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Corporate R&D Activities, Financing Constraints, Performance and Diversification

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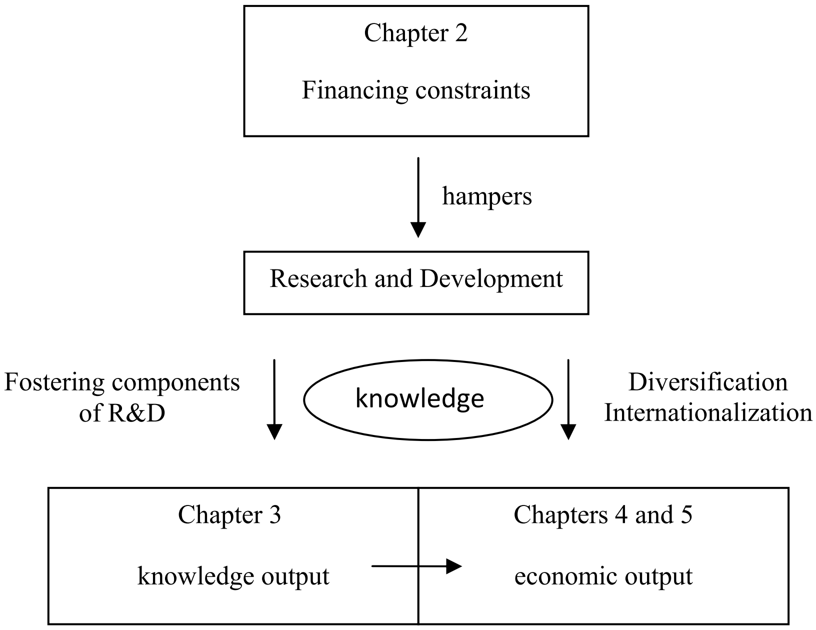
Chapter 1 - Introduction

SUMMARY

This chapter establishes the context and the scope of the thesis. Several topics directly related to the research and development activities of the companies are investigated: the financing constraints on R&D (chapter 2), the components of R&D that foster the innovative outcome of the companies (chapter 3), and the relationship between the performance of R&D and the industrial diversification and the globalization of economic activities (chapter 4), as well as the internationalization of R&D (chapter 5). This chapter introduces the motivations related to this research, defines the research objectives and questions addressed by the dissertation and concludes with the outline and the contributions of the thesis.

Context and motivations

Innovation is nowadays recognized as a crucial driver for the European economy. Since the Lisbon Agenda, the Members States of the European Union have been aspiring to make Europe the most dynamic and competitive economy in the world. The recently adopted EU2020 strategy illustrates that a key factor for achieving this common and ambitious objective is the focus on comprehensive policies oriented towards the development of a European economy that is based on innovation and knowledge. EU2020 emphasizes the importance of a smart, sustainable and inclusive growth and advocates efforts to increase the investments in science, technology and innovation. In this context, this thesis proposes to enlighten several channels that favor the emergence and the outcome of creative ideas and innovation in general amongst private firms, with a particular focus on European companies.



The first motivation for this thesis resides in the acknowledged gap between EU and US private Research and Development[1]. Recent R&D figures[2] stress the inability of Europe to reach its R&D target of 3%[3] of gross domestic product since it was fixed in 2002 at the Barcelona Council. Besides, US companies appear to perform better than their EU

[1] See the recent work by Cincera and Veugelers (2011).
[2] EC Key Figures 2011.
[3] Objective related to the Gross Expenditures on R&D (GERD).

counterparts on the same period. In 2009, R&D performed by US private companies consisted in more than 2% of the US GDP while business R&D in Europe only accounted for 1.25% of EU GDP[4]. A major factor that may alleviate the size of the R&D expenditures is the difficulty for a firm to access sufficient resources to finance its innovative projects. Hence, chapter 2 aims at assessing the extent to which financing constraints on R&D occur in Europe, with an international comparison focusing mainly on the EU-US comparison. While chapter 2 is dedicated to the stimulation of R&D expenditures, another concern of the policy makers is to ensure that innovative ideas lead to outcomes in terms of products and services and eventually boost the growth and the competitiveness of the economy. The motivation of chapter 3 lies in the so-called blackbox representation[5] of R&D. Indeed, R&D expenditures encompass numerous dimensions according to their nature (research versus development, human capital versus investments), their objective (product versus process), their funding or their location. The importance of specific types of R&D is likely to foster the outcome of the innovative process, as measured here by patents. Chapter 3 investigates in this matter the determinants of the knowledge production of R&D activities when R&D is disaggregated into several components. The evolution over the last decade of innovation, which is recognized as becoming increasingly complex, open and internationalized[6], motivates the research conducted in chapters 4 and 5. Nowadays most of the R&D in the world is performed by Multinational enterprises (MNEs)[7]. The top 1000 EU and the top 1000 non-EU R&D spenders represent together about 80% of worldwide business enterprise expenditures on R&D[8]. This growing complexity of the MNEs deserves to be investigated in terms of innovative performance. The mergers and acquisitions strategies of the MNEs are primarily a matter of competition policies, but they may correlate with an underlying diversification process of the companies that affects their R&D performance. A firm that diversifies its line of products across several industries or countries is likely to suffer from losses of efficiencies due to complexity, especially for high degrees of diversification, but this diversification strategy may also benefit to R&D productivity through, for instance, economies of scope when the firm is industrially diversified, or home-based augmenting/exploiting strategies for a globalized firm. Concerning the internationalization of R&D, the location of R&D centers in non European countries may still benefit to European growth and alleviate the fears of doing

[4] Eurostat, OECD.
[5] Rosenberg (1982).
[6] Anvret, Granieri, Renda (2010).
[7] UNCTAD (2005).
[8] MEMO/11/705 of the 2011 EU Industrial R&D Investment Scoreboard.

R&D outside rather than inside the European geographic area. This thesis investigates whether these diversification and internationalization considerations do benefit to the innovation performance of Europe.

Objectives and research questions

This thesis investigates, based on quantitative methods, three matters directly related to the research and development activities of the companies:

- the financing constraints on R&D;
- the components of R&D that foster the innovative outcome of the companies;
- the relationship between the performance of R&D and the industrial and international diversification of economic activities as well as the internationalization of R&D.

The analysis is empirical and its nature is exclusively micro-economic. A significant work that underlies the findings of this dissertation was performed on four datasets which include firm-level information related to the innovative activities of the companies.

Do financing constraints explain a part of the acknowledged R&D gap between Europe and the US? A first objective of this thesis is to assess whether there is evidence that European companies that are willing to invest in R&D projects are facing financing constraints. Financial systems that are more market-oriented (like the US economy) are theoretically more likely to see the emergence of financing constraints due to less ability to manage information asymmetry problems. Empirical literature over the 80s-90s mainly relies on this explanation to justify findings of a sensitivity of R&D to internal funds amongst US firms. However, US firms do not suffer, unlike their EU counterparts, from the fragmentation of the European financial market, which is pointed out by recent recommendations of the CEPS[9]. Furthermore, the improvement of US equity markets over the past decades is illustrated over time by a lower sensitivity of US investments to internal funds for large public firms[10]. This dissertation provides two sets of original results which contribute to the empirical literature on this subject. First, our analysis addresses the following question: do the leading innovators in US and Europe, which are both likely to rely partially on the market to finance their R&D, differ in terms of financing constraints after year 2000? This analysis gives a picture of the financing constraints on most R&D in Europe and compares it with the situation in the US. A second question that is addressed is whether older firms actually face less severe or no

[9] Anvret, Granieri, Renda (2010).
[10] Brown and Petersen (2009).

financing constraints, as opposed to younger firms. Our analysis assesses whether the constraints faced by the young US and EU leading innovators, i.e. the yollies in Cincera and Veugelers (2011), differ from the old ones (ollies). An international comparison is also established.

Does the heterogeneity of R&D activities affect the technology performance of a firm, and if so, what are the effects that can be observed for the numerous faces of R&D? A second objective of the thesis is to identify the components of R&D activities that are the main drivers of the innovative performance of the companies. This performance is assessed by the patent applications of the companies. The analysis opposes research to development, product to process-oriented activities, human capital to investments, sources of funding and subcontractors. On the basis of Belgian data for 2004-2005, hypotheses on the components of R&D will be tested. As the technological Belgian landscape is highly internationalized, a substantial work was realized on the gathering of patents filed outside Belgium by foreign applicants but based on inventions which were likely created in Belgian R&D centers.

Do diversification strategies of economic activities (industrial and international) and R&D internationalization of EU MNEs improve the economic performance of R&D activities? A third objective of the thesis is to link R&D productivity with the following strategies of European MNEs in the 2000s: industrial diversification of the economic activities, globalization of the economic activities and internationalization of the R&D activities. The analysis aims at assessing whether these strategies benefit to the performance of innovative activities as measured by the production of the MNEs. In order to capture these strategies, an original work in two steps is realized. First, information on the subsidiaries of the top R&D spenders in Europe is collected. The industries of the subsidiaries and their location are used to assess the diversification of the activities of the EU MNEs. Second, additional information is gathered on the location of the inventors that contributed to the patents of each European MNE as well as each subsidiary identified in the first step. The location of the inventors is used as a proxy of the location of the R&D centers of the MNEs. The key dimension of this work resides in the consolidation of the information at the level of the European MNEs.

All these topics have a high degree of relevancy in terms of innovation policies. Hence, each chapter of the thesis intends to provide a discussion of the policy implications on the basis of our findings.

Outline of the thesis and main features

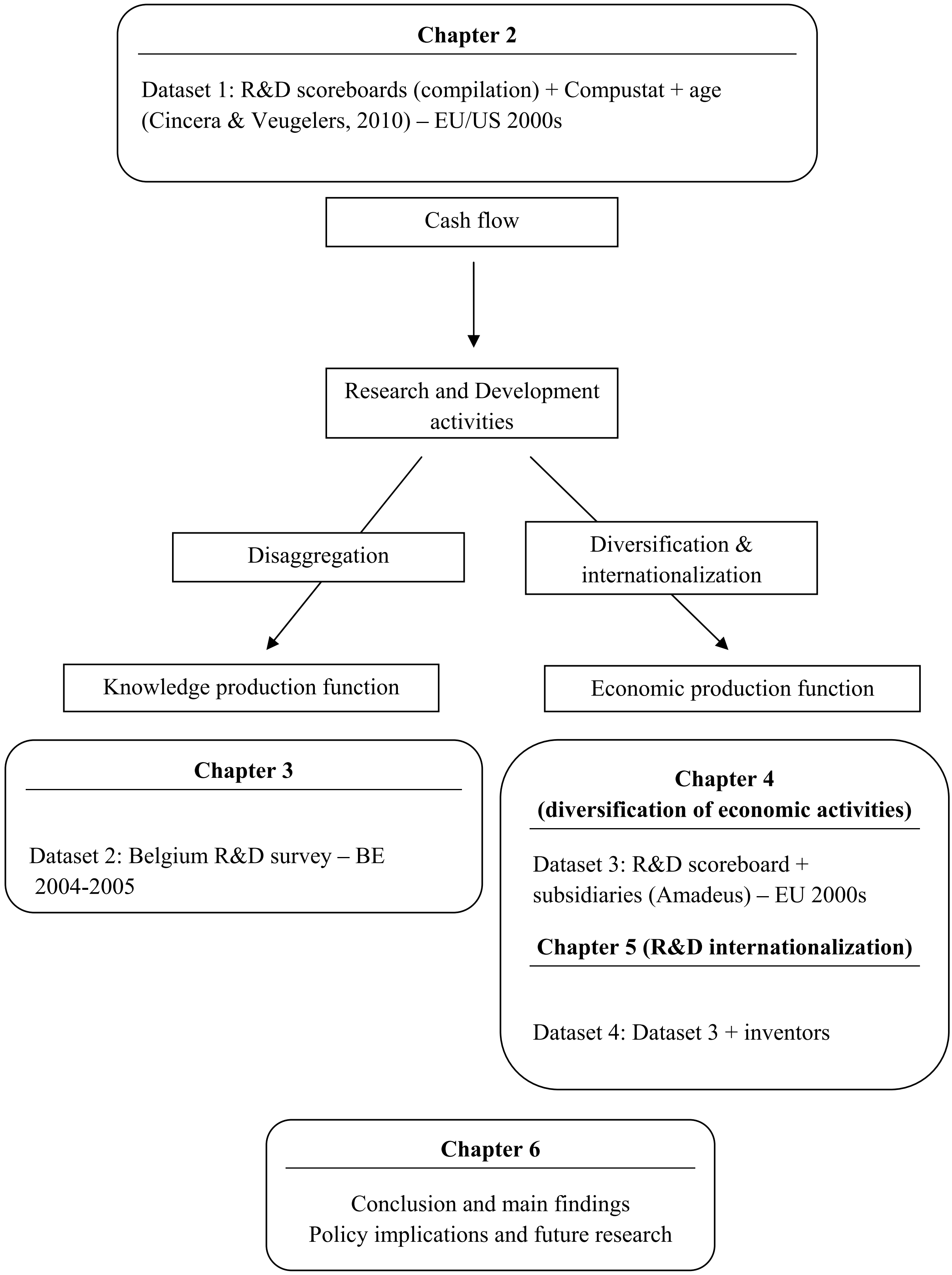
The structures of chapters 2, 3, 4 and 5 are similar. They first provide outlines of the literature and methodological framework. Data and empirical findings are then reported and discussed. Figure 1 presents the outline of the thesis.

The financing constraints on R&D are investigated in chapter 2. A dataset of companies active in R&D is constructed for this purpose. This dataset is based on a compilation of R&D scoreboards[11] and is used to establish a US-EU comparison in the 2000s. Cash flow data were collected using the Compustat database. The findings of this chapter are based on a sensitivity analysis of R&D to cash flow using estimates of dynamic R&D equations derived from the optimal level of R&D investment when considering a Constant Elasticity of Substitution (CES) production function of a profit-maximizing firm. Investments of firms that face liquidity constraints are assumed to be more likely to be sensitive to the availability of internal finance. Estimations of R&D sensitivities are provided for both datasets. The relationship between the financing constraints on R&D and the age of the companies is analyzed in an additional set of results with parametric as well as non parametric estimations. Nonparametric estimations were used as a complementary approach in order to release restrictions in the modeling of the R&D accumulation rates and in the shape of the relationship between the R&D sensitivity and the age of the companies.

Chapter 3 measures the knowledge production of R&D expenditures when they are disaggregated into the following components: intramural versus extramural expenditures, research versus development expenditures, product-oriented versus process-oriented, human capital versus investments. Furthermore, the sources of funding are also analyzed, which gives another perspective to the analysis performed in chapter 2. The types and location of the subcontractors is considered as well. The disaggregated R&D expenditures are implemented in a knowledge production function with knowledge outcome measured by the quantity of patent applications of the companies. A count data econometric method is used in order to assess the elasticity of patents to the R&D components. Hypotheses about the R&D components and their role in the R&D-patent relationship are tested on the basis of Belgian data from the Belgian R&D survey that was conducted in 2004 and 2005. This survey does not provide patent information and required patent matching, which was performed taking into account the international nature of Belgian R&D.

[11]Industrial R&D scoreboards are released by the EC-JRC-Institute for Prospective Technological Studies.

Figure 1. Outline of the thesis



While chapter 3 gives a glimpse of the international nature of R&D, chapters 4 and 5 investigate deeper this type of strategy. Estimates of economic production functions that include R&D capital are reported. The industrial and international diversification strategies of the activities of European MNEs are assessed through their subsidiaries in chapter 4. A dataset that covers the period 2000-2008 is constructed based on consolidated data from the European R&D scoreboards with their related subsidiaries found in Amadeus database. The number of industries and the number of countries covered by the EU MNEs as well as Herfindhal-Hirschman indexes are used as interaction effects with R&D in the production process. In chapter 5, an extension of the dataset of chapter 4 leads to the construction of an additional dataset that includes the location of the inventors related to the MNEs and their subsidiaries in order to proxy the location of the R&D activities. The productivity effect of different geographic locations is investigated, with a focus on the location of subsidiaries and inventors in the US as opposed to EU.

Chapter 6 concludes the dissertation by reviewing the main findings of the previous chapters. The limitations of the thesis are addressed and policy implications are summarized. Finally, extensions of the scope of the analysis and ideas for future research are suggested.

To our knowledge, the contributions of this dissertation can be summarized as follows. The analyses address relevant questions in the literature on the basis of four original databases related in different ways to the R&D activities that take place within the companies. The construction of these original datasets represents a substantial work that underlies all the findings of this dissertation. Econometrics methods are implemented in every chapter in order to conduct the quantitative analyses. Chapter 2 contributes to the literature related to the financing constraints by investigating the investments in non tangible capital, i.e. R&D capital and addressing questions for which there is no evidence in prior literature. An original set of results related to the financing constraints provides a global (rather than national) analysis of most R&D in Europe and compares it to US R&D in order to update the findings in the literature and to enlighten the role of the financial dimension on innovation in the post-Lisbon context. Another contribution lies in the nonparametric methods that are used in order to relax restrictions on the modeling of R&D and to shape the relationship between the sensitivity of R&D to cash flow and the age of the companies. Chapter 3 provides a new and unified set of findings that encompass at the same time several dimensions of R&D. To our knowledge, this is the first analysis on the R&D-patent relationship that implements these dimensions in such an integrated framework. Given the high dependency of the Belgian innovation system towards the foreign MNEs, another contribution of Chapter 3 resides in the matching process that was performed between Belgian R&D and patents related to Belgian inventors in order to capture the patents filed outside Belgium but related to inventions created by firms located in Belgium (i.e. subsidiaries of foreign groups). Chapter 4 and 5 aim at answering questions related to modern topics and provide original and innovative findings regarding the growing complexity of the MNEs based on new consolidated data and an original work on the subsidiaries and the inventors of the companies.

Chapter 2 - R&D and Financing Constraints

SUMMARY

This chapter analyzes the financing constraints on R&D investments. The central question in this chapter is whether financing constraints can explain a part of the acknowledged R&D gap between Europe and the US. In order to address this question, a dataset is constructed on the basis of a compilation of R&D scoreboards. The findings of this chapter are based on a sensitivity analysis of R&D to cash flow using estimates of dynamic R&D equations. The relationship between the financing constraints on R&D and the age of the companies is analyzed in an additional set of results with parametric as well as non parametric estimations. European firms appear to be affected by financing constraints in the 2000's while this is not the case for the US companies. The age seems to affect negatively the R&D sensitivity for EU and US leading innovators, with higher sensitivities for old and low-tech EU firms than their US counterparts.

2.1 Introduction[12]

Recent R&D figures[13] stress the inability of Europe to reach its R&D target of 3%[14] of gross domestic product since it was fixed in 2002 at the Barcelona Council. Besides, US companies appear to perform better than their EU counterparts on the same period. In 2009, R&D performed by US private companies consisted in more than 2% of the US GDP while business R&D in Europe only accounted for 1.25% of EU GDP[15].

The central question in this chapter is whether financing constraints can explain a part of the acknowledged R&D gap between Europe and the US. The existence of capital market imperfections such as asymmetric information between lenders and borrowers affects the capital investment decisions of a firm and introduces possible financing constraints, like credit rationing by lenders. Such constraints may actually be even more pronounced in the case of intangible investments such as Research and Development since these activities are more risky by nature and typically provide less collateral to lenders than capital goods do.

Observing the sensitivity of R&D investment decisions to cash flow (CF) is a way to reveal the existence of financing constraints, assuming that investments of firms that face liquidity constraints are more likely to be sensitive to the availability of internal finance. While there is a large literature on the relationship between cash flow and ordinary investment, only few studies have focused on the sensitivity of R&D to cash flow (Brown and Petersen, 2009). This chapter contributes to this literature by providing a new and original US-EU analysis of the R&D-CF sensitivity after 2000.

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[12] This chapter compiles two sets of research about the financing constraints on R&D (US-EU in the 2000's and impact of age in the 2000's). The findings related to the US-EU comparison in the 2000's come directly from *Cincera and Ravet (2010) "Financing constraints and R&D investments of large corporations in Europe and the USA", IPTS Working Paper on Corporate R&D and Innovation, No. 2/2010, European Commission Directorate General for Research* and *Cincera and Ravet (2010) "Financing constraints and R&D investments of large corporations in Europe and the USA", Science and Public Policy, 37(6), pp. 455-466*. These results were presented at internal seminars at ULB, workshops, like the 2010 Workshop on Tax Incentives for Research and Innovation organized by the European Commission, and conferences amongst which the EC Conference on Corporate R&D 2010.

[13] EC Key Figures 2011.

[14] Objective related to the Gross Expenditures on R&D (GERD).

[15] Eurostat, OECD.

Another question that is investigated in this chapter is whether older firms actually face less severe or no financing constraints, as opposed to younger firms. Cincera and Veugelers (2011) show that young leading innovators (yollies) play a more pivotal role in the US than in Europe. As young firms are more likely to be subject to information problems, uncertain returns and lack of collateral value[16], they may have more difficulties to get external finance for their investment projects. This would imply that younger firms rely more heavily on their internal finance when they finance their R&D projects. This question is investigated by using the data on the age of firms used in Cincera and Veugelers (2011).

The empirical analysis is based on a sample of US and EU R&D active companies in the manufacturing and services sectors in the years 2000. We used the successive editions of the EU industrial R&D investment scoreboards (2004 – 2008) conducted by the JRC-IPTS of the European Commission. According to JRC-IPTS[17], these scoreboards are representative of about 80 % of all R&D carried out in the private sector in the world. This source is matched with the Compustat database in order to gather financial information, including the cash flow of the firms. The final sample used in the empirical analysis consists of an unbalanced panel of 1962 firms over 2000 – 2007. All variables are presented using constant exchange rates and price indexes, and R&D stocks are constructed for each firm on the basis of the perpetual inventory method (Griliches, 1979).

The model used to identify the potential liquidity constraints of the firms is an error correction model for R&D investment. This model is derived from the optimal level of R&D investment when considering a Constant Elasticity of Substitution (CES) production function of a profit-maximizing firm. This model is estimated using econometric methods for panel data. Traditional fixed-effect estimators are not suited for this model when the explanatory variables are weakly exogenous and contain random measurement errors. In order to address these issues and the dynamic structure of the model, GMM estimators are implemented. These estimators allow one to deal with the possibly correlated specific unobserved fixed effects of the firms and the weak exogeneity of the explanatory variables. Further results in this chapter relate to the impact of the age of the US and EU firms on the financing constraints of the firms. The error correction model is estimated by considering different categories of age of the firms. A non parametric approach is also used in order to get a better picture of the shape

[16] Brown and Petersen (2009).
[17] Background information and methodology of the 2008 R&D Scoreboard: http://iri.jrc.ec.europa.eu/research/docs/2008/Methodology.pdf.

of the relationship between R&D and cash flow, as well as the relationship between the sensitivity of R&D to cash flow and the age of the firms.

Our findings have important implications for EU R&D policy. First, we show that most of EU R&D is significantly sensitive to the availability of internal finance, which is likely to be due to the existence of financing constraints on R&D. This is not the case for the US firms. As stock markets are likely to be an important source of funds for the companies in our sample, this result advocates a better focus on the development and integration of EU equity markets, which are highly fragmented. Second, tax policies that affect the after-tax cash flow should also have a significant impact on the R&D activities in Europe. Third, given evidence that younger firms rely more on their cash flow to finance their R&D projects, EU policies would do well relaxing this constraint by providing them an easier acces to external funds and eventually encouraging the development of their R&D activities.

The chapter is organized as follows. Section 2.2 reviews some theoretical aspects of the literature on the financing constraints on the investments in R&D as well as the main empirical findings of some selected studies. The methodological framework is presented in section 2.3. The construction of the dataset and its main features are documented in section 2.4. The main estimation results are presented and discussed in section 2.5. Section 2.6 covers conclusions and implications.

2.2 R&D and financing constraints

It is widely agreed that given the existence of asymmetric information between firms and lenders and other agency costs or moral hazard problems, investments in physical capital and more particularly in Research and Development must be primarily funded by internal resources of firms. On the theoretical side, Stiglitz and Weiss (1981) and Myers and Majluf (1984) developed formal models of moral hazard problems in debt and equity markets. On the empirical side, since the pioneering work of Fazzari, Hubbard and Petersen (1988), many studies have examined the extent of liquidity constraints in the financing of physical investment. The agency costs between the shareholders and the R&D management, i.e. risk-adverse R&D managers will under-invest in risky R&D projects and managers tend to spend on activities that benefit them, can be avoided by leveraging the firm. However, the costs of the external funds to finance the R&D projects will be higher (Jensen and Meckling, 1976). Then, investments in intangibles such as R&D are riskier by essence than ordinary investments and R&D managers often have better information regarding the likelihood of the success of their R&D projects than outside investors or lenders. Furthermore, R&D investments provide less collateral to outsiders since they cannot make accurate appraisals of the values associated with this type of investment[18]. As a result, R&D firms may encounter credit rationing by potential lenders and be constrained if they do not have enough internal resources to finance their R&D projects[19].

Besides the risks and uncertainties inherent to R&D activities, strategic considerations are another source of asymmetric information between the borrower and the lender. Inventors may indeed be reluctant to fully or partly disclose to the outside world information as regards the contents and the objectives of their technological activities since this knowledge could leak out to rivals. This imperfect appropriability of the returns of innovative activities arises from the non-rival and partially excludable property of the knowledge good. Non rivalry means that the use of an innovation by an economic agent does not preclude others from using it, while partial excludability implies that the owner of an innovation can not impede others to benefit from it free of charge.

Another essential characteristic of R&D that makes it different from ordinary investment is the presence of high adjustment and sunk costs[20]. The wages of the R&D personnel for instance represent more than 50% of R&D expenditures and training, firing or re-hiring this highly specialized personnel embedded in the firm's intangible asset implies substantial costs[21]. Hence the levels of R&D expenditures associated to any innovation projects are unlikely to change substantially from year to year. This feature could make it difficult to assess empirically the relationship between possible liquidity constraints and expenses in

[18] The output of R&D activities consists of new products and processes, which are typically hard to use as collateral. According to Himmelberg and Petersen (1994) who refer to Ackerlof's (1970) classic example of a car market with asymmetric information and adverse selection problems, "*A potential buyer of a used car can, at relatively low cost, hire a mechanic to assess the car's true quality. In contrast, a potential investor might have to hire a team of scientists to make an accurate appraisal of the potential value of a firm's R&D projects.*"

[19] Capital market imperfections can prevent firms to access to these external funds at least at the same costs than the internal resources. As stressed by Harhoff (1998), "*If providers of finance face greater uncertainty with respect to R&D than to investment projects, they will require a higher lemon's premium for the former type of investment. Hence, even without rationing behaviour on behalf of banks and other financial institutions, there will be a premium to be paid for obtaining external funding.*"

[20] As emphasized by Arrow (1962), given the time it takes to succeed, a typical R&D project involves important fixed set-up costs. This 'indivisible' aspect of R&D as an input views R&D activities mainly as a fixed factor of production.

[21] In Belgium in 1995, the distribution of intramural R&D expenditures by type of costs was as follows: 58% for the R&D personnel, 9% for investment and 33% for the organization of these activities (Cincera, 2005).

R&D investments since the changes in the costs of this type of capital can be weak in the short term. This also makes lagged variables poor instruments for estimations. Unfortunately, there are not many other alternative choices available as instruments for R&D. More fundamentally, given these high adjustment costs, a firm may decide to start new R&D programs only if she knows that she will have sufficient resources to pursue the R&D from the very beginning of the project to its end. In that case, liquidity constraints should not be a concern for the decision of the firm to engage in R&D activities.

There have been only a few studies examining financing constraints and R&D[22]. Table 1 provides some features of some selected studies that have investigated the relationship between internal finance and R&D.

Hall (2002) and more recently Hall and Lerner (2010) provide an extended review of the literature about financing constraints. According to Hall and Lerner (2010), most authors in the empirical literature on financing constraints have been relying on two main approaches based on investment equations. The first is to use a neoclassical accelerator model, which can be augmented with dynamics and transformed into an error correction model (ECM). The second approach is based on an Euler equation (an example is Harhoff, 1998). The authors conclude their review stating that there is evidence that "*debt is a disfavored source of finance for R&D investment [...], Anglo-Saxon economies seem to exhibit more sensitivity and responsiveness of R&D to cash flow than continental economies [...] and this greater responsiveness may arise because they are financially constrained, in the sense that they view external sources of finance as much more costly than internal*". However, this responsiveness may also be related to demand signals in thick financial equity markets.

Table 1 presents a summary of selected studies that investigate the financing constraints on R&D investments using firm-level data. Comparisons between financing constraints faced by US firms and European firms, and more specifically French firms, have been investigated for mid-80s and early 90s by Hall et al. (1999) and Mulkay, Hall, Mairesse (2001). The paper by Hall et al. (1999) indicate that investment and R&D are sensitive to cash flow in the US only and show evidence of a positive impact of both investment and R&D in predicting sales and cash flow for the US firms while the results are somewhat more mixed in France and Japan.

[22] Schiantarelli (1996) and Hubbard (1998) provide reviews of the literature regarding the role of financial constraints on firms' investment activities on fixed capital. Mairesse, Mulkay and Hall (1999) discuss and compare alternative modelling specifications, i.e. simple accelerator and error correction specifications, as well as panel data econometric methodologies, i.e. traditional between and within firm estimations versus GMM estimators, for estimating firms' investment equations.

Mulkay, Hall and Mairesse (2001) do not find any significant differences (for France and US) in the effects of output on physical and R&D investments. Yet, cash flow or profit appears to have a much higher impact on both types of investments in the US than in France. Hence the impact of financial factors on investment and R&D does not differ within a country but rather across them. This finding indicates that it is the financial market environment specific to a country, which matters in explaining the impact of financial factors on investment.

Table 1. Features of some selected studies on R&D and financing constraints

	Firms	Countries	Period	Model - Econometrics
Hall (1992)	Large manufacturing	US	1973-1987	Tobin's Q
Himmelberg and Petersen (1994)	Small high-tech	US	1983-1987	Acc., Tobin's Q – Within/FD GMM
Harhoff (1998)	Large manufacturing	DE	1990-1994	Acc., ECM, Euler- FD GMM
Bond et al. (1999)	Manufacturing and high-tech	UK, DE	1985-1994	ECM – GMM SYS
Hall et al. (1999)	High-Tech	FR, JP, US	1978-1989	VAR – GMM SYS
Mulkay et al. (2001)	Large manufacturing	FR, US	1982-1993	ECM – Within/GMM FD & SYS
Bougheas et al. (2001)	Manufacturing	IE	1991-1997	Acc. – OLS
Cincera (2003)	Large manufacturing	BE	1991-2000	Acc. and ECM – Within/GMM FD & SYS
Czarnitsky (2006)	SMEs manufacturing	DE	1994-1998	Tobit
Savignac (2008)	Large manufacturing	FR	1997-1999	Bivariate probit
Aghion et al. (2008)	SMEs and Large manufacturing and services	FR	1993-2004	Acc./GLS/Tobit/ GMM FD
Brown et al. (2009)	High-Tech	US	1990-2004	Euler – GMM FD & SYS
Brown and Petersen (2009)	Large manufacturing	US	1970-2006	Tobin's Q – GMM

Notes: Acc; = accelerator investment model; ECM = Error correction model; GMM FD and SYS = First difference and system generalized method of moment estimator; VAR = Vector Autoregressive Regression.

Examples of studies focused on US firms are Hall (1992) and Himmelberg and Petersen (1994). The study of Hall (1992) explores the relationship between investment, R&D and cash flow for US firms by taking into account firms specific unobserved fixed effects and simultaneity. The results point to a positive impact of cash flow on both types of investments, although more significant for physical investment, hence indicating the presence of liquidity constraints in addition to just future demand expectations. On the basis of a sample of 179 US small firms in high-tech industries, Himmelberg and Petersen (1994) estimate the relationship between R&D investment, physical capital and internal finance. The results support the schumpeterian hypothesis, which states that internal finance is an important determinant of R&D expenditures. As stressed by Arrow (1962), moral hazard problems hinder external financing of highly risky business activities such as innovation. The absence of collateral value for investment like R&D creates adverse incentives and selection problems in debt and equity markets.

Examples of studies carried out for European countries are Harhoff (1998), Bond, Harhoff and Van Reenen (1999), Czarnitzki (2006), Bougheas, Goerg and Strobl (2001), Cincera (2003), Aghion et al.(2008) and Savignac (2008).

Harhoff (1998) shows evidence for German firms of a large sensitivity of R&D and investment to cash flow for accelerator and error-correction equations. Significant results are found for small firms only for the latter specification. No conclusion for R&D can be drawn from the Euler equation model probably because the sample is too small for a precise estimation.

Results from Bond, Harhoff and Van Reenen (1999) lead one to conclude that the differences between British and German firms in the effects of cash flow cannot be simply explained by a greater role of this variable in predicting future sales. On the whole, the empirical findings indicate that financial constraints are significant in the UK economy while no effect is found for German firms, which can be explained by the institutional differences across the financial systems in the two countries[23]. Furthermore cash flow has an impact on the decision to engage in R&D rather than on the levels of R&D expenditures.

Bougheas, Goerg and Strobl (2001) test the effect of liquidity constraints on the R&D investments of Irish companies. They also come up to the conclusion that R&D investments in these companies are subject to liquidity constraints. This result is in line with previous findings for UK and US companies.

Using a sample of about 10000 Belgian manufacturing firms active in R&D over the 1990's, Cincera (2003) compares financing constraints on both fixed tangible capital and R&D. The empirical analysis is performed on biannual survey data, supplemented with annual accounts

[23] Quoting the authors, "*Share ownership in Germany tends to be more concentrated than in Britain, which may mitigate asymmetric information and conflicts of interest between shareholders and managers. Bank representation on supervisory boards and long-term repeated relationships between banks and firms in Germany may mitigate asymmetric information between lenders and borrowers. Large German firms are more likely to remain unquoted, hostile takeovers are extremely rare, and dividend payout ratios tend to be both lower and less rigid in German firms than in British firms.*"

data. The analysis is founded on two reduced form equations for investment: an accelerator and an error correction model. Although the results indicate the presence of financial constraints on tangible as well as R&D investment, this effect is unexpectedly not larger for R&D. Furthermore, for fixed capital investment, the author investigates the type of firms for which these constraints are stronger. The estimates show that young firms, small firms, firms that are not part of a multinational company, firms that do not perform R&D on a permanent basis, firms that benefit from public funds to support R&D activities, and firms located in the Walloon region face higher financial constraints.

Czarnitzki (2006) uses a modified price-cost margin as a proxy for internal funds of German SMEs, while external financing constraints are measured by a lagged credit rating index. R&D expenditures of West Germany firms are found to be sensitive to internal and external resources while there is no evidence of financial constraints for East Germany firms. The role of public funding is shown as relevant for R&D expenditures in both regions, with a higher importance in East Germany.

Savignac (2008) provides evidence for 1940 French firms about the role of financing constraints in the decision to undertake innovative activities. A direct measure for financing constraints is obtained from the FIT survey[24]. The author considers the decision to innovate and the likelihood to be financially constrained as two simultaneous issues. In order to address this endogeneity of financing constraints to innovation decisions, a recursive bivariate probit model is estimated. Results show that the likelihood for a firm to undertake innovative activities is decreased by more than 20% when the firm faces financial constraints.

In a more recent study based on French data, Aghion et al. (2008) found that the share of R&D investment over total investment is countercyclical without credit constraints, but less if firms face tighter credit constraints. According to the authors, "*this result is magnified for firms in sectors that depend more heavily upon external finance, or that are characterized by a low degree of asset tangibility*".

Brown, Fazzari and Petersen (2009) test the age of the company for a representative sample of 1347 publicly traded high-tech US companies from 1990 to 2004. Their results show that young firms, i.e. firms created less than 15 years ago, that almost entirely finance their R&D investment with cash flow or public share issue are financially constrained which is not the

[24] The "Financement de l'Innovation Technologique" (FIT) survey is based upon the technological innovation concept exposed in the Oslo manual (OECD and EUROSTAT, 1997).

case for mature companies. The authors then propose an explanation for the R&D boom in the US during the 1990's (and its subsequent decline) which is mainly attributed (75%) to young high-tech companies. Controlling for demand side effects and departing from the idea that these firms "*typically exhaust internal finance and then issue stock as their marginal source of funds*", they claim that the shift in the last decade in the supply of both internal and external equity to finance R&D relaxed the financing constraints these young US R&D companies faced and that restricted their R&D investments.

Brown and Petersen (2009) provide the first study that analyzes the evolution of the sensitivity of R&D to cash flow over time (1970-2006) and include measures of debt and stock issues in their model based on Tobin's Q. Their findings show that the sensitivity of total investment (physical and R&D) to cash flow declines over time in the US, with young firms displaying a higher sensitivity than mature firms. They attribute this decline to the substantial improvement of equity markets in the last decades. Moreover, they argue that the dramatic increase over time in R&D's share of total investment should have led to higher R&D to cash flow sensitivities. However, their results do not confirm higher sensitivities and corroborate the improvement of equity markets and the fact that public equity finance became a closer substitute to internal equity over the investigated period.

We contribute to this literature by providing two new sets of results that answer questions for which there is no prior evidence. The first question is to determine whether the acknowledge R&D gap between European firms and US firms may be attributed to the financing constraints faced in the European R&D landscape. Especially for companies that use equity finance for their R&D investment, the improvement of the US equity markets over the last decades (Brown and Petersen, 2009) should have relaxed the dependency of US R&D on the internal finance of the companies. On the other hand, European equity markets are known to be highly fragmented[25] and the lack of a clear functioning internal market in Europe may force firms to rely more on their internal funds when they finance their R&D.

The second question that is investigated is whether young firms face more severe financing constraints on R&D than mature firms. This question is addressed by using the data on the age of firms used in Cincera and Veugelers (2011). Young leading innovators (yollies) play a more pivotal role in the US R&D landscape than in Europe (Cincera and Veugelers, 2011). However, information problems, uncertain returns and lack of collateral value are more likely

[25] Anvret, Granieri, Renda (2010).

to arise amongst young companies than mature companies (Brown and Petersen, 2009). Hence, young firms are more likely to be financially constrained. This would imply that younger firms rely more heavily on their internal finance when they finance their R&D projects. On the other hand, mature firms often have sufficient cash flow for their investment and do less depend on equity or debt issue (Brown, Fazzari and Petersen, 2009). Hence, increasing the supply of internal funds should have less impact on the R&D decisions of mature firms.

2.3 Methodology

2.3.1 R&D equation

In order to investigate whether there is evidence that financing constraints on R&D arise within the US or EU R&D landscape, we will test the significance of internal funds (as measured by the cash flow) in the determination of R&D investments. This section presents the investment error-correction equation as well as the econometric methodology to be implemented for estimating the relationship between cash flow and R&D investments. As stressed by Hall and Lerner (2010), this is a standard methodology based on an investment equation. The methodological framework is close to the one used by Harhoff (1998), Bond et al. (1999), Mairesse, Mulkay and Hall (1999) and Mulkay et al. (2001). Following the neo-classical long run model (Jorgenson, 1963), the logarithm of the desired (or long run) stock of capital is proportional to the logarithm of output and user cost of capital

$$c_{it} = \alpha_t + \beta y_{it} - \sigma ucc_{it} \tag{2.1}$$

where *c* is the logarithm of the stock of R&D, *y* is the logarithm of the sales and *ucc* is the logarithm of the user cost of capital (*UCC*). This model can be derived by assuming a profit maximizing firm with a CES production function with elasticity σ.

The user cost of capital, $UCC_{it} = \left(P_t^I / P_t\right)\left(r_t P_{t-1}^I / P_t^I + \delta_i - \Delta P_t^I / P_t^I\right)$, as noted by Mulkay et al. (2001), is difficult to measure at the firm level given the absence (in general) of the output price P_t and investment price P_t^I at such a disaggregated level. This problem is in general addressed by assuming that the variations in the user costs can be represented by time dummies and the specific fixed (long-term) effects[26] of a firm.

