section a dynamic specification is used (equation [1.6] and [1.7]) to account for persistency and time-adjustment in firm employment and, with such a specification, these three main results will be tested.

[1.6] $$emp_{i,t} = \rho emp_{t-1} + \beta_1 sales_{i,t} + \beta_2 wage_{i,t} + \beta_3 inno_{i,t} + \left(a_i + \delta_t + \varepsilon_{i,t}\right).$$

[1.7] $$emp_{i,t} = \rho emp_{t-1} + \beta_1 sales_{i,t} + \beta_2 wage_{i,t} + \beta_{31} proc_{i,t} + \beta_{32} prod_{i,t} + \left(a_i + \delta_t + \varepsilon_{i,t}\right).$$

Differently from the FE estimator, which produces inconsistent estimates due to the endogeneity of the one-period lagged dependent variable ($emp_{i,t-1}$), the GMM-SYS approach takes full advantage of the panel dimension to solve simultaneously the problems of unobserved heterogeneity and endogeneity of lagged dependent variable. First issue is addressed estimating the equation in the first difference (i.e. taking the one-year change) instead of in levels, in a way that fixed effects drop out. As the one-year lag change in employment is still endogenous (second issue) internal instruments are used. In particular it is argued that the two-year lag dependent variable[16], emp_{t-2} in this case, can be a good instrument for the endogenous term in the first differenced equation, Δemp_{t-1} in this case, as long as, by construction, it is correlated with the endogenous variable ($\Delta emp_{t-1} = emp_{t-1} - emp_{t-2}$) but not with the error term of the differenced equation $\Delta\varepsilon_t = \varepsilon_t - \varepsilon_{t-1}$, unless this last is serially correlated with an order greater than one. The use of emp_{t-2} as instrument for Δemp_{t-1} produces exactly the Anderson-Hsiao (1981) estimator, further extended by Arellano and Bond (1991)

[16] Omitting firm subscript.

to include more lags of the dependent variable as instruments in the so-called "GMM style" and then by Blundell and Bond (1998) to treat other variables as predetermined or possibly endogenous. Common practice in empirical works is to follow estimates with tests assessing the validity of the two main assumptions of the GMM formulation, namely validity of instruments and the absence of high order[17] serial correlation in residuals of the difference equation. These are exactly the assumptions tested by the Hansen test (under H_0) for over-identifying restrictions and by the AR test (again under H_0) for second order serial correlation.

Table 1.7: Dynamic Labour Demand

	POLS	FE	GMM-SYS
	Overall R&D Expenditure		
emp$_{-1}$	0.824***	0.281***	0.593***
	(0.018)	(0.076)	(0.195)
sales	0.108***	0.285***	0.250**
	(0.013)	(0.041)	(0.115)
wage	-0.069***	-0.199***	-0.133***
	(0.009)	(0.030)	(0.036)
inno	0.029***	0.024**	0.060**
	(0.004)	(0.010)	(0.031)
intercept	0.603***	3.735***	1.121***
	(0.120)	(0.509)	(0.256)
AR1			-2.83 [0.005]
AR2			1.82 [0.069]
Hansen test			18.12 [0.153]
	R&D Expenditure for Product and Process Innovation		
emp$_{-1}$	0.828***	0.286***	0.530**
	(0.018)	(0.075)	(0.228)
sales	0.115***	0.292***	0.316**
	(0.013)	(0.042)	(0.148)
wage	-0.066	-0.197***	-0.140***
	(0.009)	(0.030)	(0.040)
prod	0.012***	0.003	0.023*
	(0.003)	(0.003)	(0.014)
proc	0.005***	0.003	0.008*
	(0.001)	(0.002)	(0.005)
intercept	0.582***	3.756***	1.031***
	(0.120)	(0.510)	(0.275)
AR1			-2.84 [0.005]
AR2			1.74 [0.082]
Hansen test			17.14 [0.193]

Notes to Table:
Robust SE in parenthesis, p-values in brackets.
***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.

The results are presented in Table 1.7 for both the specification with the overall R&D expenditure and the product/process expenditure and using the total number of employees as dependent variable. For each of the two models, results of the Hansen test and the AR tests are provided. In the first two columns models are estimated by using the biased and inconsistent POLS estimator and the inconsistent FE estimator, while the results of the GMM-SYS estimates are presented in the third

[17] By construction so the result of the AR test is expected to reveal a strong negative first order autocorrelation.

column. In this last case only the lagged employment is assumed to be endogenous and all the other variables are assumed to be exogenous[18]. As expected, the GMM-SYS estimate of the coefficient of lagged employment lies in between the FE estimate and the POLS estimate. It is positively sloped and strongly significant. Also the coefficients for sales and wage are correctly sloped and strongly significant both when the total amount of expenditure is used and when product/process differentiation is applied. The effect of innovation continues to be positive and significant. The estimated employment change consequent to a 1% increase in the amount of R&D expenditure is about 0.06% when the overall expenditure is considered, and respectively 0.023% and 0.008% for expenditures in product and process innovation. In both cases estimates are larger than those achieved applying the FE estimator within a static specification. For each of the two models additional tests confirm the validity of the model specification. The value of the Hansen statistics reject the null hypothesis of over-identifying restrictions and the hypothesis of second order serial correlation is always rejected at a 5% confidence level. Accordingly, the hypothesis that R&D expenditure has a positive effect on employment and that such an effect is larger when expenditures are made for product innovations, are confirmed by the empirical evidence of GMM-SYS model.

In order to assess the validity of the third hypothesis, dynamic models in equations 1.6 and 1.7 are re-estimated excluding the number of researchers from the number of employees. Results are summarized in Table 1.8. Again the GMM-SYS estimate of the coefficient related to lagged employment lies in between the POLS estimate and the FE estimate. All the coefficients are correctly sloped and significant. However, while coefficients associated to the wage and sales variables show only marginal changes compared to those in Table 1.7, the coefficient of innovation sizably decreases. The estimated change of non-research employment following a 1% increase in the firm R&D expenditures is now only 0.034. Coefficients are even not significant when the overall expenditure is divided in product/process expenditure. As for estimates using total employment, AR tests and the Hansen test confirm the robustness of the specification.

1.4.3 Discussion

Results bring us to the conclusion that the evidence emerging from using the static specification is almost completely robust to the use of a dynamic specification. Concerning the hypothesis that R&D in Korean firms has a direct labour saving effect, this has been strongly rejected using the static specification and the result is strengthened by the evidence emerging by using a dynamic specification. Concerning the product/process differentiation it is true that the effect of product innovation on employment is larger than that of process innovation. This result is the same when using both the static and the dynamic specification. Consistent with the previous evidence on Korean firms (Lee et al.,

[18] Specific Hansen tests for this hypothesis have been carried out.

2010), however, the greater effect seems to appear when the two are considered together. To a large extent this may be the result of the use of R&D as a proxy for innovation. At the time when firms invest in R&D, in fact, it will probably be difficult to assess what the outcomes of the innovation process will be, if the process will either produce a process innovation or a product innovation. It is thus difficult for them to declare the exact percentage of R&D designated to each of the two and this obviously questions the relevance of the product/process differentiation used in this work. Finally, concerning the role of research-employment, the evidence excludes the existence of a labour saving effect of innovation on employment, although the estimate of the innovation coefficient in both the static and the dynamic specifications decrease and loose significance after the number of researchers is subtracted from the total employment.

Table 1.8: Dynamic Labour Demand – Employment without Researchers

	POLS	FE	GMM-SYS
		Overall R&D Expenditure	
emp_{-1}	0.814***	0.241***	0.695***
	(0.020)	(0.066)	(0.131)
sales	0.127***	0.329***	0.204**
	(0.016)	(0.050)	(0.083)
wage	-0.079***	-0.223***	-0.129***
	(0.011)	(0.037)	(0.026)
inno	0.018***	0.015	0.034*
	(0.005)	(0.015)	(0.018)
intercept	0.665***	3.799***	1.150***
	(0.145)	(0.608)	(0.229)
AR1			-3.29 [0.001]
AR2			1.79 [0.074]
Hansen test			15.46 [0.279]
		R&D Expenditure for Product and Process Innovation	
emp_{-1}	0.813***	0.242***	0.657***
	(0.020)	(0.066)	(0.150)
sales	0.131***	0.333***	0.241**
	(0.016)	(0.051)	(0.102)
wage	-0.077***	-0.222***	-0.133***
	(0.011)	(0.037)	(0.029)
prod	0.009**	0.004	0.016
	(0.004)	(0.007)	(0.010)
proc	0.005***	0.002	0.005
	(0.002)	(0.002)	(0.003)
intercept	0.680***	3.817***	1.104***
	(0.145)	(0.607)	(0.251)
AR1			-3.26 [0.001]
AR2			1.75 [0.079]
Hansen test			15.86 [0.257]

Notes to Table:
Robust SE in parenthesis, p-values in brackets.
***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.

1.5 Conclusion

This chapter has investigated the innovation employment-relation at the micro level on a panel of Korean manufacturing firms. The main result of the paper is that there is no trace of labour saving effect of innovation, here measured by firm's investments in R&D expenditure. The result is robust to changes in the model specification and is consistent with a dynamic specification of the firm's labour demand. More precisely, it is found that investments for product innovation bring forth greater positive effect than investments in process innovation do.

In terms of policy implications the study suggest that, at least at the micro-level, innovation has only a positive effect on employment growth and that an R&D-based strategy of growth cannot be addressed as the cause of unemployment. Admittedly, the 'business stealing' effect is not accounted for in this study due to the firm-level nature of the dataset. From a policy perspective this turns out to be a crucial issue since only innovative firms (firms with non-zero R&D expenditure) are considered in this study, while it is possible that job-losses are registered in non-innovative firms as a consequence of the decline in their market shares.

The advantage of the firm level dataset is, however, in the fact that the direct effect is tested. Evidence provided in this study suggests that this effect is positive and it is such especially for the research employment, which means the number of employees actively taking part in research programs. In other words research expenditure leads to the increase of skilled workforce within the firm, not necessary at the expense of non-research workers. This result is particularly meaningful for policy makers, because it means that the decision to invest in innovation not only does not cause a decrease in employment but even provides new job opportunities for skilled workers, like for example young students of science faculties.

References 1

Anderson, T. W. and Hsiao, C. (1981). *Estimation of Dynamic Models with Error Components*. Journal of the American Statistical Association. 76: 598–606.

Arellano, M. and Bond, S. (1991). *Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations*. Review of Economic Studies. 58: 277–297.

Bae, Y. H., Ha, T. J., Kim, B. W. and Jang, P. Y. (2006). *Direction of Innovation Policy to Promote the Growth and the Employment (in Korean).* Korean Science & Technology Policy Institute (STEPI).

Blanchflower, D. and Burgess, S. M. (1998). *New Technology and Jobs: Comparative Evidence from a Two-country Study.* Economics of Innovation and New Technology. 5: 109–138.

Blechinger, D., Kleinknecht, A., Licht, G. and Pfeiffer, F. (1998). *The Impact of Innovation on Employment in Europe - An Analysis Using CIS Data.* ZEW 98-02. Mannheim.

Blundell, R. and Bond, S. (1998). *Initial Conditions and Moment Restrictions in Dynamic Panel Data Models.* Journal of Econometrics. 87: 115-143.

Bogliacino, F. and Vivarelli, M. (2010). *The Job Creation Effect of R&D Expenditures.* IPTS Working Paper on Corporate R&D and Innovation. No. 04/2010.

Brouwer, E., Kleinknecht, A. and Reijnen, J.O.N. (1993). *Employment Growth and Innovation at the Firm Level.* Journal of Evolutionary Economics. 3: 153-159.

Choi, Y. C. (2008). *Effects of Globalization and Technological Advancement on Demand for Manufacturing Workforce* (*in Korean*). Monthly Bulletin. May. 2008 : 23-58. Bank of Korea.

Coad, A. and Rao, R. (2008). *Innovation and Firm Growth in High-tech Sectors: A Quantile Regression Approach*. Research Policy. 37: 633-648.

Coad, A. and Rao, R. (2011). *The Firm-Level Employment Effects of Innovations in High-Tech US Manufacturing Industries*. Journal of Evolutionary Economics. 21: 255-283.

Doms, M., Dunne, T. and Trotske, K. (1997). *Workers, Wages, and Technology*. Quarterly Journal of Economics. 112: 253-289.

Entorf, H. and Pohlmeier, W. (1990). Employment, Innovation and Export Activities. In *Microeconometrics: Surveys and Applications*. Edited by Florens, J. P. London: Basil Blackwell.

Greenan, N. and Guellec, D. (2000). *Technological Innovation and Employment Reallocation.* Labour. 14: 547-590.

Ha, T. J. and Moon, S. U. (2010). *The Effect of Technological Innovation on Structural Unemployment: A Panel Analysis (in Korean)*. Labour Policy. 10: Number 1.

Hatzichronoglou, T. (1997). *Revision of the High-Technology Sector and Product Classification.* OECD Science, Technology and Industry Working Papers. OECD Publishing.

Kang, K. H. (2006). *Technological Innovation and Employment Creation (in Korean)*. Economy Analysis. 12: 1. Korea Finance and Economy Institute.

Katsoulacos, Y. (1984). *Product Innovation and Employment*. European Economic Review. 26: 83–108.

Kim, B.W. (2010). *R&D Investiment, Job Creation and Job Destruction in Korea: Technical Progress and Labour Market Equilibrium (in Korean)*. Labour Policy. 10: 2.

KISTEP (Korea Institute of Science and Technology Evaluation and Planning). (2001-2011). *Survey of R & D in Korea, 2001-2011*.

Klette, T. J. and Førre, S. E. (1998). *Innovation and Job Creation in a Small Open Economy - Evidence from Norwegian Manufacturing Plants 1982-92*. Economics of Innovation & New Technology. 5: 247-272.

Jaumandreu, J. (2003). *Does Innovation Spur Employment? A Firm-Level Analysis Using Spanish CIS Data*. mimeo.

Lachenmaier, S. and Rottmann, H. (2006). *Employment Effects of Innovation at the Firm Level*. IFO. Working Papers 27. Munich.

Lachenmaier, S. and Rottmann, H. (2011). *Effects of Innovation on Employment : A Dynamic Panel Analysis*. International Journal of Industrial Organization. 29: 210-220.

Lee, K. R., Kang, H. J., Hwang, J. T. and Lee, J. H. (2010). *Technological Innovation and Job Creation: Innovation Policies for Expanding Employment (in Korean)*. Science and Technology Policy Research Institute (STEPI).

MEST (Ministry of Education, Science and Technology). (2011). *Year 2011 Plan Report.* (http://www.mest.go.kr/main.do).

Moon, S. B., Jeon, H. B. and Lee, E. M. (2006). *Innovation Activities of ICT Enterprises and Employment (in Korean).* Korea Information Society Development Institute (KISDI).

Peters, B. (2004). *Employment Effects of Different Innovation Activities: Microeconometric Evidence.* ZEW 04-73. Mannheim.

Pianta, M. (2004). Innovation and Employment. In *Handbook of Innovation.* Edited by Fagerberg, J., Mowery, D. and Nelson, R. Oxford: Oxford University Press.

Piva, M. and Vivarelli, M. (2005). *Innovation and Employment: Evidence from Italian Microdata.* Journal of Economics. 86: 65-83.

Shin, T. Y. (2002). *International Comparison of R&D Investment and Knowledge Accumulation (in Korean).* Science and Technology Policy Institute (STEPI).

Smolny, W. (1998). *Innovations, Prices and Employment: A Theoretical Model and an Empirical Application for West German Manufacturing Firms*. The Journal of Industrial Economics. 46: 359-381.

Statistics Korea. *Korea Statistical Information Service*. (http://www.kosis.kr).

Stoneman, P. (1983). *The Economic Analysis of Technological Change.* Oxford : Blackwell.