In order to allow dynamic adjustments of R&D capital, we transform equation 2.1 in an autoregressive distributed lag model ADL(2,2). This is a standard specification in the literature that is convenient for short period samples as it captures temporal dynamics without abusively dropping data in the estimations because of the lag variables. We obtain the following equation:

$$c_{it} = \alpha_i + \alpha_t + \rho_1 c_{it-1} + \rho_2 c_{it-2} + \beta_0 y_{it} + \beta_1 y_{it-1} + \beta_2 y_{it-2} + \varepsilon_{it} \tag{2.2}$$

Following Bond and Meghir (1994), Harhoff (1998) and Mulkay et al. (2001), this equation can be rewritten in an error correction framework:

$$\Delta c_{it} = \alpha_i + \alpha_t + \delta_0 \Delta c_{it-1} + \delta_1 \Delta y_{it} + \delta_2 \Delta y_{it-1} + \delta_3 (c_{it-2} - y_{it-2}) + \delta_4 y_{it-2} + \varepsilon_{it} \tag{2.3}$$

where $\delta_0 = \rho_1 - 1$, $\delta_1 = \beta_0$, $\delta_2 = \beta_0 + \beta_1$, $\delta_3 = \rho_1 + \rho_2 - 1$ and $\delta_4 = \beta_0 + \beta_1 + \beta_2 + \rho_1 + \rho_2 - 1$.

δ_3 is the coefficient of the error correction term and is expected to be negative. δ_4, if non-significant, indicates that returns to scales are constant. By applying the usual approximation[27] $\Delta c_{it} \approx R_{it} / C_{it-1} - \delta$, with R being the R&D expenditures and δ the depreciation rate of R&D capital, equation 2.3 becomes:

$$\frac{R_{it}}{C_{it-1}} = \alpha_i + \alpha_t + \delta_0 \frac{R_{it-1}}{C_{it-2}} + \delta_1 \Delta y_{it} + \delta_2 \Delta y_{it-1} + \delta_3 (c_{it-2} - y_{it-2}) + \delta_4 y_{it-2} + \varepsilon_{it} \tag{2.4}$$

Following the seminal work of Fazzari et al. (1988), if we assume that investments of credit-constrained firms are more sensitive to the availability of internal finance, equation 2.4 can be augmented with cash flow effects (divided by one period lagged C for normalization) to test

[26] See, however, Butzen, Fuss and Vermeulen (2001) for an application that estimates the user cost of capital.

[27] $\Delta c_{it} = \log(C_{it}) - \log(C_{it-1}) = \log\left(\frac{C_{it}}{C_{it-1}}\right) = \log\left(\frac{C_{it} - C_{it-1} + C_{it-1}}{C_{it-1}}\right) = \log\left(1 + \frac{\Delta C_{it}}{C_{it-1}}\right) \cong \frac{\Delta C_{it}}{C_{it-1}} \cong \frac{R_{it}}{C_{it-1}} - \delta$

for the presence of financial constraints. Hence, financial constraints can be assessed by analyzing the sensitivity of R&D investments to variations in cash flow available to firms:

$$\frac{R_{it}}{C_{it-1}} = \alpha_i + \alpha_t + \delta_0 \frac{R_{it-1}}{C_{it-2}} + \delta_1 \Delta y_{it} + \delta_2 \Delta y_{it-1} + \delta_3 (c_{it-2} - y_{it-2}) + \delta_4 y_{it-2}$$
$$+ \delta_5 \frac{CF_{it}}{C_{it-1}} + \delta_6 \frac{CF_{it-1}}{C_{it-2}} + \varepsilon_{it} \tag{2.5}$$

The idea behind the R&D-CF sensitivity is to measure the importance of retained earnings in the R&D investment decision. Hall and Lerner (2010) present this measure as an experiment that consists in giving additional cash to a company, and observing whether they use it for investment or not. If they pass it to shareholders, either there is no good investment opportunity, or the cost of capital has not fallen. If the additional amount of cash is used for investment, it would mean that the firms has unexploited investment opportunities for which external finance is too costly.

Kaplan and Zingales (1997) question the monotonicity of the relationship between the investment to cash flow sensitivity and the level of financing constraints. However, Bond et al. (2003) argue that firms with no financing constraints should still display no excess sensitivity of investment to cash flow and that Kaplan and Zingales (1997) critiscism does not apply in this case.

Moyen (2004) runs OLS regressions on simulated data and shows that a sensitivity of investment to cash flow can be generated even when there is no financing friction. Her model is based on firms that use debt as a substitute for internal finance. This result arises when current debt is correlated with contemporaneous cash flow. However, the author argues that the conventional interpretation of the investment to cash flow sensitivity of Fazzari, Hubbard and Petersen (i.e. a sensitivity that reveals financing constraints) still holds for constrained firms that do not have "*sufficient funds to invest as much as desired. Constrained firms without funds to invest more have investment policies that are more sensitive to cash flow fluctuations than those of other firms.*"

Furthermore, as claimed by Kaplan and Zingales (1997, 2000), the interpretation of the estimated coefficient associated with the cash flow ratio can be misleading since cash flow can be correlated with current profitability. In this case, cash flow will also be a proxy of profit or demand expectations and this variable cannot be interpreted directly as evidence of financing constraints[28]. We follow the view point of Himmelberg and Petersen (1994), which states that changes in output, i.e. Δy_{it} and Δy_{it-1} in equation 2.5, are better proxies for changes in demand than the cash flow variable and thus allow to control, even if imperfectly, for the expectations role played by this variable in terms of expected demand. Equation 2.5 can also be augmented with the Tobin's q to control for investment opportunities. Another possibility is to consider the projections of future profits on past variables and use them as implicit proxies for the expectations of future profits (Abel and Blanchard, 1986) or implement a structural Euler equation model derived from the intertemporal maximization problem of the firms (Bond and Meghir, 1994). However, as pointed out by Butzen, Fuss and Vermeulen (2001) among others, this last approach, while more appropriate from a theoretical point of view, has often failed to produce significant and correctly signed adjustment costs parameters.

Equation 2.5 can be estimated using a within estimator by taking deviations from individual means or by taking all variables in first differences in order to remove the specific unobserved effect of the firm, α_i, which is assumed to be constant over the period under investigation, and which may be correlated with other regressors. The ability of the R&D personnel to find new inventions is one example of such an unobserved effect specific to the firm[29]. These unobserved variables are likely to be 'transmitted' to the R&D decision since firms with higher technological opportunities or abilities of their scientists and engineers will generally invest more in research activities. This in turn will imply a (positive) correlation between these unobservable variables and the R&D which invalidates the inference that can be made from equation 2.5.

While the within and first differences estimators take care of the biases arising from possible correlated effects, it should be noted that these estimators could still be biased for three other possibly important reasons. The first source of bias rests in possible random measurement errors in the right hand side variables of the equation. These errors typically tend to be magnified when applying the first difference or within transformations (Griliches and Hausman, 1986). The two other sources of bias refer to the simultaneity between the contemporaneous regressors and the disturbances and the endogeneity of the contemporaneous regressors and the past disturbances. A solution to these three potential

[28] For Fazzari, Hubbard and Petersen (2000), however, the theoretical model of Kaplan and Zingales fails to capture the approach used in this literature and therefore does not provide a relevant critique.
[29] R&D opportunity or managerial skills may also be mentioned.

sources of biases consists of using an instrumental variable approach by choosing an appropriate set of lagged values of the regressors for the instruments. This approach can be implemented by means of a GMM framework such as the one developed by Arellano and Bond (1991) among others. If the original error term follows a white noise process, then values in levels of these variables lagged two or more periods will be admissible instruments[30]. The validity of the instruments is generally verified by the classical Sargan test and Hansen test of the over-identifying restrictions.

Arellano and Bover (1995) and Blundell and Bond (1998) developed a system GMM estimator, which combines the instruments of the first difference equation with additional instruments of the untransformed equation in level. Given the higher number of instruments, the system GMM estimator can lead to dramatic improvements in terms of efficiency compared with the first difference GMM estimator[31]. The validity of these additional instruments, which consist of past first difference values of the regressors, can again be tested through Difference Sargan over-identification tests.

2.3.2 Nonparametric specification

In order to analyze the impact of age on the R&D-CF sensitivity, we propose a nonparametric approach that will allow capturing a potential nonlinear pattern between the variables. Furthermore, we aim at assessing the relationship between the sensitivity of R&D to cash flow and the age of the companies. This approach relies on the direct estimation of the dependant variable instead of estimates of parameters on the right-hand side of the equation, which allows relaxing restrictions on the modeling of R&D and focuses on the observation of data in given dimensional surfaces. Increasing the number of investigated dimensions is made difficult because of the sparcity of data in high-dimensional spaces. As in Fazzari, Hubbard and Petersen (1988), we consider the relationship between the accumulation rate of R&D R_t/C_{t-1} and the normalized cash flow CF_t/C_{t-1}, with C being the R&D capital stock. Modeling this relationship nonparametrically and implementing the age of the firms as an additional explanatory variable lead to

[30] As noted by Bond et al. (2003), if the error term in levels is serially uncorrelated, then the error term in the first difference has a moving average structure of order 1 (MA(1)) and only instruments lagged two periods or more will be valid. If the error term in levels already has a moving average structure, then longer lags will have to be considered.

[31] More fundamentally, as shown by Blundell and Bond (1998), when the autoregressive parameter is high and the number of time periods is low, the first difference GMM estimator can be subject to serious finite sample bias as a result of the weak explanatory power of the instruments.

$$R_{it} / C_{i,t-1} = m_{it}\left(CF_{it} / C_{i,t-1}, age_{it}\right) + \varepsilon_{it} \ , \tag{2.6}$$

with $i = 1, \dots, N$ and $t = 1, \dots, T$. ε_{it} is an error term with mean zero.

$m_{it}\left(x_1, x_2\right) = E\left[R_{it} / C_{i,t-1} \mid CF_{it} / C_{i,t-1} = x_1, age_{it} = x_2\right]$ is the conditionnal mean of $R_{it} / C_{i,t-1}$ and is an unspecified nonlinear function of the cash flow and the age of the firms. For a more concise notation, let r be the accumulation rate of R&D, cf the cash flow variable and A the age of the firms. Equation 2.6 can be rewritten as

$r_{it} = m_{it}\left(cf_{it}, A_{it}\right) + \varepsilon_{it}$.

The conditional expectation of r is

$$m\left(x_1, x_2\right) = E(r \mid cf = x_1, A = x_2) = \int r f_{r|cf,A}(y \mid x1, x2) dy = \int r \frac{f(x_1, x_2, y)}{f_{cf,A}(x_1, x_2)} dy = \frac{\int r f(x_1, x_2, y) dy}{f_{cf,A}(x_1, x_2)}$$

The use of kernel estimates for the density functions and a product kernel form for the multivariate kernels (i.e. $K(u_1, \dots, u_m) = K(u_1) \dots K(u_m)$) yield a standard kernel estimation of m_{it} (Nadaraya, 1964; Watson, 1964), which is

$$\hat{m}(x_1, x_2) = \frac{\frac{1}{NTh_1h_2} \sum_{t=1}^{T} \sum_{i=1}^{N} r_{it} K(cf_{it}, x_1, h_1) K(A_{it}, x_2, h_2)}{\frac{1}{NTh_1h_2} \sum_{t=1}^{T} \sum_{i=1}^{N} K(cf_{it}, x_1, h_1) K(A_{it}, x_2, h_2)} .$$

K is a smoothing kernel associated to a bandwidth h. The estimation of m can be seen as a weighted local average of the observed accumulation rates of R&D. A larger bandwidth gives more weight to observations further away from (x_1, x_2) and results in a stronger smoothing of the estimation. A standard rule of thumb for the bandwidth selection can be derived from Silverman (1986): $h = \hat{\sigma}(NT)^{-1/5}$. The estimated conditional variance of the expected accumulation rate of R&D is

$$\hat{V}(x_1, x_2) = \frac{\frac{1}{NTh_1h_2} \sum_{t=1}^{T} \sum_{i=1}^{N} (r_{it})^2 K(cf_{it}, x_1, h_1) K(A_{it}, x_2, h_2)}{\frac{1}{NTh_1h_2} \sum_{t=1}^{T} \sum_{i=1}^{N} K(cf_{it}, x_1, h_1) K(A_{it}, x_2, h_2)} - \left(\hat{m}(x_1, x_2)\right)^2 .$$

Two types of kernel are used in our analysis: a Gaussian kernel and a Gamma kernel. While the Gaussian kernel is standard in kernel estimation, the gamma kernel specification is preferred for variables with a non-negative nature (Chen, 2000) as it overcomes a boundary bias issue for values near zero.

The Gaussian kernel is defined as

$$K\left(X,x,h\right)=\frac{1}{\sqrt{2\pi}}e^{-\frac{((X-x)/h)^2}{2}},$$

and the Gamma kernel is

$$K\left(X,x,h\right)=\frac{X^{x/h}e^{-X/h}}{h^{x/h+1}\Gamma(x/h+1)}.$$

where $\Gamma(x/h+1)=\int_0^{\infty}e^{-u}u^{x/h}du$.

Based on a direct estimation of derivatives, the following derivative of the expected R&D is used to measure the responsiveness of R&D to cash flow:

$$D\hat{m}(x_1,x_2)=\frac{d\hat{m}_{it}(x_1,x_2)}{dx_1}$$

Average derivatives are computed by age along with their corresponding bootstrapped confidence intervals[32]. The average derivatives by age are the weighted sums of the derivatives for each x_1, with the weights being the estimated density in (x_1,x_2)[33]:

$$\hat{\phi}(x_1,x_2)=\frac{1}{NTh_1h_2}\sum_{t=1}^{T}\sum_{i=1}^{N}K(cf_{it},x_1,h_1)K(A_{it},x_2,h_2)$$

The estimated average derivative for an age x_2 is then

$$\hat{\delta}(x_2)=\sum_{x_1}D\hat{m}(x_1,x_2)\frac{\hat{\phi}(x_1,x_2)}{\hat{\varphi}(x_2)}$$

where $\hat{\varphi}(x_2)=\sum_{x_1}\hat{\phi}(x_1,x_2)$ normalizes the estimated density for a given age.

32 The boostrap procedure is based on a large number of random resamplings with replacement for each age (1000 resamplings in our analysis).
33 Normalized to 1 by age.

2.4 Data

The results presented in this chapter are based on a dataset that covers the period 2000-2007 and includes information on US and EU firms. R&D equations will be estimated parametrically as well as nonparametrically using this dataset. The data of Cincera and Veugelers (2011) concerning the age of the firms are used in order to investigate the impact of age on the R&D-CF sensitivity.

In order to estimate the R&D equation, we use data about net sales and R&D from the R&D scoreboards while information about cash flow is given by the financial reports of the companies. The data come from the five R&D scoreboards issued every year between 2004 and 2008 by the JRC-IPTS, except for the cash flow variable which comes from the Computast database[34]. Each annual scoreboard provides information on the R&D expenditures, net sales, total employees, capital expenditures, operating profit and market capitalization of the top firms that were active in R&D during the previous year (e.g. the 2008 scoreboard provides information on the year 2007 and not 2008). Growth rates of these variables are also available for the years before and allow adding more observations over time for each firm. R&D data from the Scoreboards represent all R&D financed by the companies, regardless of the geographical location of R&D activities. Data are collected from audited financial accounts and reports[35].

When stacking the scoreboards together, we obtain a total of 33600 observations (unbalanced panel). However many observations are redundant as the information for a same firm and year can be provided by more than one scoreboard. For example, the 2007 scoreboard provides information about R&D of firm X for year 2006. But if firm X is present in the 2008 scoreboard, the growth rate of its R&D expenditures between 2006 and 2007 is available in the latter scoreboard, which also allows us to retrieve the amount of R&D of firm X in 2006. As a consequence, both scoreboards give information on the R&D expenditures of firm X in 2006. In order to avoid multiple counting of the same observation, we choose to keep only the most recent scoreboard as a source for each redundant information. This process results in an unbalanced panel of 16553 observations, for 2696 firms' names. 706 names concern US firms and 1438 are related to firms in the EU.

[34] Release of 2009.
[35] See Moncada Paternò Castello et al. (2009) for more details.

Based on this sample, a matching procedure is conducted with the annual financial reports of firms in order to add more information about the cash flow of the companies. The cash flow variable that is used in this study is equal to the income before extraordinary items, which represents the income of a company after all expenses except provisions for common and or preferred dividends, plus depreciation and amortization, which are the non-cash charges for obsolescence and wear and tear on property[36]. The methodology for the matching between both databases combines automatic procedures and manual procedures. Automatic procedures consist in two steps. First we try to find the financial states of firms whose names are exactly the same as the ones in the R&D scoreboards. Second, we match firms' names after having cleaned these names by deleting the following terms: AG, SA, CO, PLC, INC, LTD, SPA, BHD and CORP. These terms are the suffixes that appear the most often in the database. This automatic procedure does not take into account other less common prefixes or suffixes or punctuation differences. A manual procedure compares the remaining unmatched names.

Out of the 2696 names of the R&D scoreboards, 1962 (73%) were matched, with matching procedures consisting in about 36% of automatic procedures, 33% of manual procedures and 31% of combination of both procedures. Ex post validation of the matching is carried up by checking the location and industry of the firms as well as comparing the currency of the monetary data and the values of financial data in both sources.

For the sake of comparison of R&D investment liquidity constraints between Europe and the USA, two samples of similar companies have been constructed for the EU and the US. Following Moncada Paternò Castello et al. (2009), size as measured by the amount of R&D investment in the firm is used as the criteria for matching similar firms. It turns out that the sample of the 1962 firms among which 942 are from the EU and 525 from the USA comprises firms with different volumes of R&D investment. For the 2008 edition of the Scoreboard, the lowest R&D investment for the EU subsample is 4.35 million Euro and that for the non-EU subsample 24.21 million. In order to construct sub-samples of comparable EU and non-EU companies in terms of the size of their R&D investments, it is preferable to consider only companies with R&D above the US threshold.

Furthermore, in order to trim the dataset from outliers the following procedure has been implemented. All observations for which the R&D intensity (defined as the R&D investments divided by the firm's net sales) was below 0.1% or above 100% were deleted. This removed

[36] Compustat (2009).

29 firms for the first threshold (mainly firms from the retail and travel and leisure industry sectors) and 93 firms for the second criteria (firms mainly in the pharmaceuticals sector[37]). 1% extreme values for the ratio cash flow to R&D capital stock where also removed as these observations might refer to errors from the matching procedure.

Table 2 presents some descriptive statistics of the variables used in the models with comparisons between the EU27 and the US samples. The Global sample refers to the sample including both EU and US firms. The average number of employees is large due to the nature of the R&D scoreboards. The median number of employees is about 6000 employees. We assume that this is a limitation in our analysis of financing constraints as large firms are expected to be less constrained compared to SMEs. However this bias concerns both US and European samples. The comparison of Table A.1 in Appendix 1 and Table 2 shows the effect of having comparable samples in terms of size. The companies in the matched samples look much more similar in terms of the distribution of quartiles and standard errors of the main variables used in the regressions[38].

Table 2. Descriptive statistics

		Mean	*Std.dev.*	*Quantile 25%*	*Quantile 50%*	*Quantile 75%*
Employees	*Global*	22916	48707	1860	6108	22000
	EU27	25957	55300	2143	6892	24264
	US	19899	40924	1634	5600	18803
R_t / C_{t-1}	*Global*	0.237	0.101	0.175	0.213	0.270
	EU27	0.229	0.103	0.169	0.206	0.257
	US	0.245	0.099	0.182	0.221	0.283
CF_t / C_{t-1}	*Global*	0.835	1.277	0.236	0.454	0.932
	EU27	0.994	1.552	0.262	0.494	1.038
	US	0.693	0.945	0.210	0.430	0.823
Δy_t	*Global*	0.074	0.221	-0.019	0.052	0.138
	EU27	0.056	0.214	-0.029	0.035	0.110
	US	0.092	0.225	-0.006	0.069	0.161
c_t	*Global*	5.879	1.391	4.845	5.572	6.630
	EU27	5.697	1.456	4.602	5.329	6.434
	US	6.059	1.300	5.123	5.727	6.777

Period: 2000-2007. Source: own computation.

[37] These firms are research specialized laboratories whose unique activity is R&D. Their sales are therefore very limited which explains their very high R&D intensity, i.e. above 100%.

[38] Table A.2 in Appendix 1 presents a measure that consists in the difference between US and EU statistics based on the initial sample divided by the difference between the same statistics when using the corrected sample.

Information about the age of the companies was collected by Cincera and Veugelers (2011). The authors manually collected the first year of the firms' creation. In case of mergers, the age of the merged entity is the one of the oldest of the merged companies. The final data were crosschecked with other databases like Amadeus for the EU companies. As this work is also based on the R&D scoreboards, the matching procedure with our dataset is straightforward. Table 3 reports some statistics about the age of the firms.

Table 3. Age of the companies

	Mean	Median	Std Dev	Min	Max
All	74	63	60	1	661
EU	99	93	74	1	661
US	55	33	47	3	340

Source: own computation.

While the average and median EU firm is almost 100 years old, it appears that US firms are much younger, with a median and average age of 33 and 55 years respectively. The oldest EU company is the Finnish manufacturer Stora Enso, which was founded in 1347[39]. The oldest US firm is Merck and was founded in 1668.

Average ages by technological sector (i.e. high-, medium- and low-tech sectors) are reported in Table 4. For both US and EU datasets, the high-tech[40] companies are younger in average while the oldest firms seem to be more represented in the lowest technological sectors. This illustrates the conclusions drawn by Cincera and Veugelers (2011) with young leading innovators (yollies) more present in sectors with high R&D intensity than the old leading innovators (ollies). Furthermore, when comparing the US and EU samples, the share of yollies in high-tech sectors is higher for the US dataset, which stresses, according to Cincera and Veugelers (2011), that "*US R&D performance can to a large extent be attributed to young leading innovators playing a more pivotal role in the US R&D landscape*".

Table 4. Average age by technology

	US (sample)	EU (sample)
High	45 (66%)	73 (46%)
Medium	82 (28%)	117 (40%)
Low	74 (7%)	151 (14%)

Source: own computation. Percentage of firms in brackets (by country).

[39] Stora Enso is the result of the merger between Enso and Stora. The latter was actually founded in 1347.
[40] High-, medium- and low-tech sectors for ICB industries are defined as in Ortega-Argiles, Potters and Vivarelli (2009) and Cincera and Ravet (2011).

Each monetary observation was converted into constant euros and prices[41]. It should be noted that monetary values in the R&D scoreboards are already expressed in euros and that a single scoreboard uses a fixed exchange rate for each currency to convert data for every periods that it covers. This is convenient when analyzing data from one single scoreboard as they are unaffected by exchange rate variations in time. However, different scoreboards use different exchange rates. As we combine scoreboards from different years, as well as several years within each scoreboard, we had to convert the data into constant euros with the following procedure. First, we converted the data into original currencies by using the exchange rates specific to each Scoreboard. Second, data in original currencies were converted into euros using a fixed exchange rate[42]. Transforming data into constant prices was performed by using national GDP price deflators[43] with 2007 as the reference year.

The R&D stock was constructed for both datasets by using the perpetual inventory method developed by Griliches (1979). For each firm, the R&D stock at time t is defined by

$$C_t = (1-\delta)C_{t-1} + R_t = R_t + (1-\delta)R_{t-1} + (1-\delta)^2 R_{t-2} + ... = \sum_{s=0}^{\infty}(1-\delta)^s R_{t-s} \qquad (2.7)$$

where δ is the depreciation rate of R&D capital and R is the deflated amount of R&D expenditures. This expression assumes that the current state of knowledge relies on current and past R&D expenditures. Fixing the magnitude of the depreciation rate is not straightforward as it is likely to vary in time and across firms (for instance according to the technology level). An estimation of the depreciation rate of R&D has been performed by Bosworth (1978). The estimated range is 0.1 to 0.15. Hence, most literature assumes a depreciation rate of 15%. By testing different values for δ, Hall and Mairesse (1995) find small or no changes in the estimation of the R&D capital effect[44]. Hence we also rely on a classical depreciation rate set to 0.15. Initial value of C can be computed by using the following expression[45] :

[41] Exchange rates and deflators were found in Eurostat.
[42] We used the 2007 exchange rates found in Eurostat.
[43] Eurostat GDP deflators.
[44] See also Griliches and Mairesse (1983, 1984).
[45] This expression can be derived from the definition of the R&D stock in equation 2.7, $C_t = \sum_{s=0}^{\infty}(1-\delta)^s R_{t-s}$.

The latter equation leads to $C_0 = \sum_{s=0}^{\infty}\frac{(1-\delta)^s}{(1-g)}R_0$ and thus 2.8.

$$C_0 = \frac{R_0}{g + \delta} \tag{2.8}$$

where g is the growth rate of R and is assumed to be constant. The growth rate that is used in this study is the sample average[46] growth rate of R&D expenditures in the industry[47]. According to Hall and Mairesse (1995), the choice of g affects directly the initial stock but its importance declines over time.

2.5 Results

2.5.1 EU and US in the 2000s

Table 5 presents the system GMM results as regards the R&D investment error correction model when all firms in the dataset are considered. These estimates are obtained from a two-step procedure and different sets of instruments. Column 2 for instance uses as instruments the level of the series lagged two periods and more, combined with the first lag of their first difference. The validity of different sets of instruments can be tested through the difference between Sargan or Hansen over-identification tests. The null hypothesis is that the instruments are valid, i.e. they are uncorrelated with the error terms. Under the null hypothesis, the test statistic follows a chi-squared distribution with a number of degrees of freedom being equal to the number of over-identifying restrictions. Rejection of the null hypothesis casts a doubt on the validity of the set of instruments. This appears to always be the case for the Sargan test and only for the model in the second column for the Hansen test[48]. The second order correlation test statistics do not suggest any problems with the time structure of the sets of instruments. With the exception of column 4, the error correction term has the expected negative sign and is statistically significant at the 1 % level.

[46] The average growth rate for an industry is computed as the average of the distribution of individual growth rates inside the range [Q1 – 1.5(Q3-Q1) , Q3 + 1.5(Q3-Q1)] where Q1 and Q3 are the first and third quartiles of the distribution.
[47] ICB classification.
[48] As pointed out by Roodman (2006), Sargan's statistic is a special case of Hansen's J test under the assumption of homoscedasticity. Therefore, for robust GMM estimation, the Sargan test statistic is inconsistent.

Table 5. System GMM two step estimates - all firms

Instruments set	lag(2,.)		lag(3,.)		lag(4,.)	
R_{t-1}/C_{t-2}	-0.059	(0.108)	0.175	(0.071)**	0.400	(0.153)***
Δy_t	0.009	(0.112)	0.228	(0.115)**	0.111	(0.119)
Δy_{t-1}	0.019	(0.031)	0.037	(0.062)	0.018	(0.084)
$c_{t-2} - y_{t-2}$	-0.093	(0.034)***	-0.053	(0.02)***	0.002	(0.032)
CF_t/C_{t-1}	0.074	(0.033)**	0.061	(0.028)**	0.030	(0.020)
CF_{t-1}/C_{t-2}	0.013	(0.011)	-0.009	(0.010)	0.011	(0.019)
y_{t-2}	-0.078	(0.014)***	-0.048	(0.012)***	-0.025	(0.020)
Obs			3 590			
N			888			
AR(1)	-0.46	[0.647]	-1.58	[0.115]	-1.90	[0.058]
AR(2)	-1.31	[0.190]	-1.19	[0.235]	-1.18	[0.238]
Sargan test	2904.02	[0.000]	607.12	[0.000]	370.69	[0.000]
Hansen test	145.95	[0.000]	77.83	[0.072]	49.68	[0.117]

Dependent variable: R_t/C_{t-1}. *** (respectively ** and *): statistically significant at the 1 % (respectively 5 % and 10 %) level. Estimation performed using xtabond2 (Roodman, 2006); all equations include time dummies; Windmeijer corrected standard errors in brackets; P-values in square brackets; AR(1) and AR(2): tests for first order and second order serial correlation in the first difference residuals; Two-step estimates; instruments used in column s (s=2,3,4): observations dated t-s or earlier for X_t (transformed equation) and t-s+1 for ΔX_t (equation in level).

The coefficient of output lagged by two periods is negative and significant albeit only slightly. This suggests the presence of slightly decreasing returns to scale. Cash flow variables have a positive and significant effect on investment (the long-term coefficient is about .489) which indicates the presence of liquidity constraints. Finally, the positive and significant coefficients associated with the changes in output suggest positive expectations of future profitability to the extent that these variables are a proxy of the investment opportunities of a firm.

In Table 6 we compare the presence and extent of R&D financing constraints of EU and US firms. Note that the different test statistics vindicate the use of the specification of column 3 for EU firms and column 4 for US firms. The coefficients associated with the cash flow variables are positive and significant for the EU while for the US no evidence of liquidity constraints is found. In particular, a one unit increase of the contemporaneous cash flow variable yields an increase of the EU accumulation rate of R&D that stands between 0.04 and 0.07 while US R&D is not significantly affected.

In order to assess to robustness of the US-EU comparison, alternative regression analyses were performed. The tables reporting the results discussed in this section are available in Cincera and Ravet (2010). When a fixed effects model (within transformation) is estimated, only EU firms are subject to liquidity constraints; as for the US ones, the coefficients associated with the cash flow variables are not significantly different from zero. The Hausman test is statistically significant at the 1 % level which rejects the null hypothesis of no correlation between the unobserved specific effects of the firms and the regressors, hence invalidating the random specification.

The results are obtained from two-step GMM estimators. One-step GMM estimators are calculated by weighting the moment conditions with an arbitrary chosen matrix which does not depend on estimated parameters while two-step estimators use a weight matrix based on the consistent one-step estimation. Arellano and Bond (1991, 1998), Windmeijer (2005) and Roodman (2006) have shown that the one-step GMM estimator may be more reliable than the two-step one for statistical inference as the latter provide downward biased asymptotic standard errors. However, Windmeijer (2005) developed a small-sample correction for the standard errors of two-step estimators that allows for more accurate inference. We used this correction for the reported two-step estimators. When a consistent one-step estimator is implemented for the EU sample, both the Sargan and Hansen tests reject the validity of the different sets of instruments used. Yet a positive coefficient is still observed for the EU cash flow variables. This is not the case for the US firms which once again do not appear to be financially constrained.

Table 6. System GMM two-step estimates - EU27 and US samples

	EU27			USA		
Instruments set	lag(2,.)	lag(3,.)	lag(4,.)	lag(2,.)	lag(3,.)	lag(4,.)
R_{t-1}/C_{t-2}	-0.145 (0.065)**	-0.074 (0.159)	-0.000 (0.142)	0.673 (0.055)***	0.691 (0.038)***	0.728 (0.039)***
Δy_t	-0.181 (0.133)	-0.077 (0.071)	0.02 (0.122)	0.129 (0.039)***	0.193 (0.05)***	0.111 (0.046)**
Δy_{t-1}	0.007 (0.052)	0.156 (0.071)**	0.096 (0.150)	0.029 (0.011)***	0.012 (0.025)	-0.005 (0.038)
$c_{t-2}-y_{t-2}$	-0.031 (0.044)	-0.083 (0.035)**	-0.050 (0.057)	-0.007 (0.009)	-0.014 (0.007)*	-0.006 (0.014)
CF_t/C_{t-1}	0.073 (0.019)***	0.042 (0.020)**	0.038 (0.023)*	-0.005 (0.008)	-0.000 (0.012)	0.000 (0.015)
CF_{t-1}/C_{t-2}	0.031 (0.01)***	0.018 (0.015)	0.010 (0.016)	0.002 (0.004)	-0.002 (0.003)	0.007 (0.018)
y_{t-2}	-0.094 (0.017)***	-0.082 (0.027)***	-0.084 (0.034)**	-0.006 (0.003)**	-0.004 (0.003)	-0.003 (0.005)
Obs	1 675			1 915		
N	421			467		
AR(1)	-0.94 [0.348]	-1.87 [0.061]	-1.15 [0.250]	-2.09 [0.037]	-2.24 [0.025]	-2.03 [0.042]
AR(2)	-1.32 [0.188]	-0.28 [0.783]	-1.27 [0.202]	-0.90 [0.366]	-0.79 [0.428]	-0.91 [0.361]
Sargan test	2304.69 [0.000]	971.10 [0.000]	287.71 [0.000]	494.51 [0.000]	215.47 [0.000]	84.33 [0.000]
Hansen test	103.52 [0.084]	62.24 [0.432]	20.18 [0.995]	99.50 [0.135]	74.72 [0.111]	52.44 [0.074]

Dependent variable: R_t/C_{t-1}. *** (respectively ** and *): statistically significant at the 1 % (respectively 5 % and 10 %) level. Estimation performed using xtabond2 (Roodman, 2006); all equations include time dummies; Windmeijer corrected standard errors in brackets; P-values in square brackets; AR(1) and AR(2): tests for first order and second order serial correlation in the first difference residuals; Two-step estimates; instruments used in column s (s=2,3,4): observations dated t-s or earlier for X_t (transformed equation) and t-s+1 for ΔX_t (equation in level).

Estimating a simpler accelerator R&D investment specification leads one to the conclusion that only EU firms are sensitive to cash flow variations. We considered alternative specifications where only the current value of the cash flow variable, the one-year lagged value or the current, one-year and two-year lagged values of this variable are considered altogether. These specifications allow one to control for the presence of multicollinearity which could alter the estimated coefficients of cash flow variables when different periods of this variable are introduced simultaneously in the specification. While the results as regards these specifications are not conclusive for the US sample, on the whole, the findings clearly indicate that financing constraints are present for EU R&D companies.

As an additional test, we investigated the role played by the size of the companies. Indeed, several studies have shown the central role played by the size of a firm in explaining the sensitivity of capital and R&D investment to cash flow variations[49]. Small firms are more dependent upon internal resources since the loan rates charged by commercial banks tend to be higher[50]. Conversely, larger firms can more easily finance capital expenditures from internal resources, issuance of equity or debt. In this study, we measure the size of a firm in two ways. First, a proxy for size is directly introduced in the specification, i.e. the number of employees at time t and at time t-1. Second, the regression is performed on a subset of the largest companies, i.e. the ones with more than 1000 employees. Note that this results in a cut of the sample by about one half. For the EU companies, the results appear to be in line with these theoretical predictions as the magnitude of the estimated coefficient associated with the cash flow variables are somewhat smaller as compared with the results when the full sample is considered. For the US firms, again, no effect of liquidity constraints is detected except to some extent for the specification based on the sub-sample with the largest companies. Yet, in this case, the estimated effects appear to be much smaller than the ones obtained for the EU subset.

As an alternative to the cash flow variable, the operating profit of the firm is also considered to proxy the internal available financial resources of a firm. This variable is defined as profit (or loss) before taxation, plus net interest cost (or minus interest cost) and government grants, less gains (or plus losses) arising from the sale/disposal of businesses or fixed assets. Here too the main conclusions are not altered when the operating profit is used as an alternative proxy for cash flow.

[49] See Schiantarelli (1996) for a survey of the empirical literature on this subject.
[50] See, for example, Stoll (1984) for the US credit market.

The last robustness check consists of estimating the R&D investment error correction model for the EU-27 sample but without the UK companies. The rationale for this test is that the UK financial system may be different than the European continental one and more similar to the US one. The results do not change our main conclusion: continental European R&D firms are more likely to be hit by financing constraints for their R&D investments than US ones. However, the cash flow coefficient is lower (0.02) when UK is removed from the sample, which indicates that UK firms contribute to raise the R&D-CF sensitivity of the EU sample.

2.5.2 Age and financing constraints

This section aims at providing a deeper analysis of the R&D to cash flow sensitivity by using a complementary approach (i.e. a nonparametric approach) to the previous results and by implementing an external variable related to the age of the companies. As mentioned in section 2.3, this information was collected by Cincera and Veugelers (2011). Table 7 provides estimates[51] of the R&D equation related to US and EU firms in the 2000's. The cash flow coefficients were estimated by splitting the EU and US samples with respect to the age of the companies and by estimating the error correction model with a System GMM method.

Table 7. Results of an error-correction type investment model (System GMM)

	EU-27		US	
	CF_t/C_{t-1}	CF_{t-1}/C_{t-2}	CF_t/C_{t-1}	CF_{t-1}/C_{t-2}
Age < 30	**(145 obs)**		**(613 obs)**	
lag(2,.)	0.005*	0.003	0.004	0.004***
lag(3,.)	-0.003	-0.001	0.005	0.044***
lag(4,.)	0.001	0.002	0.014	0.087***
Age > 30	**(1530 obs)**		**(1302 obs)**	
lag(2,.)	0.095***	0.026***	0.001	0.002***
lag(3,.)	0.042***	0.019***	0.007*	0.001
lag(4,.)	0.039***	0.032***	0.002	0.004
Age > 100	**(1178 obs)**		**(666 obs)**	
lag(2,.)	0.100***	0.028***	0.017***	-0.000
lag(3,.)	0.050***	0.032***	0.012***	-0.002**
lag(4,.)	0.041***	0.021**	0.028***	-0.002

Dependent variable: R_t/C_{t-1}. Estimations of equation 2.5. *** (respectively ** and *): statistically significant at the 1 % (respectively 5 % and 10 %) level. Estimation performed using xtabond2 (Roodman, 2006); all equations include time dummies; Windmeijer corrected standard errors in brackets; P-values in square brackets; Two-step estimates; instruments used in column s (s=2,3,4): observations dated t-s or earlier for X_t (transformed equation) and t-s+1 for ΔX_t (equation in level).

[51] Details of the regressions are presented in Appendix 2.

For both EU and US datasets, the oldest companies (i.e. older than 100 years old in this case) exhibit a large sensitivity of R&D to cash flow (but only to current cash flow in the US). The results suggest that EU firms between 30 and 100 years old rely on their cash flow to finance their R&D investments, while the sensitivity is lower for US companies and even non significant, except for the lagged cash flow with the lag(2,.) specification of the instruments and the current cash flow with the lag(3,.) specification. R&D amongst US firms younger than 30 years old seem to significantly rely on past cash flow but not current cash flow with a coefficient of the lagged cash flow significant for the three sets of instruments.

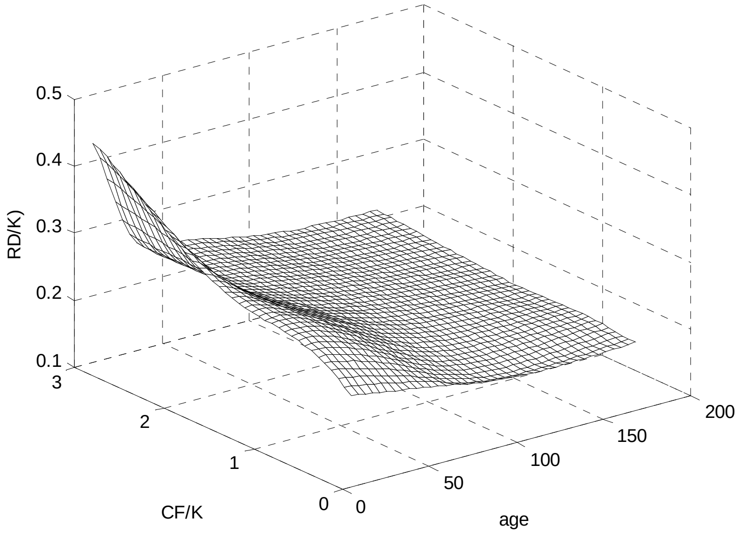
A non parametric estimation of the conditional mean of the accumulation rate of R&D was performed for the US and the EU datasets. The bandwithes for the cash flow and the age variables were computed using the standard rule of thumb $h = \hat{\sigma}(NT)^{-1/5}$. Other bandwithes were tested, resulting in a stronger (if h is larger) or weaker (if h is smaller) smoothing. For all estimations of the conditional mean, the range considered for the cash flow variable and the age variable is a range going from the the first to the last 2 percentiles of the observations. The investigated range of the age variable is the same for the US and EU datasets for the purpose of the comparison between both sets. A classical gaussian kernel is used for the cash flow variable while a gamma kernel is used for the age variable. Gamma and gaussian kernel were tested for both variables leading to similar results.

Three-dimensional representations of the estimations are illustrated in Figure 2. The estimations of the accumulation rates of R&D are represented on the vertical axis, given 1600 different combinations of ages and cash flow ratios. A direct interpretation of these shapes may be difficult, but the three-dimensional perspective allows one to visualize the smoothing that was performed on the data with bandwidthes h_1 and h_2 respectively for the cash flow and the age variables.

Figure 3 presents the relationship between the R&D and the cash flow variables for differents ages. For both US and EU firms, it appears that younger companies are characterized by a higher accumulation rate of R&D. As expected, the relationship between the R&D and the cash flow variables seems to be globally positive. The sensitivity of R&D to cash flow seems to be stronger for low levels of cash flow. The relationship between R&D and cash flow appears to be monotonic for all US companies. The EU shapes suggest a non monotonic relationship for younger European companies. However, the likelihood of a high cash flow ratio may be small for young European companies and further results will take into account this likelihood in the computation of the average derivatives.

Figure 2. Estimations of the R&D accumulation rate

US – h1 = 0.16, h2 = 10.59



EU – h1 = 0.42, h2 = 16.11

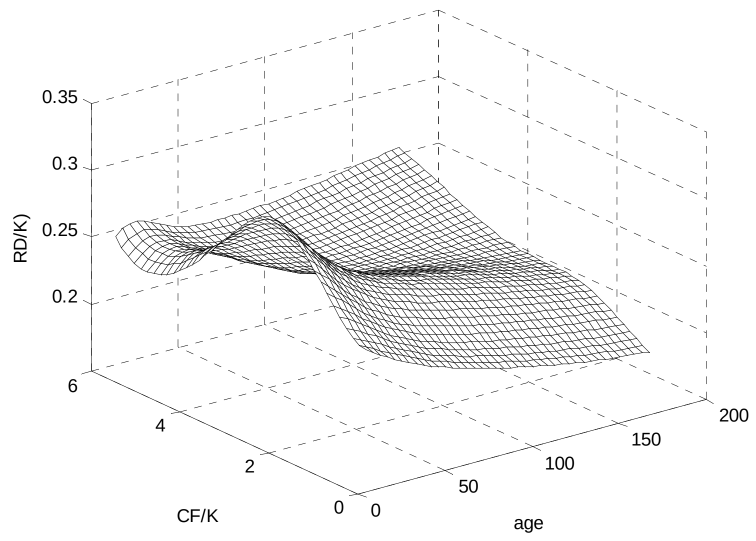
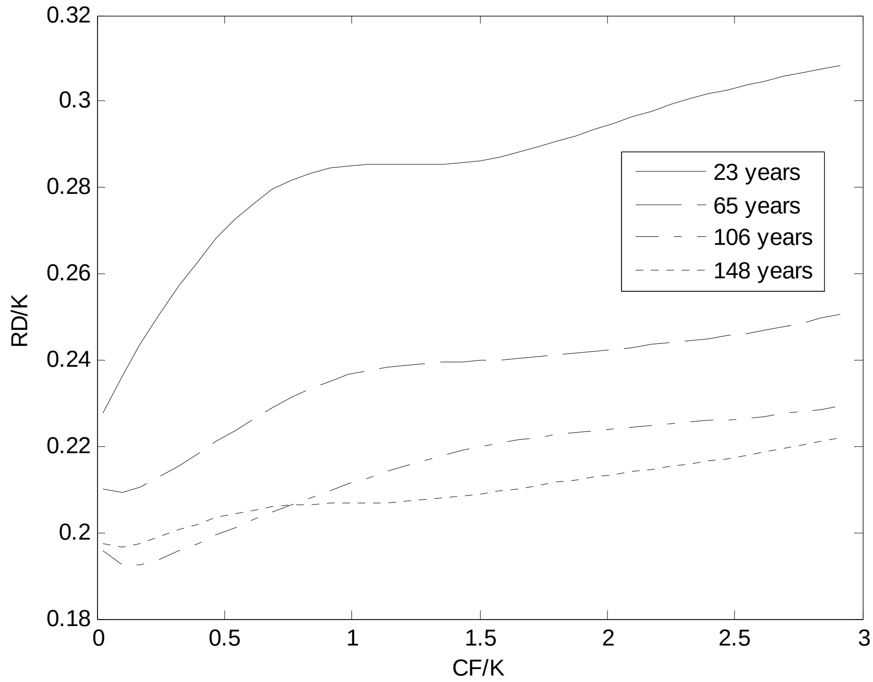
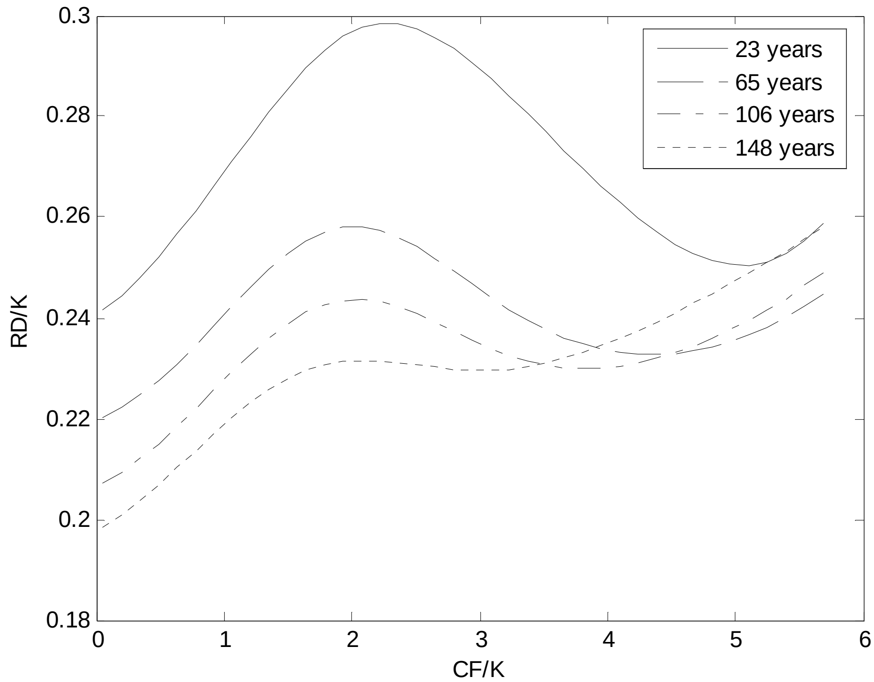


Figure 3. The relationship between R&D and CF

US

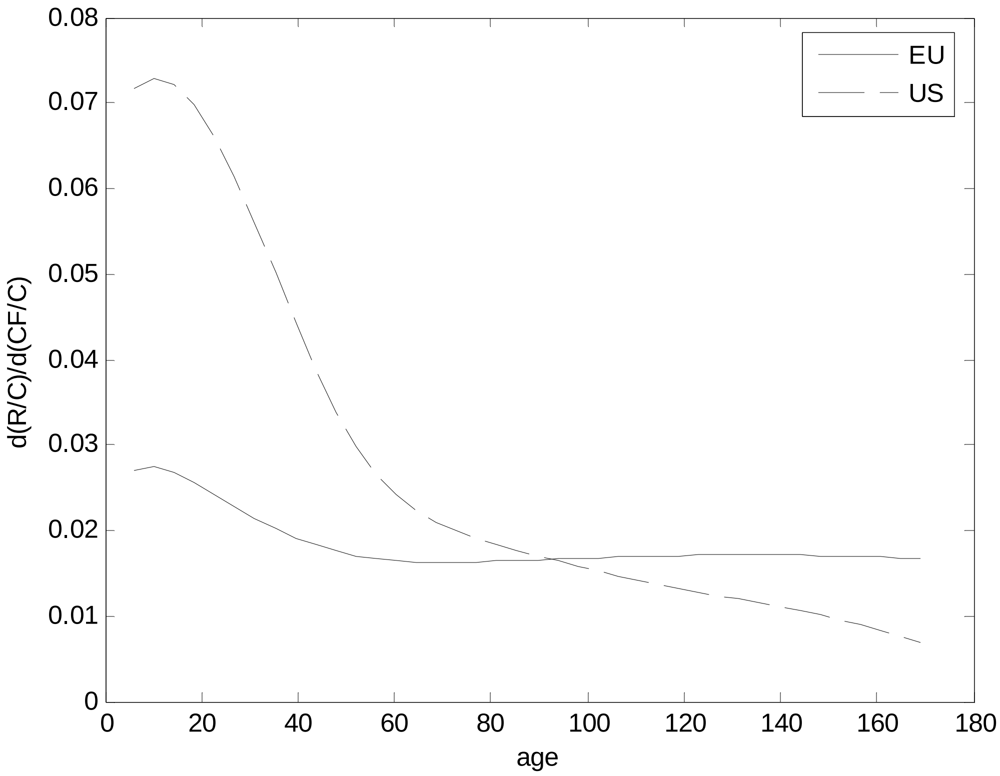


EU



The average derivatives reported in Figure 4 are the weighted averages of the derivatives of the estimated functions, with weights being the estimated densities. Figure 4 represents the relationship between the sensitivity of R&D to cash flow (i.e. the average derivatives of R&D with respect to cash flow) and the age of the companies. The sensitivity of R&D to cash flow of US companies is strongly decreasing with age, especially for firms younger than 60 years old. The sensitivity of European companies is also decreasing with age for younger firms, but it is slightly increasing for older firms. Interestingly, Figure 4 shows a sensitivity of R&D to cash flow that is higher for young US firms than young EU firms, while it is higher for old EU firms than old US firms.

Figure 4. Average sensitivity of R&D to CF



Confidence intervals were computed for each average derivative using bootstrapping methods[52]. Table 8 reports for selected ages the measures of the sensitivities along with their 95% confidence intervals. The sensitivity of young US firms is above 0.07 while it decreases to less than 0.007 when the firm is 169 years old. Young EU firms are also characterized by a

[52] The confidence intervals are based on 1000 bootstrapped samples with replacement of the derivatives (with the associated density).

decreasing sensitivity that goes from 0.03 to 0.017 and that even slightly increases after reaching 0.016. After 90 years old, the sensitivity of the EU firms becomes larger than the sensitivity of the US firms.

Table 8. US and EU sensitivity and confidence intervals.

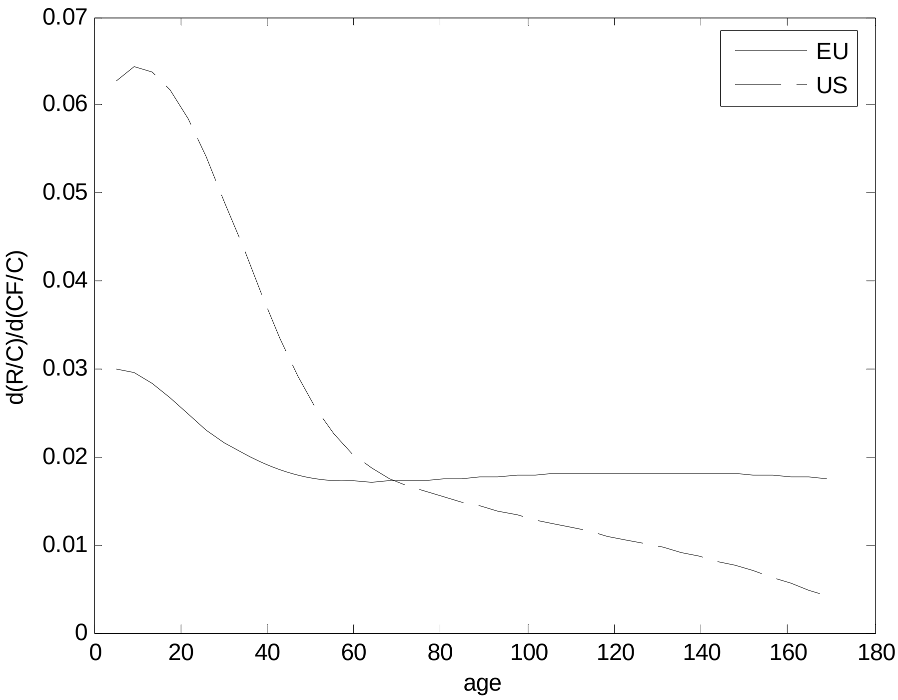
Age	US sensitivity	CI (95%)		EU sensitivity	CI (95%)	
6	0.0717	0.0512	0.0882	0.027	0.0172	0.0362
10	0.0729	0.0525	0.0887	0.0274	0.0199	0.0341
14	0.0722	0.0515	0.0878	0.0268	0.0208	0.0318
…						
52	0.0298	0.0217	0.0359	0.0171	0.0128	0.0198
56	0.0266	0.0195	0.032	0.0167	0.0124	0.0195
60	0.0241	0.0172	0.0293	0.0165	0.0121	0.0193
…						
85	0.0177	0.0082	0.0241	0.0165	0.0121	0.0194
90	**0.017**	**0.0075**	**0.0233**	**0.0166**	**0.0123**	**0.0194**
94	**0.0164**	**0.0069**	**0.0226**	**0.0167**	**0.0124**	**0.0195**
98	0.0158	0.0065	0.0218	0.0167	0.0126	0.0195
…						
161	0.0083	0.0048	0.0116	0.0168	0.0135	0.019
165	0.0076	0.0043	0.0108	0.0168	0.0135	0.0189
169	0.0068	0.0035	0.01	0.0167	0.0134	0.0187

Lower and upper bounds of the confidence intervals CI were bootstrapped based on 1000 resamplings with replacement.

As the sensitivity of R&D to cash flow may capture future demand growth, we may be interested in disentangling this effect from the financing constraints effect. This can be done, even not perfectly, by comparing firms with high and low growth anticipations. Assuming correct anticipations of future sales growth, $E_t[\Delta Y_{t+1}/Y_t] = \Delta Y_{t+1}/Y_t$, Figure 5 compares firms with positive and negative growth in t+1. It appears that the sensitivity is globally lower for firms with negative expected growth. The shape of the relationship between the sensitivity and the age remains the same for the young US firms but the negative relationship for older firms remains only when the growth expectation is positive. The relationship is still negative then slightly positive for EU companies with positive growth expectation. However, the impact of the age on the sensitivity seems to be positive for young EU firms with negative expectations. Young US companies are still characterized by a higher sensitivity while the inverse is not clearly true for older firms with negative growth expectations.

Figure 5. Positive and negative growth expectations

Positive growth expectation



Negative growth expectation

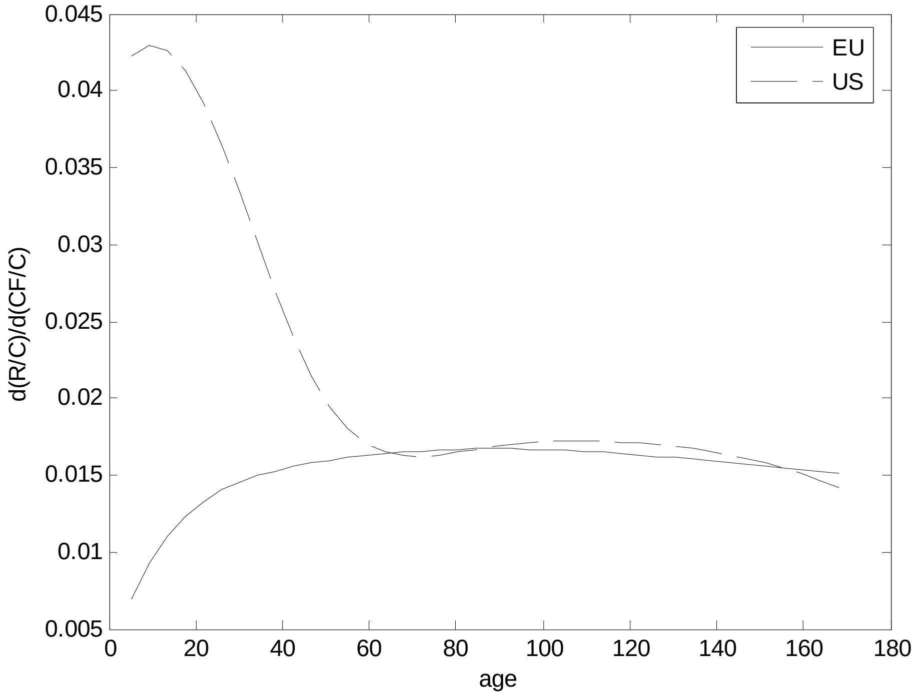


Figure 6 and Table 9 present the relationship between the sensitivity of R&D to cash flow and the age of the firms in the high-tech sectors. The sensitivity is higher for EU firms than US firms after 59 years old. The relationship is monotonically decreasing for the US dataset, while it is non monotonic for the EU companies. Again, the age appears to have a slightly positive impact on the EU sensitivity for high-tech firms older than 51 years old.

The sensitivity of medium and low-tech companies is presented in Figure 7 and Table 10. The EU sensitivity remains higher than the sensitivity of US firms for all ages. The curve of the US sensitivity differs from the previous figures as it is increasing for middle aged companies between 27 and 93 years old.

Figure 6. High-tech firms

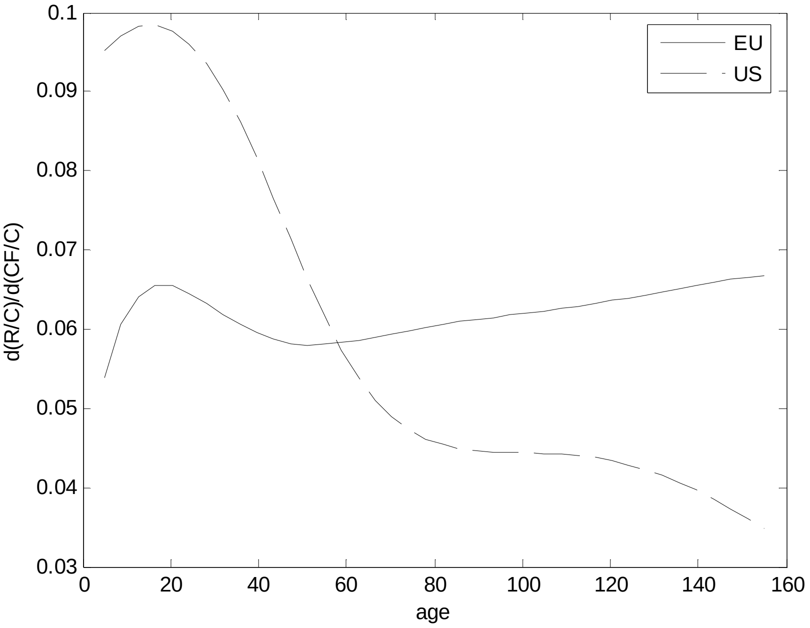


Table 9. R&D sensitivity – High-tech firms

Age	US high-tech sensitivity	CI (95%)		EU high-tech sensitivity	CI (95%)	
5	0.0952	0.0688	0.1136	0.0538	0.0128	0.0909
…						
20	0.0977	0.0803	0.1094	0.0654	0.0487	0.0822
….						
55	**0.0616**	**0.0491**	**0.0728**	**0.0581**	**0.0479**	**0.0728**
59	**0.0574**	**0.0425**	**0.0702**	**0.0583**	**0.0477**	**0.0735**
…						
101	0.0444	0.0369	0.0507	0.062	0.0516	0.0767
105	0.0443	0.0384	0.0496	0.0623	0.0521	0.0768
…						
128	0.0422	0.0407	0.0438	0.0643	0.0548	0.0774
132	0.0415	0.0397	0.0435	0.0647	0.0553	0.0777
…						
151	0.0361	0.0319	0.0407	0.0666	0.0574	0.0786
155	0.0347	0.0301	0.0399	0.0668	0.0578	0.0786

Lower and upper bounds of the confidence intervals CI were bootstrapped based on 1000 resamplings with replacement.

Figure 7. Medium/low-tech

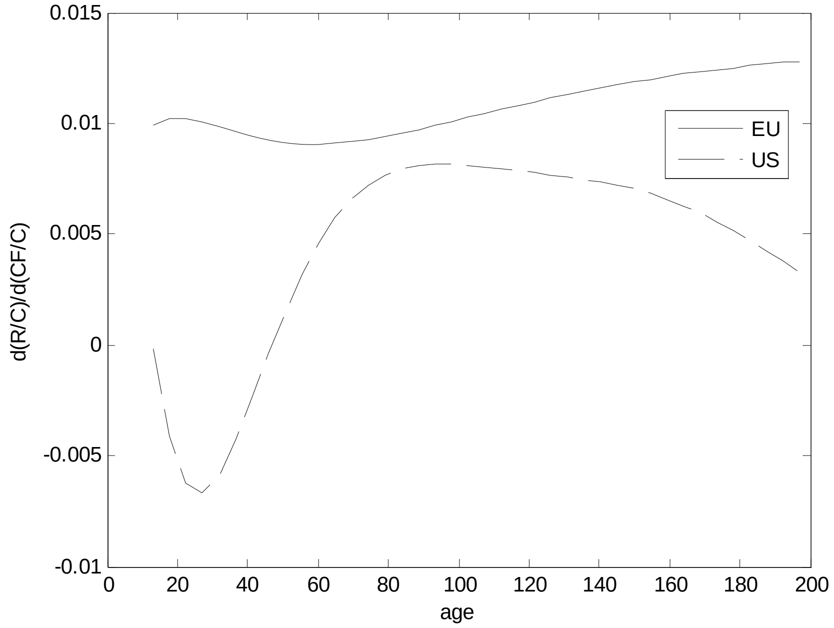


Table 10. R&D sensitivity – Medium/low-tech firms

Age	US med-low T	CI (95%)		EU med-low T	CI (95%)	
13	-0.0002	-0.0024	0.0022	0.0099	0.004	0.0136
…						
37	-0.0043	-0.0058	-0.0019	0.0096	0.0061	0.0117
41	-0.0024	-0.0039	0	0.0094	0.0063	0.0114
46	-0.0004	-0.0019	0.0018	0.0092	0.0063	0.0112
51	0.0015	0	0.0035	0.0091	0.0064	0.011
…						
70	0.0066	0.0035	0.0092	0.0092	0.0067	0.0109
74	0.0072	0.0035	0.0103	0.0093	0.0069	0.011
…						
103	0.0081	0.0007	0.013	0.0103	0.0082	0.0119
107	0.008	0.0004	0.013	0.0104	0.0084	0.012
…						
150	0.007	0.0018	0.011	0.0119	0.0103	0.0134
155	0.0068	0.002	0.0107	0.012	0.0105	0.0135
…						
192	0.0038	0.001	0.0072	0.0127	0.0116	0.0144
197	0.0033	0.0006	0.0067	0.0128	0.0117	0.0145

Lower and upper bounds of the confidence intervals CI were bootstrapped based on 1000 resamplings with replacement.

2.5.3 Discussion

The main finding related to the US-EU comparison in the 2000's is that large European firms are subject to liquidity constraints in the financing of their R&D investments, whereas US ones do not appear to be financially constrained. This result is robust to different specifications of the R&D investment model, sub-samples of data, outliers, and econometric methods that address the heterogeneity and possible endogeneity of the variables of interest of the firms, i.e. cash flow and R&D. These different robustness checks are presented and discussed in Cincera and Ravet (2010).

The results concerning the age of the companies give another perspective to the US-EU comparison. The shape of the relationship between the R&D sensitivity and the age of the US companies is clearly decreasing, which implies that older US companies rely less on their internal finance for their R&D investments. This may illustrate the fact that older US companies do have an easier access to external financing for their R&D investments. The decrease in the R&D sensitivity is the strongest for firms under 60 years old. The R&D sensitivity of EU companies is also negatively correlated with ages under 55 years old and it remains stable or slightly increasing for older companies. The R&D sensitivity to cash flow appears to be higher for early aged US firms while the old EU companies rely more on their cash flow in order to finance their R&D investments. The pattern remains similar for the high-tech companies. Concerning the medium- and low-tech firms, the sensitivity is higher in the EU dataset for all ages. Hence, the yollies (young leading innovators) of Cincera and Veugelers (2011) seem to face financing constraints, but the R&D sensitivity is higher in the US than in Europe. The global higher sensitivity of R&D in Europe in the 2000's seems to be primarily attributed to the larger presence of ollies (old leading innovators) in EU as these firms appear to rely more on their cash flow than the US ollies to finance their R&D. According to Cincera and Veugelers (2011), the few yollies in Europe are less R&D intensive than their US counterparts. Hence our results may illustrate the fact that EU yollies do less R&D and are conducting less risky activities, which would explain why they are likely to face less severe financing constraints. A way to control for this risk would be to compare firms with similar R&D intensities. This can be done in our analysis at the sectoral level: when comparing US and EU lower-tech sectors (i.e. sectors with medium or low R&D intensities), the financing constraints are indeed more severe amongst EU firms. Furthermore, it is not clear whether the low representation of young firms within the European innovation leaders (i.e. the top R&D spenders) is due to a low access to external financial resources. We could also consider that, given the low representation of young firms within the EU R&D leaders, the few EU young firms that are reported in the Scoreboard are the best young innovative firms in Europe, hence these yollies are less likely to be constrained than other EU young firms which are not included in the scoreboards.

Different factors may explain the difference between our findings for the 2000's period and the ones in the literature. We briefly discuss them here. In sum, in our view, the main explanation for the divergence between these results and previous studies is the period and dataset investigated. Our study is actually the only one which uses data after 2000, a period during which the world's financial systems have undergone fundamental changes that may have affected the EU and the US differently.

Since the beginning of this decade, within the framework of the Lisbon process of transforming the EU into a knowledge-based and more dynamic and competitive economy, several product market reforms have been put in place in the EU to catch up with the US, especially in the capital market (Cincera and Galgau, 2005). As a result, financial institutions face stronger competition and the conditions for borrowing money for investments, in particular for intangibles such as R&D, are more difficult.

The firms in our dataset are mainly large firms with access to equity market. Brown and Petersen (2009) use comparable Compustat data to analyze the sensitivity of investment (physical and R&D) to cash flow within US firms and observe that the firms in their sample mainly rely on equity issues rather than debt as external sources of finance. They argue that R&D-intensive companies are known to make little use of debt and are highly dependent on the availability of public equity finance. They also stress how the improvement of the US equity markets over the last decades tends to decrease the sensitivity of investment to cash flow. In our view, this sheds a light on the interpretation of our results which are to be related to structural differences in the US and EU equity markets, the latter being highly fragmented.

Furthermore, the first decade of the 21st century has been a period with a lack of regulation in lending, one of the fundamental causes of the recent burst of the financial bubble in the US and the ensuing financial and economic turmoil in the world. This lack of regulation and the risks taken by banks may have alleviated the constraints to get loans for investment projects and therefore firms investing in R&D may well have been less concerned by financing constraints to fund their R&D investments, especially in the US.

R&D activities are riskier by nature and generally provide less collateral to lenders as compared to investments in capital goods. As a result, financing constraints may be even more pronounced in the case of such intangible investments. However, given the existence of high adjustment and sunk costs associated with this kind of investment, firms will engage in R&D activities if they do not expect to be seriously affected by financial constraints. As such, cash flow effects tend to matter less for large investors than for smaller companies. Moreover, the provision of public support to R&D may interfere with the investment decision of a firm by alleviating liquidity constraints problems, if present at all.

The outcome has been factors hampering R&D and innovation activities, exemplified by a scarcity of venture capital. And there are indications, corroborated by the empirical findings of our study that one of these factors - the difficulty to get access to external sources of financing - has affected the EU more than the US in the 2000s.

2.6 Conclusion and implications

Based on a sample of private companies, this chapter investigates the impact of financing constraints on R&D investments in the 2000s. The results, based on an error correction equation, have been obtained by using a system GMM estimator, which compared to the usual first difference GMM estimator produces in general more precise estimates and reduces the possible bias arising from the weak explanatory power of the instruments and high values of the autoregressive parameter. A non parametric approach was used to investigate the relationship between the accumulation rate of R&D, the cash flow and the age of the companies.

The main question in this chapter was whether financing constraints explain a part of the acknowledged R&D gap between Europe and the US. In our view, the answer is yes, though it is difficult to extrapolate at a macroeconomic level the extent to which financing frictions widen this gap. Our results suggest that only EU R&D companies are facing liquidity constraints, not their large US R&D competitors. This finding is robust to alternative modeling strategies, econometric methods implemented and data sub-samples. A second question was whether older firms actually face less severe or no financing constraints, as opposed to younger firms. We provide evidence that confirm that the R&D sensitivity decreases with age, especially for young US firms. However, old EU companies seem to rely more on their cash flow to finance their R&D investments than old US firms.

From a European perspective in terms of policy implications, our results suggest improving conditions in the EU for access to external capital, i.e. debt and equity. Policy makers would do well providing direct R&D support for EU firms, i.e. tax incentives and R&D subsidies and further develop the availability of risk capital. Tax policies that affect the after-tax cash flow of the firms are likely to affect the R&D activities of EU companies as they seem to rely on the availability of internal finance. The low representation of young companies within the top innovation leaders in Europe suggests a need of measures to stimulate R&D activities amongst young firms, especially in innovative sectors. On the other hand, well established companies (ollies) seem to benefit from more efficient external capital markets in the US than in Europe. Indirectly, clearer framework conditions in the EU, in particular for private equity should be achieved. Our findings support the view that Europe needs a functioning internal market[53], which is currently hampered by the fragmentation of EU financial markets. However, in terms of direct support, it is not clear whether policy makers should primarily allocate public resources to support large firms which are top R&D investors and fewer to smaller companies as the former may be less concerned with financing constraints of funding their R&D investments than the latter. In order to further investigate this question, it would be useful to consider a larger sample which would include, besides large R&D corporations, small and medium R&D investors.

[53] Anvret, Granieri, Renda (2010).

Chapter 3 - The Productivity of R&D Components

SUMMARY

This chapter is dedicated to the measuring of the knowledge production of R&D expenditures when they are disaggregated into the following components: intramural versus extramural expenditures, research versus development expenditures, product-oriented versus process-oriented, human capital versus investments. The sources of funding and the types of subcontractors are also considered. The main question of this chapter is whether the heterogeneity of R&D affects the technology performance of the companies, as measured by patent applications. A cross-sectional Belgian R&D survey conducted over 2004-2005 is used for the purpose of the analysis. Given the high dependency of the Belgian innovation system towards the foreign MNEs, a matching process was performed between Belgian R&D and patents related to Belgian inventors in order to capture the patents filed outside Belgium but related to inventions created by firms located in Belgium (i.e. subsidiaries of foreign groups). Estimates of the elasticity of the quantity of patents with respect to the components of R&D are provided.

3.1 Introduction[54]

This chapter proposes an empirical study of the relationship between R&D activities and patent applications when R&D is disaggregated into several components. This relationship is estimated by means of an extended knowledge production function (Griliches, 1979) using a representative sample of Belgian manufacturing firms active in R&D in 2004-2005. Traditional studies model R&D as a single variable in the knowledge production function and ignore its underlying heterogeneity. The main question of this chapter is whether R&D heterogeneity affects the technology performance of the companies. The objective is to test hypotheses on the role of several R&D components in the process that yields knowledge outcomes, which are measured by the patenting activities of the firms. Hence, one novelty of this research is to consider different types of R&D activities and sources of financing of these intangible investments rather than total R&D expenditures as in previous studies examining the R&D-patent relationship[55]. For instance because of their more fundamental nature, the impact of basic and applied research may be different than the effect of development activities on the output of the innovative process as measured by patent counts. Another interesting question is to look at the sources for the financing of research activities. Public funds for R&D may also have a different impact on patenting as compared to the firm's own funds. To our knowledge, this is the first study that gives a comprehensive set of results that covers together these dimensions in a R&D-patent relationship. Hence, the integrated framework in which the analysis is conducted is a key feature of this chapter. Our findings have important implications in terms of innovation policy as the heterogeneity of R&D may advocate differenciated public support.

The Belgian R&D survey that covers years 2004 and 2005 is used in order to conduct our analysis. The Belgian innovation system is highly dependent on foreign multinational enterprises (MNEs), which could be an important reason for its lower propensity to patent. On the one hand, foreign subsidiaries can be specialized in the adaptation to the local market of products and processes developed in the first place in the headquarters of MNEs. On the other

[54] This chapter presents the results from a research conducted on Belgian R&D and knowledge outcomes. This work was realized at the Belspo (Belgian Federal Science Policy) and presented to the Belspo Committee in charge of the R&D analyses. The patent information related to the 2005 R&D survey was extracted from PATSTAT by Gaétan de Rassenfosse, to which I am grateful for his comments during the research and help in the matching procedure.

[55] See for instance Hausman, Hall and Griliches (1984), Crépon and Duguet (1997a, 1997b), Cincera (1997) or Guo and Trivedi (2002).

hand, head offices could hoard a significant part of the R&D output of their subsidiaries, these firms taking advantage of the local availability of a highly qualified workforce and knowledge base. As a result, R&D conducted in Belgium could lead to inventions patented by foreign firms within the same MNE. This issue is addressed in this chapter by trying to relate Belgian R&D to patents that report at least one Belgian inventor even when they are not filed by a firm located in Belgium.

On the whole the results indicate that R&D activities exhibit slightly decreasing returns to scale with respect to patenting and significant differences are observed in the estimated impacts of these activities according to their type and source of financing.

The plan of the chapter is as follows. Section 3.2 discusses the main determinants of firms' patenting activities and presents the Belgian technology base. Section 3.3 presents the dataset and the extended knowledge production function. Section 3.4 develops the econometric framework that is used to estimate the knowledge production functions. The main empirical findings are reported in section 3.5. The main conclusions and implications are drawn in section 3.6.

3.2 Patents, R&D and MNEs R&D activities in Belgium

3.2.1 Determinants of patenting activities and S&T activities

The purpose of our analysis is to provide an overview of the contribution of the components of R&D activities to the outcome of the knowledge process as measured by the patent applications of the companies. We assume that companies intentionally allocate their R&D efforts according to several dimensions. By analyzing the role of these dimensions in the framework of a R&D-patents relationship, we aim at validating hypotheses on the faces of R&D that yield patenting activities. Belgian data from the Belgian R&D survey are used for the purpose of validating or rejecting these hypotheses. To our knowledge, this is the first study that provides a comprehensive and simultaneous review of these dimensions in an integrated framework.

The imperfect appropriability of the outcomes of innovative activities has been acknowledged since a long time. This appropriability problem arises from the non-rival and partially excludable property of the knowledge good. Non rivalry means that the use of an innovation by an economic agent does not preclude others from using it, while partial excludability implies that the owner of an innovation can not impede others to benefit from it free of charge. This public characteristic of the knowledge good is a source of market failure to the extent that firms will invest less in R&D than the socially optimal level[56]. The literature on public R&D discusses several ways to compensate for the imperfect functioning of such markets[57]. Public technology procurement, R&D subsidies or tax breaks for instance increase the expected returns by lowering the costs of these activities while R&D collaborations facilitate the exploitation of scale economies in R&D and the internalization of the externalities generated by these activities. More directly, the intellectual property right system with patents, trademarks or copyrights restricts to competitors the exploitation that can be made from the knowledge created. Patents for instance are granted as a temporary monopoly right for the innovator while at the same time disclosing technical information in the public domain. These appropriability and patenting strategies affect the firm's performance[58]. However, despite several measures taken to strengthen the enforcement of patent rights or to reduce the costs of filing a patent, their effectiveness varies considerably across industry sectors[59]. Patenting behaviours are not only linked to the costs of patenting but also to the appropriability conditions of the R&D output as well as the nature of these activities, in particular the type of research, for example whether it is basic or more applied, tacit or codified, product or process oriented. These characteristics will affect the speed of technological diffusion or the ability of rivals to invent around a patented invention. The sources of financing of these activities, the size, the market share, the technological diversification, the degree of internationalization of firms or the importance of entry barriers for potential competitors are other determinants that influence the costs of patenting. For instance large companies that benefit from public R&D support may be less financially constrained while worldwide firms may have to register their patents in several patent offices thus increasing the costs of these activities. Firms more exposed to potential competition may also have to apply for more patents.

The R&D efforts can be categorized into in-house or intramural R&D and subcontracted or extramural R&D. Veugelers and Cassiman (1999a) investigate the determinants of the decision for a firm to produce technology itself (make) or to source it externally (buy). They

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[56] Indivisibilities and uncertainties (or high risks) associated with R&D activities are two other sources (Arrow, 1962).

[57] See Geroski (1995) for a discussion.

[58] According to Ceccagnoli (2009), "*Stronger appropriability at the firm level, achieved through patent protection or the ownership of specialized complementary assets, leads to superior economic performance, as measured by the stock market valuation of a firm's R&D assets*".

[59] See Levin et al. (1987) for a study of differences in appropriability conditions across industries.

find that companies that consider internal information as an important source of information tend to combine internal and external technology sources (make and buy) rather than sourcing exclusively. According to the authors, "*strong appropriation, legally or through complexity, secrecy or lead-time on competitors, leads the firms to reduce the probability of an exclusive external knowledge sourcing strategy*". Furthermore, extramural R&D is characterized by major transaction costs and external research facilities tend to provide inputs with a low level of specialization into the R&D projects that a firm subcontracts (Geroski, 1995). This subcontracted R&D is less likely to lead to successful inventions and patent applications. Hence we aim at validating the following hypothesis:

> *H1: The main drivers of the patenting activities of a company lie inside its intramural R&D activities.*

Concerning the research versus development dichotomy, recent work by Czarnitzki, Kraft and Thorwarth (2009) has emphasized the premium of research over development activities in the propensity to patent inventions using a sample of Belgian firms. This result stresses the importance of research as a driver of innovation. Seminal results by Griliches (1986) also indicate a significant impact of research on productivity growth in the US. Frascati manual[60] distinguishes basic research from applied research. The results of basic research are not expected to be sold as this type of research is conducted without any application in view. However, applied research, i.e. research conducted with a specific objective, is often patented according to Frascati manual. On the other hand, patenting activities may also arise from development oriented activities as they are "*directed to producing new materials, products and devices; to installing new processes, systems and services; or to improving substantially those already produced or installed*". The manual illustrates the difference between basic research, applied research and expreminental development with examples among which this one about antibodies: "*the determination of the amino acid sequence of an antibody molecule is basic research. Investigations undertaken in an effort to distinguish between antibodies for various diseases is applied research. Experimental development then consists of devising a method for synthesising the antibody for a particular disease on the basis of knowledge of its structure and clinically testing the effectiveness of the synthesised antibody on patients who have agreed to accept experimental advanced treatment*". Given the literature, research activities as well as experminental development activities are likely to lead to patent

[60] OECD (2002).

applications. However, the degree of novelty related to successful research activities is higher and may be illustrated by more patented inventions. Thus our analysis aims at validating the following hypothesis:

> *H2: Research activities and development activities both contribute to the patenting activities, with a premium for research activities.*

R&D activities oriented towards new products aim at giving the firm a clear advantage on the product market to face its competitors. This type of R&D should lead to higher patenting propensities when firms consider patenting as an effective method to protect their new products. On the other hand, process-oriented R&D activities are conducted in order to improve the production process and decrease the costs of the firm. Firms may be reluctant to protect the outcomes of this type of activities as patenting new processes would disclose information that would benefit to the production processes of their competitors[61]. Arundel and Kabla (1998) investigate the role of secrecy in the propensity to patent product versus process innovations. Their findings confirm that the importance of secrecy to prevent copying negatively affects the propensity to patent product innovations, while they suggest that secrecy and patenting strategies are complementary for process innovations, depending on their quality. Cohen, Nelson and Walsh (2000) stress the role of secrecy in most manufacturing US industries. They find that firms heavily emphasize secrecy as a strategy to protect the profits due to invention while patenting activities are less emphasized in the majority of industries. Thus, R&D activities oriented toward process innovations are expected to yield fewer patents than product-oriented R&D activities as firms may be reluctant to disclose information that could benefit to the production processes of their competitors. If secrecy is preferred for such activities, we can expect the following hypothesis to be validated.

> *H3: The role of process-oriented R&D activities is not a significant determinant of patent applications.*

Tacit and experiential skills are embodied in human capital (Penrose, 1959) and R&D workers generally benefit from firm sponsored training that raises their productivity, in addition to impacting their wages and careers. However, modern and ICT equipment are expected to raise the capabilities of R&D. New equipment increase the performance of R&D as it allows producing knowledge earlier and faster (Rosenberg, 1974; Nightingale, 2000;

[61] See Cohen (1995) for a discussion.

Becker et al., 2005). Though, labor-capital substitution can occur when R&D workers are replaced by new equipment and a more specific use of the skills of the workers (Baba and Nobeoka, 1998; Nightingale, 2000). Thus, we expect both the human capital and equipment dimensions of R&D to contribute significantly to the knowledge production process. However, because new ideas in a company are expected to arise from the pool of its high skilled labor, the role of human capital is expected to be crucial in the knowledge process, while the role of investments should be secondary, yet complementary.

H4: R&D workers and R&D equipment both contribute to the knowledge production process, with a premium for R&D workers.