Van Reenen, J. (1997). *Employment and Technological Innovation: Evidence from U.K. Manufaturing Firms.* Journal of Labor Economics. 15: 255-284.

Vivarelli, M. (1995). *The Economics of Technology and Employment: Theory and Empirical Evidence.* Cheltenham: Elgar.

Vivarelli, M., Evangelista R. and Pianta, M. (1996). *Innovation and Employment in Italian Manufacturing Industry*. Research Policy. 25: 1013-1026.

Appendix 1

A) Description of Survey of R&D in Korea and KISVALUE

Survey of R&D in Korea

The survey is conducted annually by the Korea Institute of Science & Technology Evaluation and Planning (KISTEP) under the supervision of the Korean Ministry of Education, Science and Technology (MEST) for the purposes of collecting statistical data on Korean R&D activities and personnel in order to apply them to national science and technology policies. The Survey is designated as a set of official statistics and reported to the OECD, as the survey has been implemented in accordance with the guidelines of the “FRASCATI MANUAL” since 1995. Companies owning any research institute or R&D division are required, according to the regulation, to report to the Survey each year, among which the numbers of manufacturing firms that reported their R&D activities during the period between 2002-2008 are as follows;

Year	No. of Firms
2002	6,743
2003	6,648
2004	6,802
2005	7,368
2006	9,036
2007	10,690
2008	12,256

KISVALUE

According to Korean law any stock company whose total assets are equal to or more than seven billion won (ten billion since 2009) are subject to being audited by an external auditor and their financial statements are made public. The service of the management of the data (called “KISVALUES”) such as collecting and disseminating of the micro data of financial statements are provided by Korea Information Service Co. which changed its name to the NICE Information Service Co. in 2009.

B) Major Questionnaires

R&D Expenditures by Expenditure Item

Firms are asked to declare the exact amount of resources invested in R&D projects according to the following categories:

a) expenditure for labour

b) expenditure for training

c) expenditure for materials

d) expenditure for other things

e) expenditure for machinery and equipment

f) expenditure for land and buildings

g) expenditure for computers and software

Summing up answers from a) to d) it is obtained the amount of current expenditures, while summing up answers from e) to g) it is obtained the capital expenditure. The sum of all the answers gives the amount of intramural R&D expenditure.

Component Ratio of Intramural R&D Expenditures by Usage

This question follows the one in which firms are asked to declare the overall amount of expenditure in research and development. The firm is here asked to declare the percentage of the total R&D declared above which is respectively oriented to:

a) new product development

b) existing product improvement

c) new process development

d) existing process improvement

Summing up the first two and the last two there have been obtained the shares of R&D for product innovation and for process innovation.

C) Descriptive Statistics - Variables in Logs

	Total Employment	Employment Without Researchers	Sales	Wage	Total R&D	R&D for Product Innovation	R&D for Process Innovation
Mean	5.353	5.197	11.085	16.069	7.078	6.693	3.555
St Dev	1.311	1.377	1.653	0.694	1.599	1.915	3.124
- between	1.287	1.345	1.602	0.639	1.505	1.608	2.254
- within	0.252	0.295	0.411	0.272	0.543	1.041	2.164
Min	1.609	0.000	6.438	12.649	0.674	0.000	0.000
Max	11.367	10.897	18.458	18.448	16.100	15.699	15.589

D) Additional Tables: Multiple Regression for Technology Regimes

Dependent Variable: Total Employment

	High Tech	Medium/High Tech	Medium/Low Tech	Low Tech
	R&D Expenditure			
sales	0.345***	0.402***	0.322***	0.421***
	(0.048)	(0.036)	(0.080)	(0.091)
wage	-0.174***	-0.149***	-0.199**	-0.431***
	(0.054)	(0.032)	(0.094)	(0.079)
inno	0.058***	0.057***	0.023*	0.048***
	(0.019)	(0.015)	(0.014)	(0.017)
intercept	4.043***	2.762***	4.838***	7.439***
	(1.008)	(0.489)	(1.497)	(1.551)
	R&D Expenditure for Product and Process Innovation			
sales	0.367***	0.417***	0.321***	0.426***
	(0.050)	(0.036)	(0.077)	(0.091)
wage	-0.169***	-0.149***	-0.198**	-0.421***
	(0.055)	(0.032)	(0.093)	(0.078)
prod	0.007	0.015***	0.011**	0.004
	(0.007)	(0.006)	(0.006)	(0.008)
proc	0.001	0.005**	0.006	0.003
	(0.003)	(0.002)	(0.005)	(0.004)
intercept	4.089***	2.865***	4.883***	7.494***
	(1.017)	(0.505)	(1.500)	(1.591)
N firms	200	321	137	74

Notes to Table:
Robust SE in parenthesis
***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.

Dependent Variable: Employment without Researchers

	High Tech	Medium/High Tech	Medium/Low Tech	Low Tech
	R&D Expenditure			
sales	0.394***	0.471***	0.363***	0.415***
	(0.070)	(0.051)	(0.093)	(0.085)
wage	-0.190***	-0.184***	-0.198*	-0.449***
	(0.063)	(0.046)	(0.110)	(0.085)
inno	0.041	0.039**	0.016	0.041**
	(0.032)	(0.017)	(0.015)	(0.017)
intercept	3.702***	2.537***	4.320**	7.787***
	(1.246)	(0.615)	(1.761)	(1.660)
	R&D Expenditure for Product and Process Innovation			
sales	0.367***	0.417***	0.321***	0.426***
	(0.050)	(0.036)	(0.077)	(0.091)
wage	-0.169***	-0.149***	-0.198**	-0.421***
	(0.055)	(0.032)	(0.093)	(0.078)
prod	0.007	0.015*	0.011*	0.004
	(0.007)	(0.006)	(0.006)	(0.008)
proc	0.001	0.005**	0.006	0.003
	(0.003)	(0.002)	(0.005)	(0.004)
intercept	4.089***	2.865***	4.883***	7.494***
	(1.017)	(0.505)	(1.500)	(1.591)

Notes to Table:
Robust SE in parenthesis
***, **, and * indicate significance at confidence levels of 99%, 95% and 90%.

CHAPTER 2

A Study on the Effectiveness of R&D Investments in Korean Manufacturing Firms

2.1 Introduction

It is broadly understood that the accumulation of knowledge capital through Research and Development (R&D) investment plays a key role in determining the growth and development path of a nation. Not surprisingly large shares of R&D investments are positively associated with high productivity levels in cross-country comparisons. Nonetheless existing technology gaps can only in part explain cross-country differences in productivity, as nations with similar (and usually high) levels of R&D investments continue to demonstrate persistent disparities in labour productivity.

As argued by Ortega-Argilés et al. (2010) one possible explanation might dwell in the differences in R&D productivities, denoting the ability to translate new knowledge into an increase in labour productivity. From a policy perspective the attention should not only be focused on how much is expended but also drawn on the effectiveness of the expenditure. Effectiveness, in turn, might depend on both the institutional environment (i.e. factors facilitating the exploitation of the market potential of R&D investments output) and the industrial environment (i.e. the industrial concentration in those sectors characterized by high R&D productivity).

Consequently, the analysis of the R&D-productivity linkage at the firm level appears to be doubly important. On one hand, in fact, private firms usually hold the largest share of total R&D investments, and a better understanding of the way these investments impact productivity at the firm level seems to be necessary. On the other hand, firm level database enables an analysis of possible cross-industry differences in the effectiveness of R&D investments (i.e. Cuneo and Mairesse, 1984 ; Griliches and Mairesse, 1984), which may eventually explain the persistence of productivity gaps.

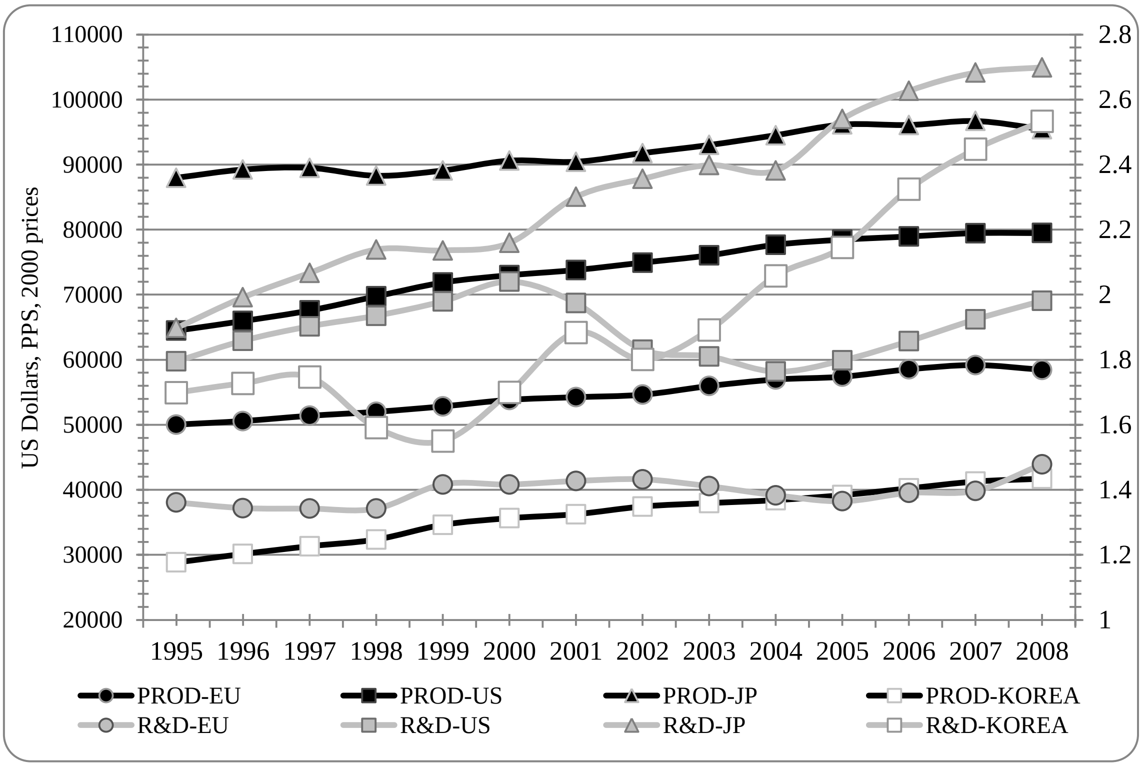
A full understanding of these issues seems to be especially important for a country like Korea which is very active in R&D investment. Korean R&D investment started to expand since the 1980s, with the growing necessity to sharpen the nation's technological competitiveness, and demonstrated an annual average increase rate of 12.7%[1] in real terms during the last three decades (1980-2009). Its R&D investment to GDP ratio has reached 3% since 2006, similar to the levels of major countries such as the United States and Japan. But, in spite of such a high level of aggregate R&D intensity, Korea shows some important asymmetries compared to other economies, in particular those leading in R&D investment. Figure 2.1 shows the level of productivity (measured with Value Added per employee – values on the left scale) and the R&D intensity (measured by the ratio of Business Enterprise R&D to GDP – values on the right scale) for United States, Japan, Korea and some of the wealthier European countries[2]. As far as R&D investments are concerned, at least in the last fourteen years, Korea fared very well as compared to the EU and U.S., with a level of R&D spending close to that of Japan, considered a leading nation in technological developments. However, the level of labour productivity of Korea is still very low, compared to that of other nations. One possible explanation might lie in the sector composition of the Korean economy. As reported by Mathieu and van Pottelsberghe de la Potterie (2010), the relatively high level of R&D in Korea is explained by the importance of R&D intensive industries in the Korean economy more than by a particularly encouraging macroeconomic environment.

As a matter of fact, the R&D investment gap in Korea among industries has not narrowed and R&D activities continue to be concentrated within a small number of large firms[3]. Since the beginning of the 1990s Korean R&D investment was highly concentrated in a few specific industries such as computers and electronics, motor vehicles, machinery and chemical industries. Particular attention was focused on computers and electronics, an industry which has contributed enormously to the nation's economic growth. Although the industry accounts for more than a half of the nation's total R&D expenditures in the manufacturing sector[4] the productivity of firms in this industry is, on average, very low. Considering the information technology (IT) industry as a whole[5], there is evidence that, in Korea, the productivity of firms in IT is lower than that of non-IT (Kim and Hwang, 2006; Suh et al., 2008). Among the potential explanations for this phenomenon it is worth discussing the role of diminishing returns, given the large size of the firms in the industry. Alongside this explanation it is

[1] The figure is calculated by using Shin (2002), KISTEP's Surveys of R&D in Korea (hereinafter referred to as "KISTEP"-Appendix A provides a description of the survey) and the GDP deflator index of Statistics Korea.
[2] Source: OECD. Europe is obtained as simple average of UK, France and Germany as OECD data are not completely available for all European countries.
[3] The average shares per annum in the decade 2000-2009 of the first five, ten, and twenty firms in R&D investment scale are 38.2%, 44.6%, and 51.5% respectively (source: KISTEP).
[4] According to KISTEP computer and electronics industry's average annual R&D investment share was 50.5% during the decade 2000-2009.
[5] This comprises the manufacturing of computers and electronics and IT related services.

important to highlight that firms in this industry have to face the challenges of increasing global competition which, while lowering prices, requires strong R&D investments aimed at both the differentiation through product innovation and at the cutting of costs through process innovations.

Figure 2.1: R&D and Productivity in Korea, EU, US and Japan (source: OECD-STAN)



This evidence, combined with the fact that the amount of private corporate R&D expenditure (BERD) corresponds to 73.4%[6] of the total national R&D expenditure, strongly motivates the use of micro-level data in an attempt to understand the way R&D contributes to productivity in Korea.

The issue is addressed in this paper by estimating the output elasticity of R&D activities at the firm level for a new balanced panel of 496 Korean manufacturing firms during the period between 2002-2008. The period is considered of fundamental relevance to Korea, given that more than 63% of Korea's knowledge capital stock has been accumulated during the 2000-2009 decade[7]. It is found here that the link between the R&D investment and productivity is positive and sizable, although the effectiveness of R&D investment varies across firms of different industries and sizes.

[6] Average annual figure, during the decade 2000-2009, counted by KISTEP.
[7] The portions of four decades' R&D investment are 1.5% (1970s), 8.0% (1980s), 27.2% (1990s) and 63.3% (2000s) respectively, which are calculated by using Shin (2002) and KISTEP.

In the rest of this paper, the next section is dedicated to the empirical model and a survey of previous empirical results is provided as well. Descriptive statistics and econometric results are summarized in the third section, and the conclusion follows.

2.2 R&D and Productivity

2.2.1 Empirical Model and Data

The empirical analysis of returns from R&D investments has traditionally been approached by using a production function framework, in which R&D capital is included among the inputs of the production process[8]. In this we follow this stream of literature to explore the contribution of R&D to labour productivity from a sample of Korean manufacturing firms.

The point of departure is the traditional log-linearized Cobb-Douglas production function described in [2.1] in which output, here measured by value added (VA), depends on physical capital (C), labour (L), and knowledge capital (K):

[2.1] $$va_{it} = a_i + d_t + \beta c_{it} + \gamma l_{it} + \delta k_{it} + u_{it}.$$

Lower cases denote logarithm of variables (divided by the number of employees in the case of C, K and VA). The term u_{it} is the common stochastic disturbance, d_t is the time trend of value added, replaced by a series of time dummies in the empirical model, and a_i are firm-specific characteristics. Coefficients β and δ represent elasticities of output with respect to physical and knowledge capital and both are expected to show a positive coefficient. In this paper, particular attention is paid to the latter. Using employment standardized values of C, K and VA implies γ to measure the departure from the Constant Returns to Scale (CRS) hypothesis. For this reason, and contrary to the case of β and δ, the γ is expected to show a negative sign. The model is estimated using both the Pooled OLS and the within estimator; this latter is employed in order to wipe out firm-specific effects and thus obtain unbiased estimates of parameters.

The dataset has been obtained matching data on value added and change in fixed assets, obtained from financial statements of Korea Information Service Co. (hereinafter referred to as "KISVALUE")[9] with the micro data of the annual R&D Surveys carried out by the Korea Institute of Science and Technology Evaluation and Planning (KISTEP). There are a total of 496 manufacturing firms left in the sample after the elimination of inconsistencies and outlier values of R&D expenditure[10]. To the

8 See Hall et al. (2010) for a recent review of empirical methodologies.
9 See Appendix A.
10 The cleaning procedure is described more carefully in Appendix B.

author's knowledge, this is the first time Korean R&D expenditures derived from R&D survey micro data has been used for the investigation of the R&D-productivity relation.

Physical capital and knowledge capital are computed using the perpetual inventory method described in [2.2] and [2.3]. I_t and $R\&D_t$ respectively indicate investments in fixed assets and in Research and Development, with g and d being the values of annual growth rate and depreciation rate of both physical and knowledge capital:

[2.2] $$C_0 = \frac{I_0}{(g_c+d_c)}; C_t = C_{t-1}(1-d_c) + I_t \ ;$$

[2.3] $$K_0 = \frac{R\&D_0}{(g_k+d_k)}; K_t = K_{t-1}(1-d_k) + R\&D_t.$$

As far as the values of g and d for both physical and knowledge capital are concerned, values of d taken by the reference literature and computed values of g using annual data on gross fixed capital formation and R&D spending at the country level from OECD database are used. This resulted in values of d being equal to 6% and 15% respectively for the physical and knowledge capital, a growth rate for physical capital of 5.4% per year and a growth rate for knowledge capital of 10.4% a year[11].

All the monetary values (VA, C, K) are deflated using industry specific price deflators and the contribution of R&D to both labour and capital is subtracted from the relative variable in order to avoid the double-counting bias described by Cuneo and Mairesse (1984). That means subtracting the number of R&D personnel from the total number of employees and the amount of R&D expenditures declared by the firm as "capital expenditures"[12] from the physical capital variable.

2.2.2 Previous Empirical Results

To understand the R&D-productivity relationship, various empirical literature has sought to estimate the returns from R&D since the pioneering analytical surveys by Griliches (1979, 1980 and 1986), Cuneo and Mairesse (1984) and Hall and Mairesse (1995)[13]. Even though the estimates of returns from R&D vary depending on the data, method, year, industry and country considered for study, it has been generally found that the relationship between firm productivity and R&D is a positive one. Notable exceptions are represented by the studies authored by Link (1981), Scherer (1983), in which the relation was found to be statistically insignificant.

[11] The growth rates are calculated in annual average increase rates during 1996-2001 by OECD data.

[12] According to the question in the survey capital expenditure is considered as such is made for the acquisition of a) R&D related land and buildings, b) R&D related machineries or c) computers and software.

[13] This work focuses on R&D although actually R&D is only one of the several determinants of productivity at the firms level. Admittedly most of the other determinants are ignored either because they are not relevant for the research question or because of the impossibility of obtaining the necessary data. A recent and comprehensive survey of the firm-level determinants of productivity can be found in Syverson (2011).

Table 2.1 summarizes the various results of previous literature; including Korean studies, on the economic measurement of returns from R&D. The survey majorly covers studies that include the estimates of returns from R&D obtained using firm level data. Most of the illustrated output elasticities, estimated based on both the cross-sectional dimension and the temporal dimension, range from 0.007 to 0.38 centered on the value of around 0.10. In almost all the studies considered the cross sectional estimates are higher than the within estimates, which are sometimes not even statistically significant. Admittedly, large variations can be noticed in all those cases the analysis is made for separate industries.

Table 2.1: R&D Elasticities of Output at the Firm Level

Authors	Sample	Methodology	Elasticity
Griliches (1980)	US 883firms (1963)	Cross Section, VA	0.07
Schankerman (1981)	US 110firms (1963)	Cross Section, Sales	0.16
Griliches-Mairesse (1984)	US 133firms (1966-77)	Panel, Sales -POLS -FE	 0.05 0.09
Cuneo-Mairesse (1984)	France 182 firms (1974-79)	Panel, VA -POLS -FE	 0.20 0.11
Hall (1993)	US 1,200 firms (1964-90)	Panel, Sales -FE	 0.06
Mairesse-Hall (1994)	France 1,232 firms (1981-89) US 1,073 firms (1981-89)	Panel, VA -POLS industry dummy -FE -FD Panel, Sales -POLS industry dummy	 0.176 0.07 0.08 0.173
Harhoff (1998)	Germany 443 firms (1979-89)	Panel, Sales -POLS -FE	 0.14 0.09
Crepon et al. (1998)	France 6,145 firms (1990)	Cross Section, VA	0.12
Los-Verspagen (2000)	US 485 firms (1974-93)	Panel, VA -POLS time dummy -FE	 0.014 0.017
Bond et al. (2003)	Germany 205 firms (1987-96) UK 230 firms (1987-96)	Panel, VA -POLS -GMM-SYS Panel, Sales -POLS -GMM-SYS	 0.10 0.079 0.04 0.065
Wang-Tsai (2003)	Taiwan 136 firms (1994-2000)	Panel, VA -RE -RE high tech -RE non high tech	 0.20 0.31 0.07
Griffith et al. (2006)	UK 188 firms (1990-2000)	Panel, VA -POLS -GMM-SYS	 0.03 0.03
Rogers (2010)	UK 719 firms (1989-2000) UK 86 firms (1990-1999)	Panel, VA -POLS (unbalanced - 719) -POLS (balanced - 86)	 0.12 0.16
Ortega-Argiles et al. (2010)	EU 532 firms (2000-05)	Panel, VA -POLS	 0.10

		-RE -POLS different industries -RE different industries	0.10 0.12-0.16 0.13-0.14
Korean studies at macro, industry and firm level			
Shin* (2004)	Korea Macro data (1981-2002)	Time Series, GDP -NLLS	 0.14
Jang-Ahn* (1992)	Korea 15 industries (KSIC 3 digit) (1982-87)	Panel, VA -POLS	 0.26
Lee* (1995)	Korea 15 industries (KSIC 3 digit) (1988-92)	Panel, VA -POLS	 0.045
Lee and Kim* (2003)	Korea 8 industries (KSIC 3 digit) (1980-2001)	Panel, VA -RE -RE major ind.(chem. metal.mach. electronics)	 0.13 0.21
Song (1994)	Korea 150 firms (1985-90)	Panel, VA -POLS different industries	 0.03-0.076
Moon (1997)	Korea 100 firms (1988-96)	Panel, VA -POLS -POLS different industries	 0.03 0.07-0.38
Suh (2002)	Korea 4,017 firms (1995-2000)	Panel, VA -POLS	 0.26
Cho (2004)	Korea 54,961 firms (1979-2002)	Panel, VA -POLS intramural exp., different industries -POLS extramural exp., different industries -POLS intramural exp., different sizes -POLS extramural exp., different sizes	 0.007-0.05 0.04-0.15 0.02-0.03 0.02-0.05
* not at firm level.			

Among the recent studies directed at the estimation of the output elasticity to R&D by means of either cross-sectional or temporal analysis, Los and Verspagen (2000), Bond et al. (2003), Wang and Tsai (2003), Rogers (2010) and Ortega-Argiles et al. (2010) offer valuable examples. Los and Verspagen (2000), using a panel data consisting of 485 American firms during 1974-1993, make a dynamic analysis to explore the impact of technology spillovers on productivity. Their estimates of output elasticity are 0.14 and 0.17, respectively obtained by applying the between and within estimators. Spillover effects are found to be positive, although their magnitudes differ by the level of technology involved. Bond et al. (2003), using two datasets comprised respectively of 205 German firms and 230 UK firms, apply a dynamic production function approach to analyze differences in R&D expenditures and in the effect of R&D between the two countries. It is found that the output elasticity to R&D is approximately the same in both countries: 0.079 for Germany and 0.065 for UK, although it is true that the expenditure in German firms is higher by a ratio of roughly two to one when compared to their UK counterparts.

Wang and Tsai (2003) explore the R&D-Productivity link based on a sample of 136 large Taiwanese firms quoted in the Taiwan Stock Exchange during 1994-2000, finding the output elasticity to be 0.20, increasing to 0.31 for only high-tech firms, clearly a larger value if compared to the 0.07 of other, non-high-tech, firms. Rogers (2010), using an unbalanced panel data consisting of 719 UK firms during 1989-2000 together with a balanced panel data consisting of 86 UK firms during 1990-1999, analyzed R&D-Productivity relation. The estimates resulted in 0.12 or 0.16 which differ, respectively, by the use of balanced or unbalanced panel data. Finally, Ortega-Argiles et al. (2010) analyze a panel data consisting of 532 top European R&D investing firms over the period of 2000-2005, finding an elasticity of about 0.10 in both Pooled OLS and Random Effects estimates. The analysis also finds that the R&D coefficient increases monotonically from the low-tech towards the medium and high-tech sectors between 0.12-0.16.

With regard to Korean literature on the relationship between R&D and productivity, several empirical analyses exist at both the firm and the aggregate level, even though some studies point out that the lack of adequate firm level panel data impedes the development of a comprehensive analysis (Suh, 2005; Kim and Hwang, 2006). First glance findings show a larger difference in the figure of elasticity. Shin (2004) uses national aggregate data on R&D investment and output for the period 1981-2002 and estimates an elasticity to R&D of 0.14. Jang and Ahn (1992), Lee (1995) and Lee and Kim (2003) make sector level analyses finding estimates of industrial output elasticity between 0.045-0.26.

Firm level studies are made by Song (1994), Moon (1997), Suh (2002) and Cho (2004) and they share common aspects. First of all, all four studies use KISVAUE data and estimate the elasticity of R&D activities by industry. And studies of Suh (2002) and Cho (2004) also divide the sample into seven groups of firm size. Song (1994), using KISVALUEs of 150 good reputation firms quoted on the Korea Stock Exchange during 1985-1990, classifies the firms into ten industries and estimates each industry’s R&D elasticity. The study demonstrates elasticity as varying between 0.03-0.076 across industries. Among the industries, the electronic and textile sectors show higher levels of elasticity.

Moon (1997) analyzes a panel KISVALUE data consisting of one hundred large firms over the period between 1988-1996 and finds an average output elasticity to R&D of about 0.03. The value of the elasticity varies between 0.07 and 0.38 by industry. Suh (2002) builds an unbalanced panel data consisting of 4,017 firms using the number of researchers in R&D Survey data over the period 1995-2000 and matched with KISVALUE data during the same years, 1995-2000, from which he derives an output elasticity of R&D as 0.26. The study finds technology-intensive industries such as high-precision machinery and electronics industries as exerting a greater impact on productivity. Surprisingly also the textile industry shows a relatively high elasticity. The study finally suggests that the smaller a corporation, the higher the R&D contribution to production. Cho (2004) using KISVALUE data during 1979-2002 compares the effect of intramural capital with extramural capital. The study classifies the data by nineteen sectors and seven firm sizes and concludes that the effect of extramural capital (0.04 to 0.15) is larger than that of intramural capital (0.007 to 0.05) not only in sectors but also by firm sizes (0.026 to 0.030 in larger firms).

2.3 Results

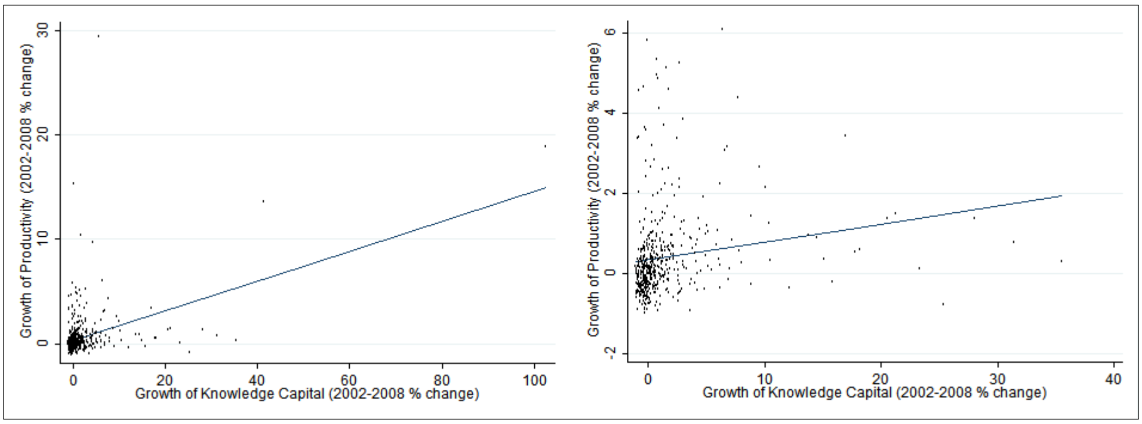
An initial exploratory statistical analysis of both the data and the R&D productivity linkage is carried out in Tables 2.2 and 2.3 and in Figure 2.2. Table 2.2 summarizes means and standard deviations of variables, and it is possible to see how the *between* component of the variance clearly dominates the *within* one for each variable.

Table 2.2: Descriptive Statistics of Variables

	VA (million Won)	L (employees)	C (million Won)	K (million Won)
Mean	1584.790	810.891	345.947	109.014
Min	4.061	4	.020	.010
Max	109595.30	48065	39710.75	12297.42
SD				
- overall	7021.562	3051.596	1854.418	651.651
- between	6819.996	3036.375	1692.426	618.217
- within	1694.222	329.556	761.256	207.647

Figure 2.2 shows the sample correlation between productivity growth and knowledge capital growth. The two are clearly positively correlated although the size of correlation decreases once outliers are excluded from the sample. Moreover, a larger dispersion is noticeable in productivity growth for low values of knowledge capital growth.

Figure 2.2: Productivity Growth and Knowledge Capital
(Without Outliers on the Right)



In Table 2.3 the mean values of value added, physical capital and knowledge capital (all of them per employee) are summarized for each industry, in order to get insights about differences in the use of production factors across firms belonging to different industries. For this purpose also the correlation between value added per employee and physical and knowledge capital per employee are also summarized.

Table 2.3: Summary Statistics and Correlations by Industry

Industry	Obs	L	VA/L	C/L	K/L	Cor (VA/L,C/L)	Cor (VA/L,K/L)
Food, Beverages and Tobacco	217	728.93	1.390	0.173	0.037	0.43	0.40
Textile and Clothing	92	313.90	0.927	0.174	0.017	0.30	0.69
Wood	3	179.67	0.947	0.246	0.013	-0.93	0.97
Paper, Publishing and Printing	57	392.03	2.364	0.297	0.019	0.14	-0.02
Petroleum	35	1515.17	6.676	0.882	0.114	0.92	0.88
Chemicals	550	436.80	2.311	0.508	0.116	0.42	0.46
Pharmaceuticals	291	437.45	1.386	0.143	0.107	0.35	0.46
Rubber	182	513.65	1.537	0.330	0.089	0.33	0.31
Non-metal Minerals	142	456.81	1.840	0.348	0.039	0.56	-0.04
Basic Metals	215	1109.64	4.008	1.053	0.092	0.58	0.26
Fabricated Metal Products	179	326.23	1.274	0.235	0.050	0.27	0.04
Computers and Electronics	433	879.14	1.776	0.683	0.258	0.97	0.31
Medical Instruments	113	211.21	1.497	0.247	0.174	0.25	0.44
Electrical Equipment	138	169.86	1.067	0.167	0.073	0.22	-0.01
Other Machinery	353	333.09	1.784	0.314	0.124	0.97	0.42
Motor Vehicles and Other Transport Equipment	416	2067.92	1.628	0.280	0.177	0.68	0.40
Other Manufacturing and Recycling	14	350.14	0.780	0.111	0.058	0.24	0.59
Shipbuilding	42	7592.09	1.480	0.340	0.055	0.34	0.36

It is noticeable, at a glance, that the descriptive statistics in Table 2.3 reveal that R&D-intensive sectors like computer and electronics, motor vehicles, medical instruments and other machinery industries, show added-value figures relatively lower compared to other sectors like petroleum, chemicals and basic metals industries. On the contrary, sectors such as paper and publishing, or basic metals, in which a clear above-than-average performance in terms of productivity is not accompanied by high R&D intensity. The overall picture confirms the findings of other studies on Korean manufacturing. A very strong correlation between value added and knowledge capital is highlighted for low-tech sectors like textile or other manufacturing and recycling, while such a correlation is not evident in high-tech industries like computers and electronics, such cases have already been discussed by Cho (2004). In her work relatively low added value is reported for industries like electronics, motors and precision instruments, having all these industries in common to be finished-good-related and, hence, suffering more from the effect of market competition. On the contrary, a relatively higher added value is reported for material-related sectors such as petroleum, chemical and basic metals, provided that these are less subject to market competition. In addition, these industries appear to be more protected by internal market regulation against foreign penetration (Lee et al., 2009).