Concerning the sources of R&D funding, it is expected that external private funds finance the intramural R&D projects that are likely to be effective and yield economic returns. Furthermore, given the high degree of internationalization of the Belgian technology landscape (see section 3.2.2), the external private funding of Belgian R&D should substantially reflect the financial support by foreign groups to their Belgian R&D subsidiaries. Large foreign companies can be motivated to locate their R&D centers in another country for different motives (Belderbos, 2001). From the view point of these MNEs, a first motive, which consists in the exploitation of the firm's technology abroad, means that companies adapt their products and processes to suit local markets and manufacturing processes and to fulfil local standards or manufacturing conditions. A second motive is the sourcing of foreign technology, which explains the founding of basic R&D for world market. In this case, firms access distinctive expertise in the local science base and hire skilled foreign engineers and researchers[62]. New established subsidiaries generally focus on the design and the development of products to local markets on the basis of the mother company's existing technologies, while R&D activities of acquired subsidiaries are more concerned with applied research and scanning of local technologies. Public aids also aim at encouraging efficient R&D projects, but government administrations may not always subsidize the most effective R&D projects with the highest economic returns given the existence of asymmetric information and moral hazard issues[63]. Moreover, public aids are intended to support long-term fundamental research and as such it may take some time for the benefits to show up in

[62] The notions of Home Base Augmenting (HBA) and Home Base Exploiting (HBE) are often used to characterize these motives. For Kuemmerle (1999), HBA sites are more likely to be located near universities or public research and technology organizations. HBA units have increasingly been used as part of the MNE's strategy to build up and exploit S&T know-how located beyond the boundaries of the group while the activities of HBE sites are more aimed at transferring the knowledge developed within the group.

[63] See Hall (2002) for a survey and a discussion of these questions.

the output of R&D activities. Hence the role of public funding in the R&D-patent relationship is not clear. Though, we consider here that an efficient public aid policy should be a determinant of the knowledge outcome of the firms and aim at validating the following hypothesis:

H5: Private and public funds both finance R&D activities with significant returns.

Table 11 presents the structure that encompasses the hypotheses that will be tested in this chapter.

Table 11. Hypotheses

Research and Development	
H1: **Intramural**	H1: **Extramural**
Nature H2: Research / Development	**Subcontractors**
Orientation H3: Product/Process	
Costs H4: Human capital / Investments	
H5: **Financing**	

3.2.2 The Belgian technological base

MNEs largely dominate the Belgian innovation system. The share of subsidiaries of large foreign firms in national innovative activities of 54% is by far the largest among the industrialized countries (Patel and Pavitt, 1991). In the 1980s, this share was about 40% and this suggests that there have been since a long time strong linkages between MNEs and the national science and technology base in Belgium. Thus, because of its relative size and the ensuing need for a high degree of specialization, the internationalization of the Belgian technology base is indisputable. As stressed by Veugelers and Cassiman (1999b) among others, external knowledge is an important determinant for the innovation process of firms. Increasingly, this knowledge is likely to originate from outside of their national borders, especially in a small size economy characterized by a high openness of its S&T system. Several studies have quantified the magnitude and direction of technology diffusion through different channels across industry sectors and nations and its impact on innovation and economic performance[64]. In a survey, Blomström and Kokko (1998) examine the effects of knowledge spillovers generated by MNEs. These effects influence domestic firms in the MNE's own industry as well as firms in other sectors. The authors conclude to a positive impact of these effects, which vary systematically between countries and industries and increase with the local capability and the level of competition[65]. On the other hand, the effects on the home country of MNEs are more difficult to identify. There have been only a few studies examining the impact of international spillovers in the Belgian economy. Veugelers and Vanden Houte (1990), in an analysis of Belgian data on domestic R&D, find that the higher the presence of multinationals in an industry, the weaker will be the innovative efforts of domestic firms in that same industry. The study of Fecher (1990) reports a positive impact of domestic R&D spillovers on Belgian firms' productivity performance while no effect of international spillovers is found. Veugelers and Cassiman (1999b), find that MNEs are more likely to transfer technology to the Belgian economy. However the main conclusion of the study is that it is not so much the international dimension of the firms, but rather their access to the international technology market that is important for generating external knowledge transfers to the local economy.

Another feature of the Belgian technological landscape is the high concentration of innovation activities among a few large firms. Cincera (2005) sheds some light on the patenting activities of the top 50 Belgian firms over the 1980-2000 decades and observes that this activity is quite concentrated. Indeed, in terms of European patents, the two firms with the highest number of patent applications hold 15.6% and 6.4% respectively of the total number of patents applied for by Belgian applicants between 1980 and 2000. In terms of US patents, these shares are even higher (24.4% and 10.3% respectively). The cumulated share of US patents of the top 50 Belgian firms is about 78% against 61% for European patents suggesting that patents outside the European market are mainly attributed to the largest firms.

Another specificity of Belgian patenting activities is that a significant number of these companies are subsidiaries of foreign MNEs. The high dependency of the Belgian innovation system towards foreign MNEs could be an important reason for its lower propensity to

[64] See for instance the surveys of Cincera and van Pottelsberghe (2001) and Mohnen (1996) on international R&D spillovers.
[65] In Jaffe's opinion (1986: p.984), "*from a purely technological point of view, R&D spillovers constitute an unambiguous positive externality. Unfortunately, we can only observe various economic manifestations of the firm's R&D success. For this reason, the positive technologically externality is potentially confounded with a negative effect of other's research due to competition*".

patent[66]. Subsidiaries can be specialized in the adaptation to the Belgian market of products and services developed and patented in the first place in the research labs of the multinational. These subsidiaries could also be involved in home based augmenting research activities, the local availability of a highly qualified workforce and knowledge base being the main reasons for their presence in the foreign country. In the first case, one can expect a lower propensity to patent for a given amount of R&D since the original invention is already protected. Then, in both cases the output of the R&D performed by the subsidiary can be directly patented by the multinational in its home country and not in Belgium. Finally, the geographic distance between the MNE's home base and the domestic country can be another reason explaining a lower patenting propensity[67]. These points deserve further attention. In particular, the high concentration of technological activities among a few large companies and the presence of foreign firms that could bring back to their home country an important part of their research output ask for a closer examination of the outcomes of R&D as measured by patenting activities as well as the main determinants influencing these activities.

As regards the degree of internationalization of R&D, technology production has usually been centralized in the host country of MNEs. The reduction of the costs of communications and control, economies of scale in R&D and a better coordination between central and peripheral research labs are often mentioned in the literature to explain this situation (Terpstra, 1985)[68]. However, during the past decades, the involvement of MNEs in overseas R&D has increased significantly. Companies all over the world are investing more and more in overseas R&D as a tool to increase their competitive advantages and to exploit their resources in order to create higher quality products[69]. MNEs have accelerated the pace of their direct investments in overseas R&D, and have established or acquired multiple R&D laboratories abroad and are increasingly integrating these laboratories into global R&D networks[70]. According to Granstrand et al. (1992), the reasons for this growing decentralization and internationalization

[66] As shown in Capron and Cincera (2000), the R&D productivity index as measured by the ratio of patents on R&D expenditures was 95 for Belgium in 1995 against 100 for the EU average.

[67] Maskus (1998), for instance, finds that the number of patents filed by US subsidiaries in host countries depends positively from the strength of intellectual property protection in these countries as well as from the distance to the USA.

[68] As pointed out by Cantwell and Santangelo (1999), non-codified technological activities that necessitate highly tacit capabilities require a higher proximity.

[69] Angel and Savage (1996) and Belderbos (2001) among others, analyze the determinants of the localization of Japanese R&D labs abroad; Cantwell and Harding (1998) measure the R&D internationalization of German firms; Dunning and Narula (1995) and Florida (1997) examine the R&D activities of foreign firms in the USA and Pearce and Papanastasiou (1999) in the UK.

[70] Research joint ventures, firm's acquisitions and the establishment of greenfield units are the three main ways to access a foreign market.

of R&D activities can be classified into three main groups of factors: demand-side, supply-side and environmental factors. The demand-side factors include a greater adaptation of products and technologies to local markets, a higher proximity to customers, an increase of competitiveness through the transfer of technology and the pressures of subsidiaries to enhance their status within a corporation. Among the main supply-side factors, the monitoring of the development of technology abroad and the hiring of a foreign and barely mobile highly skilled labor can be mentioned. Finally, the environmental factors concern the legislation on intellectual property, the provision of R&D incentives by the domestic government, e.g. tax advantages and subsidies for R&D, as well as governmental pressures to improve the subsidiary's capabilities beyond the simple assembly of proven products to innovative activities.

Given the high dependency of the Belgian innovation system towards foreign MNEs and the related high degree of internationalization of Belgian R&D, it is expected that the share of R&D that is financed by foreign funds significantly affects the knowledge production of the firms that belong to the Belgian technology base (i.e. firms located in Belgium), given that the outcome of Belgian R&D that flows outside Belgium is taken into account. Hence, in order to capture the information about inventions produced in Belgium but patented outside Belgium, the analysis will rely on patent counts based on inventors located in Belgium (see section 3.3.2).

> *H6: Foreign funds play a significant role in the knowledge production of the Belgian technology landscape.*

3.3 Data

3.3.1 The Belgian R&D survey

The data have been collected as part of the Belgian National R&D biannual survey organized jointly by the Belgian Federal Science Policy Office and the Regional authorities in charge of S&T statistics. The questionnaire that was used for this study covers the 2004-2005 period. The survey aims at covering a representative set of firms with R&D activities that are located in Belgium. This list of R&D firms is in constant evolution. The questionnaire includes about 100 variables as regards innovation and economic activities with definitions of R&D activities analogous to the ones presented in the Frascati manual. As the purpose of the analysis is to determine the drivers inside the R&D aggregate that significantly affect both patent counts, patent data for the firms in the survey are needed. The number of patent applications is not available in the 2004-2005 survey though it was reported in previous surveys. Therefore patents were manually collected. This allows a direct observation of the patent applications of the firms instead of relying on the information that they disclose in the survey.

The dataset includes observations over the 2004-2005 period and is limited to the firms of the R&D survey that do not present missing information for at least one of the following variables: share of intramural/extramural R&D, share of research/development oriented R&D, share of product/process oriented R&D, share of R&D by type of cost (workers/equipment), share of R&D by type of funding, share of R&D by type of subcontractor. We also exclude firms that do not perform R&D activities. Following these criteria, we obtain a final sample of 858 firms, representing 70% of the total R&D covered by the survey.

The empirical framework of this chapter proposes to estimate the elasticity of patents with respect to R&D. This relationship aims at investigating the production of innovation to the extent that R&D efforts are considered as the inputs that lead to inventions that are likely to be patented. As regards the literature[71], the elasticity of patents to R&D is expected to be large for cross-sectional analyses, which is the case for our datasets. However, empirical findings in the literature show that introducing a time dimension and using within-firm variables lead to weaker elasticities (Hall et al, 1986; Danguy et al., 2010). It should be noted that recent contributions to the literature of the R&D-patents relationship (de Rassenfosse and van Pottelsberghe, 2009; Danguy et al. 2010) disentangle the impact of R&D efforts on the patents applications into three effects: the research productivity, the appropriability propensity and the strategic propensity. As strategic and appropriability propensities are likely to be partially industry-specific, our empirical findings use industry effects in the R&D-patents relationship in order to capture (even not perfectly) these non-productive components of the R&D elasticity of patents.

[71] See for examples Pakes and Griliches (1980), Hall et al. (1986), Hausman et al. (1984), Jaffe (1986), Duguet and Kabla (1998), Crépon et al. (1998), Brouwer and Kleinknecht (1999), Cincera (1997), Hall and Ziedonis (2001), Blundell et al. (2002).

Table 12. Sample's distribution of total R&D expenditures by type of activities and source of financing

Total R&D	Intramural R&D	70%
	Extramural R&D	30%
Intramural	Research	43%
	Development	57%
Intramural	Product	68%
	Process	13%
	Other	20%
Intramural	Wages	61%
	Investments	8%
	Organization	30%
Intramural	Internal funding	83%
	External funding	17%
Extramural	Other firms	88%
	Research centers	4%
	HEI's and RTO's	8%

858 Belgian R&D firms in 2004-2005. HEIs = Higher Education Institutions; RTOs = public Research and Technology Organizations. Other product/process includes R&D not dedicated exclusively to either product-oriented or process-oriented activities. Source: own computation.

Table 12 lists the different components of R&D as well as the distribution of total R&D expenditures among them. It follows that the firms of the sample are mainly performing development and product research activities. R&D activities are principally financed with the firms' own funds and the share of subcontracted R&D is smaller than the share of intramural R&D. Subcontracted R&D is performed mainly in other private companies.

3.3.2 Matching R&D to patents

The companies of the Belgian R&D survey were associated manually to their patents applications. The patents were collected using PATSTAT. A first issue when matching the firms in the survey with their patents is that the names of the applicants are not harmonized. The VAT registration number would be convenient for the matching as each firm in Belgium is identified with this code, but it does not appear in the patents forms. Furthermore, the names of the applicants may differ from the names of the firms in the R&D survey when the patents were filed through a firm with a different name (e.g. another subsidiary inside the same corporate group). The matching is thus not straightforward. A second issue is related to the highly international nature of the Belgian technological landscape[72]. As stressed in section 3.2, MNEs may conduct R&D activities in Belgium (which is accounted for in the R&D survey) and patent the related inventions outside Belgium via a foreign firm (which is not a Belgian applicant). The Baxter Company illustrates this situation. Baxter's European R&D department was located in Nivelle until 2010 and in Braine-l'Alleud afterwards, but the patents filed by Baxter are filed by Baxter US and not the Belgian counterpart. The opposite situation is also possible, as foreign firms with non Belgian R&D centers can file patents using a Belgian subsidiary. An example is Electrolux Home Products Corp. which patents as a Belgian applicant but is not included in the R&D survey as it is not conducting any R&D in Belgium. A third issue resides in the counting of the patents when one invention leads to more than one patent if the company applied at different patent offices, that is, when an invention leads to a family of patents. Counting all the observed patents of the family would inflate the number of inventions.

In order to address these issues, the following procedure was implemented[73]. First, the number of patents associated with the companies in the R&D survey is the number of priority filings, i.e. the first patent filed for a given invention. This method yields a measure of the innovation output of the firms that is not inflated by the patent family size. We count the patents filed at the Belgian office, but also at the EPO, USPTO and other patent offices reported in PATSTAT. Second, as the R&D survey exclusively concerns the R&D activities conducted in Belgium, only priority filings with at least one inventor residing in Belgium were taken into account. As reported in Table 13, these first filters lead to a total number of priority filings related to 17884 patents in 2000-2005. The period investigated for the patents was extended before 2004-2005, i.e. the period of the R&D survey, as a robustness check in the identification procedure of the companies in order to ensure that the firms in the survey with no observed patent in 2004-2005 did not file other patents in the years before. Each one of these 17884 patents was manually categorized into individual applicants, universities applicants and other applicants. The last category includes private companies as well as public institutions and collective research centers. As none of the firms in the R&D survey is an individual or a university, this procedure leaves 11147 patents to be matched. An automatic matching procedure comparing the names in the R&D survey with the names of the applicants was completed by a manual matching. The manual matching consisted in manual cleaning of

[72] See Cincera, van Pottelsberghe and Veugelers (2006) who quantify the international generation of knowledge in Belgium using EPO and USPTO patent data.
[73] This work was done jointly with Gaétan de Rassenfosse (University of Melbourne).

the names, comparing the addresses of the companies (when available in the patent information) as well as collecting the names of the subsidiaries of the firms that may file the patents for them. The 858 firms in the final sample represent 36% of all the patents filed by non individuals and non universities applicants. When performing the matching for the entire R&D survey, this rate increases to 60%.

Table 13. Matching patents to Belgian R&D

	# priority filings in 2000-2005
Total	17884
– Individuals	– 5867
– Universities	– 870
= Other applicants	= 11147 (100%)
Firms in the survey[a]	6688 (60%)
Firms in the sample[b]	3962 (36%)

a) Belgian R&D survey.
b) Firms with available information on the R&D disaggregation.

Table 14 reports the distribution of the patents across patent offices. EPO is the European Patent Office, USPTO is the US Patent and Trademark Office and NEXT refers to the national patent offices of UK, France, Germany, Luxembourg and the Netherlands (i.e. countries geographically close to Belgium). All applicants appear to file their patents mainly at the European Patent Office, especially the universities with 62% of their priority filings at the EPO.

Table 14. Belgian priority filings across Patent Offices 2000-2005

	Belgium	EPO	USPTO	NEXT	Other	Total
Individuals	1355	1928	755	1622	207	5867
	23%	33%	13%	28%	4%	100%
Universities	18	536	41	254	21	870
	2%	62%	5%	29%	2%	100%
Other applicants	1552	4425	1624	3211	335	11147
	14%	40%	15%	29%	3%	100%
Total	2925	6889	2420	5087	563	17884
	16%	39%	14%	28%	3%	100%

Source: PATSTAT

Table 15 presents the nationality of the applicants that filed a patent with a Belgian contribution. These statistics show that 53% of the patents filed by non individuals and non universities applicants are located outside Belgium, with 16% of them being US applicants.

These statistics illustrate to a certain extent the repatriation of inventions created in Belgium by the MNEs through Belgian research centers.

Table 15. Nationality of applicants 2000-2005

	Belgium	Europe	US	Other	Total
Individuals	4522	901	301	143	5867
	77%	15%	5%	2%	100%
Universities	790	53	17	10	870
	91%	6%	2%	1%	100%
Other applicants	5879	3214	1762	292	11147
	53%	29%	16%	3%	100%
Total	11191	4168	2080	445	17884
	63%	23%	12%	2%	100%

Source: PATSTAT

Table 16 reports the repartition of the firms in the dataset along with their priority filings for years 2004-2005, which is the period covered by the survey.

Table 16. Descriptive statistics of the sample

	#firms	Priority filings (2004-2005)
Industry		
High-tech	327 (38%)	875 (59%)
Medium/low-tech	531 (62%)	610 (41%)
Region		
Brussels	63 (7%)	48 (3%)
Flanders	586 (68%)	1265 (85%)
Wallonia	209 (24%)	172 (12%)
Size		
Small	137 (16%)	16 (1%)
Medium	574 (67%)	352 (24%)
Large	147 (17%)	1117 (75%)
Total	858 (100%)	1485 (100%)

Source: own computation based on a working sample of 858 Belgian firms.

3.4 Econometric models for count data

The impact of R&D on patenting activities is estimated by means of an extended ‘knowledge production function’ (Griliches, 1979). This exercise extends previous work on the R&D-patent relationship by considering several components of R&D activities, for instance the ‘R’ and ‘D’ component, product- versus process-oriented R&D, intramural and subcontracted R&D, rather than total R&D expenditures. The distinction between the origin of the financing, i.e., internal versus external funding, is also considered. As regards the external funding of R&D, information is available on whether the funds originate from public authorities or private sources.

In order to assess the impact of R&D activities and other technological determinants on firms' patenting, the discrete non-negative nature of patent counts has to be taken into account. For instance, because of difficulties and uncertainties inherent to R&D activities, firms do not always apply for patents and hence a zero value is a natural outcome of this variable. The usual way to deal with the discrete non-negative nature of the patent dependent variable is to consider the simple Poisson regression model. Let y_i be this variable which represents the number of patent applications by firm i, where $i = 1,...,N$. The y_i are assumed to be independent and have Poisson distributions with parameters λ_i. Parameters λ_i depend on a set of explanatory variables, which are in this case the determinants of the knowledge production function:

$$\lambda_{\mathrm{i}} = \exp(x_{\mathrm{i}}\beta)$$

where: x_i represents a set of k explanatory variables,

β is the vector of associated coefficients to be estimated.

The dependent patent variable is related to this function through the conditional mean of the Poisson model. An advantage of such a specification is that when variables x_i are expressed in logarithms (as for the R&D expenditures), coefficients are elasticities. The Poisson distribution is given by:

$$P(Y_{\mathrm{i}} = y_{\mathrm{i}}) = \frac{\exp(-\lambda_{\mathrm{i}})\lambda_{\mathrm{t}}^{y_{\mathrm{i}}}}{y_{\mathrm{i}}!}$$

The coefficients are estimated by the maximum likelihood method and the log-likelihood is:

$$l(y;\beta) = \sum_{i=1}^{N}\left[y_i x_i \beta - \exp(x_{\mathrm{i}}\beta) - \ln(y_i!)\right]$$

This function is β globally concave, hence unicity of the global maximum is ensured. An important property of the Poisson model is the equality between its first two conditional moments:

$$E(y_i \mid x_i, \beta) = V(y_i \mid x_i, \beta) = \lambda_i$$

In most empirical studies, the equality of conditional mean and conditional variance of the dependent variable as implied by the Poisson model appears to be too restrictive. Very often, the conditional variance exceeds conditional mean, when estimating a cross-section model such as Poisson, which is known as ‘overdispersion’. Two statistical sources can explain overdispersion: positive contagion and unobserved heterogeneity (Winkelmann and Zimmermann, 1995). For instance, when a firm has made a new important invention (drastic invention) which is patented, often this drastic invention is followed by small and continuous improvements and/or further developments, which can lead to subsequent patent applications. The failure to include individual specific effects is one explanation for unobserved heterogeneity. For instance, in the R&D-patent relationship the presence of firms’ unobserved effects like the uncertainty inherent to R&D activities, the ability of engineers to discover new products or the commercial risk of selling an invention, find expression in the fact that only a few successful firms are likely to apply for a large number of patents in a given time period while for a majority of firms the importance of patenting may be limited or even nul.

In order to address these issues, one possible extension of the Poisson model is to include a firm unobserved specific effect ε_i into the λ_i parameters. This firm-specific effect which is assumed to be invariant over time can be treated as random or as fixed. In the case of random effects, the Poisson’s parameters become:

$$\tilde{\lambda}_i = \exp(x_i \beta + \varepsilon_i)$$

The random terms ε_i takes into account possible specification errors of $\tilde{\lambda}_i$. These misspecifications may result from the omission of non observable explanatory variables or from measurement errors of these variables. The precise form of the distribution of the compound Poisson model depends upon the specific choice of the probability distribution of $\exp(\varepsilon_i)$:

$$P(Y_i = y_i) = \int_{-\infty}^{+\infty} \frac{\exp(-\exp(x_i \beta + \varepsilon_i))(\exp(x_i \beta + \varepsilon_i))^{y_i}}{y_i!} g(\varepsilon_i) d\varepsilon_i$$

where $g(\varepsilon_i)$ indicates the probability distribution of ε_i.

The computation of the compound Poisson’s distribution may be a difficult task - at least from an analytic point of view - because of the integral arising in the equation. However, when it is assumed that exp(ε_i) follows a gamma distribution with parameters (λ_i, θ_i)[74] and are independent and identically distributed, the computation of the last formula leads to the well known negative binomial model. The probability distribution of this model is given by:

$$P(Y_i = y_i) = \frac{\Gamma(y_i + \theta_i)}{\Gamma(y_i + 1)\Gamma(\theta_i)} \left(\frac{\theta_i}{\lambda_i + \theta_i} \right)^{\theta_i} \left(\frac{\lambda_i}{\lambda_i + \theta_i} \right)^{y_i}$$

A parameterization of the variance parameter θ_i is proposed by Cameron and Trivedi (1986):

$$\theta_i = \frac{1}{\alpha}$$

The variance-mean relationship implied by this specification allows for overdispersion:

$$V(y_i) = E(y_i) + \alpha E(y_i)^2$$

Furthermore the Poisson model is nested in this negative binomial model, that is when parameter α tends to 0, the model converges to the Poisson model.

3.5 Results

The estimates of the elasticities of patents with respect to total R&D expenditures are reported in Table 17. Poisson and negative binomial estimates are reported. The likelihood-ratio test reports that the alpha value for the negative binomial is significantly different from 0, which indicates the presence of overdispersion and supports the use of negative binomial models rather than Poisson estimations. Furthermore, the predictions of the models suggest that Poisson estimators perform more poorly than the negative binomial estimators[75]. On the whole, total R&D activities exhibit slightly decreasing returns to scale with respect to patenting[76]. The negative binomial estimates imply that, when controlling for size, industry and region effects, a 1% increase of R&D yields a 0.8% increased number of priority filings. . The elasticity is rather high because of the cross-sectional nature of the datasets. A dynamic specification of the R&D-patent relationship is expected to provide lower estimates (see

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[74] If the set of explanatory variables contains a constant term, this assumption is not too restrictive.

[75] Using the "countfit" command in Stata developed by Long and Freeze (made available by the UCLA Academic Technology Services), it appears that negative binomial estimations fit the data better. The tests significantly reject the Poisson estimates in favor of the Negative Binomial ones.

[76] This result corroborates previous findings of related studies. See Cincera (1998), for a survey.

Danguy et al., 2010 for example). Patents may not be a perfect measure of innovation, especially for sectors where secrecy is favored to patenting strategies. Moreover, the elasticity of patents to R&D is likely to capture not only research productivity, but also appropriability and strategic propensities. However, as our findings are based on firm-level data, the implementation of control variables for the different industries is expected to capture partially these non productive effects and mostly the differences in patenting strategies that are sector-specific.

Table 17. Elasticity of patents to total R&D expenditures

	Poisson		**Negative binomial**	
Intercept	-4.905	(1.028)***	-7.422	(0.871)***
Total R&D expenditures	0.779	(0.114)***	0.806	(0.075)***
Small size	0.017	(0.430)	0.202	(0.381)
Large size	0.604	(0.301)**	0.498	(0.269)*
Flanders	0.012	(0.907)	1.292	(0.526)**
Wallonia	-0.085	(0.961)	1.15	(0.558)**
Nace industry (2-digit)	Jointly significant		Jointly significant	
#firms	858		858	
LogL	-1246		-646	
Alpha			3.635	(0.544)
Lik.-ratio test of Alpha = 0			Prob. =	0.000

Dependent variable: priority filings. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

The results as regards the impact of R&D activities and their different components on patenting are presented according to the hypotheses that we want to test. Control variables for size, industry and region are systematically included in the regressions. The coefficients of the components are compared with coefficient tests based on chi-square statistics.

H1: The main drivers of the patenting activities of a company lie inside its intramural R&D activities.

Table 18. Hypothesis H1

Dependent variable : patents		
Intramural R&D expenditures	0.699	(0.087)***
Extramural R&D expenditures	0.104	(0.045)**
Intramural R&D	0.691	(0.136)***
Extramural R&D		
Firms subcontractors	0.062	(0.054)
Univ. subcontractors	0.105	(0.058)*
Research centers subcontractors	0.123	(0.083)
Other subcontractors	-0.077	(0.103)
Intramural R&D	0.687	(0.137)***
Extramural R&D		
Belgian subcontractors		
■ Regional	0.193	(0.091)**
■ Non regional	-0.085	(0.057)
Foreign subcontractors	0.116	(0.05)**

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

The distinction between in-house and sub-contracted R&D in Table 18 indicates that it is mainly the former activity that contributes to technological output as measured by patents, which validates H1. One argument to explain the lower 'productivity' of R&D carried out outside the firm is the occurrence of major transaction costs. As emphasized by Geroski (1995), given these costs, external research facilities will generally provide generic rather than specialized inputs into the R&D programmes of their clients. These generic inputs are less likely to lead to successful inventions and to patent applications. The higher returns of out-sourced R&D on own patenting come mainly from Belgian subcontractors that are regionally close to firms while interregional collaborations do not seem to provide evidence of patenting activities. Non Belgian subcontractors contribute also to the patenting activities of Belgian firms. A disaggregation of R&D into the types of subcontractors (firms, universities, research centers and others) does not provide significant results, except for the impact of collaborations with universities.

A deeper look at how companies allocate their intramural R&D is presented in Table 19. These estimates allow one to test Hypotheses H2, H3 and H4.

Table 19. Hypotheses H2-H3-H4

Dependent variable : patents – NB estimations	**priority filings**	
Intramural R&D		
Research	0.243	(0.056)***
Development	0.248	(0.037)***
Extramural R&D	0.165	(0.044)***
Intramural R&D expenditures		
Product oriented	0.236	(0.052)***
Process oriented	0.08	(0.045)*
Product & process	0.254	(0.05)***
No specific orientation	-0.112	(0.055)**
Extramural R&D expenditures	0.209	(0.045)***
Intramural R&D expenditures		
Human capital	0.263	(0.154)*
Equipment	0.186	(0.048)***
Extramural R&D expenditures	0.132	(0.044)***

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

H2: Research activities and development activities both contribute to the patenting activities, with a premium for research activities.

The results concerning the Research/Development separation indicate that both activities yield outcomes as measured by the patents of the companies, which is in line with our hypothesis. However, the estimates suggest that the difference between the contribution of 'R' and 'D' is not significantly different[77]. This invalidates H2 as we expected that the higher degree of novelty associated to research activities would be illustrated by more patented inventions. However, this result is not surprising since most of the R&D of the firms, especially the top patenting firms, in the sample consist of development activities.

H3: The role of process-oriented R&D activities is not a significant determinant of patent applications.

The estimates in Table 19 validate H3. The low estimated elasticity associated with the R&D allocated to process oriented R&D confirm the fact that in many industries, secrecy to protect innovation processes is viewed as more effective as compared to patenting[78] when firms are reluctant to disclose information that could benefit to the production processes of their competitors. The differences between the elasticities associated to product and process

[77] Coefficient equality test: chi-square = 0.01, probability = 0.93.
[78] See Cohen (1995) for a discussion.

activities are significant. However, our results suggest that patenting activities are preferred to secrecy for the outcomes of R&D dedicated to a combination of product and process activities.

H4: R&D workers and R&D equipment both significantly contribute to the knowledge production process, with a premium for R&D workers.

Our results give credit to the role of human capital in the knowledge process that leads to the creation of new inventions. Indeed, the coefficient associated to human capital is significantly larger[79] than the coefficient of R&D equipment, which is significant as well in the R&D-patent relationship. Hence H4 Is validated. On the one hand, knowledge and high skills embodied in R&D workers are expected to be crucial determinants of the production of new and succesful inventions. On the other hand, modern and ICT equipment are expected to raise the capabilities of R&D and improve its productivity. Both faces of R&D appear to be crucial determinants of the patenting activities of Belgian firms.

Results in Table 20 consider the sources of funding for the R&D activities. These results directly relate to our last hypotheses H5-H6.

H5: Private and public funds both finance R&D activities with significant returns.

H6: Foreign funds play a significant role in the knowledge production of the Belgian technology landscape

[79] Coefficient equality test: chi-square = 34.66, probability = 0.000.

Table 20. Hypotheses H5-H6

Dependent variable : patents – NB estimations	NegBin	
Intramural R&D		
Own funds	0.182	(0.049)***
External funds	0.315	(0.04)***
Extramural R&D	0.166	(0.037)***
Intramural R&D		
Own funds	0.156	(0.072)**
External funds		
■ from firms	0.298	(0.079)***
■ public funds	0.244	(0.076)***
■ from RTO/HEI	-0.084	(0.281)
Extramural R&D	0.207	(0.047)***
Intramural R&D		
Own funds	0.127	(0.064)**
External funds		
■ Belgian funds	0.167	(0.069)**
■ Foreign funds	0.261	(0.063)***
Extramural R&D	0.194	(0.048)***

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

The contribution of R&D financed by own funds to the outcome of the knowledge process is lower than the contribution of R&D funded by external funds (the difference is significant at 5%). Hypothesis H5 is validated by our results, with external private and public funds both financing R&D activities with significant returns. On the one hand, external private funds are expected to finance the intramural R&D projects that are likely to be effective and yield economic returns. On the other hand, our results concerning public aids suggest that the outcome of Belgian R&D is significantly fostered by public funds. This result can be interpreted as an efficient identification by public authorities of the firms with promising R&D projects. These findings suggest that the lack of public funds would prevent firms to start R&D projects with significant returns. Moreover, a non significant elasticity is found for the RTOs and HEIs. The non-commercial orientation of the research financed by such organizations may account for this result. The geographic location of the external funds indicates that both Belgian and foreign funds finance efficient R&D activities. This validates hypothesis H6. The estimates suggest that the contribution of R&D financed by foreign sources is even significantly higher than the contribution of R&D funded by Belgian sources[80]. This result corroborates that the high degree of internationalization of the Belgian

[80] Coefficient equality test: chi-square = 7.04, probability = 0.008.

technology base correlates with a significant role of foreign funding in the performance of Belgian technology.

3.6 Conclusion and implications

This chapter has investigated the impact at the firm level of R&D activities on the outcomes of such activities as measured by patents filed by a representative sample of Belgian manufacturing companies. A set of cross-sectional results is proposed for 2004-2005 and was used to empirically test six hypotheses related to several faces of R&D. The econometric results show that the R&D-patent relationship presents slightly decreasing returns to scale. While this result confirms the findings of previous studies examining the impact of total R&D on patenting, differences are observed in the estimated impacts of these activities according to their type and source of financing.

The findings suggest a major role of intramural R&D expenditures in the innovation process and a weaker impact of subcontracted R&D. Research activities play a significant role in the innovative process, but we found no significant difference with development activities. Strategies based on secrecy for process oriented innovations seem to be illustrated by our findings, as the role of product oriented R&D is mainly dominant over process oriented R&D in the determination of patenting activities. The findings indicate that human capital is a major driver of the innovative process along with ICT equipment. Larger impacts of intramural R&D financed by external funds rather than own funds are found. We find evidence that both external private and public funds, Belgian or foreign, encourage the emergence of R&D activities that yield significant returns.

Our results have important implications in terms of innovation policy. First, while our findings confirm the role of R&D activities in the production of knowledge outcomes, we show evidence of high degrees of heterogeneity in the channels through which R&D contributes to the technology performance of the companies. This heterogeneity advocates differentiated public support to these components given that the patent propensity of each R&D component is controlled for. The importance of public aid is supported by our findings as we show evidence that public funds are actually helpful in the creation of new inventions. Second, the heterogeneity of R&D correlates with differences in the efficiency of the protection of R&D activities through patents and should be optimally addressed by IPR policies.

In order to further investigate the outcomes of the knowledge process, other measures of the performance of R&D activities could be considered and would extend the scope of the analysis. For instance, other intellectual property rights like copyright and trademarks may be worth being implemented in the knowledge production function and related to the components of R&D (Greenhalgh and Rogers, 2007). Moreove, quality indicators[81] could be considered in order to investigate the impact of R&D components on the quality of patents rather than their quantity[82]. Furthermore, improving the methodological framework with panel data analyses would benefit from the dynamics that underlie the evolution of innovative activities. A structural model that addresses the dimensions of R&D that foster the knowledge outcome could be considered by using simultaneous equations.

[81] See Guellec and van Pottelsberghe (2007), Harhoff, Scherer and Vopel (2003).
[82] See de Rassenfosse and Guellec (2009).

Chapter 4 - R&D performance in Europe, industrial and international diversification

SUMMARY

The main question of this chapter is whether the diversification strategies of the economic activities of the R&D leaders in Europe affect, positively or negatively, the performance of their R&D activities. We propose an original approach based on the analysis of the subsidiaries of EU MNEs. We measure the performance of the firms according to their level of industrial diversification and globalization that we proxy with the presence and importance of subsidiaries in the EU, North America and Asia-Pacific regions. The sample consists of large R&D firms that represent about 80% of total European R&D. In general, the results indicate a positive impact from globalization on firms' R&D productivity, especially in the US, while a negative impact for industrial diversification is found.

4.1 Introduction[83]

According to Schumpeter's view (1942) on the role played by the size of firms on Research and Development (R&D) activities, large R&D firms can be expected to benefit from economies of scope by diversifying their research portfolio and the intrinsic technological risk of R&D activities. Nakamura (1999) finds evidence of a positive relationship between R&D diversification and knowledge spillovers both among research programmes within a firm and across firms. This technology diversification is closely related to product diversification as the latter strategy allows a better appropriation of the results of diversified R&D activites as well as creating a need for a more diversified technology (Granstrand, 1998; Belderbos et al. 2009). Industrial or product diversification can however increase the agency costs between shareholders and managers (Denis et al. 2002) through personal risk reduction, increased power and prestige or compensation arrangements for the latter.

International or global diversification is another source for enhancing R&D productivity. Firms delocalizing research facilities abroad can benefit from the availability of the local knowledge base and supply of a skilled workforce (Kuemmerle, 1997). Outsourcing R&D outside the home country allows firms to exploit existing innovations in local market conditions. When the competition on the local market is severe, widening its activities to cover additional foreign markets also allows a better appropriation of the economic returns of R&D. On the other hand, the diversification of activities can also be detrimental to the R&D productivity of firms. Diversified economic and research activities prevent firms from exploiting economies of scale and can also increase managerial costs (Asakawa, 2001).

Both types of diversification, i.e. industrial and international, may even be linked when a trade-off between both diversification strategies occurs as a firm expands internationally and

[83] The research on the diversification strategies and the subsidiaries of the EU MNEs was conducted with Michele Cincera at the EC-JRC-Institute for Prospective Technological Research. The findings presented in this chapter are found in *Cincera M. and J. Ravet. 2011. Globalisation, industrial diversification and productivity growth in large European R&D companies, IPTS Working Paper on Corporate R&D and Innovation, No.01/2011. Luxembourg: Office for Official Publications of the European Communities.* We are grateful to Pierre Mohnen, Teoman Pamukçu, Betina Peeters, Andrew Toole as well as participants of the 2010 CISS Summer School hold in Turunç, Turkey for their useful comments. We are also grateful to participants of the Asia-Pacific Productivity Conference 2010 (Taipei, Taiwan), Conference on Corporate R&D 2011 (Seville, Spain) and 4th ZEW conference on Economics of Innovation and Patenting (Manheim, Germany).

has to concentrate its resources on a narrower range of products in order to develop a significant position on the wider market (Belderbos et al., 2009).

The main question of this chapter is whether the diversification strategies of the economic activities of the R&D leaders in Europe affect, positively or negatively, the performance of their R&D activities. We propose an original approach based on the analysis of the subsidiaries of EU MNEs. Using consolidated data for R&D, labor, sales and physical capital, we estimate firm-level production functions augmented with R&D capital stocks (Griliches, 1979), and we pay particular attention to the partial elasticities of sales to R&D capital. Several model specifications are tested in order to measure the impact of both sources of diversification, i.e. industrial and global diversification on the productivity performance of firms. In doing so, we are also interested in comparing the productivity growth according to the three main regions where large EU MNEs delocalize their research and production activities, i.e. the EU, North America and the Asia-Pacific region.

We use two sources of information to construct the database for the empirical study: the 2009 edition of the EU industrial R&D scoreboard released by the JRC-IPTS and the Amadeus database (Bureau van Dijk). The sample consists of the top 1,000 R&D-active MNEs in the EU in 2008 with times series covering the 2000-2008 period. The empirical analysis is based on 43,966 subsidiaries of these MNEs. We compute different globalization indicators, such as Herfindahl-Hirschman indexes based on the number of countries covered by firms and their subsidiaries, their number of employees and net sales. Indicators for industrial diversification are constructed on the basis of firms' industrial classifications and subsidiaries.

The results of the econometric analysis show a positive impact for globalization on R&D productivity but a negative impact for industrial diversification. European MNEs with a higher share of subsidiaries in the US and Canada and in the Asia-Pacific region globally exhibit a higher R&D intensity and productivity performance. These findings have implications in terms of managerial practices and give credit to the role of EU innovation policies in supporting relevant international S&T collaborations and partnerships as well as paying attention to the diversification strategies that affect the performance of EU R&D.

The chapter is arranged as follows. Section 4.2 briefly reviews theoretical aspects of the literature on the geographic and industrial diversification of firms. Section 4.3 documents the data and the empirical framework. The estimated results are presented in section 4.4. Finally, conclusions are drawn, and suggestions for future work are made in the last section.

4.2 Diversification of activities

Nowadays, a significant portion of companies diversify their productive activities, either across multiple lines of business, i.e. product or industrial diversification, across different geographic markets, i.e. international diversification or globalization, or both (Denis et al., 2002). The purpose of this section is to review some of the main theoretical arguments as well as empirical findings on the effect of industrial diversification and globalization on R&D activities and firms' economic performance.

Studies in the literature report potential benefits as well as costs for R&D and the economic performance of both types of diversification strategies. We define industrial diversification as the diversification of the economic activities of a firm across several industries (i.e. product diversification). The diversification of a product portfolio may be closely related to the diversification of the R&D activities (i.e. technology diversification) for several reasons (Granstrand, 1998; Belderbos et al., 2009). First, product diversification allows a better appropriation of the results of diversified R&D activities. Second, a diversified product portfolio may require more diversified technology activities.

Industrial diversification is likely to positively affect productivity performance when firms benefit from economies of scope (Kamien and Schwartz, 1982; Porter, 1985) and an excess of technological resources. These new technological opportunities are in turn deployed in new directions and industries. A classical example to illustrate this concept is the DuPont de Nemours company (Penrose, 1959; Chandler, 1962), which was created at the beginning of the 19th century as a gunpowder mill, invented nylon in 1935 and is now one of the largest worldwide chemical companies.

According to Williamson (1975, 1985), multi-product firms increase the willingness of managers to engage in riskier activities such as R&D and innovation, which enhance the firm's productivity. Within a multidivisional firm, "*corporate managers usually evaluate division managers' performance on the basis of both financial performance and other relevant information. Top managers generally have access to information that is both more abundant and superior to that available in the external capital market. Thus, although the number of investment opportunities available within multidivisional firms is limited, at least in comparison to the number of opportunities in the external capital market, top management's knowledge with respect to each is 'incredibly deep'* " (Williamson, 1970: 177).