High correlation in the textile industry, which belongs to low-tech sector does not surprise and confirms the findings of previous studies (Song, 1994 ; Suh, 2002). In addition, it is possible that the result is caused by a sampling bias due to the fact that only firms making innovation through R&D are included in the sample. The reason such a correlation is not evident in the high-tech sector seems to be because there is the possibility that the IT industry is more active with the scale of R&D investment than other industries, the productivity impact of R&D in IT industry can decline over time due to increasing marginal cost of new product development and also due to the effects of diminishing returns to scale. Consequently, the effect of R&D investment in other sectors can be relatively larger. Cho (2004) underlines that the textile industry is a labour-intensive industry so its average expenditure is in the low range. But its higher effect seems to be explained by the fact that the textile industry played a locomotive role for Korean economic growth from the beginning stages of its economic development, related fields are evenly and widely developed through the industry and it enabled the accumulation of technological knowledge as well as a spill-over effect in the industry.

Furthermore, nowadays the textile industry is also engaged in more sophisticated technology coordinated with other related high-tech industries such as nano-technology and bio-technology. In addition, small and medium enterprises (SMEs) are very active in R&D investment in textile and leather industry. During 2003-2005 Korean SMEs' average annual investment share was over 50 percent of total R&D investment in the textile industry (Suh et al. 2008).

Estimates of the production function augmented by knowledge capital are presented in Table 2.4. Two estimators have been used. The Pooled OLS (POLS) is used in the first two columns. Industry dummy is included in the specification in the first case and technology dummy is included in the second case. In both specifications, the firm's size is controlled for through the inclusion of a dummy for large firms. Estimates using the fixed effect (FE) estimator are reported in the third column[14]. Relatively small differences appear comparing POLS estimates with industry and technology dummy. Coefficients for physical capital and knowledge capital are rightly sloped and both significantly different from zero. On the contrary the coefficient for labour shows an unexpected positive sign, probably resulting from the bias due to the omission of fixed effects. When the within estimator is used the magnitude of both coefficients for physical and knowledge capital decrease but the significance levels remain unchanged. In terms of relative contribution of factors, results indicate that

[14] The FE estimator has been used in place of the random effect (RE) based on the value of the Hausman statistic (132.83) and of the associated p-value (0.000). In this case the RE estimates would be revealed to be inconsistent.

the elasticity of output to R&D investments is higher than the one to physical capital investments. The labour coefficient turns out to be negatively sloped and significant, indicating that the CRS assumption does not hold.

Table 2.4: Estimates of Production Function - Whole Sample

	POLS	POLS	FE
LnC	0.174***	0.179***	0.060***
	(0.010)	(0.010)	(0.009)
LnK	0.184***	0.180***	0.155***
	(0.010)	(0.010)	(0.020)
LnL	0.037***	0.034***	-0.409***
	(0.012)	(0.012)	(0.054)
2003	0.019	0.020	0.040***
	(0.029)	(0.032)	(0.015)
2004	0.028	0.029	0.065***
	(0.030)	(0.033)	(0.019)
2005	0.062**	0.067**	0.101***
	(0.031)	(0.033)	(0.021)
2006	0.079***	0.084**	0.133***
	(0.031)	(0.033)	(0.023)
2007	0.143***	0.144***	0.193***
	(0.031)	(0.033)	(0.025)
2008	0.053	0.055	0.095***
	(0.035)	(0.036)	(0.032)
intercept	0.597***	0.887***	2.903***
	(0.153)	(0.079)	(0.293)
Industry Dummy	Yes		
Technology Dummy		Yes	
Size Dummy	Yes	Yes	

Notes to Table:
Robust SE in parenthesis for POLS models. Cluster-adjusted SE in parenthesis for FE model.
***, ** and * indicate significance at 99%, 95% and 90% confidence levels

In order to examine the hypothesis that investments in knowledge capital are more productive in firms belonging to high-tech industries, the whole sample of firms has been split into three sub groups in line with OECD classifications[15] of industries based on technological levels, and the model has been estimated allowing parameters to vary across the three groups. The estimates reported in Table 2.5 are thus obtained by applying the within estimator to a model specification which includes interactions between variables and the three categorical group dummies. Results obtained from separate regressions are available in the Appendix E. As expected, the coefficient for knowledge capital is higher for the group of high-tech firms, slightly lower in the group of medium-high-tech firms and low for low-tech firms (less than a quarter as compared to the high-tech firms). In all of the cases the significance is very high. Turning to the other two production inputs, the elasticity of capital appears to be higher in the medium-high-tech group while the coefficient for labour picks its lowest value in the group of low-tech firms. For every group the knowledge capital elasticity is higher than the physical capital one. However, the difference between the two monotonically decreases with the

[15] See Appendix C

level of technology. The evidence indicates that, although the same invested amount is more productive if invested in knowledge capital rather than in physical capital for every firm, the gain in productivity from substituting physical capital with knowledge capital is greater the higher the level of technology. In addition both the F-tests indicate that the differences between each of the two category-related group of estimates are significantly different from the estimates in the high-tech sample.

Table 2.5: Estimates of Production Function – Technology Regimes

	HT	MHT	LT/MLT
lnC	0.044**	0.071***	0.042***
	(0.020)	(0.013)	(0.012)
lnK	0.304***	0.114***	0.071***
	(0.040)	(0.018)	(0.019)
lnL	-0.358***	-0.424***	-0.463***
	(0.057)	(0.053)	(0.053)
Intercept	2.913***		
	(0.287)		
Hausman test			321.69
			[0.000]
F-stat		6.59	10.17
		[0.000]	[0.000]

Notes to Table:
All models are estimated with FE. Cluster-adjusted SE in parenthesis. p-values in brackets
***, ** and * indicate significance at 99%, 95% and 90% confidence levels
F-stat is the value of the test statistic for the null hypothesis that all the category-related interaction terms are jointly insignificant. Under the null the set of category coefficients is not statistically different from the HT set.

To test the robustness of this conclusion estimates are also obtained for the four most important industries, one high-tech, namely computers and electronics, and three medium-high-tech, namely chemicals, motor vehicles and other machinery. These four industries account for about 80%[16] of the total R&D investment in the manufacturing sector. Moreover, these industries are considered very important because, being strongly export-oriented, they represent the engine of industrial development and, more generally, of country growth. Results are provided in Appendix D. In general, the R&D coefficients of those four industries range between 0.051 and 0.103 (although insignificant in the chemicals case and only barely significant in the computers case), thus lower than the whole sample estimate (0.155). On the contrary, returns to physical capital seem to be higher than that of knowledge capital in motor vehicles and other machinery. The low number of observations used for industry-specific estimation, however, can seriously cast doubt on the reliability of these results.

The same grouping exercise has been repeated classifying firms according to the number of employees and separating large firms from small and medium size firms. The idea behind this is that, when firm size is measured by number of employees, large firms[17] are denoted as those that make

[16] Approximate average annual figure, during the 2000-2009 decade, is from KISTEP.
[17] A firm is classified as "large" if the number of employees is equal or higher than 300.

extensive use of labour. Thus, it is possible to expect that small firms, on the contrary, use more knowledge and/or physical capital in their production. As in the previous case the estimates were obtained by including interaction terms between the set of covariates and the dummy for large firms and results using multiple regression are in Appendix E. Results in Table 2.6 indicate that the coefficients for labour are not very different among the two groups and the same holds for physical capital. Concerning knowledge capital, the coefficient is higher in the group of small firms. It is possible that such a result is influenced by the industry composition of the two sub-groups of firms, which suggests the possibility that high-tech firms are concentrated in the group of small firms, an attempt is made to eliminate such an effect by including a series of technological dummy as controls in the regressions. Thus, the explanation refers to the higher productivity gains that small firms are capable of realizing given that they are still in the increasing returns of scale phase of activity. Overall, however, the difference between the two sets of coefficients appears not significant based on the value of the F statistic.

Table 2.6: Estimates of Production Function – Size Regimes

	Small Firms	Large Firms
lnC	0.059***	0.060***
	(0.010)	(0.015)
lnK	0.177***	0.123***
	(0.024)	(0.029)
lnL	-0.418***	-0.434***
	(0.061)	(0.055)
iIntercept	2.988***	
	(0.313)	
F-stat		1.84
		[0.138]

Notes to Table:
All models are estimated with FE. Cluster-adjusted SE in parenthesis. Probabilities in brackets.
***, ** and * indicate significance at 99%, 95% and 90% confidence levels
F-stat is the value of the test statistic for the null hypothesis that all Large Firms related interaction terms are jointly insignificant. Under the null the set of Large Firms coefficients is not statistically different from the Small Firms set.

2.4 Conclusion

This work has analyzed the contribution of R&D to productivity in a panel of Korean manufacturing firms to test the hypothesis that research investments lead to productivity gains not only in the high-tech industries but also in the low-tech ones. At a macroeconomic level Korea seems in fact to have low productivity when compared to the amount of research investment, with respect to which the country is, according to official statistics, considered one of the world leaders. Admittedly, large corporations in high-tech industries conduct most of this research; therefore, one can suspect that research investments are unproductive in small firms and in non-high-tech industries.

Preliminary empirical evidence based on the dataset indicates two main features of R&D investments by private firms in Korea. First, they are, on average, high relative to the amount of sales. Secondly, consistently with more general evidence on Korea, they are concentrated in some specific industries that are, among other things, dominated by the presence of large firms. This paper asks the question, to what extent such concentration depends on the fact that R&D investments are productive only for firms in these industries and only for large firms.

Econometric models estimates reveal that, consistent with previous empirical literature, research investments lead to important gains in firm productivity levels. These gains are realized by firms across all industries, although the evidence suggests they are larger for firms in the high-tech industries. This probably contributes to the concentration of investments in these industries. Concerning size the evidence is not as clear. Contrary to expectations, R&D investments are more productive in small firms rather than in large ones.

From a policy perspective, the evidence in this paper reveals that R&D investments are effective not only in certain industries. Accordingly, it is important to recognize the role of high-tech industries for the technological and economic development of Korea. Given the higher productivity of R&D investments in high-tech industries, it is likely that the catch-up process of Korea is driven through innovative investments made by these industries. Nonetheless, this does not represent an obstacle for the economy, as R&D investments are also effective in other industries. Moreover, there is evidence that R&D investments are particularly productive for small firms, which suggests continuing the boosting of innovation through SME-oriented policy measures. As a matter of fact small firms have started to play a more and more important role for the economic development of Korea and the evidence in the paper has shown that such economic development can be achieved by productivity gains by SMEs, gains which are in turn related to research investments.

References 2

Bond, S., Harhoff, D. and Van Reenen, J. (2003). *Corporate R&D and Productivity in Germany and the United Kingdom*. Annales d'Economie et Statistique. 79/80: 435-462.

Cho, Y. H. (2004). *R&D Spillover Effects in Korean Manufacturing Industries (in Korean)*. Applied Economics. 6: 209-232.

Crépon, B., Duguet, E. and Mairesse, J. (1998). *Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level.* Economics of Innovation and New Technology. 7: 115-156.

Cunéo, P. and Mairesse. J. (1984). Productivity and R&D at the Firm Level in French Manufacturing. In Griliches, Z. (ed.). *R&D, Patents and Productivity*. Chicago: University of Chicago Press, 375-392.

Griffith, R., Harrison, R. and Van Reenen, J. (2006). *How Special Is the Special Relationship? Using the Impact of U.S. R&D Spillovers on U.K. Firms as a Test of Technology Sourcing*. American Economic Review. 96: 1859-1875.

Griliches, Z. (1979). *Issues in Assessing the Contribution of Research and Development to Productivity Growth*. Bell Journal of Economics 10: 92-116.

Griliches, Z. (1980). Returns to Research and Development Expenditures in the Private Sector. In Kendrick, J.W. and Vaccara, B.N. (eds.). *New Developments in Productivity Measurement and Analysis*. Chicago: Chicago University Press, 419-454.

Griliches, Z. (1986). *Productivity, R&D, and Basic Research at the Firm Level in the 1970s*. American Economic Review. 76: 141-154.

Griliches, Z. and Mairesse, J. (1984). Productivity and R&D at the Firm Level in Z. Griliches (ed.). *R&D, Patents, and Productivity*. Chicago: Chicago University Press, 339-374.

Hall, B. H. (1993). *Industrial Research During the 1980s: Did the Rate of Return Fall?* Brookings Papers On Economic Activity – Microeconomics. 2: 289-343.

Hall, B. H. and Mairesse, J. (1995). *Exploring the Relationship between R&D and Productivity in French Manufacturing Firms*. Journal of Econometrics. 65: 263–293.

Hall, B. H., Mairesse, J. and Mohnen, P. (2010). Measuring the Returns to R&D. in B. Hall and N. Rosenberg (eds.). *Handbook of the Economics of Innovation.* Amsterdam: Elsevier. Vol. I.

Harhoff, D. (1998). *R&D and Productivity in German Manufacturing Firms.* Economics of Innovation and New Technology. 6: 29-49.

Jang, J. K. and Ahn, D. H. (1992). *R&D Investment and Productivity of Korean Manufacturing Sector (in Korean).* Science and Technology. 4(2). Korea Advanced Institute of Science and Technology (KAIST).

Kim, J. Y. and Hwang, M. W. (2006). *The Impact of Enterprises' R&D Investment on Their Business Performance (in Korean).* Monthly Bulletin. 23-69. The Bank of Korea.

KISTEP (Korea Institute of Science and Technology Evaluation and Planning). (2001-2011). *Survey of R & D in Korea, 2001-2011.*

Lee, B. K. (1995). *An Analysis of the Relation between R&D and Productivity in Manufacturing Sector (in Korean).* Korea Economy. 22. Sungkyunkwan University.

Lee, W. K. and Kim, B. K. (2003). *The Spillover Effects of Research and Development Investment on Productivity (in Korean).* Monthly Bulletin. 24-51. The Bank of Korea.

Lee, W. S., Byun, I. S., Kim, B. H. and Park, J. H. (2009). *The Policy Agendas of Promoting Private Sectors' R&D Investments in order to Achieve the R&D Intensity Ratio as 5% of GDP (in Korean).* Science and Technology Policy Institute (STEPI).

Link, A. N. (1981). *Research and Development Activity in US Manufacturing*. New York: Proger.

Los, B. and Verspagen, B. (2000). *R&D Spillovers and Productivity: Evidence from U. S. Manufacturing Industries*. Empirical Economics. 25: 127-148.

Mairesse, J. and Hall, B. H. (1994). Estimating the Productivity of R&D in French and U.S. Manufacturing Firms: An Exploration of Simultaneity Issues with GMM. In Wagner, K. and Van Ark, B. (eds.). *International Productivity Differences and Their Explanations.* Amsterdam: Elsevier-North Holland, 285-315.