However, other authors in the strategy literature (Burgelman, 1983a and 1983b; Hayes and Abernathy, 1980 and Hill et al. 1988) have suggested a negative impact for industrial diversification on the propensity of firms to engage in R&D. Division managers operating in this type of M-form companies have a tendency to avoid risky strategies, such as R&D, and invest in projects with a more immediate financial performance. For instance, Baysinger and Hoskisson (1989) argue that "*in large diversified firms, corporate managers tend to use a return-on-investment (ROI) criterion for evaluating division managers' performance*[84]*, causing division managers to meet short-term ROI objectives by reducing expenditures that are not essential for the attainment of short-run returns but are critical to the maximisation of organisational efficiency in the long run*". A second argument is that when the M-firm is too diversified it becomes difficult for the corporate manager to know precisely all the businesses in the firm's portfolio. "*Even for firms engaged in related diversification, top-level managers' ability to gather, process, and interpret the information needed to evaluate divisional performance accurately and allocate resources and rewards may be highly limited*" (Williamson, 1975). Therefore, industrial diversification can potentially benefit corporate managers through increased power and prestige, compensation arrangements, or personal risk reduction. In this case, industrial diversification is more likely to represent a cost for the agency relationship between the managers and shareholders.

Industrial diversification that is based on high degrees of technology diversification may hamper the performance of R&D activities because of a lack of coherence in the technology portfolio. Leten, Belderbos and Van Looy (2007) provide evidence of an inverted U-shape between technology performance and technology diversification. According to the authors, "*high levels of diversification may yield few marginal benefits as firms risk lacking sufficient levels of scale to benefit from wide-ranging technological capabilities, and firms may encounter high levels of coordination and integration costs*".

As regards the determinants and the impact of globalization on firms' R&D activities and productivity performance, theoretical studies (Dunning and Narula, 1995; Kuemmerle, 1997) and empirical studies (Kuemmerle, 1999; Kumar, 2001; Von Zedwitz and Gassmann, 2002) on the internationalization of R&D over the last two decades have highlighted a shift from the so-called home-base exploiting to home-base augmenting R&D strategies. Within such a framework, MNEs set up R&D laboratories abroad not only for adapting technologies and

[84] Dundas and Richardson (1982).

products developed at home to local market conditions, but also to tap into the knowledge and technological resources in centers of scientific excellence located worldwide. Such location strategies have multiple dimensions: the technological strengths of the countries with respect to those of the company (Patel and Vega, 1999; Le Bas and Sierra, 2002); institutional factors, such as public support for R&D, IPR systems, quality of technological infrastructures; and lowering the costs of qualified research, especially in emerging countries (UNCTAD, 2005).

The empirical evidence on the effects of industrial and global diversification is somewhat limited and has produced mixed findings. A study by Denis et al. (2002), based on 44,288 firm-year observations over the period 1984-1997, showed that an increase in industrial diversification negatively affects the excess values of the firms. A positive impact, however, was found for globalization, which can be explained by an increase in flexibility to address changes in local environments, such as relative prices, differences in tax codes, and other institutional differences. Global diversification tends also to positively affect firms' market capitalization by exploiting firm-specific assets, e.g. intangible assets such as R&D, marketing skills, and management quality, increasing operating flexibility, and satisfying investor preferences for holding globally diversified portfolios. Morck and Yeung (1998) also found a positive effect for internalization of foreign markets on productivity performance.

Conversely, because of its higher complexity in terms of management, coordination costs and information asymmetries between corporate headquarters and divisional managers, more globalized corporations are less efficient and exhibit lower performance. Thus, global diversification can also lead to the inefficient cross-subsidization of less profitable business units (Meyer et al., 1992), and divisional managers may have incentives to adopt and maintain value-reducing diversification strategies, which in turn reduce shareholder wealth (Jensen and Murphy, 1990).

Given the literature, there are benefits and costs arising from diversification strategies. The purpose of our analysis is to measure the net effect of diversification on the performance of EU R&D. Hence, the main question of this chapter is whether the diversification strategies of the economic activities of the R&D leaders in Europe affect, positively or negatively, the performance of their R&D activities.

4.3 Empirical framework and data

4.3.1 Empirical framework

The role of diversification indicators is analyzed based on a Cobb-Douglas functional form for the production function of the companies. The use of a Cobb-Douglas form relies on a functional form that is first-order flexible[85] (Coeli et al., 2005). Adding more flexibility to the model, using for instance a translog specification, in order to have a second-order flexible function has a cost (more parameters to estimate) and may enhance econometric issues like multicollinearity. As we implement R&D capital stock as an input, in addition to traditional labor and physical capital stock, as well as additional variables related to diversification indicators, we choose to rely on a Cobb-Douglas form in order to have a parsimonious number of parameters to estimate. Assuming a standard Cobb-Douglas production function,

$$Y = AL^{\alpha}C^{\beta}K^{\gamma}e^{u} \tag{4.1}$$

with *L, C* and *K* being factors of production, i.e. respectively labor, physical capital and R&D capital. Equation 4.1 taken in logarithm form is:

$$\log(Y_{it}) = \lambda + \alpha\log(L_{it}) + \beta\log(C_{it}) + \gamma\log(K_{it}) + u_{it} \tag{4.2}$$

In order to test the relationship between a diversification indicator *I* and the productivity of R&D, we implement an interaction term between *I* and *K*, which may reflect a potential complementarity between both variables. When controlling for country, industry and time effects, equation 4.2 becomes:

$$\begin{aligned}\log(Y_{it}) &= \lambda + \alpha\log(L_{it}) + \beta\log(C_{it}) + \gamma\log(K_{it})\\ &+ \gamma_0\log(K_{it}) + \gamma_1\log(K_{it})I_i + I_i + country_i + industry_i + \delta_t + u_{it}\end{aligned} \tag{4.3}$$

[85] It presents enough parameters to provide a first order approximation of the function at a single point.

The elasticity of output to R&D capital is:

$$d \log Y / d \log K = \gamma_0 + \gamma_1 I \tag{4.4}$$

The stocks of R&D and physical capital were constructed by using the perpetual inventory method[86] (Griliches, 1979). For each firm, the stock of capital at time t is defined by:

$$ST_t = (1-\delta)ST_{t-1} + Inv_t \tag{4.5}$$

where δ is the depreciation rate of the capital and Inv is the amount of investment (R&D expenditure for R&D stock, or capital expenditures for physical capital stock). The depreciation rates were set to 0.15 for R&D and 0.08 for physical capital, which are the rates that are usually assumed in the literature[87]. The initial value of the stock can be computed by using the following expression:

$$ST_0 = \frac{Inv_0}{g+\delta} \tag{4.6}$$

where g is the growth rate of investment and is assumed to be constant. The growth rate used for R&D stock is the average sample growth rate for R&D expenditure, i.e. 7.5%. The growth rate for physical capital is the average sample growth rate for capital expenditure, i.e. 11.5%.

4.3.2 Constructed data set and variables

We use two sources of information for the empirical study. The first one is the 2009 edition of the EU industrial R&D scoreboard, released annually by the JRC-IPTS of the European Commission. The second data source is the Amadeus database published by the Bureau van Dijk. The R&D scoreboard has been issued every year since 2004 and provides data at the firm level for the top 1,000 R&D-active firms in the EU-27 and the top 1,000 outside the EU-27.

Our analysis focuses on the EU firms in the scoreboard. The information available in the R&D scoreboards is consolidated at the group level and includes, among others, R&D investments[88], net sales, number of employees, capital expenditures, the country where the

[86] See section 2.3.1 for a discussion about this method.
[87] See for instance Hall and Mairesse (1995) or Capron and Cincera (1998).
[88] The definition of "R&D" is that used by companies, following accepted international accounting standards (IAS38), in accordance with the definitions used in official statistics (as defined in the OECD's Frascati Manual). The term "R&D Investment" is used in the Scoreboard.

MNE has its registered headquarters and the main business sector, based on the Industry Classification Benchmark (ICB) at the two digits level, i.e. 45 industry and services sectors[89]. The period covered by the 2009 R&D scoreboard is 2005-2008, but previous R&D scoreboards allowed us to extend the observed period for the firms from 2000 to 2008. Each monetary observation was converted into constant currency (in euros) and prices.

The Amadeus database[90] contains financial information from 14 million companies in Europe. We extracted the following data from Amadeus for the subsidiaries of the EU-27 firms available in the 2009 R&D scoreboard: the number of subsidiaries and, for each subsidiary, its turnover, number of employees, ownership, location and business sector. The data for these subsidiaries are collected by Amadeus only once between 2005 and 2007, and therefore time series for these variables are not available. As a result, the dataset used in the empirical analysis consists of a panel of firms from the R&D scoreboards over the period 2000-2008 augmented with a cross-section of their subsidiaries extracted from the Amadeus database. The date of the information for these subsidiaries is the most up-to-date over the 2005-2007 period.

Table 21 summarizes the main variables and data sources used in this study.

Table 21. Data sources, variables and period covered

2009 R&D scoreboard	Amadeus
R&D, net sales, employees, capital expenditures, country, industry (ICB)	# subsidiaries, turnover of subsidiaries, # employees of subsidiaries, localization of subsidiaries, industry of subsidiaries (ICB)
2000-2008	Most up-to-date information over 2005-2007

The matching between the 1,000 European firms in the R&D scoreboard and their counterpart in Amadeus is not straightforward and involves a manual matching procedure considering several criteria. Following our criteria, each firm in the scoreboard is matched manually with one firm in Amadeus with the same or slightly different name (e.g. Philips Electronics and Koninklijke Philips Electronics), located in the same country, with the same status (e.g. Ltd, SA, OY) and with consolidated financial data in Amadeus.

[89] See http://www.icbenchmark.com/.
[90] Amadeus, September 2009 version.

Table 22. Sample of 835 EU R&D companies

Industry	# firms	R&D 2008 in mio EUR	R&D intensity 2008
High-tech	**385**	**81173**	**7.2%**
Biotechnology	52	1296	21.3%
Semiconductors	19	3270	16.9%
Pharmaceuticals	50	14433	15.8%
Telecommunications equipment	26	12013	13.1%
Software	71	3798	13.1%
Electronic office equipment	2	303	7.9%
Electronic equipment	33	974	7.1%
Leisure goods	9	1892	6.2%
Aerospace & defence	25	7482	5.9%
Computer hardware	6	123	5.9%
Automobiles & parts	40	29564	5.3%
Electrical components & equipment	26	5239	4.0%
Computer services	26	786	3.2%
Medium-tech	**243**	**20589**	**2.7%**
Health care equipment & services	29	1671	4.7%
Commercial vehicles & trucks	15	2356	3.7%
Chemicals	42	7075	3.2%
Alternative energy	4	286	3.0%
Industrial machinery	69	3289	2.7%
General industrials	20	1318	2.4%
Household goods & home construction	22	1352	2.3%
Media	12	1292	2.2%
Food producers	30	1951	1.5%
Low-tech	**207**	**14828**	**0.5%**
Banks	2	70	1.9%
Personal goods	16	963	1.7%
Life insurance	1	29	1.7%
Fixed line telecommunications	13	4321	1.6%
Support services	25	449	1.1%
Tobacco	2	151	1.1%
Internet	4	31	0.9%
Other financials	11	269	0.8%
Mobile telecommunications	4	334	0.8%
Oil equipment, services & distribution	4	91	0.7%
Electricity	15	1449	0.6%
Construction & materials	26	671	0.5%
Forestry & paper	6	235	0.5%
Mining	5	485	0.5%
Industrial metals & mining	12	859	0.4%
Industrial transportation	12	432	0.3%
Nonlife insurance	1	5	0.3%
General retailers	13	406	0.3%
Oil & gas producers	9	2458	0.3%
Gas, water & multiutilities	8	584	0.2%
Travel & leisure	9	167	0.2%
Beverages	4	88	0.2%
Food & drug retailers	5	282	0.2%
All	**835**	**116590**	**2.4%**

Source: own computation.

We also made use of the information provided in the contact list used by the European Commission to contact the firms when assembling the R&D scoreboard[91]. This allows us to compare the city of the firm in the contact list with the city disclosed in Amadeus as a further criterion for validating the match. We also compare information as regards sales and employees in both databases[92].

Out of the 1,000 EU scoreboards firms in 2008, 55 could not be found in Amadeus[93] and 110 were found but not kept because of unconsolidated accounts or doubts about the matching procedure. Our final sample consists of the 835 remaining firms in the R&D scoreboard.

Table 22 presents an overview of the sample and some aggregate sector figures. We use the same classification as Ortega-Argiles et al. (2008) to assign the ICB industry and service sectors into high-, medium- or low-tech sectors.

4.3.3 Subsidiaries and diversification

The Amadeus database records 43,966 subsidiaries affiliated with the 835 EU MNEs in our sample. The R&D scoreboard firms hold at least 50% of the ownership of about 93% of these subsidiaries and at least 90% of the ownership of 84% of them. Table 23 presents some characteristics regarding the subsidiaries of the sample.

Table 23. Subsidiary characteristics

Industry	average #subsidiaries	average subs. Turnover (mil. USD[a])	average subs. employees
High-tech	38	199	436
Medium-tech	47	237	597
Low-tech	86	1005	2583
All	52	410	1015

Sample: 835 EU R&D companies. a) Amadeus provides data for subsidiaries only in US Dollars and not Euros. This will not affect the empirical analysis, as we are only interested in the share of the sales across countries and industries. Source: own computation.

[91] This contact list is confidential and the work on this information was performed by Michele Cincera as a visiting scientist at the DG-JRC Institute for Prospective Technological Studies, European Commission, Seville.

[92] Comparison is made for 2007 as it is the most recent year available in our version of Amadeus. Correlation between employees or sales in both databases is 0.99. The mean sales ratio for scoreboard/sales in Amadeus is 1.04, with a median of 1. The mean employees ratio in scoreboard/employees in Amadeus is 1.05, with a median of 1.

[93] 34 of them belong to the financial sector (bank, insurance and other financials) which is not covered in Amadeus.

We use two types of indicators to identify the level of geographic diversification of firms. The first is the number of countries covered by the subsidiaries and the main firm. If all subsidiaries are located in the same country as the parent company, it implies no country diversification and a value of 1 is given for this indicator. Higher values are related to a stronger level of internationalization. The second indicator is a Herfindahl-Hirschman Index[94] (HHI) based on the sales and employee shares for the subsidiaries across countries. We calculate a HHI based on sales and another based on employees, given that for some subsidiaries we have information on the number of employees but not on sales[95]. The sales-based HHI for a firm present in C countries is defined as:

$$HHI^{S}{}_{country} = \sum_{c=1}^{C} \left(\frac{sales_c}{S} \right)^2$$

where $sales_c$ represents the sum of the sales of the subsidiaries in country c and S is the sum of the sales of all subsidiaries. The employees-based HHI is given by:

$$HHI^{E}{}_{country} = \sum_{c=1}^{C} \left(\frac{emp_c}{E} \right)^2$$

Where emp_c represents the sum of the employees of the subsidiaries in country c and E is the sum of the employees of all subsidiaries. An increase in the HHI implies a more concentrated distribution of sales or employees across countries.

[94] The indicators to measure the global diversification and industrial diversification used in this chapter are based on HHI index. While this index is normally used to measure the level of concentration rather than diversification use of the HHI index to measure geographic and or business diversification is also well documented in the literature (Comment and Jarrell, 1995; Berger and Ofek, 1995).

[95] Data on employees are only available for some subsidiaries, while data on sales are only available for other subsidiaries. In total, we do not have information on sales or employees for 48% of these subsidiaries.
In addition, financial information for these subsidiaries is only available for a given year (over 2005-2007). One limitation of the study is that it was not possible to collect this information over the period investigated, i.e. 2000-2008, since 63% of these subsidiaries do not have any BvD ID in the Amadeus Database. The reasons explaining why this information is partially available (only for some subsidiaries and only for one year) are twofold. First, a large share of these subsidiaries are small companies in terms of size, i.e. in terms of number of employees, total revenues or total assets, and therefore no information on sales and on employees is collected by Amadeus. The second reason rests in the geographic coverage of the Amadeus database which contains information only for companies in both Western and Eastern Europe. Therefore, if a subsidiary is registered in a country outside Europe, it is not included in the database. A further complication rests in the fact that the number of subsidiaries itself is changing over time through the process of merger and divestiture of the multinational companies listed in the R&D scoreboards.

Table 24. Average geographic diversification measurements

Firms	#countries	HHI sales	HHI emp
High-tech	11	0.61	0.62
Medium-tech	14	0.56	0.58
Low-tech	16	0.65	0.64
All	13	0.61	0.61

Sample: 835 EU R&D companies. Source: own computation.

The average measurements for these indicators are presented in Table 24. The firms in our sample are located on average in 13 countries. Firms in high-tech industries cover fewer countries. This may reflect a size effect, as these firms are also smaller on average. HHI indicators are close to 0.6.

Table 25 reports the shares of the subsidiaries in the main geographic areas represented in our sample: Europe[96], US-Canada, Asia-Pacific[97] and the rest of the world. While most of the subsidiaries are located in Europe, it appears that the share of European subsidiaries is even higher for low-tech industries, with a share that is 10 points higher for the low-tech firms (78%) than for the high-tech firms (68%). Higher-tech firms seem to favour US-Canada and Asia-Pacific regions when they want to locate their subsidiaries out of Europe.

Table 25. Share of subsidiaries (in %) by regions

Industry	**EU27**	**US-CA**	**Asia-Pacific**	**RoW**
High-tech	68	13	9	9
Medium-tech	71	11	8	10
Low-tech	78	7	5	10
All	72	11	7	10

Sample: 835 EU R&D companies. Source : own computation.

As a first measure of industrial diversification, we count the number of industries in which the MNE and its subsidiaries are active. We use the information available in the Amadeus database only: the NACE code that corresponds to the main industry sector for the subsidiaries. The number of sectors is measured according to the 4-digit Nace industry of the

[96] European Union (27 Member States).
[97] American Samoa, Australia, Brunei, People's Republic of China, Fiji, Federated States of Micronesia, Guam, Hong Kong, Indonesia, Japan, Cambodia, Kiribati, North Korea, South Korea, Laos, Marshall Islands, Myanmar, Macau, Northern Mariana Islands, Malaysia, Nauru, New Zealand, Papua New Guinea, Philippines, Palau, Solomon Islands, Singapore, Thailand, Timor-Leste, Tonga, Tuvalu, Taiwan, Vietnam, Vanuatu and Samoa.

subsidiaries but we also calculate a more aggregate indicator based on the 2-digit Nace level. We also consider two other measures of industrial diversification: the sales-based and employee-based HHI across industries. These indicators are calculated at the 2-digit Nace level. The sales-based HHI for a firm present in *K* industries is defined as:

$$HHI^{S}{}_{nace} = \sum_{k=1}^{K} \left(\frac{sales_k}{S} \right)^2$$

where $sales_k$ represents the sum of the sales of the subsidiaries in industry k and S is the sum of the sales of all subsidiaries. The employees-based HHI is given by:

$$HHI^{E}{}_{nace} = \sum_{k=1}^{K} \left(\frac{emp_k}{E} \right)^2$$

where emp_k represents the sum of the employees of the subsidiaries in industry k and E is the sum of the employees of all subsidiaries. An increase in the HHI implies a more concentrated distribution of sales or employees across industries.

Table 26. Industrial diversification measurements

Industry	#Nace 4 digit	#Nace 2 digit	HHI sales	HHI emp
High-tech	10	6	0.67	0.68
Medium-tech	14	7	0.59	0.58
Low-tech	18	9	0.62	0.58
All	13	7	0.61	0.61

Sample: 835 EU R&D companies. Source : own computation.

The average measurements of industrial diversification are reported in Table 26. On average, the firms in our sample are active in 13 4-digit Nace industries. Firms in low-tech industries are active in more industries, and, as in Table 25, a reason for this may be the large size of these firms.

Descriptive statistics

The 835 firms are observed during the 2000-2008 period, with data missing for some firms. In order to remove outliers, the sample was trimmed by dropping observations in the first and last centile of sales, labor, physical capital and R&D capital variables. The sample is also restricted to observations with no abnormally high R&D intensity, i.e. above the 95th centile, which is 1 (100%). The panel is unbalanced with an average observed period of 5 years per firm and a total of 4,230 observations. Because of missing observations for some subsidiaries, there are less than 4,230 observations for variables related to the subsidiary country and industry. Table 27 shows some descriptive statistics for the sample[98].

Table 27. Descriptive statistics

Variable	Obs	Mean	Med	Std dev	Min	Max
ln(sales)	4230	6.65	6.64	1.94	.45	11.16
ln(labor)	4230	8.28	8.34	1.81	3.47	12.46
ln(physical capital)	4230	5.61	5.56	2.24	.17	11.12
ln(R&D capital)	4230	4.75	4.48	1.57	1.52	9.68
R&D/sales	4230	0.08	0.04	0.12	0	.99
#subsidiaries	4230	52	24	83	1	534
#countries	4207	13.65	9	14.17	1	126
HHI countries - sales	3773	0.59	0.56	0.29	0.11	1
HHI countries - emp	3783	0.59	0.54	0.29	0.08	1
#nace 4 digit	4190	13.45	9	12.80	1	119
#nace 2 digit	4190	7.32	6	5.36	1	42
HHI nace - sales	3821	0.63	0.59	0.25	0.14	1
HHI nace – emp	3892	0.61	0.55	0.25	0.18	1

Sample: 835 EU R&D companies. Source : own computation.

Table 28 lists the 20 firms in our sample with the highest share of subsidiaries in Asia-Pacific for R&D. High-tech industries related to electronic equipment, semiconductors, software and telecommunications equipment are the main industries present in this ranking.

[98] See Appendix 3 for more detailed statistics.

Table 28. Top 20 EU firms with subsidiaries in Asia-Pacific

Firm	%AP	ICB
James Hardie Industries	76%	Construction & materials
Micronic Laser Systems	60%	Semiconductors
Ilog	50%	Software
FRIWO (ex CEAG)	50%	Telecommunications equipment
BE Semiconductor Industries	41%	Semiconductors
Anoto	40%	Computer hardware
AVEVA	40%	Software
EPCOS	39%	Electronic equipment
ASM International	39%	Semiconductors
Rio Tinto	38%	Mining
Aixtron	38%	Semiconductors
ASML	36%	Semiconductors
SAES Getters	36%	Electronic equipment
Oberthur Technologies	36%	Electronic equipment
Novozymes	35%	Biotechnology
Option	33%	Telecommunications equipment
Manz Automation	33%	Industrial machinery
Wavecom	33%	Telecommunications equipment
ARM	33%	Semiconductors
Tekla	33%	Software

Sample: 835 EU R&D companies. Source : own computation.

Interestingly, Table 29 shows a different industrial specialization pattern for the subsidiaries present in North America. The most represented industries in the top 20 ranking of firms with subsidiaries in US-Canada are the biotechnology and pharmaceuticals industries.

Table 29. Top 20 EU firms with subsidiaries in US-Canada

Firm	%US	ICB
Transgene	100%	Biotechnology
Flamel Technologies	100%	Biotechnology
Clipper Windpower	100%	Electricity
Basler	100%	Electrical components & equipment
ExonHit Therapeutics	100%	Biotechnology
Exiqon	100%	Biotechnology
Reed Elsevier	69%	Media
Gas Turbine Efficiency	67%	Industrial machinery
ARC International	65%	Semiconductors
Glunz & Jensen	60%	Computer hardware
Sophos	57%	Software
nCipher	57%	Software
Merial	50%	Biotechnology
Reckitt Benckiser	50%	Household goods & home construction
NicOx	50%	Pharmaceuticals
Boliden	50%	Mining
MediGene	50%	Biotechnology
Antisoma	50%	Biotechnology
AGI Therapeutics	50%	Pharmaceuticals
Plethora Solutions	50%	Pharmaceuticals

Sample: 835 EU R&D companies. Source : own computation.

4.4 Results

Table 30 provides the estimates from equation 4.3 when using the number of EU MNE subsidiaries as diversification indicators, as well as the number of countries and the number of industries where the firm is active. We use a logarithmic specification for these indicators[99]. Because the diversification indicators are not observed over time, a within or first difference transformation would drop one of the variables included in the interaction term. The following results are based on pooled-OLS estimates and we try to control for individual heterogeneity with sets of industry dummies and country dummies[100]. Time dummies are also included in the estimates. We do not correct variables for the double-counting of R&D in other inputs (i.e. labor and capital used for R&D activities) because of data limitation.

As the estimation of the elasticity of output with respect to R&D capital may be affected by the simultaneity in the choices of output and inputs, estimates using predetermined factors of

[99] A non-logarithmic specification does not affect the significance or signs of the diversification measurements.
[100] When the model in column 1 of Table 30 is estimated with fixed-effects, the elasticities of labor, physical capital and R&D capital are 0.72, 0.15 and 0.12, respectively.

production at time t-1 rather than factors at time t are reported in Appendix 5. Note that since the information about the subsidiaries is the most up-to-date available information and is only available in the cross-sectional dimension, it is not possible to use lagged periods as instruments for this variable. Lagged periods for the number of subsidiaries could be implemented as instruments in a GMM system framework in order to tackle potential endogeneity issues arising when subsidiaries are created based on high productivity performances. Furthermore, structural models could be used in order to add an equation that explains the evolution of the MNEs landscape in terms of subsidiaries based on past performances and home-based augmenting and exploiting purposes. The lack of time dimension and good instruments for the subsidiaries in the dataset hampers the use of instrumental methods in this analysis. However, we know that the information related to the subsidiaries is dated between 2005 and 2007. Hence, as additional robustness tests we considered regressions were early observations for *Y*, *K*, *C* and *L* are excluded (i.e. observations before 2006[101] (see Appendix 6)). It follows that these additional results are not substantially different from the ones reported in Table 30.

Table 30. Estimates – Diversification indicators

	(1)	(2)	(3)
log(*L*)	.65 (.02)***	.65 (.02)***	.64 (.02)***
log(*C*)	.24 (.01)***	.24 (.01)***	.24 (.01)***
log(*K*)	.11 (.01)***	.09 (.02)***	.16 (.02)***
log(*K*) x log(#count)		.01 (.004)**	
log(#countries)		-.06 (.02)**	
log(*K*) x log(#indus)			-.02 (.01)***
log(#industries)			.10 (.03)***
R-sq	.95	.95	.95
#obs	4230	4159	4148

Dependent variable: log(*Y*). Sample of 835 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. 'Industries' is the number of 4-digit Nace industries where the firm is active. Estimates conducted without observations above 99th percentile of diversification.

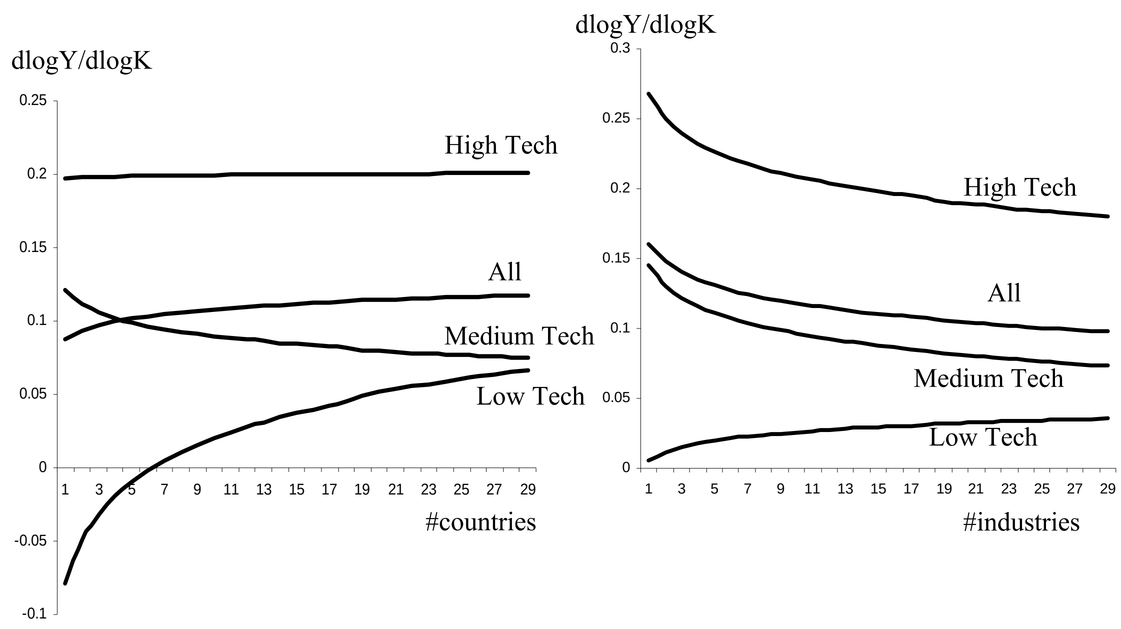
According to column 1 in Table 30, the output elasticities of labor, physical capital and R&D capital are respectively 0.65, 0.24 and 0.11. Columns 2 and 3 report estimates of the

[101] Excluding observations in 2006 yields similar conclusions.

production function augmented with an interaction term between R&D capital and a diversification indicator. The coefficient of the interaction term is negative and significant when using the number of 4-digit Nace industries as an industrial diversification indicator (column 3). However, it appears that the coefficient of the interaction between R&D capital and the number of countries covered by the firms is positive and significant (column 2).

Figure 8 represents the output elasticity of R&D capital with respect to the number of countries and 4-digit Nace industries based on the results of columns 2 and 3 in Table 30. The pattern by technology level (i.e. sectors classified as high-, medium- and low-tech, based on Table 22) is also reported. The curves are not linear as the coefficients are estimated using a logarithmic specification for the diversification measures. It appears that there is a positive relationship between the elasticity of R&D capital and the number of countries and industries for firms in low-technology industries. The relationship between this elasticity and the number of industries is negative for higher technology industries. The number of countries is negatively correlated with the elasticity of R&D capital for firms in medium-tech industries.

Figure 8. Output elasticity of R&D capital by technology level



Note: logarithmic specification in the model estimated for the number of countries and industries.

Table 31 reports the interaction term coefficients from equation 4.3 when using the Herfindhal-Hirschman indexes presented in section 4.3.3. Results show that a higher concentration of the MNEs across countries is related to lower R&D capital elasticity for firms in low-tech and medium-tech industries, while the effect is positive for firms in high-tech industries. A higher concentration across Nace industries seems to positively affect the R&D capital output elasticity for firms, especially those in high- and low-tech industries.

Table 31. Concentration index estimates

	Countries		Industries	
Firms	log(*K*) x HHI sales	log(*K*) x HHI emp	log(*K*) x HHI sales	log(*K*) x HHI emp
All	-0.02 (0.02)	-0.03 (0.02)	0.05 (0.02)***	-0.01 (0.02)
High-tech	0.04 (0.02)*	0.04 (0.02)	0.1 (0.03)***	0.04 (0.03)
Medium-tech	-0.03 (0.02)	-0.06 (0.02)***	-0.05 (0.03)	-0.03 (0.03)
Low-tech	-0.15 (0.06)**	-0.11 (0.06)*	0.14 (0.06)**	0.01 (0.06)

Dependent variable: log(*Y*). Sample of 835 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including log(*L*), log(*C*), log(*L*) and sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. HHI emp and sales are Herfindahl-Hirschman indexes based, respectively, on the number of employees and sales. Estimates conducted without observations above 99^{th} percentile of diversification.

To analyze the relationship between the output elasticity of R&D capital and the location of the subsidiaries in Europe, US-Canada and Asia-Pacific, estimates of equation 4.3 are performed using the share of subsidiaries in these regions as diversification indicators, and the results can be seen in Table 32. As shown in column 2, the coefficient of the interaction term with the share of European subsidiaries is negative and significant, which indicates a strong negative correlation between the R&D capital elasticity and the percentage of European MNE subsidiaries located within Europe rather than outside. Column 3 reports a positive and significant coefficient for the interaction terms with the share of subsidiaries in North America, while column 4 indicates a positive but non significant coefficient for the interaction term with the share of subsidiaries in Asia-Pacific.

Table 32. Estimates for Shares of subsidiaries in main regions

	(1)	(2)	(3)	(4)
log(*L*)	.65 (.02)***	.64 (.02)***	.65 (.02)***	.64 (.02)***
log(*C*)	.24 (.01)***	.24 (.01)***	.24 (.01)***	.24 (.01)***
log(*K*)	.11 (.01)***	.20 (.02)***	.09 (.01)***	.11 (.01)***
log(*K*) x %EU subs		-.12 (.03)***		
%EU subs		.85 (.13)***		
log(*K*) x %US subs			.23 (.04)***	
%US subs			-1.4 (.21)***	
log(*K*) x %AP subs				.05 (.06)
%AP subs				-.66 (.28)**
R-sq	.95	.95	.95	.95
#obs	4230	4207	4207	4207

Dependent variable: log(*Y*). Sample of 835 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. %EU subs, %US subs and %AP subs mean shares of subsidiaries in the EU27, US-Canada and Asia-Pacific regions, respectively.

Table 33 gives the coefficients of the interaction term by technology level. The coefficient is positive and significant for the interaction between the R&D capital and the share of subsidiaries in US-Canada for firms in the high-, medium- and low-tech industries. The interaction with the share of EU subsidiaries is associated with a negative and significant coefficient for high- and low-tech sectors. The coefficient of the interaction term with the share of Asia Pacific subsidiaries appears to be positive and significant only for firms in low-tech industries.

Table 33. Estimates for Shares of subsidiaries in main regions by technology level

Firms	log(K) x %EU subs	log(K) x %US subs	log(K) x %AP subs
All	-0.12 (0.03)***	0.23 (0.04)***	0.05 (0.06)
High-tech	-0.07 (0.03)***	0.17 (0.04)***	-0.07 (0.08)
Medium-tech	-0.001 (0.04)	0.13 (0.07)*	-0.01 (0.08)
Low-tech	-0.39 (0.08)***	0.49 (0.15)***	0.63 (0.17)***

Dependent variable: log(Y). Sample of 835 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including log(L), log(C), log(K) and sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. %EU subs, %US subs and %AP subs mean shares of subsidiaries in the EU27, US-Canada and Asia-Pacific regions, respectively.

4.5 Conclusion and implications

This chapter aims to assess the relationship between both industrial and global diversification of large European R&D MNEs and the productivity of their R&D activities. The question addressed by our study is whether the diversification strategies of EU MNEs improve the economic performance of R&D activities. According to our estimations, the answer is yes for international diversification, but no for industrial diversification. By estimating production functions including labor, physical capital and R&D capital, we find that the globalization of EU MNEs is associated with a higher productivity for R&D capital, while industrial diversification appears to hinder R&D productivity. The R&D expenditures considered in this study represents about 80% of total European R&D. We propose an original approach to assess the effects of these two types of diversification based on the subsidiaries of the firms. This chapter also provides recent estimates of output elasticities for large EU firms.

Our findings suggest that the benefits for R&D activities from European MNE industrial diversification strategies, i.e. economies of scope and new technological opportunities deployed in new directions, do not compensate for the loss of efficiency, which may be related to the greater complexity of corporate management. Furthermore, it supports the idea that divisional managers may favour less risky investments and may not optimally invest in R&D projects.

On the other hand, although coordination costs and information asymmetries are expected to arise from the globalization of EU MNEs, we show that the geographic diversification benefits the R&D productivity of large EU firms. This may be explained by the strategic locations of the subsidiaries, whose aim is to make use of the knowledge and technological resources in centers of scientific excellence located worldwide.

This chapter also investigates the strategic location of the subsidiaries in Europe, North America and Asia Pacific, which are the three main regions for EU firms to locate their subsidiaries. EU firms with the highest shares of subsidiaries in North America belong mainly to the biotechnology and pharmaceutical industries, while the MNEs mostly present in Asia Pacific are related to the electronic equipment, semiconductors, software and telecommunications equipment sectors. Figures in Appendix 7 seem to corroborate a positive link between a higher R&D intensity for EU firms and the share of subsidiaries in North America or Asia-Pacific, while R&D intensity tends to decrease with the share of EU subsidiaries. Regarding R&D productivity, we find that a higher share of subsidiaries in Europe decreases the output elasticity of R&D capital, while the share of subsidiaries in North America positively affects the elasticity. The share of subsidiaries in Asia Pacific seems to increase this elasticity only for firms in low-tech industries.

One issue in the empirical framework is the data limitation regarding subsidiaries only observed in a cross-sectional dimension. This prevents the use of within or first difference transformations for the production function to capture unobserved individual heterogeneity other than industry or country effects, which are taken into account in our estimates. Another concern is the causality in the relationship between R&D productivity and diversification. While there are theoretical reasons to explain that diversification may enhance or alter the productivity of R&D activities, one may also expect firms with a higher R&D productivity to adopt a diversification strategy.

These results have potentially important implications for competition policies and the EU 2020 strategy for jobs and smart, sustainable and inclusive growth recently adopted by the European Council[102].

As an acknowledged channel for industrial diversification is through mergers and acquisitions (M&A) (Porter, 1987), antitrust authorities may be careful regarding decisions allowing M&A, as these activities, besides increasing the market power of the merged entities, may also reduce their efficiency and economic performance. While combining different companies (M&A) may allow them to develop new products more efficiently or reduce production or distribution costs, their increased efficiency means the market becomes more competitive and

[102] http://ec.europa.eu/eu2020/pdf/council_conclusion_17_june_en.pdf.

consumers benefit from higher-quality goods at fairer prices. However, some M&A may reduce competition in a market, usually by creating or strengthening a dominant player. This is likely to harm consumers through higher prices, reduced choice or less innovation.

To the extent that industrial diversification is initially mainly pursued through M&A, and that increased industrial diversification reduces the efficiency and economic performance of the merged entities (for instance, due to less innovation because divisional managers have lower incentives to engage in risky activities, and increased power and prestige through compensation arrangements), consumers may be harmed by reduced product choice and/or quality and eventually higher prices (with less efficient firms being forced at some point to increase their prices to compensate for the higher marginal costs resulting from these efficiency losses). Furthermore, as these effects may take some time to appear (dynamic efficiency - in this case - losses), they could affect the immediate decisions of the competitive authorities which would not take them into account, but rather base their decisions on the short term visible static efficiency gains of M&As.

From the firms view point, our results imply that industrial diversification has a cost that is likely to be magnified when the levels of diversification are high and marginal benefits of diversification strategies are low. Hence, managerial practices should rely on coherent product and technology portfolios[103].

As increased globalization appears to have beneficial effects on large European R&D companies, this advocates increasing support for international S&T collaborations and partnerships, and supports one of the recommendations proposed in the Innovation Union Communication: "The European Union's scientific cooperation with third countries must become a matter of common concern and contribute to the establishment of a level playing field (removing market access barriers, facilitating standardization, IPR protection, access to procurement, etc). By 2011, the Commission will propose common EU/Member States S&T priorities as a basis for coordinated positions or joint initiatives vis-à-vis third countries, building on the work of the strategic forum for international cooperation. In the meantime, the EU and Member States should act in a concerted way when engaging in national (regional or local) S&T agreements and activities with third countries. The potential of 'umbrella' agreements between the EU and Member States with third countries will be explored."

[103] See Leten, Belderbos and Van Looy (2007).

An interesting extension of the work regarding industrial diversification may be to investigate the characteristics of the industries the MNEs are active in. We do not have information about the R&D activities conducted by the subsidiaries, but the industrial classification of the subsidiaries may give a clue about their role in the group. This approach would also be helpful in analysing the relationship between the strategies of vertical integration and the productivity of the firms.

This chapter considered three major regions of EU MNEs' activities, i.e. EU, North America and Asian-Pacific regions. However, R&D and productivities of MNEs are closely related with the purposes of their global diversification. It would be interesting to investigate what would happen to the results if the purpose difference were taking into consideration. One way to address this question could be to enrich the empirical framework by directly estimating an equation linking the geographic diversification measure with the motives for doing so[104]. This equation could then be estimated jointly with the productivity performance equation in a simultaneous equations framework which would allow for controlling for the possible endogeneity between the motives for diversifying and the resulting performance[105.]

To better understand the activities of European MNEs outside Europe, it may be worth having a closer look at the industrial diversification or concentration strategies in North America and Asia Pacific, and their impact on R&D productivity. Moreover, one could investigate the efficiency in these regions of the Home-Based Augmenting and Home-Based Exploiting R&D strategies for EU MNEs.

[104] There is a huge literature dealing with these motives. See Cincera et al. (2010) for a recent review and discussion.
[105] A similar equation could also be estimated for the industrial diversification.

Chapter 5 - R&D Internationalization of EU MNEs and inventor location

SUMMARY

The main question of this chapter is whether the R&D activities that are conducted outside Europe still benefit to European growth. If so, how does the regional location of R&D centers matter in the production process of EU MNEs? The analysis is conducted on the basis of a unique sample of 637 European R&D leaders with information that is consolidated with respect to about 8000 worldwide patenting subsidiaries. The assessment of R&D internationalization is proxied by the regional repartition of the inventors of each firm. Hence, it is assumed that the location of the inventors reveals to some extent the location of the R&D subsidiaries of the MNEs. The empirical findings suggest that R&D located in Europe yields significant economic results, but a reallocation of R&D located in Europe instead of outside Europe seems to be correlated with lower R&D performances in high-tech sectors, but not in lower-tech industries. Conversely, a larger share of R&D located in the US seems to improve the economic performance of R&D activities within high-tech EU MNEs while the effect is negative for lower-tech companies. Nevertheless, the economic performance of R&D centers in Europe and US is jointly positive and significant for both regions.

5.1 Introduction[106]

In the current era of increasing globalization, demographic revolutions, climate change, crisis recovery and anxiety of sovereign debt insolvency, the world is evolving at exponential speed. Adapting to these evolving trends is for Europe a crucial factor to protect its economical competitiveness and its position as one of the world powers. In order to answer these upcoming challenges in a sustainable way, the European Member States recently adopted the European Union (EU) 2020 Strategy placing innovation at its heart. According to the European Innovation Scoreboard (2009) the current state of innovation in Europe is worse than its main historical competitors, namely the United States of America (US) and Japan. However, European innovation indicators remain superior to the ones of emerging countries such as Brazil, Russia, India and China (BRIC). Initially set in March 2002 for the horizon 2010, the European objective of investing 3% of Gross Domestic Product (GDP) in Research and Development (R&D) had to be postponed to the horizon 2020. Consequently, the EU 2020 strategy's flagship that fosters an "Innovation Union", aiming a sharp growth of R&D expenditure, seems adequate to lead the European economy towards its future.

Nowadays most of the R&D in the world is performed by Multinational enterprises (MNEs). The top 1000 EU and the top 1000 non-EU R&D spenders represent together about 80% of worldwide business enterprise expenditures on R&D[107]. The OECD forum of March 2005 recognized internationalization of R&D as a complex while fundamental feature of globalization, significantly impacting economic development and public policy (OECD, 2005). Since the mid 90s, R&D internationalization extended outside of the Triad (i.e. the US, the EU and Japan), spreading to new global players such as the BRIC countries (OECD, 2008). In these conditions, European MNEs have R&D affiliates branched out across the globe. However, the contribution of the different R&D centers to the output of the parent company varies.

The main question of this chapter is whether the R&D activities that are conducted outside Europe still benefit to European growth. If so, how does the regional location of R&D centers

[106] The research on the inventors is an extension of the work on the subsidiaries that was realized jointly with Stephane Jeegers and supervised by Michele Cincera. We also gratefully acknowledge Carine Peeters for her comments.

[107] MEMO/11/705 of the 2011 EU Industrial R&D Investment Scoreboard.

matter in the production process of EU MNEs? This chapter provides estimations of the elasticity of output to R&D capital considering the geographical location of the R&D subsidiaries of EU MNEs. To our knowledge, very few studies have analyzed R&D internationalization through the lense of the inventor location[108] and our analysis aims at contributing to a better understanding of international R&D activities of EU MNEs.

Our results have important implications in terms of European S&T policies. As the role of R&D internationalization is highly relevant in the microeconomic process that yields economic performance, comprehensive EU priorities and strategies should integrate the international dimension of R&D in order to address the challenges related to the globalization of EU MNEs.

To measure those contributions, we use microeconomic data from the EU Industrial R&D Investment Scoreboards, which are yearly published. These reports gather data such as sales or R&D investment for the top 1000 European largest R&D spending companies. The accounts are consolidated by the parent company. However, the Scoreboards do not provide information about the repartition of R&D accross subsidiaries. Hence, considering that most of these companies are MNEs with foreign R&D affiliates, the R&D Scoreboards reports do not disclose pertinent indicators to assess the R&D internationalization. As a consequence, a subsequent objective of our analysis is to pertinently link the share of R&D internationalization for each of these European MNEs with their respective consolidated data found in the R&D scoreboards. In order to achieve this objective, a unique and original dataset has been created, which assesses R&D internationalization through the geographical repartition of the inventors that contributed to the patents of the companies.

Matching procedures are used in order to identify the inventors of the firms reported in the R&D Scoreboard. First, 635 EU R&D leaders were related to about 8000 worldwide patenting subsidiaries. Second, the patenting subsidiaries were linked to their respective patent information for the period 2000-2008. Third, the assessment of MNEs' R&D internationalization considers the geographical repartition of the inventors based on their country of residence. As a result, the final database gathers consolidated data from the EU R&D Scoreboards' firms with the proxy of their respective R&D internationalization.

[108] See the recent work by Harhoff and Thoma (2010) and the survey by Hall (2011).

Based on extended forms of the traditional Cobb-Douglas production function, two specifications are used in order to investigate the role of the location of R&D centers in the performance of R&D activities. These specifications are based on a complementary and a substitution effect between the R&D centers. The results highlight the differences in R&D productivity between technological clusters, i.e. high-, medium- and low-tech sectors.

This chapter is structured as follows. Section 5.2 reviews the literature related to the internationalization perspective of R&D. Section 5.3 presents the empirical framework and the construction of the dataset. Section 5.4 reports and discusses the estimates. Finally, the last section concludes the chapter and sums up the main findings.

5.2 R&D internationalization

On the international perspective of R&D, literature refers to Dunning and Narula (1995) and Kuemmerle (1997) regarding the theoretical background. Coe and Helpman (1995) provide theoretical clues about the contribution of foreign R&D capital to a country's total factor productivity. These authors also provide empirical results emphasizing the existence of R&D international spillovers, based on a proxy of national effective stock of knowledge. R&D, and especially its internationalization, represents a quite modern topic. During the 60s and the 70s, a desire to centralize R&D in companies' home laboratories was observed (OECD, 2008). This geographical proximity between companies' headquarters and R&D laboratories was driven by firms' willingness to keep strategic decisions closely related to R&D facilities (Kuemmerle 1997). However, since 1980, it became obvious that a growing share of R&D was internationalized. This trend accelerated during the 90s and partly reflects the globalization of MNEs in developed economies. The spreading of MNEs R&D activities internationally began as a result of mergers and acquisitions rather than using foreign direct investments (FDIs) to build laboratories abroad (UNCTAD 2005).

Table 34 shows the geographical repartition of the 700 largest R&D spending firms in 2003 and 2009. This repartition illustrates the domination of R&D by companies that are home-based in the Triad. By observing the changes between 2003 and 2009, it can be seen that this domination is slightly decreasing with the emergence of MNEs from the rest of the world. Table 35 reports the repartition of the R&D based on the EU Industrial R&D Investment Scoreboard (2010). Europe and US companies account for almost two third of worldwide R&D. Germany is the top R&D spender in Europe and the European company that does the most R&D is Volkswagen, which is a German group. France and UK are the second and third European countries in the R&D ranking, with the leading companies in these countries being Sanofi-Aventis and Glaxosmithkline, which are respectively French and UK pharmaceutical groups.

Table 34. Largest R&D spenders in 2003 and 2009

	Top **700** R&D Spenders			
Year	2003		2009	
	%	Number of Companies	%	Number of Companies
US	42,3%	296	32,4%	227
Japan	22,0%	154	21,0%	147
Europe	26,7%	187	30,6%	214
Switzerland	2,9%	20	3,0%	21
South Korea	1,4%	10	2,3%	16
Taiwan	1,1%	8	2,9%	20
Rest of the world	3,6%	25	7,9%	55
Total	100%	700	100%	700

Sources: UNCTAD (2005) and EU Industrial R&D Investment Scoreboard (2010).

Table 35. R&D in the world (2009)

Countries	% of total €422.2bn	Number of Companies	% of total €422.2bn
US	34.3%	**Germany**	10.7%
Japan	22.0%	**France**	5.9%
Europe	30.6%	**UK**	4.5%
Switzerland	4.4%	**The Netherlands**	2.3%
South Korea	2.6%	**Sweden**	1.5%
Taiwan	1.4%	**Finland**	1.5%
China	1.3%	**Italy**	1.5%
Rest of the World	3.4%	**Denmark**	0.8%
		Other EU	2%

Source: EU Industrial R&D Investment Scoreboard (2010)

MNEs are key players in R&D and perform the majority of the R&D activities in the world. The top 1000 EU and the top 1000 non-EU R&D spenders represent together more than 80% of worldwide business enterprise expenditures on R&D[109]. The companies leading R&D internationalization are mostly from the Triad and their internationalization was mainly an intra-Triad phenomenon before being recently extended to R&D facilities in the rest of the world[110].

The current trend towards a more global expansion of R&D affects the nature of its internationalization. Between 1996 and 2002, the share of foreign business R&D affiliates significantly grew in developed countries from 11% to 16% and, at the same time, this ratio dramatically increased from 2% to 18% in developing countries (UNCTAD, 2005). In 1994, R&D spending performed by foreign affiliates represented 12% of total OECD industrial R&D spending, which was mainly[111] undertaken by only 15 OECD countries[112]. In 1993, foreign affiliates spent 10% ($29 billion) of global business R&D[113]. In 2002, this part of the

[109] MEMO/11/705 of the 2011 EU Industrial R&D Investment Scoreboard.
[110] OECD (2005).
[111] 95% of OECD total industrial R&D.
[112] Australia, Canada, France, Finland, Germany, Greece, Ireland, Japan, the Netherlands, Poland, Spain, Sweden, Turkey, the United Kingdom and the United States (OECD, 1998)
[113] UNCTAD(2005).

worldwide R&D spending was estimated to be around 16% ($67 billion) of global business R&D expenditures.

Drivers of R&D internationalization

Drivers of R&D internationalization result from conditions and interactions existing at different levels: country, industry and firm levels. Nevertheless, the final choice of locating R&D home or abroad arises from companies' strategies[114].

At the country level, the national or local environment and policies affect the location strategies of R&D centers. Moreover, current regional endowments and potential for growth have huge impacts on R&D location. The countries' income characteristics indirectly affect factors such as the level of foreign direct investments, the market size and the market growth potential, which are recognized as being R&D drivers (Dachs et al., 2010)[115]. The difference in labor costs between home and host countries can be another factor of R&D location, though empirical evidence is weak in comparison with other factors. Nevertheless, it still has an impact, especially for the location in emerging countries (Cincera et al., 2010). In addition, the proximity of countries, a similar technology specialization and the sharing of a common language increase collaboration and cross-border R&D investments (Guellec and van Pottelsberghe, 2001). Finally, government actions and the regional public policies clearly impact the attractiveness of R&D location (UNCTAD, 2005; OECD, 2008).

At the sector level, inherent differences between industries directly affect the degree of R&D internationalization. Specific sectoral characteristics, such as R&D intensity, foreign market openness (relations with foreign markets for supply, sales, universities) or foreign direct investment levels and technological intensity, imply different levels of R&D internationalization. The latter phenomenon will be mostly present in knowledge-intensive and R&D intensive sectors[116]. R&D intensive sectors[117] will have by definition a higher share of R&D abroad (UNCTAD 2005). According to Cohen (2010), current demand and demand expectation, technological opportunity and protection of innovation are the leading drivers of sector-wide innovation. Knowledge related characteristics are determinant factors[118] to

[114] Dachs et al. (2010).
[115] See Ekholm and Midelfart (2004), Blonigen (2005) and Jensen (2006) for foreign direct investments and Cohen (1995) for market size and market growth.
[116] Dachs et al. (2010).
[117] See for instance the classification used in Ortega-Argiles and al. (2009) based on ICB codes.
[118] Dachs et al (2010).

internationalize R&D, especially knowledge appropriability, tacitness and cumulativeness[119]. At the sectoral level, these factors seem to play a large role in the location decision process. This role can be positive or negative depending on industry specificities. According to Blomstrom and Kokko (2003), knowledge and foreign technology spillovers are the main reason for a country to attract inward FDIs. To some extent, industry's network relations with suppliers, clients and universities can affect the location of their R&D (Marsili, 2001).

At the firm level, a firm's decision to locate its R&D abroad is closely related with its strategy and its own capabilities. This choice will mainly depend on a trade-off between potential advantages and drawbacks of home versus foreign R&D location. Furthermore, the size of the company and its experience matter (Dachs et al. 2010). Indeed, large firms, i.e. MNEs, will tend to invest much more in R&D and have a broader international perspective of their business than local SMEs. The concept of experience encompasses the general capabilities and internal knowledge that enables a company to benefit from external knowledge. It refers to both its past export experience and its relations with foreign markets. Consequently, these two features of a firm's experience as well as the size of the firm allow exploiting FDIs and positively affecting their internationalization potential.

Aside from firm's characteristics, Kuemmerle (1997) and Dunning and Narula (1995) stress the existence of two main drivers of the company's decision to internationalize their R&D activities. The first benefit for a company to locate its R&D abroad is to tap into the host country's local knowledge. In this home-based augmenting (HBA) or asset-seeking motive approach, firms locate a R&D subsidiary abroad to access local technological assets and to absorb foreign local knowledge through interactions with scientific excellence of the local community. As a result, HBA sites will tend to be located in regional knowledge clusters in order to maximize their knowledge spillover absorption potential, thus setting aside the need to be located near production facilities or the final market. This supply side approach allows the company to better monitor or gain competitive advantages. In this framework, the knowledge transfer direction is from abroad towards home. The second benefit is the potential for better adapting companies' products to the foreign demand. This home-based exploiting (HBE) or asset-exploiting approach supports companies' foreign activities by focusing the R&D activities on the demand side, market access and cost considerations such as adaptation to local demand, "taylorization" of local production, exploitation of foreign immobile input

[119] See for each factor respectively Cohen (2010), Cowan and al. (2000) and Marsili (2001).

for research or R&D rationalization based on efficiency-seeking production. Within this context, HBE sites will tend to be located close to manufacturing plants or commercializing facilities. As opposed to HBA, HBE strategies rather direct technology and knowledge flows from home to abroad. Dunning and Narula (1995) point out that even if the asset-exploiting strategies or HBE R&D represent the majority of R&D internationalization by MNEs, the asset-seeking motive or HBA has grown the most rapidly since 1980.

Patel and Vega (1999) identify four possible MNEs strategies for FDI in R&D based on home and host country technological profiles. The authors suggest that the location for foreign technological activities of MNEs happens in their core areas where they are strong at home. This is mainly done according to the following strategies: "learning-oriented" FDI in R&D (myopic learning) and "efficiency-oriented" FDI in R&D (dynamic learning) corresponding respectively to HBA and HBE. Their results underline the importance of both strategies and illustrate differences across industries[120]. Le Bas and Sierra (2002), using the same classification and methodology, confirm the strong predominance of HBE and HBA strategies. However, their results[121] suggest that HBA strategies prevail. According to OECD (2005), both home base augmenting (i.e. supply related motives) and home base exploiting (i.e. demand related motives) incentives coexist while technology-sourcing motives (HBA) are rising.

Impacts of R&D on host and home country

This section summarizes the arguments of OECD (2005), UNCTAD (2005) and Dachs et al. (2010) and introduces the underlying impacts of innovation activities of foreign-owned company on host and home countries.

For the host country, the location of foreign-owned R&D facilities increases its aggregate innovation expenditure and its technological capability. Foreign affiliates increase the general amount of FDI and may facilitate access to international financing sources. However, threats arise for domestic companies from stronger innovation competition by the market entrance of foreign R&D subsidiaries. The main concern of the presence of foreign R&D activities is the loss of control over domestic innovative capacity and R&D actors. The R&D strategy of

[120] According to the authors, HBA strategies tend to be prevalent in chemicals, pharmaceuticals, mining, food and materials while metal and electronics industries exploit HBE strategy relatively more.
[121] Le Bas and Sierra (2002) use a dataset of European MNEs while Patel and Vega (1999) analyze US MNEs.

foreign MNEs may change the nature of R&D leading to less radical innovation and may not comply with national interest or may only search for rents.

Concurrently, as already stressed in this section, the location of innovation facilities abroad that tap into knowledge centers – HBA – may benefit the host country by increasing technology intensity and specific knowledge diffusion levels to local stakeholders[122] through local collaboration and non-compensated spillovers. These centers of knowledge can create virtuous circles of clustering leading to high agglomeration effects that boost the regional economy. Such effects can slightly decrease when production facilities are separated from R&D or when HBE strategies set up low intensity R&D affiliates. Beyond the creation of skilled jobs for the local economy, the establishment of R&D facilities may increase the average level of competences of the host country's labor market and potentially lead to more competition for skilled labor.

The home country is indirectly subject to the internalization process of its MNEs. Indeed, the decision to locate R&D subsidiaries abroad is strategically taken by the MNEs in order to gain substantial benefits from this internationalization and to strengthen their R&D and global competitiveness. Hence, the effects on the home country are indirect public effects and often difficult to control. Based on increasing HBA strategies, one of the main reasons for R&D internationalization is the access to foreign knowledge. Therefore the home country can expect to benefit from reverse technological transfer. On the other hand, technological diffusion can lead to key technology leakages as well as skilled workers exports, which represent potential threats for the home country. MNEs tend to internationalize non-core R&D, implying that domestic R&D can focus on further added-value activities at home. Although in some cases, home net R&D exporters can see foreign R&D activities as a substitute to domestic ones, resulting this time in losses for the home country. Following HBE motives, foreign R&D affiliates may expand the market scope for domestic inputs, enhancing domestic product exportation, while foreign input price differences can annihilate or reverse this effect.

The capitalization on potential benefits and undergoing potential costs will mainly depend on the country's absorptive capacity, the integration of foreign affiliates and networking. To maximize R&D globalization benefits, a country continuously needs to boost its innovative

[122] For example: companies' customers, clients, competitors and surrounding universities.

capacity and attraction towards MNEs as well as skilled workers both domestically and internationally.

Given the literature, they are many channels through which the internationalization of R&D may contribute to the economic performance of MNEs. The question that we investigate is whether R&D internationalization (in particular R&D located outside Europe) is an efficient and significant driver of the economic performance of EU MNEs. If so, how does the regional location of R&D centers matter in the production process of EU MNEs?

5.3 Empirical framework and data

5.3.1 Empirical framework

The increasing availability of data allows researchers to apply theoretical frameworks with various econometric methods to estimate the impact of R&D expenditure on companies' production. Hall et al. (2010) survey a literature of almost 50 years and summarize the most important econometric findings of the returns to R&D[123]. The authors gathered estimations of elasticity, existing spillovers, private and social rate of return of R&D at firm and industry levels. In their review of various studies[124] made on firm-level datasets, the overall average elasticity of output with respect to R&D is estimated to be between 0.01 and 0.25 depending on the data and the measurement methods. The authors estimate results of industry-level datasets to be in the same range and close to firm-level empirical findings. Moreover, Hall et al. (2010) confirm a strong positive R&D rate of return in developed economies. They evaluate these rates to average in the ranges of 20% to 30%, with an increase up to 75% in some cases. At the industry level, Ortega-Argiles et al. (2009) estimate the elasticity of knowledge stocks on productivity to be around 0.125 in average, ranging between 0.07 for low-tech to 0.17 in high-tech sectors.

Similarly to the analysis conducted in chapter 4, we will analyze the role of R&D internationalization in the production process based on a Cobb-Douglas functional form for the production function.

[123] The authors follow selection criteria including accessibility to publication, methodologies and familiarity with the work in question.
[124] Based on 21 pooled estimations and 23 temporal estimations (Cf. Hall and al. (2010) - Table 2a & Table 2b).

A general Cobb-Douglas production function[125] is assumed,

$$Y = AL^{\alpha} C^{\beta} K^{\gamma} e^{\varepsilon} \tag{5.1}$$

where L, C, K represent production factors, respectively labor, physical capital and knowledge (R&D) capital. The Cobb-Douglas function can be transformed into logarithm to linearize the function. Adding fixed effects for country and industry and time dummies leads to the following linear function:

$$\log(Y_{it}) = \lambda + \alpha \log(L_{it}) + \beta \log(C_{it}) + \gamma \log(K_{it}) + country_i + industry_i + \phi_t + \varepsilon_{it} \tag{5.2}$$

In this framework, the output elasticity of R&D capital is:

$$\frac{d \log(Y)}{d \log(K)} = \gamma$$

The stocks of R&D and physical capital were constructed by using the perpetual inventory method[126] (Griliches, 1979). For each firm, the stock of capital at time t is defined by:

$$ST_t = (1-\delta) ST_{t-1} + Inv_t$$

where δ is the depreciation rate of the capital and *Inv* is the amount of investment (R&D expenditures for R&D stock, or capital expenditures for physical capital stock). The depreciation rates were set to 0.15 for R&D and 0.08 for physical capital, which are the rates that are usually assumed in the literature[127]. The initial value of the stock can be computed by using the following expression:

$$ST_0 = \frac{Inv_0}{g + \delta}$$

where g is the growth rate of investment and is assumed to be constant. Analogously to chapter 4, the growth rate used for R&D stock is the average sample growth rate for R&D expenditure, i.e. 7.5%. The growth rate for physical capital is the average sample growth rate for capital expenditure, i.e. 11.5%.

[125] See section 4.3.1 for a discussion about the use of a Cobb-Douglas form.
[126] See section 2.3.1 for a discussion about this method.
[127] See for instance Hall and Mairesse (1995) or Capron and Cincera (1998).

Concerning the inventor location, two specifications are tested. Specification 1 assumes that the geographical location disparity of the inventors affects the knowledge capital coefficient through an additive term Z_j representing the share of inventors in region j. This specification investigates the reallocation of R&D centers in region j instead of other regions, i.e. a substitution effect of conducting research in region j instead of in other regions.

$$Y = AL^{\alpha}C^{\beta}K^{\gamma_0+\gamma_1 Z_j}e^{\gamma_2 Z_j}e^{\varepsilon}$$

Using logarithm and adding individual fixed effects for country, industry and time transforms equation 5.2 into the following linear function:

$$\begin{aligned}\log(Y_{it}) &= \lambda + \alpha\log(L_{it}) + \beta\log(C_{it}) + \gamma_0\log(K_{it}) + \gamma_1 Z_{ij}\log(K_{it}) + \gamma_2 Z_{ij} \\ &+ country_i + industry_i + \phi_t + \varepsilon_{it}\end{aligned} \tag{5.3}$$

In this specification, the elasticity of output to R&D is

$$\frac{d\log(Y)}{d\log(K)} = \gamma_0 + \gamma_1 Z_j$$

Specification 2 decomposes the coefficient of the knowledge capital variable into the sum of the geographical repartition of the inventors[128] as follows:

$$Y = AL^{\alpha}C^{\beta}K^{\sum_j \gamma_j Z_j}e^{\varepsilon}$$

This expression considers a complementary approach of the R&D centers that jointly contribute to the performance of R&D. Expressing equation 5.2 in a linear form through logarithm leads to the following function:

$$\begin{aligned}\log(Y_{it}) &= \lambda + \alpha\log(L_{it}) + \beta\log(C_{it}) + \sum_j \gamma_j Z_{ij}\log(K_{it}) \\ &+ country_i + industry_i + \phi_t + \varepsilon_{it}\end{aligned} \tag{5.4}$$

In this second specification, the elasticity of output to R&D is

$$\frac{d\log(Y)}{d\log(K)} = \sum_j \gamma_j Z_j \,.$$

[128] With $\sum_j Z_j = 1$.

5.3.2 Data

This chapter focuses on the top European R&D MNEs. The database gathers 637 of the top 1000 largest EU R&D spenders relating each of them to specific patent information.

Data sources

The inventor location will be used to assess the internationalization of R&D activities. The empirical study mainly uses information from many different sources previously gathered in three different databases. The first one is the database used by Cincera and Ravet (2011), which is the database presented in chapter 4. The second database results from data collection by Thoma et al. (2010). The third database is Espace Bulletin, which is published by the European Patent Office (EPO) and gathers information on patent applications.

The starting point of Cincera and Ravet (2011) database is a matching between two databases. The objective of the authors was to retrieve the subsidiaries of the largest R&D MNEs in Europe. On the one hand they used the available EU industrial R&D investment scoreboards[129] that yearly report the top 1000 R&D European MNEs. On the other hand they used the Amadeus[130] database that reports financial data of 14 million EU companies. They matched both manually to find the corresponding subsidiaries of European companies present in the 2009 R&D scoreboard. As a result, their database gathers data[131] of 835 companies[132] of the EU R&D Scoreboard related to about 44000 subsidiaries. Their dataset covers the 2000-2008 period. The production output[133] (Y), the number of employees (L), the capital expenditures and the R&D expenditures have been directly extracted from the EU Scoreboards. The authors checked that the resulting data corresponded to a consolidation of firm subsidiaries' information (extracted from Amadeus database[134]) which also confirmed their matching with the subsidiaries.

The internationalization of R&D is investigated by creating an original dataset that is based on the dataset of Cincera and Ravet (2011). The idea is to retrieve information on the patents

[129] Annually published by the JRC-IPTS of the European Commission.
[130] Published by Bureau van Dijk.
[131] Datasets include: R&D, net sales, employees, capital expenditures, country, industry (ICB) and subsidiaries information (number, turnover, employees, localization, industry).
[132] "55 companies could not find a correspondence in Amadeus and 110 were not kept because of unconsolidated account or doubts about the matching procedure".
[133] The output is measured by the company sales reported in the R&D Scoreboards.
[134] The authors used Amadeus September 2009 version.

of the 835 MNEs and their 43,966 subsidiaries, and more precisely on the location of the inventors that contributed to the patents. Through the subsidiaries names that were collected, their database allows one to have a consolidated list at the MNE level of potential names for patent applications.

The 835 EU firms of Cincera and Ravet (2011) and their 43,966 subsidiaries can be identified by their BvD id[135], which is an identification number based on the VAT of the companies. In order to relate these companies to their patents, the database created by Thoma et al. (2010) was used. The authors propose a list of 131,000 applicant names, covering 58,8% of the EPO applications between 1979 and 2008. Our interest in their database resides in the work done on the identification of the applicants by assigning them a BvD id. Furthermore, the authors related each applicant to their granted patents and identification number at the EPO, which allows linking the firms in Cincera and Ravet (2011) to their patents. The third database, Espace Bulletin, lists information relative to all patent applications at the EPO since 1978. Information on inventor location was eventually extracted from Espace Bulletin.

Matching Process

Based on the three sources, the matching process consists mainly in coupling data throughout "key" variables available in the databases. Table 36 lists the main variables of each of the three databases:

Table 36. Main variables of the databases

Cincera and Ravet (2011)	Thoma and al. (2010)	EPO
Firm data	Firm and patent data	Patent data
R&D, sales, employees, industry (ICB), capital expenditures, **BvDid** of the firms + subsidiaries	**BvDid**, **patent publication number**	Applicant name, country, application date, **publication number**, inventors' country of residence

Source: own illustration.

The matching between the databases of Thoma and al. (2010) and Cincera and Ravet (2011) was performed in two steps. First, using a direct matching of the BvD identification numbers, the subsidiaries and headquarters of 576 out of the 835 firms in Cincera and Ravet (2011)

[135] Bureau Van Dijk's Amadeus company code.

were found. Second, a manual check of the remaining companies resulted in 61 additional matched companies based. Table 37 illustrates the manual matching process.

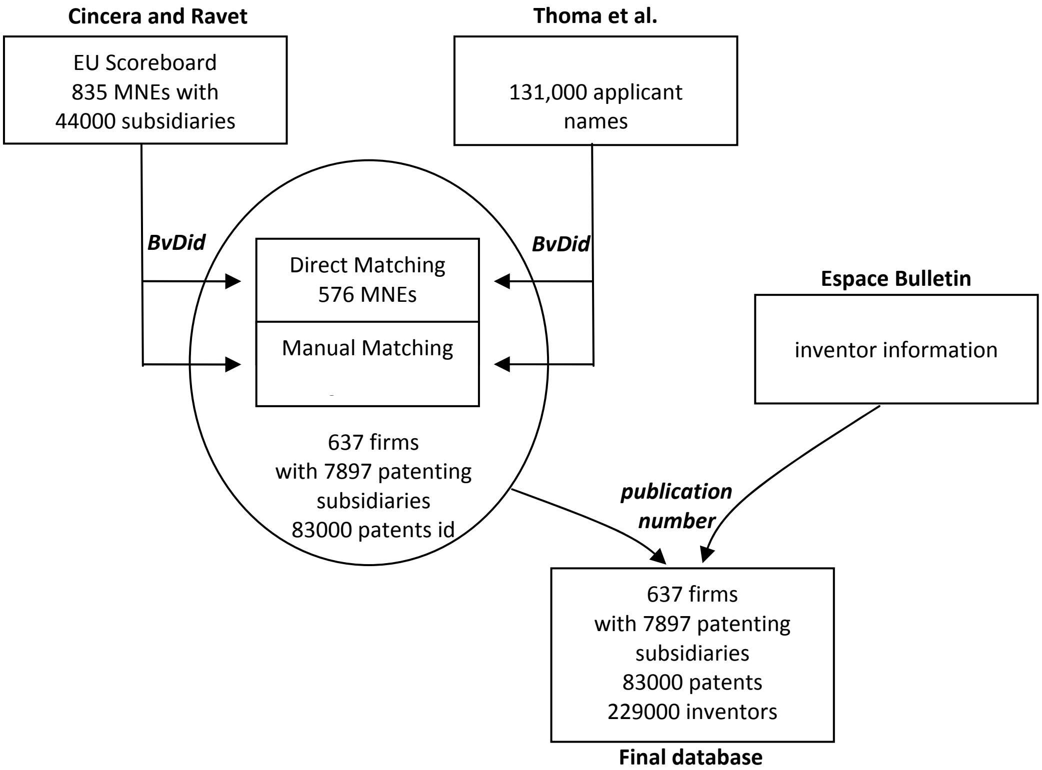
Table 37. Example of manual matching

Matching type	Source	
	Thoma and al. (2010)	Cincera and Ravet (2011)
Manual	Shell International Research Maatschappij	Royal Dutch Shell
	Behr Thermot Tronik Italia	Behr
	Reckitt Benckiser Healthcare	Reckitt Benckiser

Source: own illustration.

The final sample gathers 637 EU R&D Scoreboard companies out of the 835 of Cincera and Ravet (2011). These 637 firms and their subsidiaries were linked to around 83000 EPO granted patents with application dates within the considered period (2000-2008). As a main achievement of this first matching step, each one of the 637 firms is now related to the patents that were filed by themselves or their subsidiaries. Out of the 28575 subsidiaries of the 637 firms, 7897 subsidiaries are reported as having filed a patent at the EPO (patenting subsidiaries). The patent application number is the key variable for a direct matching between Espace Bulletin and the first matched dataset. This second matching procedure connects the patents identification numbers of Cincera and Ravet (2011) to more detailed information on the patents included in Espace Bulletin. The patents of the 637 EU MNEs were eventually related to about 229,621 inventors who contributed to these patents. Figure 9 illustrates the matching process.

Figure 9. Mapping of the matching process



Source: Own illustration

Inventor location

The location of the inventors is investigated through the patent information supplied by Espace Bulletin, which contains the country of residence of the inventors. The assumption made here is that the geographical repartition of the inventors over the considered period is a proxy of the internationalization of the R&D of each company. Indeed, the repartition of inventors across regions is likely to correspond to the geographical repartition of the R&D centers used to develop this patent. This idea is similar to recent work by Harhoff and Thoma (2010) who investigate the inventor location of EU and US firms. The authors find a strong correlation between R&D and inventors and stress the significant contribution of foreign-located inventors to productivity growth and market value.

Variables for R&D internationalization are constructed for each firm based on the repartition of the inventors across regions as the ratio of its regional inventors on its total number of inventors, expressed in percentage. For instance the inventors' repartition ratio of the company *i* in region *j* can be expressed as

$$Z_{ij} = \frac{\sum_{k}^{K_i} inventors_{ijk}}{Total\ inventors_i},$$

where K_i is the number of patents granted to firm *i* and $inventors_{ijk}$ represents company *i's* number of inventors who contributed to patent *k* while residing in region *j*. Naturally, for each firm *i*, $\sum_j Z_{ij} = 1$. The regional clusters are based on the paper of Cincera and al. (2010). The authors split the world into 7 regions that are: Europe[136], United States & Canada, China, India, Japan, other European countries[137] and the rest of the world.

Table 38 illustrates the R&D internationalization of EU MNEs by host country[138]. The average share of inventors located in Germany is 27.24% and is the largest in our sample, followed by inventors located in United Kingdom (16.32%) and France (14.5%). US-Canada is the first foreign region where inventors of European MNEs are located with a share of 4.7% of the inventors. While European industries tend to have most of their inventors located in Europe, disparities between industries exist without any intra-technological class trends. On the whole, the repartition of inventors in our sample suggests a high concentration of inventors (about 90%) located in Europe. This representation of European inventors is higher than in Harhoff and Thoma (2010), who use PCT applications and EPO applications of about 1500 EU business groups. While the European share of inventors seems to be inflated by the exclusive use of EPO granted patents, this inflation effect is not expected to vary across firms and the distribution of inventors outside Europe may still illustrate the distribution of foreign R&D centers. On top of the geographical regions reported in Table 38, three additional regions are considered. The region "Non EU27-USC" sums the repartition of inventors outside the two most represented regions: EU27 and United States-Canada. This region aggregates potential trends of internationalization outside the European Union and North America[139], some of which could not be shown with individual regions due to small inventors' counts. The regions "Same country" and "Other EU27" are complementary, the former representing the ratio of inventors resident in the country of the firm's headquarter and

[136] Europe means here the 27 countries of the European Union
[137] Countries under the "EU non 27" label are: Albania, Belarus, Croatia, Iceland, Liechtenstein, Monaco, Norway, Russia, Serbia and Montenegro, Switzerland, Turkey and Ukraine.
[138] See Appendix 8 for the repartition by industry.
[139] United States and Canada, "USC".

the latter denoting the ratio of inventors in the European Union while outside the firm's headquarter country.

Table 38. Sample 637 EU firms: Average regional repartition of patent inventors

EU15	Germany	27.24%
	United Kingdom	16.32%
	France	14.50%
	Sweden	7.60%
	Italy	6.69%
	Finland	5.03%
	Netherlands	4.30%
	Denmark	3.38%
	Belgium	2.56%
	Spain	2.55%
	Ireland	0.65%
	Austria	0.54%
	Portugal	0.34%
	Luxembourg	0.13%
	Greece	0.02%
EU27 (not EU15)	Hungary	0.41%
	Czech Republic	0.06%
	Slovenia	0.04%
	Latvia	0.04%
	Poland	0.03%
	Estonia	0.03%
	Bulgaria	0.01%
	Slovakia	0.00%
	Cyprus	0.00%
	Lettonia	0.00%
EU non27		1.79%
USC		4.72%
Japan		0.45%
China		0.02%
India		0.02%
ROW		0.54%

Source: Own computation.

The sample of the 637 selected EU R&D Scoreboard MNEs gathers available data covering the 2000-2008 period. Some of these firm data[140] is missing for some years for certain firms. These data cover in average five years per firm. The regional repartition of patent's inventors

[140] Sales, physical capital, R&D capital, employees and investment.

is available for each of these 637 companies. To limit excessive R&D values compared to sales, the sample excludes R&D intensity (i.e. the ratio R&D/Sales) superior to one. The final sample contains 4165 observations, the physical capital being the variable with the least observations. Out of these 4165 observations, 3492 include information for all variables[141]. Some descriptive statistics of the sample's main variables are presented in Table 39.

Table 39. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log(*Y*)	4165	6,96	2,07	0,45	12,71
Log(*L*)	4140	8,55	1,91	2,94	13,17
Log(*C*)	3507	6,03	2,27	-0,67	11,71
Log(*K*)	4164	5,08	1,73	-1,22	10,42
RD/Y	4165	0,07	0,12	0	0,99
Total inventors	4165	451,08	1790,34	1	25182
% EU27	4165	0,92200	0,17242	0	1
% USA-Canada	4165	0,04684	0,13703	0	1
% China	4165	0,00024	0,00171	0	0,027
% India	4165	0,00022	0,00203	0	0,028
% Japan	4165	0,00444	0,04666	0	1
% EU non 27	4165	0,02009	0,08071	0	0,870
% Rest of world	4165	0,00618	0,04061	0	0,667
% Non EU27-USC	4165	0,03116	0,10182	0	1
% Same country	4165	0,70924	0,33807	0	1
% Other EU27	4165	0,21276	0,30079	0	1

Sample : 637 EU R&D companies. Source: own computation.

Table 40 reports Top 20 available companies from the EU industrial R&D investment Scoreboard. Each firm is related to its total number of patents and the sum of their inventors in the dataset. The Scoreboard ranking is based on R&D investment in 2008.

[141] 657 observations are missing for physical capital and 25 for Labor. According to ICB code and Ortega-Argiles and al. (2009) classification, out of these 3492 observations, 1468 are in high-tech sectors, 1178 in medium-tech sectors and 846 in low-tech sectors.

Table 40. Top 20 Available EU R&D Scoreboard Companies: R&D Data

Scoreboard Rank	Firm	Number of patents	Number of inventors	R&D Investment (2008) €m	R&D Intensity 2008
1	Volkswagen	1406	3391	5926	5,2%
2	Nokia	1639	3540	5321	10,5%
4	Daimler	1522	4887	4442	4,6%
5	Robert Bosch	6018	16725	3916	8,7%
6	Siemens	7483	25182	3836	4,7%
7	GlaxoSmithKline	493	1823	3835	15,2%
8	AstraZeneca	599	1798	3622	15,9%
9	Alcatel-Lucent	1078	2429	3167	18,6%
10	Ericsson	1698	3694	2975	15,7%
11	BMW	1225	3023	2864	5,4%
12	EADS	962	2097	2756	6,4%
13	Bayer	2096	9242	2725	8,3%
14	Peugeot (PSA)	988	1567	2372	4,4%
15	Renault	682	1513	2235	6,1%
16	Boehringer Ingelheim	246	1094	2109	18,2%
17	Fiat	527	1000	1986	3,3%
18	Finmeccanica	121	239	1767	13,3%
19	SAP	64	149	1627	14,1%
20	Philips Electronics	3231	7084	1613	6,1%
21	STMicroelectronics	700	1486	1544	21,9%

Sample : 637 EU R&D companies. Source: own computation.

Table 41 provides some characteristics of the dataset by industry. The industry technological distinction has been done according to ICB code and Ortega-Argiles and al. (2009) classification. This table accentuates differences across industry especially in terms of propensity to patent and R&D intensity.

Table 41. Sample 637 EU firms: R&D Data by industry

Industry - ICB	# Firms	# Patents	# Inventors	R&D 2008 €m	R&D Intensity 2008
High-tech	**286**	**47316**	**124179**	**78625**	**7,12%**
Biotechnology	49	862	2747	1082	18,13%
Semiconductors	17	2902	6921	3235	16,89%
Pharmaceuticals	44	2806	10407	14369	15,90%
Telecommunications equipment	21	4560	9959	11951	13,16%
Software	25	184	393	2297	12,79%
Electronic office equipment	2	345	822	303	7,91%
Electronic equipment	25	1250	3125	911	7,09%
Leisure goods	6	3367	7346	1827	6,31%
Aerospace & defense	20	2928	6252	7420	5,92%
Computer hardware	5	78	157	76	4,77%
Automobiles & parts	37	19051	47524	29544	5,27%
Electrical components & equipment	24	8772	28086	5226	4,00%
Computer services	11	211	440	384	2,44%
Medium-tech	**206**	**24686**	**75031**	**19973**	**2,87%**
Health care equipment & services	26	1215	2993	1655	4,70%
Commercial vehicles & trucks	15	1017	2108	2356	3,66%
Chemicals	40	10432	39479	7064	3,16%
Alternative energy	3	51	140	256	3,14%
Industrial machinery	63	4497	9676	3232	2,71%
General industrials	18	1892	4475	1306	2,64%
Household goods & home construction	18	2285	6317	1308	2,38%
Media	4	813	1863	1042	2,77%
Food producers	19	2484	7980	1754	1,69%
Low-tech	**145**	**11892**	**30411**	**13304**	**0,50%**
Personal goods	12	1843	3782	871	1,59%
Fixed line telecommunications	10	2893	6417	4279	1,66%
Support services	12	536	1179	320	1,26%
Tobacco	2	79	198	151	1,10%
Internet	2	23	73	14	4,15%
Other financials	9	262	684	152	0,49%
Mobile telecommunications	3	46	103	324	0,75%
Oil equipment, services & distribution	4	170	334	91	0,73%
Electricity	13	688	1772	1418	0,58%
Construction & materials	22	851	1991	564	0,50%
Forestry & paper	6	111	261	235	0,47%
Mining	4	32	85	459	0,53%
Industrial metals & mining	12	814	2281	859	0,42%
Industrial transportation	7	1206	4935	347	0,32%
General retailers	5	255	758	194	0,32%
Oil & gas producers	7	1387	4032	2298	0,24%
Gas, water & multi utilities	6	605	1323	570	0,22%
Travel & leisure	4	64	140	55	0,07%
Beverages	4	13	29	88	0,19%
Food & drug retailers	1	14	34	15	0,05%
All	**637**	**83894**	**229621**	**111902**	**2,51%**

Sample : 637 EU R&D companies. Source: own computation.