Mathieu, A. and van Pottelsberghe de la Potterie, B. (2010). *A Note on the Drivers of R&D Intensity*. Research in World Economy. 1: 56-65.

Moon, H. B. (1997). *The Effect of R&D Investment on the Increase of Corporation Productivity (in Korean)*. Monthly Bulletin. 36-59. Korea Development Bank.

Ortega-Argilés, R., Piva, M., Potters, L. and Vivarelli, M. (2010). *Is Corporate R&D Investment in High-tech Sectors More Effective?* Contemporary Economic Policy. 28: 353-365.

Rogers, M. (2010). *R&D and Productivity: Using UK Firm-level Data to Inform Policy*. Empirica. 37: 329-359.

Schankerman, M. (1981). *The Effect of Double Counting and Expensing on the Measured Returns to R&D.* Review of Economics and Statistics. 63: 454-458.

Scherer, F. M. (1983). *R&D and Declining Productivity Growth*. American Economic Review. 73: 215–218.

Shin, T. Y. (2002). *International Comparison of R&D Investment and Knowledge Accumulation (in Korean).* Science and Technology Policy Institute (STEPI).

Shin, T. Y. (2004). *The R&D Investment's Contribution to the Economic Growth (in Korean)*. Science and Technology Policy Institute (STEPI).

Song, J. K. (1994). *Empirical Analysis of the Relationship between R&D Capital And Productivity (in Korean).* Industrial Organization Research. 3: 37-56.

Statistics Korea. *Korea Statistical Information Service*. (http://www.kosis.kr)

Suh, J. H. (2002). *Structural Changes in Research and Development Activities of Korea Business Enterprises (in Korean).* Policy Research. 2002-2. Korea Development Institute (KDI).

Suh, J. H. (2005). *Characteristics and Economic Effects of Korean Firms' R&D Investment (in Korean)*. Korea Development Research 27. Korea Development Institute (KDI).

Suh, J. H., Kang, S. J. and Kim, J. E. (2008). *Analysis of R&D Efficiency for IT SMEs (in Korean).* Technology Innovation Research. 16. The Korean Society for Innovation Management & Economics.

Syverson, C. (2011). *What Determines Productivity?* Journal of Economic Literature. 49:326–365.

Wang, J-C. and Tsai, K-H. (2003). *Productivity Growth and R&D Expenditure in Taiwan's Manufacturing Firms*. National Bureau of Economic Research Working Paper Series No. 9724. Cambridge, MA.

Appendix 2

A) Description of Survey of R&D in Korea and KISVALUE

<u>Survey of R&D in Korea</u>

The survey is conducted annually by the Korea Institute of Science & Technology Evaluation and Planning (KISTEP) under the supervision of the Korean Ministry of Education, Science and Technology (MEST) for the purposes of collecting statistical data on Korean R&D activities and personnel in order to apply them to national science and technology policies. The Survey is designated as a set of official statistics, reported to the OECD, as the survey has been implemented in accordance with the guidelines of the "FRASCATI MANUAL" since 1995. Companies owning any research institute or R&D division are required, according to the regulation, to report to the Survey each year, among which the number of manufacturing firms that reported their R&D activity during the period between 2002-2008 are as follows;

Year	No. of Firms
2002	6,743
2003	6,648
2004	6,802
2005	7,368
2006	9,036
2007	10,690
2008	12,256

<u>KISVALUES</u>

According to Korean law any stock company whose total assets are equal to or more than seven billion won (ten billion since 2009) are subject to being audited by an external auditor and their financial statements are made public. The service of the management of the data (called "KISVALUES") such as collecting and disseminating the micro data of financial statements is provided by Korea Information Service Co. which changed its name to the NICE Information Service Co in 2009.

B) Construction of the data

Value Added has been computed according to the official methodology proposed by the NICE Information Service Co., summarized herein. The data source comprises all the values in KISVALUES. Data on depreciation, missing from financial statements have been replaced with data from Audit reports, because as the reporting of other manufacturing costs, which are often demanded for empirical analysis, have become non-obligatory for firms since 2004, the relevant data in auditor's report are considered to suffice for this purpose.

Value Added = Income before Tax + Financial Charges + Personnel Expenses + Taxes and Dues + Rent + Lease - Interest Income + Depreciation + Other Manufacturing Costs

Observations for which any of the values for Income, Financial Charges, Personnel Expenses, Taxes and Dues, and Depreciation were missing have been deleted from the database. Missing values for Rent, Lease and Interest income have instead been treated as zeroes. 57 observations for which the resulting value of Value Added was lower or equal to zero have also been eliminated.

Physical Capital is measured with the Total Investments in Fixed Assets. The source for this information is again the KISVALUES. 12 observations for which the value was missing were eliminated from the database.

The resulting variables for Value Added and Physical Capital have been matched with the values of expenditures in Research and Development and the number of employees from the Surveys of R&D in Korea. The amount of R&D capital expenditures and R&D employees has also been included in the database for the double counting.

This cleaning and matching procedure produced an unbalanced panel of 4,597 observations belonging to 738 firms. Restricting the sample to the only firms for which observations were available for all the 7 years, 496 firms finally remained in the database.

C) Description of Technological Levels

High Tech	-Aerospace -Pharmaceuticals -Computer office machines -Electronics -Scientific instruments
Medium High Tech	-Electrical machinery -Motor vehicles -Chemicals excluding pharmaceuticals -Transport equipment excluding shipbuilding and aerospace -Non-electrical machinery
Medium Low Tech	-Coke, refined petroleum products and nuclear fuels -Rubber and plastic -Non-metal products -Shipbuilding -Basic metals -Fabricated metals
Low Tech	-Other manufacturing and recycling -Wood, pulp and paper -Food beverages and tobacco -Textile and clothing

D) Estimates for Selected Industries

	lnc	*lnk*	*lnl*	*intercept*	***F-test***
Chemicals	0.047**	0.063	-0.395***	2.877***	4.720
	(0.018)	(0.044)	(0.130)	(0.687)	[0.000]
Computers and Electronics	0.045	0.103*	-0.579***	2.896***	23.950
	(0.028)	(0.063)	(0.090)	(0.447)	[0.000]
Other Machinery	0.066***	0.060***	-0.478***	2.593***	10.650
	(0.018)	(0.021)	(0.107)	(0.516)	[0.000]
Motor Vehicles and Other Transport Equipment	0.075***	0.051*	-0.720***	4.598***	17.980
	(0.016)	(0.030)	(0.123)	(0.721)	[0.000]

Notes to Table:
All models are estimated with FE. Cluster-adjusted SE in parenthesis. p-values in brackets.
***, ** and * indicate significance at 99%, 95% and 90% confidence levels.

E) Additional Tables: Multiple Regression for Technology and Size Regimes

Technology Regimes

	High Tech	Medium/High Tech	Low / Medium-Low Tech
LnC	0.033**	0.076***	0.035***
	(0.016)	(0.014)	(0.012)
LnK	0.145***	0.120***	0.064***
	(0.047)	(0.021)	(0.022)
LnL	-0.520***	-0.446***	-0.421***
	(0.086)	(0.096)	(0.057)
2003	0.210***	-0.016	-0.006
	(0.042)	(0.023)	(0.018)
2004	0.357***	-0.034	-0.024
	(0.050)	(0.027)	(0.019)
2005	0.489***	0.029	-0.073***
	(0.055)	(0.032)	(0.024)
2006	0.548***	0.047	-0.057*
	(0.062)	(0.034)	(0.031)
2007	0.689***	0.096***	-0.029
	(0.074)	(0.033)	(0.031)
2008	0.602***	0.023	-0.197***
	(0.075)	(0.049)	(0.044)
Intercept	2.965***	3.053***	2.961***
	(0.464)	(0.521)	(0.311)
N Obs	784	1316	1064
N Firms	112	188	152
Hausman test [p-value]	45.52 [0.000]	138.94 [0.000]	156.90 [0.000]

Notes to Table:
All models are estimated with FE. Cluster-adjusted SE in parenthesis.
***, ** and * indicate significance at 99%, 95% and 90% confidence levels

Size Regimes

	Small Firms	Large Firms
LnC	0.050***	0.070***
	(0.010)	(0.018)
LnK	0.203***	0.142***
	(0.026)	(0.038)
LnL	-0.356***	-0.392***
	(0.081)	(0.100)
2003	0.053**	0.023
	(0.023)	(0.023)
2004	0.068**	0.053**
	(0.029)	(0.026)
2005	0.112***	0.060*
	(0.032)	(0.031)
2006	0.143***	0.107***
	(0.034)	(0.038)
2007	0.191***	0.152***
	(0.038)	(0.038)
2008	0.128***	-0.010
	(0.047)	(0.053)
Intercept	2.269***	3.565***
	(0.360)	(0.734)
N Obs	1799	1120
N Firms	257	160

Notes to Table:
All models are estimated with FE. Cluster-adjusted SE in parenthesis.
***, ** and * indicate significance at 99%, 95% and 90% confidence levels

Chapter 3

A Study on the Knowledge Production Process in Korean Young Innovative Companies

3.1 Introduction

A large body of theoretical and empirical literature has focused attention on firms' R&D investment in an attempt to explain the way these investments cause innovation, leading to productivity growth at both the macroeconomic and the microeconomic levels (see Baumol, 2002 ; Jones, 2002). For reasons usually connected to data availability, the effects of other innovative inputs have traditionally received less attention.

Among the other possible sources of innovation at the firm level it is worth mentioning the role of technological acquisition (hereinafter referred to as 'TA'), distinguishing the cases in which technological changes are embedded in the acquired good (as in the case of acquisition/replacement of machinery and equipment) from that of disembodied technological change, as in the case of the acquisition of technology from other firms (Conte and Vivarelli, 2005).

More recently the availability of innovation surveys has opened the field of investigation to inputs other than R&D, and a stream of literature has started exploring the role of TA. Not surprisingly, evidence suggests that the intensity of investments in both R&D activities and technological acquisition vary across industries and are strongly related to firm characteristics (Santamaría et al., 2009 ; Ortega-Argilés et al., 2009 and 2010).

Among the characteristics that are likely to determine the choice of innovative strategy (innovation through internal R&D vs. acquisition of technology from outside) a firm's size and firm's age are surely the most influential (Acs and Audretsch, 1987 ; Huergo and Jaumandreu, 2004). A closer focus on age might be motivated by the increasing attention that the European academic community and policy makers are redirecting to the role of Young Innovative Companies (YICs). At the base of this renewed interest lies the academic and policy debate on the transatlantic innovation gap between USA and Europe, being the lack of YICs in Europe as a reason for the persistence of such a gap. Such perception can be evidenced by the fact that recently at the EU and European country level a series of new policy initiatives have been developed to support young, innovative companies (Schneider and Veugelers, 2008 ; Moncada-Paternò-Castello, 2011). As noted by Cincera and Veugelers (2010), however, despite the high policy attention, there still exists little empirical evidence that explains the behaviour of young innovative companies.

The Korean economy is based on a technological change driven growth process, at the root of which there are R&D investments. For this reason R&D tends to be used as a key input indicator in the analysis of the innovation production, while other inputs such as those linked with the TA are considered residual and thus omitted. Within the Korean literature dealing with the effects of R&D on firms' innovation, there are different viewpoints on the issue relating to the effectiveness of R&D investments to the maturity of a firm. The two main opposite positions are both based on the same classification of a firm's growth into three stages, namely the inception, growth phase and maturing stage. However, on one hand, it is claimed that R&D plays a strategic role from the very first stage (Hong and Hong, 2008; Song et al., 2011) while, on the other hand, it is argued that R&D may be too premature at the inception and growing stages of a firm, since a firm at this stage is still small, has liquidity constraints, lacks the adequate experience to transform R&D investments into direct productivity growth. Accordingly, young firms might find it more convenient to acquire technologies as quickly as possible instead of engaging in R&D (Lee, 2008 ; Kim and Hong, 2011).

Naturally a policy issue arises on the effectiveness of any policy stimulating R&D in Young Innovative Companies in Korea. According to the first view it could be observed that incentives to R&D might be appropriate for the creation of a friendly environment for the birth of New Technology Based Firms (NTBFs), broadly defined as small and medium enterprises (SMEs) which operate in high-tech sectors[1] (Storey and Tether, 1998 ; Schneider and Veugelers, 2008) or firms willing to enter the market by exploiting the market potential of a new innovation. According to the latter view, such incentives would however be ineffective because in the first stages firms might not be capable of challenging incumbent firms with R&D driven innovation and may prefer to acquire technology from outside sources. The issue has become of relevance in the past few years in light of the recent changes in the innovation policy support.

[1] This generic definition is the most used in the literature, although the concept of NTBF has an older origin in the work of the Arthur D. Little Group (Little, 1977), in which it is defined in a more detailed way.

Korea is very aggressive in R&D. To develop new, innovative, small and medium enterprises (SMEs), the Korean government implements various supportive policy measures, among which the “Venture Firm” and “Inno-Biz Firm” certification systems and the “Korea Small Business Innovation Research Program (KSBIR)” (SMBA, 2010). The “Venture Firm” certification can be obtained by firms which actually make use of venture capital and show very high propensity to innovate, both in terms of R&D investments and of use of new technologies (this last generally proven by a patent application or similar evidence)[2]. And according to Dushnitsky and Lenox (2005) increases in corporate venture capital investments are associated with subsequent increases in firm patenting, which means corporate venture capital can be a vital part of a firm’s overall innovation strategy. Similarly, the “Inno-Biz Firm” certification can be obtained by firms scoring high in four main synthetic indicators: namely, technological innovation capacity, technological innovation performance, technological commercialization capacity, and technological innovation management capacity. The scores in these indicators, constructed following the Oslo Manual guidelines, are, in turn, obtained from a list of more than 60 base variables. Finally, the KSBIR program which benchmarks the American SBIR (Small Business Innovation Research) program. Under the program major Korean public institutions, consisting of twelve ministries and six state-run companies, are recommended to spend more than 5% of their R&D budget in supporting SMEs’ innovative activities. Special attention is given to the firms certified as “Venture or (and) Inno-Biz Firm” with the following types of support; subsidy for technological innovation, innovation feasibility studies, commercialization of innovation, advice for management and development of IT systems and university-industry cooperation, etc. In actual fact, the R&D budget share dedicated to SMEs reaches about 10%.

But even though the share of SMEs in total of firms conducting R&D activities in Korea has increased substantially from 7.6% in 1998 to 27.6% in 2008, thanks to the active role of innovative SMEs (SMBA, 2010), there remain insecure aspects as, for instance, high level of overall SMEs’ entry and exit rate[3]. As indicated by Song et al. (2011), the five-year survival rate of innovative SMEs stands at a level between 37.2% (small enterprises) and 46.3% (medium enterprises). Meanwhile the average innovation success rate, measured by Hong (2010), as the share of successful innovations over the number of trials[4], remains at 50% level. Additionally, some studies question the effectiveness of

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[2] In economic literature, Venture Firm is recognized as a firm which uses venture capital-defined as equity or equity-linked investments in young, privately held companies and it accounts for innovation (Kortum and Lerner, 1998).

[3] According to Lee and Hong (2004) annual average entry and exit rates of Korean SMEs are 16.03%, 11.75% respectively during the period between 1988 and 2001

[4] Source : Kbiz’s Survey on Technology of Small & Medium Enterprises (2005, 2007 and 2009) which is conducted biannually.

government R&D policy pointing out there are gaps between innovative SMEs' needs and government policy (Lee et al., 2008 ; KVBA, 2010).