5.4 Results

Estimates

The empirical results are presented separately for the two methods explained in the empirical framework (i.e. Specifications 1 and 2). A general investigation over the different results across both methods is undergone to gather the main trends and provide further clues of the impact of R&D internationalization on the R&D performance of EU MNEs.

The estimates of the non-augmented Cobb-Douglas function are shown in Table 42.

Table 42. Cobb-Douglas production function

Variables	**Industrial Technology Cluster**			
	All	**High**	**Medium**	**Low**
	(1)	**(2)**	**(3)**	**(4)**
Log(*L*)	.688(.016)***	.664 (.028)***	.671 (.025)***	.747 (.024)***
Log(*C*)	.223(.012)***	.157 (.021)***	.225 (.024)***	.273 (.019)***
Log(*K*)	.098 (.011)***	.196 (.020)***	.091 (.015)***	-.010 (.019)
Country dummies	Yes***	Yes***	Yes***	Yes***
Industry dummies	Yes***	Yes***	Yes***	Yes***
Time dummies	Yes***	Yes***	Yes***	Yes***
R-Squared	.959	.958	.949	.952
# Observations	3492	1468	1178	846

Dependent variable: log(*Y*). Sample of 637 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. Dummies are jointly tested for significance level.

Table 42 highlights the importance of industrial technology clustering[142], as strong disparities of output elasticity of R&D capital are observed. These first results assess the impact of R&D capital to output for companies in high and medium technological industries as significantly positive, whereas this impact is not significant for the low-tech sectors. Given this disparity, further regressions are conducted given this clustering to provide a more accurate analysis of the estimated results.

[142] The Industrial technology clustering is performed according to ICB code and Ortega-Argiles and al. (2009) classification.

The empirical results are shown separately for the two specifications described in section 5.3 (i.e. Specification 1 and Specification 2). The first specification measures the impact on R&D productivity when a firm increases the share of R&D centers in a given region while decreasing it in other regions. This specification assesses the impact of substituting R&D centers between given regions. The second specification assesses the importance of the regions in the elasticity of output to R&D in a complementary approach.

The estimates of equation 5.3 (Specification 1) are presented in Table 43 for Europe, US-Canada and the remaining regions (included in the "Non EU27-USC" region). Estimates for technological clusters (high-tech, medium-tech and low-tech sectors) are also provided as the first column, describing regressions on the whole sample, reports divergent and often non significant results for the three considered regions. Considering the high-tech sector, the coefficient of the interaction between R&D and the share of European inventors (regression 2) is negative while the interaction with the share of USC inventors has a positive impact on the output (regression 6). The estimates for medium-tech companies show a positive interaction coefficient between R&D and the share of inventors in Europe (regression 3) and negative ones for inventors in US-Canada and other regions (regressions 7 and 11). Concerning firms in the low-tech industries, the interaction coefficients are positive for EU and negative for USC.

Table 43. Results for Specification 1 (substitution effect)

Geo	Variables	Industrial Technology Cluster			
		All	High	Medium	Low
EU		(1)	(2)	(3)	(4)
	Log(*L*)	.688(.016)***	.662 (.028)***	.675 (.026)***	.771 (.024)***
	Log(*C*)	.224(.012)***	.154 (.021)***	.218 (.025)***	.283 (.018)***
	Log(*K*)	.038(.032)	.324 (.048)***	-.005 (.036)	-.188 (.093)**
	Z_{EU}	-.334(.169)**	.607 (.239)**	-.456 (.191)**	-1.12 (.445)**
	Z_{EU} *Log(K)	.062(.034)*	-.134 (.048)***	.109 (.041)***	.172 (.098)*
USC		(5)	(6)	(7)	(8)
	Log(*L*)	.688(.016)***	.662 (.028)***	.674 (.025)***	.764 (.024)***
	Log(*C*)	.225(.012)***	.154 (.021)***	.221 (.024)***	.290 (.019)***
	Log(*K*)	.098(.012)***	.190 (.020)***	.100 (.015)***	-.011 (.019)
	Z_{USC}	.292 (.205)	-.836 (.305)***	.379 (.230)*	1.262 (.456)***
	Z_{USC} *Log(K)	-.045 (.420)	.190 (.057)***	-.129 (.052)**	-.199 (.106)*
Non EU27-USC		(9)	(10)	(11)	(12)
	Log(*L*)	.687(.016)***	.664 (.027)***	.670 (.025)***	.755 (.025)***
	Log(*C*)	.223(.012)***	.156(.021)***	.223(.024)***	.267(.019)***
	Log(*K*)	.101(.011)***	.198(.020)***	.097(.016)***	-.023(.020)
	Z_{Others}	.626(.253)**	.378(.654)	.682(.278)**	-.861(1.08)
	Z_{Others} *Log(K)	-.140(.054)***	-.102(.152)	-.128(.056)**	.293(.22)
	Country dummies	Yes***	Yes***	Yes***	Yes***
	Industry dummies	Yes***	Yes***	Yes***	Yes***
	Time dummies	Yes***	Yes***	Yes***	Yes***
	R-Squared[143]	.95	.95	.95	.95
	# Observations	3492	1468	1178	846

Dependent variable: log(*Y*). Sample of 637 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. Dummies are jointly tested for significance level.

The estimates reported in Table 43 illustrate the relevance of industrial technology clustering in the analysis of R&D internationalization. Considering the high-tech sectors, the positive interaction coefficient for USC[144] combined with negative ones for Europe, illustrate that European high-tech companies having higher share of R&D subsidiaries in US-Canada tend to have a higher elasticity of output with respect to their investments in R&D capital. Looking

[143] The R-Squared values for the 12 regressions range between .949 and .959.
[144] United-States and Canada.

at the medium technological industries, the elasticity of output to R&D is higher for companies with a larger share of their R&D subsidiaries located in Europe compared to other regions. At first sight, estimates for the low-tech sector show some similarity with the medium one, predicting a higher elasticity of output to R&D for European companies keeping their R&D affiliates in Europe instead of locating them in USC. “Non EU27-USC” relates to the five remaining regions presented in section 5.3.2 (CN, IN, JP, EU non 27 and ROW), based on a sum of inventors in these regions. Appendix 9 reports estimates for these five regions. The interaction coefficient is positive for inventors in China and the Rest of the world. The share of inventors located in Japan is positively related to R&D productivity only for high-tech firms, while the coefficient of the interaction is negative when considering the whole sample. Increasing the share of inventors in “EU non 27” countries (while decreasing it in other regions) is related to lower performance of R&D activities. Appendix 10 presents the results for “Same country” and “other EU27” areas applying the same technological clustering and suggests a non significance for any interaction coefficient. A last fact enlightened by the estimates is the increasing impact on output of both labor and physical capital inputs when industrial technology decreases. Contrarily to these two inputs (*L* and *C*), the impact of R&D capital on output is larger in higher-tech sectors. Table 42, Appendix 9 and Appendix 10 confirm this statement, independently of the geographical specification.

Previous estimates in Table 43 suggested how a reallocation of R&D centers (as proxied by inventors) in a given region instead of other regions affects the performance of R&D. Table 44 provides estimates of the weights of each region in the decomposition of the elasticity of output with respect to R&D activities. This specification yields an overview of the size of the regional contributions in the performance of R&D within EU MNEs and considers a complementary contribution of the R&D centers located worldwide.

Table 44. Specification 2 (complementary effect)

Variables	Industrial Technology Cluster			
	All	High	Medium	Low
Log(*L*)	.685 (.012)***	.668 (.019)***	.660 (.021)***	.763 (.022)***
Log(*C*)	.223 (.011)***	.155 (.018)***	.229 (.019)***	.275 (.019)***
$Z_{same\ country}$***Log(*K*)**	.096 (.009)***	.195 (.015)***	.089 (.014)***	-.024 (.018)
$Z_{other\ EU27}$***Log(*K*)**	.103 (.010)***	.189 (.016)***	.123 (.016)***	-.034 (.020)*
Z_{USC}***Log(*K*)**	.113 (.014)***	.214 (.023)***	.045 (.026)*	.063 (.030)**
$Z_{non\ US\text{-}EU27}$***Log(*K*)**	.089 (.018)***	.180 (.030)***	.105 (.023)***	.041 (.048)
Country dummies	Yes***	Yes***	Yes***	Yes***
Industry dummies	Yes***	Yes***	Yes***	Yes***
Time dummies	Yes***	Yes***	Yes***	Yes***
R-Squared	.959	.958	.951	.953
# Observations	3492	1468	1178	846

Dependent variable: log(*Y*). Sample of 637 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. Dummies are jointly tested for significance level.

Table 44 reports estimates of Specification 2 using aggregated groups in order to assess the role of the inventor location in Europe (in the same country or in another European country[145]), US-Canada and the remaining regions. The results indicate that the R&D activities inside the four regions contribute significantly and jointly to the economic performance of the MNEs. The coefficients for all regions are not significantly different for the high-tech firms. Concerning medium-tech companies, the coefficient related to US-Canada stands significantly lower than the ones related to the European regions. On the other hand, the USC coefficient suggests that only R&D associated with inventors located in US-Canada affects positively and significantly the output in the low-tech industries.

[145] Estimates considering Europe as a single group are available in Appendix 11.

Table 45. Specification 2 (8 regions)

Variables	**Industrial Technology Cluster**			
	All (1)	**High** (2)	**Medium** (3)	**Low** (4)
Log(*L*)	.690 (.012)***	.664 (.019)***	.673 (.021)***	.764 (.022)***
Log(*C*)	.221 (.011)***	.161 (.018)***	.216 (.019)***	.271 (.019)***
$Z_{Same\ country}$***Log(*K*)**	.095 (.009)***	.185 (.015)***	.095 (.014)***	-.018 (.017)
$Z_{Other\ EU27}$* **Log(*K*)**	.103 (.010)***	.178 (.016)***	.128 (.016)***	-.022 (.021)
Z_{USC}* **Log(*K*)**	.109 (.014)***	.198 (.023)***	.070 (.027)**	.056 (.030)*
Z_{CN}* **Log(*K*)**	-.872(.645)	2.67 (1.04)**	-3.38 (.847)***	-4.23 (1.87)**
Z_{IN}* **Log(*K*)**	-.125 (.558)	1.56 (1.11)	-.637 (.583)	5.66 (4.89)
Z_{JP}* **Log(*K*)**	.117 (.032)***	.223 (.048)***	.036 (.041)	.752 (.333)**
$Z_{EUnon27}$* **Log(*K*)**	.060 (.022)***	.123 (.038)***	.115 (.027)***	.005 (.079)
Z_{ROW}* **Log(*K*)**	.172 (.042)***	.449 (.116)***	.229 (.089)***	.055 (.056)
Country dummies	Yes***	Yes***	Yes***	Yes***
Industry dummies	Yes***	Yes***	Yes***	Yes***
Time dummies	Yes***	Yes**	Yes***	Yes***
R-Squared	.959	.958	.951	.953
# Observations	3492	1468	1178	846

Dependent variable: log(*Y*). Sample of 637 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. Dummies are jointly tested for significance level.

Table 45 presents the estimates of equation 5.4 considering 8 regions. The results related to the whole sample suggest significant and positive impact of R&D located in the regions "Same country", "Other EU27", "EU non 27", US-Canada, Japan and the rest of the world. However, while the coefficients differ in size, the differences are not significant at a 5% level. This trend holds true for high-tech and medium-tech industries, with a general positive weight of R&D capital located in these regions in the contribution to the performance of EU MNEs. USC coefficient is lower than European coefficients for Med-tech and is even significantly lower than the impact of R&D located in European countries other than the home country. Considering this sector, "Other EU27", "EU non 27" and ROW coefficients range higher than 0.1, with the latter more than two times higher. The coefficient associated to ROW is significantly higher than the others for the high-tech and the medium-tech firms. As in previous tests, the low industrial technology cluster does not disclose much interpretable regional information due to lack of significance. The small number of inventors[146] of China and India does not allow reliable interpretation of the results. On the whole, the findings related to this specification stress the significant role of inventors located inside as well as outside Europe for high and medium tech companies, but they do not provide much different coefficients across the most represented regions of the dataset.

Discussion

The range of the estimated output elasticities of R&D capital is similar to the ones in Ortega-Argiles and al. (2009) and the results compilation of Hall and al. (2010). As regards the estimates[147] of Ortega-Argiles and al. (2009) using the same industry classification, our estimated elasticities range in the same proportion, with slightly higher and lower bounds. Other studies' results compiled by Hall and al. (2010) tend to validate the scope of our estimates. The estimates confirm a larger impact of R&D in high-tech industries than in lower tech ones, while the estimated impact on output of both labor and physical capital is higher for lower technology companies. Moreover, the companies in high technological industries are characterized by a relatively higher influence on output of R&D capital than physical capital.

The results related to the internationalization of R&D are based on the assumption that inventor location is a good proxy of this internationalization as it should reveal the location of R&D subsidiaries. Regarding the high-tech sector, R&D subsidiaries located in Europe seem to reduce the general incidence of R&D capital on output. The opposite trend seems to be the norm for the medium technological cluster. The impact of the knowledge capital of R&D subsidiaries located in the home country seems to be slightly higher for high-tech MNEs as opposed to the medium-tech ones. The low-tech sectors are characterized in most of the regressions by a lack of significant coefficients.

European R&D subsidiaries located in the US and Canada provide quite divergent results for different technological clusters. The findings highlight the superior output elasticity of R&D capital from high-tech affiliates located in US-Canada rather than in Europe. On the contrary, the medium technological cluster is characterized by the opposite effect. Due to lack of significance, the low-tech sector provides unclear results with a negative interaction term for the first specification but a significant and positive elasticity for the second one.

[146] 0.11% for both countries.

[147] The authors estimate elasticity of knowledge stocks on productivity to be around 0.125 in average, ranging between 0.07 for low-tech to 0.17 in high-tech sectors.

The results of the five other regions (i.e. China, India, Japan, EU non27 and RoW) show less significance in general for both specifications, especially when the number of observations is reduced due to technological clustering. However, some evidence still emerges from the estimations. Focusing on Japan, it appears that R&D affiliates of high-tech companies located in Japan are characterized by a higher elasticity to R&D capital than their peers located in Europe. Analyzing the whole sample for other European countries reveals a minor impact of R&D capital on output for firms with higher share of R&D affiliates located in these regions. This trend seems to arise from companies in the high-tech sector. Moreover, the med-tech cluster reveals ambiguous results and the low-tech sector does not provide significant results. As previously stated, estimates for China and India rely on small amount of data, which highly influences their sensitivity. Therefore reliable analysis of these two areas cannot be provided. Gathering the remaining countries in one group, "Rest of the World" impairs the analysis of the estimates of this residual sample due to the intrinsic heterogeneity of this group.

The dataset considers 637 firms of the top 1000 R&D investing European companies. The missing companies may represent a bias whereas the sample tends to consider the maximum reliable and available data representing European R&D on a micro level. This sample of 637 firms accounts for an investment in R&D of nearly €112 billion in 2008. In comparison[148] the top 1000 EU Scoreboard Companies represent €130 billion invested in R&D in 2008.

One significant innovation of the dataset is to assess the internationalization of R&D experimenting new paths whilst providing an original and meaningful approach. However, the definition of R&D internationalization based on the inventor location relies on arguable assumptions. Indeed, assuming that the share of R&D subsidiaries corresponds to the residential place of their inventors in a region remains a questionable hypothesis. Since recent studies assess R&D internationalization up to 16% for developed countries (UNCTAD, 2005), the dataset seems to overestimate home and European localization of R&D subsidiaries against their international counterparts. In our view, this overestimation is primarily due to the exclusive use of EPO granted applications. As regards the internationalization strategies on the location of R&D centers, these applications are more likely to reflect R&D activities that are conducted in foreign countries for the purpose of home-base augmenting R&D strategies rather than home-base exploiting strategies. As the latter are implemented in order to adapt

[148] The sample of 837 firms of Cincera and Ravet (2011) invested in R&D €116,5 billion in 2008.

technologies and products to local market conditions, they may yield patents that are not filed at the EPO and, hence, do not affect our internationalization measure. The use of granted patents (even if the date of the application is considered here) implies that the total number of patents plummets over the end of the investigated period. However, we do not analyze the quantity of patents filed by the MNEs but rather the distribution of their inventors across countries, which should not be affected by the total amount of patents. Additionally, other biases of the dataset are due to uncontrollable surrounding factors linked to data features. As can already be seen on the patenting disparities across industry present in the dataset, heterogeneous propensities to patent across industries (Danguy and al., 2010) as well as international patenting strategies could probably influence the dataset and its downstream international repartition of inventors. Still the dataset contains relevant information representing an interesting proxy of the international repartition of R&D.

5.5 Conclusion and implications

Alongside the accelerating globalization of economies, the internationalization of corporate R&D seems to grow rapidly in developed countries and to surge in developing countries. Historically leading corporate R&D expenditures, Triad MNEs continue to represent most of the worldwide investments in R&D. In that context, these MNEs choose between home and foreign R&D location considering related potential benefits and drawbacks. There are numerous drivers and incentives for R&D internationalization at a national or industry scale. At the firm level, the internationalization strategy of MNEs and HBE/HBA strategies are key decision factors for the location of their R&D subsidiaries.

The main question of this chapter was whether R&D internationalization (in particular R&D located outside Europe) is an efficient and significant driver of the economic performance of EU MNEs. We provide evidence that, while R&D located in Europe shows significant performance results, a reallocation of R&D located in Europe instead of outside Europe (substitution effect) seems to be correlated with lower R&D performances in high-tech sectors, but not in lower-tech industries. Conversely, a larger share of R&D located in the US seems to improve the economic performance of R&D activities within high-tech EU MNEs while the effect is negative for lower-tech companies. Nevertheless, the economic performance of R&D centers in Europe and US is jointly positive and significant for both regions (complementary effect). In our view, our results suggest that, for high-tech firms with a high level of R&D concentration inside Europe, increasing the R&D activities in Europe yields smaller marginal benefits than increasing R&D activities outside Europe in order to exploit foreign technology resources.

These results have important implications in terms of European S&T policies and advocates comprehensive strategies on the internationalization of R&D. As the internationalization of R&D is a channel through which the performance of EU MNEs is affected, EU objectives and priorities should optimally address the globalization trends of R&D. The support and funding of international R&D activities should give firms an easier access to relevant foreign knowledge, especially for high-tech companies, and EU policies would do well improving instruments that raise the potential benefits of outward foreign direct investments related to foreign R&D centers.

The subsequent objective of the chapter relies on the creation of a unique dataset that gathers patent information and companies' quantifiable data whilst representing a consistent proxy of the R&D internationalization of these companies. This proxy is based on the internationalization pattern observed in the location of the inventors. The outcome provided by this chapter stresses the differences in R&D productivity across different world regions and technological sectors. Nevertheless, the considered technological clusters gather heterogeneous industries that have specific characteristics. It would be interesting to focus the scope of the research on a particular industry or a singular region in order to better evaluate the drivers that yield higher performances of R&D centers located abroad. Moreover, companies' strategies appear to have a non-negligible importance on R&D localization and R&D investments. This suggests that a wider scope of analysis that encompasses surveys of MNEs' top management could further explain both drivers and impact on the output of R&D internationalization.

Chapter 6 - Conclusion

SUMMARY

This chapter concludes the dissertation by reviewing the main findings of the previous chapters. Policy implications are summarized and the limitations of the thesis are addressed. Finally, extensions of the scope of the analysis and ideas for future research are suggested.

In this research, we have analyzed several topics related to the technological activities that take place within the companies. The first topic deals with the financing constraints that may occur when a firm is willing to conduct R&D activities. The second topic consists in the channels through which R&D activities yield knowledge outcomes. The third topic is the growing complexity of the MNEs in terms of product diversification (industrial or international) and R&D internationalization, and its relationship with the economic performance of R&D activities. These topics have a high level of revelancy for policy makers and each chapter aims at contributing to the literature of its respective topic.

Lessons from the financing constraints on R&D and the productivity performance of technological activities

A first objective of this research was to investigate the extent to which R&D, especially in Europe, is hampered by the presence of financing constraints. As opposed to ordinary investments, R&D investments are riskier by nature and provide outputs consisting of new products and processes that are difficult to use as collateral to outsiders. Firms that are willing to start R&D projects may be financially constrained when they face lack of internal funds and uneasy access to external funds. The presence of financing constraints is tested in this research through the measure of the sensitivity of R&D activities to cash flow as a proxy of the availability of internal funds.

The main question of chapter 2 was whether financing constraints explain a part of the acknowledged R&D gap between Europe and the US. In our view, the answer is yes, though it is difficult to extrapolate at a macroeconomic level the extent to which financing frictions widen this gap. Our findings give an assessment of the financing constraints faced by the firms in their decisions to invest in R&D over the 2000s on the basis of a dataset of private companies that confronts EU to US top R&D spenders. We show evidence of liquidity constraints for EU companies but not for their US competitors. The results are based on system GMM estimations of dynamic R&D investment equations. A second question was whether older firms actually face less severe or no financing constraints, as opposed to younger firms. A nonparametric estimation of the accumulation rate of R&D is used as a complementary approach in order to assess the relationship between R&D, cash flow and the age of the companies without any restriction on the dynamics of the accumulation rate of R&D. This approach eventually allows a descriptive view of the effect of the age on the sensitivity of R&D along with confidence intervals computed for this effect. When investigating the relationship between the R&D sensitivity to cash flow and the age of the companies, we find evidence of a sensitivity that decreases with the age of the companies, which is likely to illustrate stronger financing constraints for younger companies. While it is not clear whether the low representation of young firms within the European leading innovators (i.e. the top R&D spenders) is due to a low access to external financial resources, a US-EU comparison indicate that EU yollies are characterized by a lower but still significant R&D sensitivity while EU ollies seem to be more financially constrained than their US counterparts.

A second objective of this dissertation was to identify the main drivers of innovative performance amongst the several dimensions that characterize R&D activities. Instead of considering R&D as a whole entity, the key feature of the analysis resides in the disaggregation of R&D. The innovative performance of the firms was measured by means of a knowledge production function with outcome of the technological activities being assessed by the patents of the companies.

The main question of Chapter 3 is whether the heterogeneity of R&D activities affects the technology performance of a firm, and, if so, what are the effects that can be observed in an integrated framework like the one used in our analysis. Chapter 3 reports cross-sectional measures of the elasticity of patents to disaggregated R&D within Belgian firms. A Belgian R&D survey of firms located in Belgium in 2004-2005 was used to test hypotheses on several components of R&D at the firm level. The internationalized nature of Belgian R&D implied substantial work that was performed on retrieving priority filings related to Belgian R&D, even when applicants are not Belgian. This is likely to occur in the case of repatriation of knowledge from Belgian R&D subsidiaries to the foreign owner.

The findings of chapter 3 identify several drivers of innovative performance within the R&D activities of the companies. In-house R&D of Belgian firms is clearly the main determinant of their innovative outcomes. Sub-contracted R&D is indeed more likely to provide generic rather than specialized inputs into the R&D programmes of the clients, and these inputs are less likely to lead to successful inventions and patents applications. While the top patenting companies in the samples are mainly conducting development activities, the role of research activities still prevails in the determination of the quantity of patents filed by the companies. Conversely, the findings about process-oriented R&D seem to illustrate a preference for secrecy as opposed to disclosure of the innovations achieved by this type of activities. Another dimension of R&D that is considered is the role of human capital and R&D investment in the innovative performance of the firms. Laboratories and equipments are a necessity (depending on the technological sector) to conduct innovative activities and modern equipment improve the productive capacity of R&D. On the other hand, new ideas and new inventions are born in the pool of human capital that represents most of the R&D expenditures of the companies. Our findings confirm the importance of human capital in the technological performance and, to some extent, give credit to efficient salary strategies for the hiring of researchers as well as education and training of hired R&D workers. Concerning the subcontractors, the findings illustrate the significant role of collaborations with universities in the production of patents.

While chapter 2 assesses the impact of financing matters on the size of R&D, chapter 3 provides findings on the efficiency of different types of funding of R&D activities. R&D expenditures funded by own funds or external sources appear to jointly determine the outcome of the knowledge process that takes place within Belgian firms, with larger impacts of intramural R&D financed by external funds rather than own funds. We find evidence that both external private and public funds, Belgian or foreign, encourage the emergence of R&D activities that yield significant returns.

A first look at the importance of R&D internationalization is given in chapter 3, with a highly international nature of the Belgian R&D. Chapters 4 and 5 investigate this strategy of MNEs along with the diversification of their business activities. Indeed, a significant portion of companies diversify their productive activities, either across multiple lines of business, i.e. industrial diversification, or across different geographic markets, i.e. international diversification or globalization. The assessment of the relationship between these strategies and the productivity of R&D was the third and final objective of the thesis. The strategies of the MNEs were assessed by analyzing their subsidiaries and the location of the inventors who contributed to their patents. Chapter 4 investigates the diversification of economic activities (industrial and international) while Chapter 5 analyzes the internationalization of R&D

Chapter 4 presents the construction of a first dataset consisting in the identification of the subsidiaries of the top R&D spenders in Europe in 2008. This first dataset is used as a basis for the construction of a second dataset that extends the previous work on the subsidiaries by adding consolidated information on the patents of the MNEs (including the subsidiaries) and the location of the inventors. Indicators revealing the diversification and R&D internationalization strategies of the companies are based on the industries and countries covered by the European MNEs. The combined effect of these indicators with the R&D stock on the economic performance is estimated by means of economic production functions including labor and physical capital stocks as well as R&D.

The question addressed by Chapter 4 is whether the diversification strategies (industrial and international) of EU MNEs improve the economic performance of R&D activities. According to our estimations, the answer is yes for international diversification, but no for industrial diversification. We provide recent elasticity measures of output with respect to labor, physical capital and R&D stock for EU MNEs. These are respectively 0.65, 0.24 and 0.11. The findings about the diversification strategies of economic activities suggest that the role of industrial diversification differ from the role of globalization when assessing the economic impact of R&D activities. A firm that diversifies its lines of products across several industries implies a greater complexity in terms of management which may lead to loss of efficiency, especially for high degrees of diversification. Our findings suggest that the cost of this type of diversification on the productivity of R&D is not compensated by the benefits of exploiting the economies of scope and having new directions to deploy the resources invested in a particular technological field. On the other hand, EU MNEs that diversify their economic activities in an international perspective appear to be characterized by a higher productivity of their R&D activities. Moreover, a larger share of subsidiaries in the US-Canada region is related to a higher performance of R&D activities while a larger presence in Europe leads to a lower elasticity of output with respect to R&D capital.

The main question of Chapter 5 was whether R&D internationalization (in particular R&D located outside Europe) is an efficient and significant driver of the economic performance of EU MNEs. Our results are based on R&D internationalization indicators as proxied by the internationalization in the location of the inventors. R&D located in Europe shows significant performance results, but a reallocation of R&D located in Europe instead of outside Europe (substitution effect) seems to be correlated with lower R&D performances in high-tech sectors, but not in lower-tech industries. Given the high shares of EU inventors that we observe, these findings suggest that high-tech firms have smaller marginal benefits from increasing their R&D activities in Europe than outside Europe for high levels of technology concentration in Europe. Furthermore, a larger share of R&D located in the US seems to improve the economic performance of R&D activities within high-tech EU MNEs while the effect is negative for lower-tech companies. This illustrates high marginal benefits for high-tech firms that conduct HBA and HBE strategies in the US. Nevertheless, the economic performance of R&D centers in Europe and US is jointly positive and significant for both regions (complementary effect).

Implications

This thesis deals with several topics that all have a high level of relevancy in terms of policy implications and managerial practices.

- Our results about financing constraints suggest improving conditions in the EU for access to external capital, i.e. debt and equity. Policy makers would do well providing direct R&D support for EU firms, i.e. tax incentives and R&D subsidies and further develop the availability of risk capital.
- Tax policies that affect the after-tax cash flow of the firms are likely to affect the R&D activities of EU companies as they seem to rely on the availability of internal finance. Therefore R&D tax-incentives in Europe should be designed and implemented with the view of significantly enhancing R&D and innovative activities.
- The low representation of young companies within the top innovation leaders in Europe suggests a need of measures to stimulate R&D activities amongst young firms (yollies), especially in innovative sectors as well as measures aimed at improving the conditions and the financial factors that favour the development and growth of these firms.
- On the other hand, well established companies (ollies) appear to benefit from more efficient external capital markets in the US than in Europe. Indirectly, more favourable framework conditions in the EU are desirable, in particular for enhancing the private equity market. Our findings support the view that Europe needs a functioning internal market, which is currently hampered by the relatively high degree of fragmentation of EU financial markets.
- While the role of R&D activities in the production of knowledge outcomes is straightforward, we show evidence of a high degree of heterogeneity in the different components of R&D activities and the way they contribute to the technology performance of companies. This heterogeneity advocates a differentiated public

support to these components provided that the patent propensity of each of these R&D components is controlled for.

- The importance of public aid is supported by our findings as we show evidence that public funds are actually effective in the creation of new inventions.
- The heterogeneity of R&D correlates with differences in the efficiency of the protection of R&D activities through patents and should be optimally addressed by IPR policies.
- As a main channel for industrial diversification is through mergers and acquisitions (M&A) (Porter, 1987), antitrust authorities may be careful regarding decisions allowing M&A, as these activities, besides increasing the market power of the merged entities, may also reduce their efficiency and economic performance.
- From the firms view point, our results imply that industrial diversification has a cost that is likely to be magnified when the levels of diversification are high and marginal benefits of diversification strategies are low. Hence, managerial practices should rely on coherent product and technology portfolios[149].
- As increased globalization appears to have beneficial effects on large European R&D companies, this advocates increasing support for international S&T collaborations and partnerships.
- Given that internationalization of R&D is a channel through which the performance of EU MNEs is affected, EU objectives and priorities should optimally address the globalization trends of R&D. The support and funding of international R&D activities should give firms an easier access to relevant foreign knowledge and EU policies would do well improving instruments that raise the potential benefits of outward foreign direct investments related to foreign R&D centers.

Limitations and suggestions for future research

The main weaknesses of the analyses presented in this dissertation are the following. In chapter 2, the sensitivity of R&D to cash flow is used as the only measure of financing constraints. As explained in chapter 2, this measure of internal finance and its relation with

[149] See Leten, Belderbos and Van Looy (2007).

the financing constraints may be criticized and is likely to capture expected demand growth. The implementation of sales growth in the estimated equations is expected to control, even imperfectly, for the expectation role of cash flow. As it is inherent to nonparametric methods, the nonparametric estimation of R&D is limited in the dimensions that are used and only estimations of R&D accumulation rates for several combinations of ages and cash flow are reported. Including more dimensions implies more scarcity of data in the higher dimensional spaces and a decrease in the achievable rate of convergence of the estimation. A weakness in the analysis conducted in chapter 3 is related to the lack of temporal dimension in the analysis because of the data. An expected consequence of the exclusive use of cross-sectional samples is the inflated measure of the patent elasticity. A weakness of chapter 4 resides in the absence of time-varying data about the subsidiaries, which prevents the use of more sophisticated panel data estimates. Furthermore, despite the theoretical arguments about the effects of diversification and internationalization, lack of good instruments makes it difficult to assess the main direction of the relationships that are established. Concerning the inventor location in chapter 5, the exclusive use of EPO applications leads to inflated measures of European shares. However this bias is likely to arise for all firms in the sample and should not significantly perturb cross-sectional comparisons and firm-level econometric results.

In order to better understand the relationship between R&D investing behaviors and financing constraints, which is analyzed in chapter 2, it would be helpful to know more precisely the share of the different sources for the funding of R&D, i.e. internal financing, debt and issues of shares on the stock markets. Indeed if firms in the EU are relying less on external sources compared with their US counterparts, then this could explain why EU firms are more sensitive to liquidity constraints. Another interesting extension of this work would be to investigate which component of R&D investment, i.e. the 'R' vs. the 'D' or the outsourced R&D abroad vs. the research carried out in the home country, is more financially constrained. While maintaining the important division between European and US companies, which is because of the very different business environments for R&D firms in the two regions, it may be worth investigating separately groups of firms by sector of economic activity. Quite often, the differences in financial constraints and management of R&D resources differ significantly from one sector to another. Generally, differences are larger between sectors than between regions in the same sector of activity, particularly when considering worldwide-operating firms.

In order to further investigate the outcomes of the knowledge process, other measures of the performance of R&D activities could be considered and would extend the scope of the analysis of chapter 3. For instance, other intellectual property rights like copyright and trademarks may be worth being implemented in the knowledge production function and related to the components of R&D. Furthermore, improving the methodological framework with panel data analyzes would benefit from the dynamics that underlie the evolution of innovative activities. A structural model that addresses the dimensions of R&D that foster the knowledge outcome could be considered by using simultaneous equations.

An interesting extension of the work of chapter 4 regarding industrial diversification may be to investigate the characteristics of the industries the MNEs are active in. We do not have information about the R&D activities conducted by the subsidiaries, but the industrial classification of the subsidiaries may give a clue about their role in the group. This approach would also be helpful in analyzing the relationship between the strategies of vertical integration and the productivity of the firms. To better understand the activities of European MNEs outside Europe, it may be worth having a closer look at the industrial diversification or concentration strategies in North America and Asia Pacific, and their impact on R&D activity productivity. Moreover, one could investigate the efficiency in these regions of the Home-Based Augmenting and Home-Based Exploiting R&D strategies for EU MNEs.

The analysis of R&D internationalization in chaper 5 is to be related to more specific regional investigations in order to stress the strengths of each single region that matters today in the globalization process of R&D. It would be worth focusing the scope of the research on a particular industry or a singular region in order to better evaluate the drivers that yield higher performances of R&D centers located abroad.

REFERENCES

Abel A.B. and O.J. Blanchard. 1986. The Present Value of Profits and the Cyclical Movements in Investment, *Econometrica*, 54, 249-273.

Ackerlof G.A. 1970. The Market for ‘Lemon’: Quality, Uncertainty and the Market Mechanism, *Quarterly Journal of Economics*, 84, 488-500.

Aghion P., P. Askenazy, N. Berman, G. Cette and L. Eymard. 2008. Credit constraints and the cyclicality of R&D investment: Evidence from France, PSE Working Papers 2008-26, PSE (Ecole normale supérieure).

Angel D.P. and L.A. Savage. 1996. Global Localization? Japanese Research and Development Laboratories in the USA, *Environment and Planning*, 28(5), 819-833.

Anvret M., M. Granieri and A. Renda. 2010. A new approach to innovation policy in the european union, CEPS Task force report, Brussels.

Arellano M. and O. Bover. 1995. Another Look at the Instrumental Variable Estimation of Error-Components Models, *Journal of Econometrics*, 68(1), 29-51.

Arellano M. and S. Bond. 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and Application to Employment Equations, *Review of Economic Studies*, 58, 277-97.

Arellano M. and S. Bond. 1998. Dynamic Panel Data Estimation Using DPD98 for Gauss: A guide for Users, mimeo.

Arrow K. 1962. Economic Welfare and the Allocation of Resources for Invention, in R. Nelson (ed.), “The Rate and Direction of Inventive Activity”, Princeton, 609-626.

Arundel A. and I. Kabla. 1998. What percentage of innovations are patented? empirical estimates for European firms, *Research Policy*, 27, 127-141.

Asakawa K. 2001. Evolving headquarters-subsidiary dynamics in international R&D: the case of Japanese multinationals, *R&D Management*, 31(1), 1-14.

Baba Y. and K. Nobeoka. 1998. Towards knowledge-based product development: the 3-D CAD model of knowledge creation, *Research Policy*, 26(6), 643-659.

Baysinger B. and R. E. Hoskisson. 1989. Diversification Strategy and R&D Intensity in Multiproduct Firms, *The Academy of Management Journal*, 32(2), 310-332.

Becker M.C., P. Salvatore and F. Zirpoli. 2005. The impact of virtual simulation tools on problem-solving and new product development organization, *Research Policy*, 34 (9), 1305–1321.

Belderbos R. 2001. Overseas Innovations by Japanese Firms: An Analysis of Patent and Subsidiary Data, *Research Policy*, 30(2), 313-32.

Belderbos R., L. Sleuwaegen and R. Veugelers. 2010. Market Integration and Technological Leadership in Europe, European Economy Economic Papers #403, European Commission, Directorate General for Economic and Financial Affairs.

Berger P.G. and E. Ofek. 1995. Diversification's effect on firm value, *Journal of Financial Economics,* 37, 39-66.

Blomström M. and A. Kokko. 1998. Multinational Corporations and Spillovers, *Journal of Economic Surveys*, 12(2), 247-277.

Blomström M. and A. Kokko. 2003. The Economics of foreign direct investment incentives, *NBER Working Paper* #9489, Cambridge, MA.

Blonigen B. A. 2005. A Review of the Empirical Literature on FDI Determinants, *NBER Working Paper* #11299, Cambridge, MA.

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

Blundell R, R. Griffith and F. Windmeijer. 2002. Individual effects and dynamics in count data models, *Journal of Econometrics*, 108, 113-131.

Bond S. and C. Meghir. 1994. Dynamic Investment Models and the Firm's Financial Policy, *Review of Economic Studies*, 61(2), 197-222.

Bond S., D. Harhoff and J. Van Reenen. 1999. Investment, R&D and Financial Constraints in Britain and Germany, Institute for Fiscal Studies Working Paper #W99/05.

Bond S., J. Elston, J. Mairesse and B. Mulkay. 2003. Financial Factors and Investment in Belgium, France, Germany and the U.K.: A Comparison Using Company Panel Data, Review of Economics and Statistics, 85, 153–165.

Bosworth D. 1978. The Rate of Obsolescence of Technical Knowledge - A Note, *Journal of Industrial Economics*, 26(3), 273-279.

Bougheas S., H. Goerg and E. Strobl. 2001. Is R&D Financially Constrained? Theory and Evidence from Irish Manufacturing", GEP Research Paper 2001/16, Leverhulme Centre, University of Nottingham.

Brouwer, E. and A. Kleinknecht. 1999. Innovative output, and a firm's propensity to patent. An exploration of CIS micro data, *Research Policy*, 28(6), 615-624.

Brown J.R., S.M. Fazzari, and B.C. Petersen. 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom, *Journal of Finance*, 64(1), 151-185.

Brown J.R. and B.C. Petersen. 2009. Why has the investment-cash flow Sensitivity declined so sharply? Rising R&D and equity market developments, *Journal of Banking and Finance*, 33, 971-984.

Burgelman R.A. 1983a. A process model of internal corporate venturing in the diversified major firm, *Administrative Science Quarterly*, 28, 223-245.

Burgelman, R.A. 1983b. A model of the interaction of strategic behavior, corporate context, and the concept of strategy, *Academy of Management Review*, 8, 61-70.

Butzen P., C. Fuss and P. Vermeulen. 2001. The Interest Rate and Credit Channels in Belgium: An Investigation with Micro-Level Firm Data, National Bank of Belgium, Working Papers Research Series, 18.

Cameron A.C. and P.K. Trivedi. 1986. Econometric Models Based on Count Data: Comparisons and Applications of some Estimators and Tests, *Journal of Applied Econometrics*, 1, 29-53.

Cantwell J. and R. Harding. 1998. The Internationalisation of German Companies' R&D, *National Institute Economic Review*, 163, 99-124.

Cantwell J. and G.D. Santangelo. 1999. The Frontier of International Technology Networks: Sourcing Abroad the Most Highly Tacit Capabilities, *Information Economics and Policy*, 11(1), 101-23.

Capron H. and M. Cincera. 1998. Assessing the R&D Determinants and Productivity of World-wide Manufacturing firms, *Annales d'Economie et de Statistiques*, 49/50, 565-587.

Capron H. and M. Cincera. 2000. R&D expenditures and the National Innovation System, in H. Capron and W. Meeusen (eds.) "The National Innovation System of Belgium", Heidelberg New York: Physica-Verlag, 73-100.