This study investigates whether there is any difference in innovative behaviour between YICs' and mature incumbent companies in terms of innovative inputs-outputs relation. Using Korean Innovation Survey (KIS)[5] 2010 database recently conducted by Science Technology Policy Institute (STEPI) of Korea, the study approaches the issue building an empirical framework based on the Knowledge Production Function (KPF) approach (Griliches, 1979). The traditional approach is first extended to include inputs other than internal R&D in the innovation production process, fully exploiting the availability of such detailed information from the KIS. Secondly, the empirical model is estimated for two subgroups of firms, namely young and mature, in search of structural differences between the two in the innovation process. Results clearly indicate that such differences exist, especially concerning the effectiveness of internal R&D investments, less important or even useless in YICs. The remainder of this paper is organized as follows. The next section introduces the dataset. A description of the model follows together with empirical results. The work ends with a conclusion.

3.2 Data and Main Research Hypothesis

This section describes some of the most important features of the dataset used for the empirical analysis. Data has been extracted from the Korean Innovation Survey 2010 and reports answers by firms relative to the three previous years (2007, 2008 and 2009)[6]. It is important to note that the questionnaire has been sent only to firms belonging to any of the manufacturing industries and so, by definition, service companies as well as other types of production companies are not investigated here.

The original dataset was composed of 3,925[7] firms, 228 of which were initially eliminated because they were either subject to mergers and acquisition during the period[8] or reported unrealistic values of innovative expenditure. Since the objective of this work is to study the behavior of innovative companies, and in particular of young innovative companies, the focus was restricted to a sample of innovators[9], made of 2,203 firms. Innovators are identified as firms who either have made at

5 See Appendix A.
6 Information on firm's foundation year was not included in the survey and was taken instead from Statistics Korea.
7 Obtained from a response sample of 51.03%, which is representative of the entire Korean population of manufacturing firms, 41,485, with more than 10 employees.
8 Unfortunately, the precise information concerning possible mergers and/or acquisition was not available. Therefore, following the interpretation of questions, we simply identified a merger and or an acquisition if for at least one year the information about sales was not available because it was not declared by the firm.
9 Unfortunately, the questionnaire allows non innovators to skip a relevant number of questions and so the piece of information concerning non innovators, even though not necessary in this case, cannot be used for empirical analysis.

least one innovation or have started and then abandoned an innovation and have spent a positive amount for innovation during the last three years[10].

The innovative output (*innosales*) is measured as the share of innovative turnover. The question has been answered only by those firms who introduced at least one product innovation in the last three years and this obviously raises sample selection bias in the model estimates. This is discussed in the next section.

The innovative input is measured as the total expenditure over the last three years for innovation (not only product) and is divided according to the following four categories: expenditure for research and development made internally to the firm (*ired*), expenditure for research and development made externally to the firm (*ered*), expenditure made for the acquisition of either new machinery or machinery for replacement purposes (*mach*), expenditure made for the external acquisition of technology (*tech*). In order to maintain the same measures of variables in both the right and left hand sides of the model equation, also the inputs have been standardized by the total turnover of the last three years.

A series of *controls* are also used in an attempt to capture the effects of unobservable characteristics. These include the size of the firm, the technological level of the industry the firm operates in, the degree of openness to external markets, the group membership and, finally, dummy controls for Venture and Inno-Biz Firms.

Size is included using three dummy variables obtained from the categorical variable *legaltype*, which, according to the Korean law, classifies firms in large, medium size and small firms based on the number of employees (the cut-off values of employees for being considered medium is “at least 50” and is “more than 300” for being considered large). The expected relation between size and firm’s innovation is however unpredictable. Schumpeter (1942) first argued in favour of a clear positive relation between the two, given their relative advantage. Large firms might accordingly extract higher benefits from innovation thanks to scale economies not only in R&D activities, but also in other activities such as marketing and advertising, which increase entry barriers, causing higher possibilities of appropriation of the innovation profits. Nonetheless empirical studies often fail to find clear evidence in this regard. Whereas some studies have found a positive relationship between size and innovation (Scherer, 1992) others did not. Trying to explain these evidences, Acs and Audretsch (1987) report that small firms may also have some relative advantages, depending on the industry life-

[10] This means that some firms who made an innovation but did not spend any money to innovate have been considered as non innovators. As a matter of fact, this innovation could possibly be either the outcome of imitation or the output of investments made in an earlier period. (see Conte and Vivarelli, 2005).

cycle stage. In particular small firms might gain larger advantages from innovation at an early stage of the industry life cycle, when products are continuously subject to change. Indeed, the link between a firm's size and R&D investment depends to a great extent on the sector to which the firm belongs (Kamien and Schwarz, 1968 ; Dosi, 1988)

The technology dummy for high, medium-high, medium-low and low tech industries account for firms' heterogeneity due to sector specific factors that are likely to influence the innovative behavior of a firm (Acs and Audretsch, 1987 and 1988). The firm's degree of openness to the external market is proxied by the export intensity, measured by the ratio between exports and sales in the previous three years. According to the previous empirical literature (Hobday, 1995 ; Bhattacharya and Bloch, 2004) the coefficient associated with these variables should show a positive slope, since firms that export also need to undertake innovative activities in order to sustain international competitiveness. Membership of a business group is included among the regressors, and the coefficient is expected to be positive since group members can have easier access to finance and to the group's internal knowledge as well (Mairesse and Mohnen, 2002 ; Shin et al., 2006). Given the relevance of public programs for innovation support in Korea, two additional controls are included by using dummy variables (*venture* and *innobiz*) taking a non-zero value if the firm is respectively classified as a Venture Firm or an Inno-Biz Firm.

Additionally, hampering factors and innovation support have been also included in the model as exogenous explanation for firms' innovative activity. For each of the two groups there were several questions in the survey in which firms were asked to report, on a 0-5 scale, the relevance of every hampering or supportive factor. In order to avoid collinearity problems in the estimation, only a selected group of variables have been included, in particular those with the highest average score. Tables with the average scores and the selection procedures are included in the Appendix B. Among all the hampering factors, the four with the higher average scores were selected and four dummy variables have been constructed, each of them with non-zero value if the firm graded the factor with a value of at least one. A residual dummy variable was also constructed assigning the value of one if the firm answered at least a non-zero grade for any residual category. The four selected factors are a) risk by technical uncertainty (*uncert*), b) lack of human capital (*humcap*), c) lack of technological information (*infotech*), d) uncertainty on market demand (*demand*) and e) other obstacles (*othob*). The same method has been applied to questions asking the firm to grade support measures and the two answers receiving the highest average grades (i.e. the direct support and the participation in publicly financed innovation programs) have been merged in the variable *support*. Again a residual variable has been also created (*othsup*). (see Table 3.1)

Table 3.1: List of Variables

Variable Name	Variable Definition
ksic	Stands for Korea Standard Industrial Classification code
legaltype (s)	=1 if the firm is large-sized; =2 if the firm is medium-sized; =3 if the firm is small-sized (dummies have been constructed for each category)
tech (t)	=1 if the firm is high-tech; =2 if the firm is medium/high-tech; =3 if the firm is medium/low-tech; =4 if the firm is low-tech (dummies have been constructed for each category)
sales	total sales in last 3 years - mwon
ired	intramural expenditures - % sales
ered	extramural expenditures - % sales
mach	machinery expenditures - % sales
tacq	technological acquisition - % sales
othpr	other innovation expenditure - % sales
innosales	innovative sales - % sales
group	=1 if the firm is part of an industrial group
age	age of the firm
exp	export intensity - % sales
venture	=1 if venture capital company
innobiz	=1 if inno-business company
support	=1 if firm has either received government financial support or participated in Government R&D program
othsupp	=1 if firm has received other kind of public support
uncert	=1 if firm believes risk by technical uncertainty to be an obstacle
humcap	=1 if firm believes lack of human capital to be an obstacle
infotech	=1 if firm believes lack of technological information to be an obstacle
demand	=1 if firm believes uncertainty on market demand to be an obstacle
othob	=1 if firm has experienced other obstacles in innovation

As far as concerns the definition of young innovative companies (YICs), different approaches have been previously adopted in the empirical literature. From a reductive and simplistic point of view, two viewpoints are worth discussing. On the one side there is an input-based approach, according to which the definition of innovative firm is drawn observing the amount of expenditure made by the firm. Such a critical amount, as an example, is set at 15% in the work of Schneider and Veuglers (2008), who also define "young" firms as firms that are less than 6 years old. On the opposite side there is an output based approach, according to which firms are considered innovators if they have actually produced an innovation. Such an approach is used by Pellegrino et al. (2009), who also uses 8 years as the critical age for a firm to be considered young. As already discussed at the beginning of this section in the description of the dataset, this paper uses the output-based approach, classifying as innovators only firms which have actually carried out a product innovation project in the last three years. With regard to the critical age, this paper also takes the condition to be less than 8 years. The motivation for such an arbitrary choice relies on the evidence that normally it takes 8 to 9 years for Korean innovative firms to reach the maturity stage (Kim and Hong, 2011)[11].

3.3 Empirical Model and Results

The empirical framework adopted is derived by the idea of a Knowledge Production Function (KPF), initially proposed by Griliches (1979). This simply relates in a linear way the inputs and outputs of innovation. However, given the composition of the output variable of this model, the problem of sample selection bias would not allow to consistently estimate the parameters of the linear model. More specifically, the dependent variable is observed for only those firms that have introduced a product innovation, that is

[3.1] $$innosales_i = \begin{cases} innosales_i \; if \; prod = 1 \\ 0 \; if \; prod = 0 \end{cases}.$$

The mean of the dependent variable, denoted as y_1 for simplicity, is consequently specified as conditioned on the observation of the product innovation variable, denoted as y_2 and of a matrix of covariates X_i, including the inputs and controls

[3.2] $$E(y_{1i}|X_i) = p_i(E(y_{1i}|X_i, y_{2i} = 1) + (1 - p_i)(E(y_{1i}|X_i, y_{2i} = 0).$$

Since the second term in the right hand side of equation [3.2] equals 0 by definition the specification for the mean is reduced to

[3.3] $$E(y_{1i}|X_i) = p_i(X'\beta).$$

Consistent estimates of the β vector can be obtained as long as the probability that the firm introduces a product innovation p_i is completely exogenous and is not correlated with any of the variables in the X matrix. If this is not the case a correction for the sample selection bias is needed. The procedure to correct for such a bias is described by Heckman (1979) and consists of two steps. In the first a probit equation (called selection equation) is specified using y_2 as dependent variable and,

[11] Such a definition is, moreover, to be preferred from an econometric perspective. Although empirical results are, in fact, generally robust to the use of a different critical age (7 years) in terms of coefficient estimates, they are not in terms of goodness of fit. This is probably due to the decrease in the degrees of freedom following the decrease in the number of firms once a lower critical age is used.

in the second, a linear regression model (called main equation) is specified using y_1 as dependent variable for only those observations with a non-zero value of y_2.

[3.4] $$\begin{cases} y_{2i} = Z_i'\gamma + u_i \\ y_{1i} = X_i'\beta + \varepsilon_i \end{cases}.$$

Following Heckman's two step procedure, the two equations in [3.4] are estimated simultaneously assuming $Corr(\varepsilon_i, u_i) = 0$. Simultaneity further requires setting the condition $X \in Z$ to allow identification of parameters, which, in practical terms, means that at least one of the covariates of the selection equation has to be excluded from the main equation (exclusion restriction)[12].

Accordingly, the choice of the variable to be used for the exclusion restriction is the most demanding part of the Heckman model specification (Pellegrino et al., 2009). The variable should in fact be such that its effect on y_2 is sizable while the effect on y_1 is either negligible or altogether absent.

Lacking a good theoretical background pinpointing the variable to be used as exclusion restriction[13], this paper relies on data driven methods to select such variables. In greater detail, all the variables are included in both X and Z in a first try and the exclusion restrictions have been selected looking at those groups of variables showing large significance in the selection equation and lack of significance in the main equation[14]. Estimates of the final model are reported in Table 3.2. Here only the significant selection variables have been maintained.

Although all the coefficients for input variables report the correct sign, among the inputs only internal R&D is significant in both the main and the selection equation. External R&D is significant only in the selection equation while acquisition of machinery does only in the main equation. Technological acquisition does in neither case. Results indicate that larger firms have higher probabilities to conduct product innovation as well as firms belonging to an industrial group, but the innovative outputs seems not affected by either size or group membership. The coefficient for export intensity shows insignificant results in both the main and the selection equation. As expected venture firms have a higher probability of introducing new product innovations and also have larger shares of innovative outputs. This is clearly not the case of Inno-Biz companies, being the relative estimated

[12] Actually the non-linearity of the selection equation allows to obtain an identifiability of parameters but, at least according to Cameron and Trivedi (2010), the use of an exclusion restriction ensures better results.
[13] Actually the theoretical background would suggest using the protection of innovation as exclusion restriction, since any past experience in protecting innovation is expected to positively affect the probability to innovate and, at the same time, is not expected to affect the amount of innovative sales once the innovation is introduced. However, given the structure of the questionnaire, the information about protection is not available since only firms who have introduced product innovation responded.
[14] Results in Appendix C.

coefficient insignificant, although rightly sloped, in both equations. Turning the attention to selection variables, government support is always positive and significant, although the coefficient for the variable indicating either direct support or participation in publicly financed programs is greater in magnitude[15].

Table 3.2: Heckman Selection Model

	Main Equation		Selection Equation	
ired	0.500**	(0.234)	2.358**	(1.091)
ered	0.737	(0.493)	14.175***	(4.872)
mach	0.464**	(0.212)	1.075	(0.947)
tacq	0.300	(1.058)	6.757	(5.275)
s1	-0.016	(0.027)	0.274***	(0.107)
s2	-0.023	(0.017)	0.138**	(0.067)
te1	0.050**	(0.023)	-0.007	(0.096)
te2	0.010	(0.019)	0.031	(0.079)
te3	-0.044**	(0.021)	-0.178**	(0.078)
exp	0.035	(0.027)	0.171	(0.111)
innobiz	0.023	(0.021)	0.128	(0.083)
venture	0.060***	(0.022)	0.262***	(0.086)
group	0.006	(0.022)	0.153*	(0.093)
support			0.186**	(0.076)
othsupp			0.140*	(0.074)
demand			0.386***	(0.063)
intercept	0.268***	(0.044)	-0.170**	(0.079)
N. of Obs				2203
N. of Censored Obs.				674
Mill's Ratio				0.047 [0.413]

Notes to Table:
SE in parenthesis. p-value in brackets
***, **, and * respectively indicate significance at 0.01, 0.05 and 0.1 confidence levels

Finally, the Mill's ratio, a measure of the non-selection hazard, is insignificant indicating that the sample selection correction is unnecessary and, accordingly, OLS estimates of the linear model on the sample of innovators can be trusted as unbiased estimates[16]. Nonetheless, what is the effect of some covariates on the probability to innovate is still an interesting research question to be answered. For this reason from now on we proceed specifying the model as a two-equation model, one selection equation and one main equation, but avoiding imposition of simultaneity in the estimation (two part model). As a consequence of this choice the presence of exclusion restrictions turns out not to be a necessary condition for model parameters identification.

[15] Such a result for the government support variables could be ascribed to the potential bias affecting the relative coefficient estimates. However, the hypothesis of endogeneity is declined for the estimates in our sample because, even admitting a feedback effect from innovation to support caused by the fact that support measures are mainly attributed to innovative firms, and thus to the majority of firms in the sample, it seems that there is no explicit relationship between government support and product innovation, which is studied here. Similarly the variable was used by Pellegrino et al. (2009) as covariate in the selection equation.

[16] Also for the other two models estimated, Mill's ratio was found to be insignificant. The model has been thus estimated using several specifications in an attempt to test the robustness of this result and the hypothesis of non-selection hazard was always found to be rejectable. More results are available to the author upon request.

Table 3.3 presents the estimation results of the two-part model. In the first two columns regression results for the whole sample of firms are reported. Columns three and four report results for the subsample of mature firms and, finally, columns five and six do the same for the subsample of young firms. Estimates in columns three and five as well as in columns four and six are obtained using a single equation specification with interaction terms among all the covariates and the dummy for young firms. Additional results with estimates obtained from separate regressions are available in the Appendix C. The F-statistics reported at the bottom of the table to test the hypothesis that interaction terms are jointly significant. The first of the two tests uses all the interaction terms while the latter is limited to interactions of internal and external research, which focus is closer to the research question.

Table 3.3: Two Part Model for Different Subsamples

	All		Mature		Young	
	selection	Main	selection	main	selection	main
Ired	1.982*	0.457**	2.898**	0.603**	-1.071	-0.013
	(1.078)	(0.226)	(1.279)	(0.261)	(2.056)	(0.466)
Ered	14.748***	0.600	10.709**	0.289	53.553***	3.121**
	(4.890)	(0.474)	(5.071)	(0.503)	(20.939)	(1.583)
Mach	1.039	0.468**	0.611	0.224	2.150	0.769*
	(0.942)	(0.211)	(1.082)	(0.253)	(1.937)	(0.408)
Tacq	7.463	0.170	14.686*	0.710	4.895	-0.848
	(5.299)	(1.048)	(8.790)	(1.317)	(7.047)	()1.788
s1	0.254**	-0.022	0.258**	-0.019	-0.316	0.014
	(0.107)	(0.025)	(0.114)	(0.027)	(0.468)	(0.129)
s2	0.132**	-0.027	0.111	-0.026	0.143	-0.020
	(0.067)	(0.017)	(0.074)	(0.018)	(0.186)	(0.047)
te1	-0.021	0.047**	-0.063	0.028	0.134	0.157***
	(0.096)	(0.023)	(0.104)	(0.025)	(0.267)	(0.061)
te2	0.026	0.007	0.005	0.010	0.057	-0.007
	(0.079)	(0.019)	(0.087)	(0.021)	(0.200)	(0.052)
te3	-0.175**	-0.039**	-0.160*	-0.042**	-0.364**	-0.031
	(0.078)	(0.020)	(0.086)	(0.022)	(0.188)	(0.056)
Exp	0.185*	0.030	0.182	0.016	0.036	0.138*
	(0.111)	(0.026)	(0.118)	(0.028)	(0.364)	(0.08)
Innobiz	0.131	0.021	0.159*	0.025	-0.155	0.000
	(0.083)	(0.020)	(0.090)	(0.021)	(0.235)	(0.067)
Venture	0.261***	0.056***	0.263***	0.076***	0.275	-0.022
	(0.086)	(0.020)	(0.099)	(0.023)	(0.186)	(0.048)
Group	0.161*	0.003	0.181*	0.009	0.223	-0.069
	(0.093)	(0.021)	(0.099)	(0.023)	(0.291)	(0.069)
Uncert	-0.004	0.013	-0.008	0.017	-0.028	-0.001
	(0.076)	(0.019)	(0.085)	(0.021)	(0.185)	(0.052)
Humcap	-0.063	0.031	-0.083	0.018	-0.004	0.058
	(0.099)	(0.025)	(0.110)	(0.027)	(0.235)	(0.060)
Infotech	0.115	-0.007	0.246**	-0.016	-0.408*	0.044
	(0.103)	(0.026)	(0.117)	(0.029)	(0.238)	(0.063)
Demand	0.361***	-0.020	0.327***	-0.011	0.466**	-0.047
	(0.080)	(0.021)	(0.089)	(0.023)	(0.201)	(0.053)
Othob	-0.120	-0.045	-0.169	-0.031	0.091	-0.067
	(0.148)	(0.037)	(0.152)	(0.038)	(0.235)	(0.063)
Support	0.185**	-0.020	0.176**	-0.036	0.170	0.065
	(0.076)	(0.019)	(0.082)	(0.020)	(0.206)	(0.057)
Othsupp	0.120*	0.010	0.120	0.018	0.147	-0.055
	(0.074)	(0.019)	(0.080)	(0.020)	(0.200)	(0.055)
Intercept	-0.062	0.333***	-0.043	0.330***		
	(0.156)	(0.039)	(0.160)	(0.040)		

F-stat	26.77	1.30
(all coefficients)	[0.1419]	[0.165]
F-stat	5.74	2.03
(*ired* and *ered*)	[0.0567]	[0.132]

Notes to Table:
SE in parenthesis. p-values in brackets
***, **, and * respectively indicate significance at 0.01, 0.05 and 0.1 confidence levels
F-stat is the value of the test statistic for the null hypothesis that all the interaction terms are jointly insignificant. Under the null the set of young-related coefficients is not statistically different from the mature-related set.

Differently from the Heckman selection model specification, all the selection variables have been included in both the selection and the main equation. Not surprisingly estimates using the whole sample of firms do not differ that much from those obtained using the Heckman procedure. The results related to the inputs are unchanged. Internal R&D is confirmed as the most important source of innovation, being the relative coefficient positive and significant in both the selection and the main equations. The effect of external R&D appears significant in the selection equation, however, it is not significant in the main equation. On the contrary, expenditure for acquisition or replacement of machinery shows a significant relation with the amount of innovation produced but not with the probability of introducing a new innovation. Finally, the coefficient related to technological acquisition is neither significant in the selection equation, nor is it in the main equation.

Moving the attention to control variables, firm’s size and group membership continue to show a positive relation with the probability of introducing new innovations, but no relation with the amount of innovative output. The result on technology is unexpected, as it was also in the Heckman model. Firms engaging in high-tech produce more innovative output compared to low-tech, but firms in medium-low-tech industries both have lower probabilities of introducing innovation and produce less innovative output than firms belonging to low-tech industries. As far as it concerns venture firms, the relative coefficient continues to be positive and strongly significant in both the main and the selection equation. The coefficient, on the contrary, is never significant for Inno-Biz companies. The only difference with respect to the Heckman model is with regards to the coefficient on export intensity, which now becomes positive and significant in the selection equation.

Finally, considering the variables related to the support of innovation and obstacles to innovation, it is worth noting that none of the variables are significant in the main equation. Moreover, the variables showing a significant coefficient in the selection equation are the same ones that were significant in the Heckman model. These are the variables related to government support and to the uncertainty of market demand, which continues to enter in the selection equation with an unexpected slope. With the exception of the variable *infotech,* all the other coefficients for variables indicate the obstacles to innovation are correctly sloped.

Innovation in Young and Mature Firms

Estimates obtained dividing the whole sample in two sub-samples for mature and young firms offer a completely different perspective. These results are summarized in Table 3.3. On the mature firms side, internal R&D appears as the prevailing input of the production process, having a significant positive effect on both the probability to introduce new innovation and on the amount of innovative sales. External R&D only has a positive influence on the probability to innovation while neither the acquisition of machinery nor that of technology have any effect on firms' innovation. The picture changes when looking at young firms. Here internal R&D has no effect at all on innovation while it is clear that external R&D rules in the production process, its coefficient being significant and positive in both equations. A marginal role can be assigned to the acquisition of machinery, positive and significant in the main equation while, once again, the acquisition of technology is never significant. Accordingly, the evidence suggests that Korean YICs are not in-house R&D-based firms. On the contrary, it emerges a clear and significant role of external R&D and of machinery acquisition as well in influencing the firms' innovative performance. Overall the outcome reveals a weakness of Korean YICs in managing innovation internally and the consequent need for external knowledge sources promoting the innovative activity.

Looking at controls, size and group membership effects are noticeable only for the sample of mature firms, while the effect of technology is contradictory. Firms in high-tech industries have larger innovative sales compared to the low-tech counterparts only if they are young. By contrast, firms in medium-low-tech industries have a lower probability of innovating compared to low-tech firms, independently from the firm's age. Moreover, mature firms have also lower amounts of innovative sales. Among the remaining controls the coefficient for export is significant only in the main equation and only relatively to the group of young firms, the coefficient for Inno-Biz companies is significant only in the selection equation of mature firms and the coefficient for Venture companies is positive and significant in both equations relative to mature firms. Thus the effect of Venture Firms, which has been always strongly significant until now, has disappeared in the subsample of young firms.

Finally, focusing on the obstacles to innovation, it is possible to continue noticing differences between mature and young firms. The variable *infotech*, which previously was not significant, now enters with an unexpected positive and significant coefficient in the selection equation of mature firms and with a negative and significant coefficient in the selection equation of young firms. On the contrary, the coefficient for uncertainty in market demand continues to show a positive slope in the selection equation of both young and mature groups. The explanation for such a result related to the uncertainty on market demand might dwell in the behavior of specialist innovators. According to some studies on the Korean innovative firms (Kim and Hwang 2006, Hong 2010), in presence of an uncertain market demand, firms might attempt to invest in R&D to increase their competitiveness on the base of either product quality improvements or product differentiation. None of the other coefficients are significant. Government support through direct funding and participation in publicly financed programs has the usual positive effect on the probability of innovation by only mature firms but has no effect (the coefficient is negative but insignificant) on the amount of innovative sales. This is probably the outcome of a fund-distribution scheme linking support to the realization of innovations. Such a scheme might provide an incentive for firms to innovate in order to have access to funding. Thus it should come as no surprise that these innovations have lower market values and, accordingly, lead to lower innovative sales. In the meantime, supported firms might also experience larger difficulties in marketing innovation, meaning they may be less able to translate the innovation into value added for their customers. Other types of support are not significant for either mature or young firms.

Finally, by looking at the F-statistics it is possible to conclude that, overall, there are no significant differences between the two groups of young and mature firms, neither in the factors affecting the probability to innovate nor in the factors affecting the amount of innovative sales. A closer look at the internal and external research coefficients, however, reveals that there are significant differences among young and mature firms, but only with respect to the effect of these variables on the probability of innovation.

In order to check for possible inconsistencies of the independently combined Probit/OLS methodologies, a further consistency check has been developed by estimating the results assuming a truncation in the main dependent variable (Tobit model). The results are summarized in Appendix C and confirm the validity of the results discussed in this section, both relatively to the whole sample and to the two subgroups of mature and young firms.

3.4 Conclusion

This chapter is an empirical investigation of the determinants of innovative activity of Korean manufacturing firms and contributes to the existing theoretical and empirical literature by analyzing the extent to which the innovative activity of young innovative Korean companies differ from mature firms. Moreover, the paper sheds new light on the empirical literature on innovation in Korea since a recent (2010) survey is used for the empirical investigation.

The main questions the paper attempts to answer are whether or not internal R&D is important for innovation, whether it is the only source of innovation and whether there is any difference between young and mature companies. By looking at the empirical evidence it appears that product innovation is linked with internal R&D but also with machinery acquisition while external R&D only plays a marginal role. By dividing the sample in young and mature firms it turns out that internal R&D is the main driver of innovation in the latter while external R&D and machinery acquisition are more important in young firms.

Overall R&D investments undoubtedly represents the most important source of knowledge for Korean firms and it is no surprise that the ability of firms to first develop and then sell the innovations on the market is strongly related to the amount of resources which are dedicated to these investments. However, from a policy perspective, it might be asked whether support to these investments is effective in the early stage of the life of the firm or, if this is not so, whether it is effective for more mature firms. The evidence in this paper suggests that Korean YICs are not new technology based firms and, as such, either make limited use or do not make use at all of internal resources in their innovation process. Conversely, they rely on external knowledge sources to innovate. In addition, there is evidence that policy measures to support innovation like the Venture Firm and Inno-Biz Firm certifications are actually effective only for mature firms, while they do not probably serve as an incentive for young firms.

Therefore, policies should be cautious and selective. First of all, specific policy measures should be planned for YICs, which increase the effectiveness of external R&D. Such policies should target the scientific collaborations as for example between firms and universities, public research institutes and other firms as well. Moreover, support to internal research in young firms might produce a misallocation of resources as far as young firms actually do not take advantage of such investments. Concerning the firms' choice to use internal resources rather than to rely on external knowledge, it is claimed in the literature that there is an important industrial dimension influencing firms' behavior. Preliminary evidence illustrated in this paper reveals that, among YICs, those in high-tech industries have on average larger shares of innovative sales. Unfortunately, the lack of data prevents further investigation to the extent that input choice varies across industries. The understanding of this might better help future policy-making.

References 3

Acs, Z. J. and Audretsch, D. B. (1987). *Innovation, Market Structure and Firm Size*. Review of Economics and Statistics. 69: 567–575.

Acs, Z. J. and Audretsch, D. B. (1988). *Innovation in Large and Small Firms*. American Economic Review. 78: 678–690.

Baumol, W. J. (2002). *The Free Market Innovation Machine: Analyzing the Growth Miracle of Capitalism.* Princeton University Press.

Bhattacharya, M. and Bloch, H. (2004). *Determinants of Innovation*. Small Business Economics. 22: 155-162.

Cameron, A. C. and Trivedi, P. K. (2010). *Microeconometrics Using Stata*. Stata Press, College Station, Texas.

Cincera, M. and Veugelers, R. (2010). *Young Leading Innovators and the EU-US R&D Intensity Gap*. IPTS Working Papers on Corporate R&D and Innovation. European Commission, JRC-IPTS. No. 07/2010.

Conte, A. and Vivarelli, M. (2005). *One or Many Knowledge Production Functions? Mapping Innovative Activity Using Microdata*. IZA Discussion Paper 1878. Institute for the Study of Labour (IZA). Bonn.

Dosi, G. (1988). *Sources, procedures, and microeconomic effects of innovation*. Journal of Economic Literature. 26,

1120–1171.

Dushnitsley, G. and Lenox, M. J. (2005). *When Do Incumbents Learn from Entrepreneurial Ventures? Corporate Venture Capital and Investing Firm Innovations Rate*. Research Policy. 34: 615-639.

Griliches, Z. (1979). *Issues in Assessing the Contribution of Research and Development to Productivity Growth.* The Bell Journal of Economics. 10: 92-116.

Heckman, J. (1979). *Sample Selection as a Specification Error*. Econometrica. 47: 153-161.

Hobday, M. (1995). *Innovation in East Asia ; The Challenge to Japan*. Aldershot, Edward Elgar.

Hong, J. S. and Hong, S. I. (2008). *Characterizations of Technical Innovations of Small and Medium Enterprises and Their Policy Implications (in Korean).* Korea Institute for Industrial Economics and Trade (KIET) .

Hong, J. S. (2010). *The Pattern of Technology Innovation in SMEs -Time Series Analysis and Policy Implication (in Korean).* Korea Institute for Industrial Economics and Trade (KIET).

Huergo, E. and Jaumandreu, J. (2004). *How Does Probability of Innovation Change with Firm Age?* Small Business Economics. 22: 193-207.

Jones, C. I. (2002). *Sources of U.S. Economic Growth in a World of Ideas*. American Economic Review. 92: 220–239.

Kamien, M. I. and Schwartz, N. L. (1968). *Optimal ''Induced'' Technical Change*. Econometrica. 36: 1–17.

Kbiz (Korea Federation of Small and Medium Business). (2005, 2007, 2009). *Survey on Technology of Small & Medium Enterprises 2005, 2007 and 2009*. (stat@kbiz.or.kr)

Kim, J. Y. and Hwang, M. W. (2006). *The Impact of Enterprises' R&D Investment on Their Business Performance (in Korean).* Monthly Bulletin. 23-69. The Bank of Korea.

Kim, S. J. and Hong, S. C. (2011). *A Study on the Growth Path to Establish the Customized Support Policy for SMEs (in Korean).* Korea Small Business Institute (KOSBI).

Kortum, S. and Lerner J. (1998). *Does Venture Capital Spur Innovation?* NBER Working-Paper. 6846. Cambridge, Mass.

KVBA (Korea Venture Business Association) (2010). *Precision Survey on Venture Firms 2010*

Lee, B. H., Kang, W. J. and Park, S. M. (2008) *Comparison of Technological Innovation and Performance between Innovative SMEs and General SMEs: Empirical Evidence and Policy Implications (in Korean).* The Korean Venture Management Review. 11: 1, 79-100.

Lee, I. K. and Hong, J. B. (2004). *A Study on Entry, Exit of Korean Firms its Economic Performance (in Korean).* Korea Economic Research Institute (KERI).

Lee, Y. J. (2008). *Technology Strategy by Growth Stage of Technology-based Venture Companies (in Korean).* Korea Science and Technology Policy Institute (STEPI).

Little, A.D. (1977). *New Technology-Based Firms in the United Kingdom and the Federal Republic of Germany.* A Report prepared for the Anglo-German Foundation for the Study of Industrial Society. London.

Mairesse, J. and Mohnen, P. (2002). *Accounting for Innovation and Measuring Innovativeness: An Illustrative Framework and an Application.* The American Economic Review. Papers and Proceedings. 92: 226-230.

Moncada-Paternò-Castello, P. (2011). *Companies' Growth in the EU: What is Research and Innovation Policy's Role?* IPTS Working Paper on Corporate R&D and Innovation. No. 03/2011.

Ortega-Argilés, R., Vivarelli, M. and Voigt, P. (2009). *R&D in SMEs: a Paradox?* Small Business Economics. 33: 3-11.

Ortega-Argilés, R., Piva, M., Potters, L. and Vivarelli, M. (2010). *Is Corporate R&D Investment in High-tech Sectors More Effective?* Contemporary Economic Policy. 28: 353-365.

Pellegrino, G., Piva, M. and Vivarelli, M. (2009). *How Do Young Innovative Companies Innovate?* IZA Discussion Papers 4301. Institute for the Study of Labor (IZA).

Santamaría, L., Nieto, M. J. and Barge-Gil, A. (2009). *Beyond Formal R&D: Taking Advantage of Other Sources of Innovation in Low-and Medium-Technology Industries*. Research Policy. 38: 507-517.

Scherer, F. M. (1992). *Schumpeter and Plausible Capitalism.* Journal of Economic Literature. 30: 1416-1433.

Schneider, C. and Veugelers, R. (2008). *On Young Innovative Companies: Why They Matter and How (not) to Policy Support Them*. Department of Economics, Copenhagen Business School Working Paper. 4-2008.

Schumpeter, J. A. (1942*). Capitalism, Socialism and Democracy*. New York. Harper.

Shin, T. Y., Song, J. K., Lee, W. S., Song, C. W., Kim, H. H. and Sohn, S. J. (2006). *The Determinants of Technological Innovation in Manufacturing Industries and Policy Implications (in Korean).* Korea Science and Technology Policy Institute (STEPI).

SMBA. (2010). *Annual Report on SMEs 2010 (in Korean).* Korea Small & Medium Business Administration (SMBA).

Song, C. S., Roh, Y. H. and Choi, E. J. (2011). *The Suggestion of the Improvement of the Venture Firm Supporting System and the Studies on the Growing Path Types of the Venture Firms (in Korean).* Korea Small Business Institute (KSBI).

Statistics Korea. *Micro Data Service System*. (http://mdss.kostat.go.kr)

Storey, D. J. and Tether, B. S. (1998). *New Technology-Based Firms in the European Union: an Introduction*. Research Policy. 26: 933-946.

Appendix 3

A) Description of Korean Innovation Survey

The Korean Innovation Survey (KIS) has been carried out every three years by the Science and Technology Policy Institute (STEPI) - a public research institute - for the purpose of analyzing technological innovation of manufacturing and service industries. The definition and methodology of the survey is based on the Oslo Manual (OECD). The survey in the manufacturing industry has been conducted in 2002 (2000-2001), 2005 (2002-2004), 2008 (2005-2007) and 2010 (2007-2009) and the survey in service has been realized separately in 2003 (2001-2002), 2006 (2003-2005) and 2009 (2006-2008), and their results have been reported to the OECD as official statistics.

B) Selected Questions on Hampering Factors and Policy Measures and Relative Average Answers

<u>Hampering Factors</u>

Question: *"If your firm experiences any hampering factors during the period 2007-2009, please grade the importance of the relevant factors grading in five degrees as 1 (very low)->3 (middle)->5(very high)"*

Variable	Description	Average Answer
prodob_fund1	risk by technical uncertainty	2.055
prodob_fund2	too high cost for innovation and commercialization	1.946
prodob_fund3	lack of internal funds	1.984
prodob_fund4	lack of external investment like venture capital	0.836
prodob_fund5	lack of public fund	1.189
prodob_cap1	lack of human capital	2.332
prodob_cap2	lack of technological information	2.152
prodob_cap3	lack of market information	1.972
prodob_cap4	lack of appropriate partners for cooperation	1.637
prodob_cap5	organizational inflexibility	1.737
prodob_mkt1	uncertainty on market demand	2.303
prodob_mkt2	barriers to market by monopoly/oligopoly	1.489
prodob_inst1	lack of infrastructure	1.787
prodob_inst2	regulations (law, standards, tax, etc.)	1.507
prodob_need1	use of the output of previous technological innovation	1.124
prodob_need2	no needs for technological innovation due to lack of demand	1.222

Accordingly, and in order to obtain synthetic measures for the obstacles to innovation, the following variables have been created to represent the most important answers (average grade higher than 2) to the questions:

uncert: dummy equal one if *prodob_fund1* is greater than one;
humcap: dummy equal one if *prodob_cap1* is greater than one;
infotech: dummy equal one if *prodob_cap2* is greater than one;
demand: dummy equal one if *prodob_mkt1* is greater than one;
othob: dummy equal one if any of the other non-mentioned variables is greater than one.

Public Support

Question: *"Which types of the policy measures were utilized for your technological innovation during the period 2007-2009? Please evaluate the degree of the contribution of each policy to technological innovation in five degrees as 1 (very low)->3 (middle)->5(very high)"*

Variable	Description	Average Answer
taxred	R&D tax reduction	0.978
fund	direct financial support	1.380
pubpart	participation in publicly financed innovation	1.235
pubtech	Public program for technological support	0.804
info	technology information provision	0.804
training	training program	0.833
procurement	public procurement	0.599
marketing	marketing support (fairs etc.)	0.881

Accordingly, and in order to obtain synthetic measures for the public support, the following variables have been created to represent the most important answers (average grade higher than 1) to the questions:

support: dummy equal one if either *fund* or *pubpart* is greater than one;

othsupp: dummy equal one if any of the other non-mentioned variables is greater than one.

C) Additional Model Results

Heckman Two Step Model 1

	selection	main
Ired	2.368**	0.654***
	(1.093)	(0.324)
Ered	14.072***	0.959
	(4.884)	(0.653)
Mach	1.096	0.546**
	(0.947)	(0.240)
Tacq	6.854	0.559
	(5.291)	(1.199)
s1	0.274***	0.003
	(0.107)	(0.038)
s2	0.139**	-0.014
	(0.067)	(0.022)
te1	-0.009	0.047**
	(0.097)	(0.024)
te2	0.027	0.010
	(0.079)	(0.020)
te3	-0.176**	-0.056**
	(0.078)	(0.028)
Exp	0.169	0.044
	(0.112)	(0.031)
Innobiz	0.128	0.033
	(0.084)	(0.025)
Venture	0.264***	0.080***
	(0.086)	(0.034)
Group	0.154*	0.016
	(0.093)	(0.027)
Uncert	-0.017	0.011
	(0.077)	(0.021)
Humcap	-0.055	0.026
	(0.099)	(0.027)
Infotech	0.103	0.003
	(0.104)	(0.029)
Demand	0.370***	0.016
	(0.081)	(0.045)
Othob	-0.141	-0.059
	(0.149)	(0.042)
Support	0.187**	-0.003
	(0.076)	(0.027)
Othsupp	0.137*	0.022
	(0.074)	(0.024)
_cons	-0.044	0.190
	(0.157)	(0.163)
N. of Obs.		2203
N. of Censored Obs.		674
Lambda		0.183 [0.364]

Note to Table:
SE in parenthesis. p-value in brackets
***, **, and * respectively indicate significance at 0.01, 0.05 and 0.1 confidence levels

Heckman Two Step Model 2

	selection	main
Ired	2.368**	0.494**
	(1.093)	(0.234)
Ered	14.072***	0.722
	(4.884)	(0.492)
Mach	1.096	0.461**
	(0.947)	(0.211)
Tacq	6.854	0.283
	(5.291)	(1.056)
s1	0.274**	-0.017
	(0.107)	(0.027)
s2	0.139**	-0.024
	(0.067)	(0.017)
te1	-0.009	0.050**
	(0.097)	(0.023)
te2	0.027	0.010
	(0.079)	(0.019)
te3	-0.176**	-0.043**
	(0.078)	(0.021)
Exp	0.169	0.034
	(0.112)	(0.027)
Innobiz	0.128	0.023
	(0.084)	(0.021)
Venture	0.264***	0.059***
	(0.086)	(0.022)
Group	0.154*	0.006
	(0.093)	(0.022)
Support	0.187**	
	(0.076)	
Othsupp	0.137*	
	(0.074)	
Uncert	-0.017	
	(0.077)	
Humcap	-0.055	
	(0.099)	
Infotech	0.103	
	(0.104)	
Demand	0.370***	
	(0.081)	
Othob	-0.141	
	(0.149)	
Intercept	-0.044	0.272***
	(0.157)	(0.043)
N. of Obs.		2203
N. of Censored Obs.		674
Lambda		0.041 [0.469]

Note to Table:
SE in parenthesis. p-value in brackets
***, **, and * respectively indicate significance at 0.01, 0.05 and 0.1 confidence levels

Tobit Model

	Whole Sample	Mature Firms	Young Firms
ired	0.797***	0.995***	0.068
	(0.261)	(0.296)	(0.585)
ered	1.421**	0.852	5.730***
	(0.591)	(0.616)	(2.147)
mach	0.556**	0.297	1.049**
	(0.240)	(0.279)	(0.503)
tacq	1.172	2.080	0.916
	(1.201)	(1.558)	(2.058)
s1	0.036	0.036	-0.082
	(0.029)	(0.030)	(0.145)
s2	0.008	0.003	0.027
	(0.019)	(0.020)	(0.057)
te1	0.037	0.012	0.156**
	(0.026)	(0.027)	(0.075)
te2	0.009	0.008	-0.010
	(0.022)	(0.023)	(0.061)
te3	-0.068***	-0.065***	-0.115*
	(0.022)	(0.024)	(0.061)
exp	0.056*	0.044	0.132
	(0.030)	(0.031)	(0.103)
innobiz	0.047**	0.057**	-0.043
	(0.023)	(0.024)	(0.075)
venture	0.099***	0.116***	0.038
	(0.023)	(0.025)	(0.057)
group	0.032	0.040	-0.013
	(0.025)	(0.026)	(0.085)
uncert	0.004	0.006	-0.004
	(0.021)	(0.023)	(0.058)
humcap	0.011	0.000	0.044
	(0.028)	(0.030)	(0.071)
infotech	0.019	0.041	-0.071
	(0.029)	(0.032)	(0.073)
demand	0.069***	0.065***	0.080
	(0.023)	(0.025)	(0.061)
othob	-0.065	-0.069*	0.024
	(0.041)	(0.043)	(0.147)
support	0.025	0.010	0.091
	(.0210)	(0.022)	(0.064)
othsupp	0.031	0.035*	0.005
	(0.021)	(0.022)	(0.062)
intercept	0.040	0.050	-0.038
	(0.044)	(0.046)	(0.148)
N. of Obs.	2203	1683	340
Left-censored Obs.	681	552	129

Notes to Table:
SE in parenthesis. p-values in brackets
***, **, and * respectively indicate significance at 0.01, 0.05 and 0.1 confidence levels

Two Part Model for Young and Mature Firms: Multiple Regression

	Whole Sample		Mature Firms		Young Firms	
	selection	main	selection	main	selection	main
ired	1.982*	0.457**	2.894**	0.603**	-1.053	-0.011
	(1.078)	(0.226)	(1.279)	(0.259)	(2.063)	(0.494)
ered	14.748***	0.600	10.703**	0.288	53.433***	3.132*
	(4.890)	(0.474)	(5.072)	(0.499)	(20.926)	(1.681)
mach	1.039	0.468**	0.610	0.224	2.158	0.770*
	(0.942)	(0.211)	(1.082)	(0.250)	(1.939)	(0.433)
tacq	7.463	0.170	14.678*	0.710	4.908	-0.848
	(5.299)	(1.048)	(8.789)	(1.305)	(7.049)	(1.894)
s1	0.254**	-0.022	0.257**	-0.019	-0.316	0.014
	(0.107)	(0.025)	(0.114)	(0.026)	(0.468)	(0.137)
s2	0.132**	-0.027	0.110	-0.026	0.146	-0.019
	(0.067)	(0.017)	(0.074)	(0.018)	(0.188)	(0.051)
te1	-0.021	0.047**	-0.063	0.027	0.136	0.157**
	(0.096)	(0.023)	(0.104)	(0.024)	(0.268)	(0.065)
te2	0.026	0.007	0.005	0.010	0.058	-0.007
	(0.079)	(0.019)	(0.087)	(0.021)	(0.200)	(0.056)
te3	-0.175**	-0.039**	-0.161*	-0.042**	-0.362**	-0.031
	(0.078)	(0.020)	(0.086)	(0.022)	(0.189)	(0.059)
exp	0.185*	0.030	0.182	0.016	0.039	0.139
	(0.111)	(0.026)	(0.118)	(0.027)	(0.365)	(0.089)
innobiz	0.131	0.021	0.159*	0.025	-0.155	0.000
	(0.083)	(0.020)	(0.090)	(0.021)	(0.235)	(0.071)
venture	0.261***	0.056***	0.263***	0.076***	0.274	-0.022
	(0.086)	(0.020)	(0.099)	(0.022)	(0.186)	(0.051)
group	0.161*	0.003	0.181*	0.009	0.222	-0.069
	(0.093)	(0.021)	(0.099)	(0.022)	(0.292)	(0.073)
uncert	-0.004	0.013	-0.008	0.017	-0.026	0.000
	(0.076)	(0.019)	(0.085)	(0.021)	(0.187)	(0.055)
humcap	-0.063	0.031	-0.083	0.018	-0.001	0.058
	(0.099)	(0.025)	(0.110)	(0.027)	(0.236)	(0.063)
infotech	0.115	-0.007	0.246**	-0.016	-0.409*	0.044
	(0.103)	(0.026)	(0.117)	(0.028)	(0.238)	(0.066)
demand	0.361***	-0.020	0.327***	-0.011	0.464**	-0.047
	(0.080)	(0.021)	(0.089)	(0.023)	(0.201)	(0.057)
othob	-0.120	-0.045	-0.174	-0.032	0.140	-0.056
	(0.148)	(0.037)	(0.158)	(0.039)	(0.493)	(0.138)
support	0.185**	-0.020	0.176**	-0.036*	0.170	0.065
	(0.076)	(0.019)	(0.082)	(0.020)	(0.206)	(0.061)
othsupp	0.120*	0.010	0.120	0.018	0.147	-0.055
	(0.074)	(0.019)	(0.080)	(0.020)	(0.200)	(0.058)
_cons	-0.062	0.333***	-0.037	0.331***	-0.097	0.319***
	(0.156)	(0.039)	(0.168)	(0.041)	(0.501)	(0.139)
N. of Obs.	2003	1529	1863	1317	340	212
LR	186.130		158.520		46.380	
	[0.000]		[0.000]		[0.000]	
F		3.440		2.730		1.760
		[0.000]		[0.000]		[0.027]

Notes to Table:
SE in parenthesis. p-values in brackets
***, **, and * respectively indicate significance at 0.01, 0.05 and 0.1 confidence levels