Ceccagnoli M. 2009. Appropriability, preemption, and firm performance, *Strategic Management Journal*, 30(1), 81–98.

Chandler A. 1962. Strategy and structure: Chapters in the history of American industrial enterprise, Cambridge, Mass: MIT Press.

Chen S.X.. 2000. Probability density function estimation using gamma kernels, *Annals of the Institute of Statistical Mathematics,* 52(3), 471–480.

Cincera M. 1997. Patents, R&D and Technological Spillovers at the Firm Level: Some Evidence from Econometric Count Models for Panel Data, *Journal of Applied Econometrics*, 12, 265-280.

Cincera M. 1998. Technological and Economic Performances of International firms, Ph.D. Thesis, Université libre de Bruxelles.

Cincera M. 2003. Financing constraints, fixed capital and R&D investment decisions of Belgian firms. In P. Butzen, and C. Fuss (eds.), "Firms' Investment and Finance Decisions: Theory and Empirical Methodology", Cheltenham, UK: Edwar Elgar, 129-147.

Cincera M. 2005. The link between firms' R&D by type of activity and source of funding and the decision to patent, Working paper DULBEA, Research series, #05-10.RS, April 2005.

Cincera M., C. Cozza and A. Tübke. (2010). Drivers and policies for increasing and internationalising R&D activities of EU MNEs, *IPTS Working Paper on Corporate R&D and Innovation*, No.02/2010. Luxembourg: Office for Official Publications of the European Communities.

Cincera M. and O. Galgau. 2005. Impact of Market Entry and Exit on EU Productivity and Growth Performance. European Economy, Economic Papers #222, European Commission, Directorate General for Economic and Financial Affairs.

Cincera M. and J. Ravet. 2010. Financing constraints and R&D investments of large corporations in Europe and the USA, IPTS Working Paper on Corporate R&D and Innovation, No.03/2010, Luxembourg: Office for Official Publications of the European Communities.

Cincera M. and J. Ravet. 2011. Globalisation, industrial diversification and productivity growth in large European R&D companies, IPTS Working Paper on Corporate R&D and Innovation, No.01/2011, Luxembourg: Office for Official Publications of the European Communities.

Cincera M. and B. van Pottelsberghe de la Potterie. 2001. International R&D Spillovers: A Survey, *Cahiers Economiques de Bruxelles*, 169, 3-32.

Cincera M., B. van Pottelsberghe de la Potterie and R. Veugelers. 2006. Assessing the Foreign Control of Production of Technology: The Case of a Small Open Economy, *Scientometrics*, 66(3), 493-51.

Cincera M. and R. Veugelers. 2011. Young Leading Innovators and EU's R&D intensity gap, IPTS Working Paper on Corporate R&D and Innovation, No.07/2011, Luxembourg: Office for Official Publications of the European Communities.

Cincera M., R. Veugelers, L. Kempen, B. van Pottelsberghe de la Potterie and C. Villegas Sanchez. 2003. Productivity growth, R&D and the role of international collaborative agreements: some evidence for Belgian manufacturing companies, *Brussels Economic Review*, 46(3), 107-140.

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

Coelli T.J., D.S.P. Rao, C.J. O'Donnell and G.E. Battese. 2005. An Introduction to Efficiency and Productivity Analysis, second Edition, Springer.

Cohen W.M. 1995. Empirical Studies of Innovative Activities, in P. Stoneman (ed.), "Handbook of the Economics of Innovation and Technological Change", Oxford, UK: Blackwell Publishers Ltd, 182-264.

Cohen W.M. 2010, Fifty Years of Empirical Studies of Innovative Activity and Performance, in B.H.Hall and N Rosenberg (eds.), "Handbook of Economics of Innovation", Amsterdam, Elsevier, 129-213.

Cohen W.M., R.R. Nelson and J.P. Walsh. 2000. Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not), Working Paper 7522, National Bureau of Economic Research.

Comment R. and G.A. Jarrell. 1995. Corporate focus and stock returns, *Journal of Financial Economics*, 37, 67-87.

Cowan R., P.A. David and D. Foray. 2000. The explicit economics of knowledge codification and tacitness, *Industrial and corporate change*, 9(2), 211-253.

Crépon B. and E. Duguet. 1997a. Estimating the Innovation Function from Patent Numbers: GMM on Count Panel Data, *Journal of Applied Econometrics*, 12, 243-263.

Crépon B. and E. Duguet. 1997b. Research and Development, Competition and Innovation: Pseudo-Maximum Likelihood and Simulated Maximum Likelihood Methods Applied to Count Data Models with Heterogeneity, *Journal of Econometrics*, 79, 355-378.

Crépon et al 1998 patents

Czarnitzki D. 2006. Research and development in small and medium-sized German enterprises: The role of financial constraints and public funding, *Scottish journal of political economy*, 53(3), 335-357.

Czarnitski D., K. Kraft and S. Thorwarth. 2009. The knowledge production of 'R' and 'D', *Economic Letters*, 105, 141-143

Dachs B., N. Foster, M. Mitterhauser, W. Urban, G. Zahradnik. 2010. Internationalization of business investments in R&D and analysis of their economic impact, The Vienna Institute for International Economic Studies / Austrian Institute for Technology.

Danguy J., G. de Rassenfosse and B. van Pottelsberghe de la Potterie. 2010. The R&D-patent relationship: An industry perspective, ECARES working paper 2010-038.

de Rassenfosse G. and D. Guellec. 2009. Quality versus quantity: Strategic interactions and the patent inflation. Paper presented at the 4th annual conference of the EPIP association.

de Rassenfosse and B. van Pottelsberghe de la Potterie. 2009. A policy insight into the R&D-patent relationship, *Research Policy*, 38(5), 779-792.

Denis D. J., D.K. Denis and K. Yost. 2002. Global Diversification, Industrial Diversification, and Firm Value, *Journal of Finance*, 57(5), 1951-1979.

Duguet E. and I. Kabla. 1998. Appropriation Strategy and the Motivations to Use the Patent System: An Econometric Analysis at the Firm Level in French Manufacturing, Annales *d'Economie et de Statistique*, 49-50, 289-327.

Dundas K.N.M. and P.R. Richardson. 1982. Implementing the unrelated product strategy, *Strategic Management Journal*, 3, 287-301.

Dunning J.H. and R. Narula. 1995. The R&D activities of foreign firms in the United States, *International Studies of Management & Organization*, 25(1-2), 39-73.

Ekholm K. and K. Midelfart. 2004. Determinants of FDI: the Evidence, in G. Barba Navaretti and A. Venables (eds), "*Multinational firms in the world economy*", Princeton University Press, 127-150.

Fazzari S.M., R.G. Hubbard and B.C. Petersen. 1988. Financing Constraints and Corporate Investment. *Brookings Papers on Economic Activity*, 1, 141-195.

Fazzari S.M., R.G. Hubbard and B.C. Petersen. 2000. Investment-Cash Flow Sensitivities Are Useful: A Comment on Kaplan and Zingales. *Quarterly Journal of Economics*, 115(2), 695-705.

Fecher F. 1990. Effets Directs et Indirects de la R&D sur la Productivité: Une Analyse de l'Industrie Manufacturière Belge, *Cahiers Economiques de Bruxelles*, 128, 459-482.

Florida R. 1997. The Globalization of R&D: Results of a Survey of Foreign-Affiliated R&D Laboratories in the USA, *Research Policy*, 26(1), 85-103.

Geroski P. 1995. Markets for Technology: Knowledge, Innovation and Appropriability, in P. Stoneman (ed.), "Handbook of the Economics of Innovation and Technological Change", Blackwell publishers.

Granstrand O. 1998. Towards a theory of the technology-based firm, *Research Policy*, 27, 465-489.

Granstrand O, L. Hakanson, and S. Sjolander. 1992. Technology Management and International Business, Wiley, Chichester.

Greenhalgh C. and M. Rogers. 2007. The value of intellectual property rights to firms and society, *Oxford Review of Economic Policy*, 23(4), 541-568.

Griliches, Z. 1979. Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 10(1), 92-116.

Griliches Z. and J.A. Hausman. 1986. Errors in Variables in Panel Data, *Journal of Econometrics*, 31, 93-118.

Griliches Z. and J. Mairesse. 1983. Comparing Productivity Growth: An Exploration of French and US Industrial and Firm Data, *European Economic Review*, 21, 89-119.

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

Guellec, D. and B. van Pottelsberghe de la Potterie, 2001. The Internationalization of Technology Analysed with Patent Data, *Research Policy* 30(8), 1253-1266.

Guellec D. and B. van Pottelsberghe de la Potterie. 2007. The Economics of the European Patent System, Oxford University Press, Oxford.

Guo J.-Q. and P.K. Trivedi. 2002. Flexible Parametric Models for Long-tailed Patent Count Distributions, *Oxford Bulletin of Economics and Statistics*, 64(1), 63-82.

Hall B.H. 1992. Investment and Research and Development at the Firm Level: Does the Source of Financing Matter?, National Bureau of Economic Research Working Paper #4096.

Hall B.H. 2002. The Financing of Research and Development, *Oxford Bulletin of Economics and Statistics*, 64(1), 35-51.

Hall B.H. 2011. The internationalization of R&D, UNU-MERIT Working Paper Series 049, United Nations University, Maastricht Economic and social Research and training centre on Innovation and Technology.

Hall, B.H., Z. Griliches and J.A. Hausman. 1986. Patents and R and D: Is there a lag?, *International Economic Review*, 27(2), 265-283.

Hall B.H. and J.Lerner. 2010. Financing R&D and Innovation, forthcoming in B.H. Hall and N. Rosenberg (eds.), the Economics of Innovation, Elsevier Handbook of the Economics of Innovation.

Hall B.H. and J.Mairesse. 1995. Exploring the Relationship Between R&D and Productivity in French Manufacturing Firms, *Journal of Econometrics*, 65, 263-94.

Hall B.H., J. Mairesse, L. Branstetter and B. Crepon. 1999. Does Cash Flow Cause Investment and R&D: An Exploration Using Panel Data for French, Japanese and United States Scientific Firms, in D. Audretsch and A. R. Thurik (eds.), "Innovation, Industry Evolution and Employment", Cambridge University Press.

Hall B. H., J. Mairesse and P. Mohnen. 2010. Measuring the Returns to R&D, in Hall, B. H. and N. Rosenberg (eds), *Handbook of the Economics of Innovation*, Amsterdam and New York: Elsevier, 1034-1076.

Hall B.H. and R.H. Ziedonis. 2001. The Patent Paradox Revisited: An Empirical Study of Patenting in the US Semiconductor Industry, 1979-95, RAND Journal of Economics, 32(1), 101-128.

Harhoff D. 1998. Are There Financing Constraints for R&D and Investment in German Manufacturing Firms? *Annales d'Economie et de Statistiques*, 49-50, 421-56.

Harhoff D., F.M. Scherer, and K. Vopel. 2003. Citations; Family Size, Opposition and the Value of Patent Rights, *Research Policy*, 32

Harhoff D. and G. Thoma (2010) Inventor Location and the Globalization of R&D, Paper presented at the Conference on Patent Statistics on Decision Makers, 17-18 November 2010, Vienna, Austria.

Hausman J.A., Hall B.H. and Z. Griliches. 1984. Econometric Models for Count Data with an Application to the Patents-R&D Relationship, *Econometrica*, 52, 909-938.

Hayes R.H. and W.J. Abernathy. 1980. Managing our way to economic decline, *Harvard Business Review*, 58(4), 67-77.

Hill C.W.L., M.A. Hitt and R.E. Hoskisson. 1988. Declining U.S. competitiveness: Innovation, the M-form structure and the capital markets, *Academy of Management Executive*, 2, 51-60.

Himmelberg C.P. and B.C. Petersen. 1994. R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries, *Review of Economics and Statistics*, 76(1), 38-51.

Hubbard R.G. 1998. Capital Market Imperfections and Investments, *Journal of Economic Literature*, 36, 193-225.

Jaffe A.B. 1986. Technological Opportunity and Spillovers of R&D, *American Economic Review*, 76, 984-1001.

Jensen N.M. 2006. Nation-states and the Multinational Corporation, Princeton and Oxford, Princeton University Press.

Jensen M. and W. Meckling. 1976. Theory of the Firm: Managerial Behaviour, Agency Costs and Ownership Structure, *Journal of Financial Economics*, 3, 305-60.

Jensen M.C. and K.J. Murphy. 1990. Performance pay and top management incentives, *Journal of Political Economy*, 98: 225–264.

Jorgenson D.W. 1963. Capital Theory and Investment Behaviour, *American Economic Review*, 53(2), 247-259.

Kamien M.I. and N.L. Schwartz. 1982. Market structure and innovation, Cambridge, U.K., Cambridge University Press.

Kaplan S.N. and L. Zingales. 1997. Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints. *Quarterly Journal of Economics*, 112(1), 169-215.

Kaplan S.N. and L. Zingales. 2000. Investment-Cash Flow Sensitivities are Not Valid Measures of Financing Constraints. *Quarterly Journal of Economics*, 115(2), 707-712.

Kuemmerle W. 1997. Building effective R&D capabilities abroad, *Harvard Business Review*, March-April, 61–70.

Kuemmerle W. 1999. Foreign Direct Investment in Industrial Research in the Pharmaceutical and Electronics Industries--Results from a Survey of Multinational Firms, *Research Policy*, 28(2-3): 179-93.

Kumar N. 2001. Determinants of location of overseas R&D activity of multinational enterprises: the case of US and Japanese corporations, *Research Policy*, 30, 159-174.

Le Bas C. and C. Sierra. 2002. Location versus home country advantages' in R&D activities: some further results on multinationals' locational strategies, *Research Policy*, 31: 589-609.

Leten B., R. Belderbos and B. Van Looy. 2007. Technological diversification, coherence and performance of firms, *Journal of Product Innovation Management*, 24, 567-577.

Levin R.C., A.K. Klevorick, R.R. Nelson and S.G. Winter. 1987. Appropriating the Returns from Industrial Research and Development, *Brookings Papers on Economic Activity*, 3, 783-831.

Mairesse J., B. Mulkay and B.H. Hall. 1999. Firm-Level Investment in France and the United States: An Exploration of What we Have Learned in Twenty Years, National Bureau of Economic Research Working Paper #7437.

Marsili O. 2001. The Anatomy and Evolution of Industries: Technological Change and Industrial Dynamics, Cheltenham, UK and Northampton, MA, USA, Edward Elgar.

Maskus K. 1998. The International Regulation of Intellectual Property, *Weltwirtschaftliches Archiv*, 123(2), 186-208.

Meyer M., P. Milgrom and J. Roberts. 1992. Organizational prospects, influence costs, and ownership changes. *Journal of Economics and Management Strategy*, 1, 9–35.

Mohnen P. 1996. R&D Externalities and Productivity Growth, *STI Review*, 18, 39-66.

Moncada Paternò Castello P., C. Ciupagea, K. Smith, A. Tübke and M. Tubbs. 2009. Does Europe perform too little corporate R&D?, IPTS Working Paper on Corporate R&D and Innovation, No. 11/2009, European Commission, JRC 51955 – Joint Research Centre – Institute for Perspective Technological Studies, Luxembourg: Office for Official Publications of the European Communities.

Morck R. and B. Yeung. 1998. Why investors sometimes value size and diversification: The internalization theory on synergy, Working paper, Institute for Financial Research, University of Alberta.

Moyen N. 2004. Investment-cash flow sensitivities: Constrained versus unconstrained firms, *Journal of Finance*, 69, 2061–2092.

Mulkay B., B.H. Hall and J. Mairesse. 2001. Investment and R&D in France and the United States, in Herrmann Heinz and Rolf Strauch (eds.), “Investing Today for the World of Tomorrow”, Springer Verlag.

Myers S.C. and N.S. Majluf. 1984. Corporate Financing and Investment Decisions when Firms Have Information that Investors Do not Have, *Journal of Financial Economics*, 13, 187-221.

Nadaraya E.A. 1964. On Estimating Regression, *Theory of Probability and its Applications*, 9(1), 141–142.

Nakamura T. 1999. The Role of R&D Diversification in Exploiting Knowledge Spillover: Evidence from Major Japanese Chemical and Pharmaceutical Companies, No CIRJE-F-66, CIRJE F-Series, CIRJE, Faculty of Economics, University of Tokyo.

Nightingale P. 2000. Economics of scale in experimentation: Knowledge and technology in pharmaceutical R&D, *Industrial and Corporate Change*, 9(2), 315-359.

OECD. 1998. Internationalization of Industrial R&D Pattern and Trends, Organisation for Economic Co-operation and Development.

OECD. 2002. Frascati manual: Proposed Standard Practice for Surveys on Research and Experimental Development. Paris. France.

OECD. 2005. Background Report: Internationalization of R&D: Trends, Issues and Implications for S&T policies, *Belgian Science Policy,* Forum of the internationalization of R&D, 29-30 March 2005, Brussels, Belgium

OECD. 2008. The Internationalization of Business R&D: Evidence, Impacts and Implications, Paris, Organisation for Economic Co-operation and Development.

OECD and EUROSTAT. 1997. Oslo-Manual, Proposed Guidelines for Collecting and Interpreting Technological Innovation Data, Organization for Economic-Co-Operation and Development, Paris.

Ortega-Arguiles M., L. Potters and M. Vivarelli. 2009. R&D and Productivity: Testing Sectoral Peculiarities Using Micro, IPTS Working Paper on Corporate R&D and Innovation, No.03/2009. Luxembourg: Office.

Pakes A. and Z. Griliches. 1984. Patents and R&D at the firm level: A first look, in Z. Griliches (ed.), "R&D, Patents and Productivity", University of Chicago Press, Chicago.

Patel P. and K. Pavitt. 1991. Large Firms in the Production of the World's Technology: An Important Case of Non-Globalization, *Journal of International Business Studies*, 22, 1-20.

Patel P. and M. Vega. 1999. Patterns of Internationalization of Corporate Technology: Location vs. Home Country Advantages, *Research Policy*, 28 (2-3), 145-155.

Pearce R. and M. Papanastassiou. 1999. Overseas R&D and the strategic evolution of MNEs: evidence from laboratories in the UK, *Research Policy*, 28(1), 23-41.

Penrose E. 1959. The theory of the growth of the firm, Oxford University Press, Oxford.

Porter M. E. 1985. Competitive advantage, Free Press, New York.

Roodman D. 2006. How to do Xtabond2: An Introduction to Difference and System GMM in Stata, Center for Global Development, Working Paper 103.

Rosenberg N. 1974. Science, innovation and economic growth, *The Economic Journal*, 84, 90-108.

Rosenberg N. 1982. Inside the Black Box: Technology and Economics, Cambridge University Press, New York.

Savignac F. 2008. Impact Of Financial Constraints On Innovation: What Can Be Learned From A Direct Measure?, *Economics of Innovation and New Technology*, 17(6), 553-569.

Schiantarelli F. 1996. Financial Constraints in Investment: Methodological Issues and International Evidence. *Oxford Review of Economic Policy*, 12(2), 70-89.

Schumpeter J. 1942. Capitalism, Socialism, and Democracy, Harper and Row, New York.

Silverman B.W. 1986. Density Estimation, Chapman and Hall, London.

Stiglitz J.E. and A. Weiss. 1981. Credit Rationing in Markets with Imperfect Information, *American Economic Review*, 71(3), 393-410.

Stoll H.R. 1984. Small Firms' Access to Public Equity Financing, in P.M. Horvitz, R.R. Petit (eds.), "Small Business Finance: Problems in the Financing of Small Business", Greenwich, CT: JAI Press, 187-238.

Terpstra V. 1985. International product policy: the role of foreign R&D, in H.V. Wortzel and L.V. Wortzel (Eds.), "Strategic Management of Multinational Corporations: The Essentials", New York: Wiley.

Thoma G., S. Torrisi, A. Gambardella, D. Guellec, B.H. Hall, and D. Harhoff. 2010. Harmonizing and Combining Large Datasets – An Application to Firm-Level Patent and Accounting Data, NBER Working Paper #15851, March 2010.

UNCTAD. 2005. World Investment Report 2005. Transnational Corporations and the Internationalization of R&D. United Nations: New York and Geneva.

Veugelers R. and B. Cassiman. 1999a. Make and buy in innovation strategies: evidence from Belgian manufacturing firms, *Research Policy*, 28(1), 63-80.

Veugelers R. and B. Cassiman. 1999b. Importance of International Linkages for Local Know-How Flows: Some Econometric Evidence From Belgium, CEPR Discussion Paper # DP2337.

Veugelers R. and P. Vanden Houte. 1990. Domestic R&D in the Presence of Multinational Enterprises, *International Journal of Industrial Organization*, 8: 1-15.

Von Zedtwitz M. and O. Gassmann. 2002. Market versus Technology Drive in R&D Internationalization : Four Different Patterns of Managing Research and Development, *Research Policy,* 31(4), 569-588.

Watson G.S. 1964. Smooth regression analysis, *Sankhya, Series A*, 26, 359-372.

Williamson 0.E. 1970. Corporate control and business behavior, Englewood Cliffs, N.J.: Prentice-Hall.

Williamson 0.E. 1975. Markets and hierarchies: Analysis and antitrust implications, New York: MacMillan Free Press.

Williamson 0.E. 1985. The economic institutions of capitalism: Firms, markets, and relational contracting, New York: MacMillan Free Press.

Windmeijer F. 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators, *Journal of Econometrics*, 126, 25–51.

Winkelmann R. and K.F. Zimmermann. 1995. Recent Developments in Count Data Modelling: Theory and Application, *Journal of Economic Surveys*, 9, 1-24.

APPENDICES

Appendix 1. Corrected and initial datasets (EU27 and US, 2000-2007)

Table A.1 Descriptive statistics on the initial sample

Variables	Region	Mean	Std.dev.	Quantile 25 %	Quantile 50 %	Quantile 75 %
R_{t-1} / C_{t-2}	Global	0.245	0.112	0.178	0.215	0.277
	EU27	0.244	0.123	0.172	0.212	0.273
	US	0.247	0.101	0.182	0.222	0.286
CF_t / C_{t-1}	Global	0.907	1.335	0.256	0.478	1.007
	EU27	1.061	1.639	0.172	0.212	0.273
	US	0.692	0.945	0.209	0.430	0.821
y_t	Global	6.963	1.906	5.707	7.017	8.267
	EU27	6.430	2.089	5.014	6.452	7.816
	US	7.118	1.677	5.852	7.065	8.284
c_t	Global	5.462	1.602	4.425	5.362	6.391
	EU27	4.777	1.674	3.570	4.470	5.704
	US	6.043	1.296	5.115	5.708	6.762
Δy_t	Global	0.081	0.238	-0.012	0.058	0.145
	EU27	0.066	0.253	-0.028	0.043	0.133
	US	0.094	0.236	-0.006	0.070	0.164
Employees	Global	20184	46122	1324	5087	17725
	EU27	16966	45410	691	3101	11246
	US	19576	40663	1556	5400	18100

Source: own computation

Table A.2 Difference between initial and corrected samples[150]

	Mean	*Std.dev.*	*Quantile 25%*	*Quantile 50%*	*Quantile 75%*
R_t / C_t	0.2	5.5	0.8	0.7	0.5
CF_t / C_{t-1}	1.2	1.1	0.7	3.4	2.6
y_t	5.5	2.3	4.8	3.3	1.6
c_t	3.5	2.4	3.0	3.1	3.1
Δy_t	0.8	1.6	1.0	0.8	0.6
Employees	0.4	0.3	1.7	1.8	1.3

Source: own computation

[150] With $StatX_{match,EU}$ being a statistic for variable X using the EU corrected sample and $StatX_{nonmatch,EU}$ the same statistic for the non corrected sample, $abs\left(\frac{StatX_{nomatch,US} - StatX_{nomatch,EU}}{StatX_{match,US} - StatX_{match,EU}}\right)$ is the result reported in the table. A value superior to one means that the procedure has decreased the distance between US and EU statistics.

Appendix 2. ECM estimations by age (System-GMM)

	CF_t/C_{t-1}	CF_{t-1}/C_{t-2}	AR(1)	AR(2)	Sargan	Hansen
EU27						
Age < 30	**(145 obs)**					
lag(2,.)	0.005	0.003	-2.07	-1.61	119	24
	(0.003)*	(0.004)	[0.038]	[0.108]	[0.009]	[1]
lag(3,.)	-0.003	-0.001	-2.22	-1.43	81	22
	(0.002)	(0.003)	[0.027]	[0.151]	[0.041]	[1]
lag(4,.)	0.001	0.002	-2.12	-1.27	47	27
	(0.003)	(0.002)	[0.034]	[0.203]	[0.185]	[0.918]
Age > 30	**(1530 obs)**					
lag(2,.)	0.095	0.026	-1.21	-1.78	1330	89
	(0.005)***	(0.001)***	[0.227]	[0.076]	[0.00]	[0.361]
lag(3,.)	0.042	0.019	-2.03	-1.30	669	62
	(0.005)***	(0.004)***	[0.042]	[0.195]	[0.000]	[0.455]
lag(4,.)	0.039	0.032	-0.19	-0.35	237	36
	(0.006)***	(0.008)***	[0.848	[0.725]	[0.000]	[0.619]
Age > 100	**(1178 obs)**					
lag(2,.)	0.100	0.028	-1.09	-1.09	1154	92
	(0.004)***	(0.001)***	[0.276]	[0.211]	[0.000]	[0.276]
lag(3,.)	0.050	0.032	-1.61	0.14	580	62
	(0.005)***	(0.004)***	[0.108]	[0.890]	[0.000]	[0.436]
lag(4,.)	0.041	0.021	-2.20	0.64	191	24
	(0.007)***	(0.009)**	[0.027]	[0.525]	[0.000]	[0.971]
US						
Age < 30	**(613 obs)**					
lag(2,.)	0.004	0.004	-3.01	2.05	197	79
	(0.003)	(0.001)***	[0.003]	[0.040]	[0.000]	[0.660]
lag(3,.)	0.005	0.044	-3.25	1.80	110	53
	(0.005)	(0.005)***	[0.001]	[0.072]	[0.000]	[0.745]
lag(4,.)	0.014	0.087	-3.39	1.72	46	44
	(0.010)	(0/013)***	[0.001]	[0.086]	[0.210]	[0.265]
Age ≥ 30	**(1302 obs)**					
lag(2,.)	0.001	0.002	-1.81	-1.17	389	121
	(0.001)	(0.0001)***	[0.071]	[0.240]	[0.000]	[0.006]
lag(3,.)	0.007	0.001	-1.72	-1.24	207	77
	(0.004)*	(0.001)	[0.085]	[0.213]	[0.000]	[0.081]
lag(4,.)	0.002	0.004	-1.78	-1.23	61	39
	(0.008)	(0.006)	[0.075]	[0.218]	[0.002]	[0.480]
Age ≥ 100	**(666 obs)**					
lag(2,.)	0.017	-0.000	-1.15	-1.01	309	110
	(0.001)***	(0.001)	[0.250]	[0.310]	[0.000]	[0.034]
lag(3,.)	0.012	-0.002	-1.18	-1.02	177	84
	(0.003)***	(0.001)**	[0.238]	[0.310]	[0.000]	[0.029]
lag(4,.)	0.028	-0.002	-1.30	-1.05	75	59
	(0.009)***	(0.004)	[0.194]	[0.296]	[0.000]	[0.023]

Dependent variable: R_t/C_{t-1}. Estimation of equation 2.5. *** (respectively ** and *): statistically significant at the 1 % (respectively 5 % and 10 %) level. Estimation performed using xtabond2 (Roodman, 2006); all equations include time dummies; Windmeijer corrected standard errors in brackets; P-values in square brackets; AR(1) and AR(2): tests for first order and second order serial correlation in the first difference residuals; Two-step estimates; instruments used in column s (s=2,3,4): observations dated t-s or earlier for X_t (transformed equation) and t-s+1 for ΔX_t (equation in level).

Appendix 3. Detailed regressions on the R&D-patent relationship

Intramural / Extramural R&D expenditures

Dependent variable: patents		
Intercept	-6.757	(0.868)***
Intramural R&D expenditures	0.699	(0.087)***
Extramural R&D expenditures	0.104	(0.045)**
Small size (< 50 empl.)	0.119	(0.391)
Large size (>250 empl.)	0.558	(0.265)**
Flanders	1.155	(0.54)**
Wallonia	1.024	(0.568)*
Nace industry (2-digit)	Jointly significant	
#firms	832	
LogL	-639	
Alpha	3.547	(0.549)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

Research / Development

Dependent variable: patents		
Intercept	-2.525	(0.886)***
Intramural R&D		
Research	0.243	(0.056)***
Development	0.248	(0.037)***
Extramural R&D	0.165	(0.044)***
Small size	-0.31	(0.391)
Large size	0.82	(0.259)***
Flanders	0.208	(0.53)
Wallonia	0.219	(0.564)
Nace industry (2-digit)	joint. sign.	
#firms	797	
LogL	-630	
Alpha	4.257	(0.617)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

Product / Process

Dependent variable: patents		
Intercept	-4.3	(0.824)***
Intramural R&D expenditures		
Product oriented	0.236	(0.052)***
Process oriented	0.08	(0.045)*
Product & process	0.254	(0.05)***
No specific orientation	-0.112	(0.055)**
Extramural R&D expenditures	0.209	(0.045)***
Small size	-0.284	(0.424)
Large size	1.043	(0.279)***
Flanders	1.071	(0.623)*
Wallonia	0.777	(0.688)
Nace industry (2-digit)	Jointly significant	
#firms	731	
LogL	-590	
Alpha	4.582	(0.69)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

Human capital / Equipment

Dependent variable: patents		
Intercept	-4.085	(1.266)***
Intramural R&D expenditures		
Human capital	0.263	(0.154)*
Equipment	0.186	(0.048)***
Extramural R&D expenditures	0.134	(0.045)***
Small size (< 50 empl.)	-0.659	(0.587)
Large size (>250 empl.)	0.821	(0.253)***
Flanders	1.09	(0.591)*
Wallonia	1.431	(0.728)**
Nace industry (2-digit)	Jointly significant	
#firms	795	
LogL	-651	
Alpha	4.704	(1.204)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

Financing

Dependent variable: patents	(1)		(2)	
Intercept	-3.941	(0.83)***	-2.443	(1.014)**
Intra-mural R&D				
Own funds	0.182	(0.049)***	0.127	(0.064)**
External funds	0.315	(0.04)***		
■ Belgian funds			0.167	(0.069)**
■ Foreign funds			0.261	(0.063)***
Extra-mural R&D	0.166	(0.037)***	0.194	(0.048)***
Small size (< 50 empl.)	-0.775	(0.424)*	-0.571	(0.503)
Large size (>250 empl.)	1.173	(0.286)***	1.409	(0.36)***
Flanders	1.05	(0.613)*	0.566	(0.785)
Wallonia	0.929	(0.628)	0.654	(0.862)
Nace industry (2-digit)	joint. sign.		joint. sign.	
#firms	814		362	
LogL	-653		-418	
Alpha	4.863	(0.652)	4.138	(0.621)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

Dependent variable: patents	(3)	
Intercept	-2.97	(1.059)***
Intra-mural R&D expenditures		
Own funds	0.156	(0.072)**
External funds		
■ from firms	0.298	(0.079)***
■ public funds	0.244	(0.076)***
■ from RTO/HEI	-0.084	(0.281)
Extra-mural R&D expenditures	0.207	(0.047)***
Small size (< 50 empl.)	-0.498	(0.456)
Large size (>250 empl.)	1.368	(0.367)***
Flanders	0.475	(0.769)
Wallonia	0.5	(0.834)
Nace industry (2-digit)	Jointly significant	
#firms	362	
LogL	-418	
Alpha	4.144	(0.62)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

Subcontractors

Dependent variable: patents	**(1)**		**(2)**	
Intercept	-6.529	(1.091)***	-6.622	(1.088)***
Intra-mural R&D	0.671	(0.135)***	0.687	(0.137)***
Extra-mural R&D				
Belgian subcontractors	0.148	(0.092)		
■ Regional			0.193	(0.091)**
■ Non regional			-0.085	(0.057)
Foreign subcontractors	0.116	(0.054)**	0.116	(0.05)**
Small size (< 50 empl.)	0.541	(0.678)	0.559	(0.686)
Large size (>250 empl.)	0.634	(0.322)**	0.674	(0.325)**
Flanders	1.112	(0.687)	0.935	(0.655)
Wallonia	1.5	(0.731)**	1.435	(0.706)**
Nace industry (2-digit)	joint. sign.		joint. sign.	
#firms	360		360	
LogL	-382		-381	
Alpha	2.798	(0.522)	2.719	(0.513)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

	(3)	
Intercept	-6.351	(1.083)***
Intra-mural R&D	0.691	(0.136)***
Extra-mural R&D		
Firms subcontractors	0.062	(0.054)
Univ. subcontractors	0.105	(0.058)*
Research centers subcontractors	0.123	(0.083)
Other subcontractors	-0.077	(0.103)
RTO & HEI		
Small size (< 50 empl.)	0.54	(0.705)
Large size (>250 empl.)	0.741	(0.329)**
Flanders	0.602	(0.725)
Wallonia	1.002	(0.795)
Nace industry (2-digit)	Jointly significant	
#firms	360	
LogL	-383	
Alpha	2.856	(0.549)

Dependent variable: patents (priority filings). Negative binomial estimations. Belgian R&D firms over the period 2004-2005. Robust standard errors in brackets. ***, resp. ** and *, means statistically significant at the 1%, resp. 5% and 10% level.

Appendix 4. Additional statistics (835 EU R&D MNEs)

Industry	#firms	#subsidiaries	av. subs. Turnover (mil. USD[151])	av. subs. employees
High-tech	**385**	**38**	**199**	**436**
Biotechnology	52	7	28	119
Semiconductors	19	15	88	308
Pharmaceuticals	50	23	153	268
Telecommunications equipment	26	18	112	231
Software	71	21	23	112
Electronic office equipment	2	61	79	435
Electronic equipment	33	24	28	115
Leisure goods	9	59	154	248
Aerospace & defence	25	63	816	1686
Computer hardware	6	20	51	205
Automobiles & parts	40	91	718	1436
Electrical components & equipment	26	119	162	390
Computer services	26	38	193	404
Medium-tech	**243**	**47**	**237**	**597**
Health care equipment & services	29	40	55	163
Commercial vehicles & trucks	15	34	291	709
Chemicals	42	70	222	336
Alternative energy	4	16	175	164
Industrial machinery	69	36	81	255
General industrials	20	64	482	1603
Household goods & home construction	22	44	409	994
Media	12	36	686	1022
Food producers	30	53	306	1036
Low-tech	**207**	**86**	**1005**	**2583**
Banks	2	26	123	1028
Personal goods	16	82	139	369
Life insurance	1	5	1	0
Fixed line telecommunications	13	101	508	1424
Support services	25	46	179	835
Tobacco	2	383	382	1186
Internet	4	23	47	62
Other financials	11	76	1225	1589
Mobile telecommunications	4	20	1243	943
Oil equipment, services & distribution	4	119	86	164
Electricity	15	103	1725	2354
Construction & materials	26	89	306	910
Forestry & paper	6	64	542	1137
Mining	5	34	1027	2149
Industrial metals & mining	12	55	973	1422
Industrial transportation	12	120	1097	3686
Nonlife insurance	1	22	224	102
General retailers	13	125	764	1950
Oil & gas producers	9	129	2871	3841
Gas, water & multiutilities	8	99	1868	2732
Travel & leisure	9	101	203	1206
Beverages	4	54	1501	3812
Food & drug retailers	5	123	9776	43390
All	**835**	**53**	**410**	**1015**

Source: own computation.

[151] Amadeus provides data for subsidiaries only in US Dollars and not in Euros. This will not affect our econometric analysis as we are interested in the share of the sales across countries or industries.

(continued)

Countries	#firms	#countries	HHI sales	HHI emp
High-tech	**385**	**11**	**0.61**	**0.62**
Biotechnology	52	4	0.72	0.75
Semiconductors	19	7	0.71	0.66
Pharmaceuticals	50	10	0.68	0.63
Telecommunications equipment	26	8	0.72	0.74
Software	71	10	0.54	0.57
Electronic office equipment	2	22	0.32	0.30
Electronic equipment	33	11	0.52	0.58
Leisure goods	9	16	0.66	0.63
Aerospace & defence	25	9	0.64	0.63
Computer hardware	6	11	0.57	0.61
Automobiles & parts	40	18	0.54	0.57
Electrical components & equipment	26	18	0.51	0.50
Computer services	26	12	0.65	0.61
Medium-tech	**243**	**14**	**0.56**	**0.58**
Health care equipment & services	29	15	0.50	0.53
Commercial vehicles & trucks	15	13	0.52	0.60
Chemicals	42	17	0.61	0.63
Alternative energy	4	5	0.69	0.67
Industrial machinery	69	14	0.53	0.55
General industrials	20	12	0.71	0.70
Household goods & home construction	22	17	0.48	0.52
Media	12	7	0.79	0.77
Food producers	30	16	0.52	0.47
Low-tech	**207**	**16**	**0.65**	**0.64**
Banks	2	2	0.81	0.96
Personal goods	16	25	0.54	0.46
Life insurance	1	1	1.00	
Fixed line telecommunications	13	18	0.62	0.62
Support services	25	12	0.65	0.62
Tobacco	2	70	0.67	0.48
Internet	4	10	0.72	0.62
Other financials	11	15	0.69	0.52
Mobile telecommunications	4	10	0.78	0.86
Oil equipment, services & distribution	4	29	0.40	0.38
Electricity	15	10	0.76	0.75
Construction & materials	26	19	0.57	0.60
Forestry & paper	6	20	0.67	0.66
Mining	5	10	0.58	0.67
Industrial metals & mining	12	16	0.54	0.61
Industrial transportation	12	17	0.77	0.80
Nonlife insurance	1	2	1.00	1.00
General retailers	13	9	0.75	0.76
Oil & gas producers	9	23	0.47	0.56
Gas, water & multiutilities	8	12	0.75	0.68
Travel & leisure	9	20	0.81	0.73
Beverages	4	21	0.43	0.56
Food & drug retailers	5	9	0.88	0.85
All	**835**	**13**	**0.61**	**0.61**

Source: own computation.

(continued)

Industry	#firms	#Nace 4 digit	#Nace 2 digit	HHI sales	HHI emp
High-tech	**385**	**10**	**6**	**0.67**	**0.68**
Biotechnology	52	4	3	0.72	0.75
Semiconductors	19	7	5	0.71	0.66
Pharmaceuticals	50	7	4	0.68	0.63
Telecommunications equipment	26	8	5	0.72	0.74
Software	71	7	4	0.54	0.57
Electronic office equipment	2	20	10	0.32	0.30
Electronic equipment	33	10	6	0.52	0.58
Leisure goods	9	13	6	0.66	0.63
Aerospace & defence	25	19	11	0.64	0.63
Computer hardware	6	8	4	0.57	0.61
Automobiles & parts	40	19	10	0.54	0.57
Electrical components & equipment	26	19	9	0.51	0.50
Computer services	26	10	5	0.65	0.61
Medium-tech	**243**	**14**	**7**	**0.59**	**0.58**
Health care equipment & services	29	11	6	0.50	0.53
Commercial vehicles & trucks	15	12	8	0.52	0.60
Chemicals	42	17	9	0.61	0.63
Alternative energy	4	7	6	0.69	0.67
Industrial machinery	69	13	7	0.53	0.55
General industrials	20	18	10	0.71	0.70
Household goods & home construction	22	13	8	0.48	0.52
Media	12	11	5	0.79	0.77
Food producers	30	17	8	0.52	0.47
Low-tech	**207**	**18**	**9**	**0.62**	**0.58**
Banks	2	10	6	0.81	0.96
Personal goods	16	16	8	0.54	0.46
Life insurance	1	2	2	1.00	
Fixed line telecommunications	13	27	13	0.62	0.62
Support services	25	12	6	0.65	0.62
Tobacco	2	25	13	0.67	0.48
Internet	4	10	4	0.72	0.62
Other financials	11	15	9	0.69	0.52
Mobile telecommunications	4	8	6	0.78	0.86
Oil equipment, services & distribution	4	17	10	0.40	0.38
Electricity	15	19	11	0.76	0.75
Construction & materials	26	20	10	0.57	0.60
Forestry & paper	6	20	10	0.67	0.66
Mining	5	11	9	0.58	0.67
Industrial metals & mining	12	20	10	0.54	0.61
Industrial transportation	12	17	9	0.77	0.80
Nonlife insurance	1	9	6	1.00	1.00
General retailers	13	17	7	0.75	0.76
Oil & gas producers	9	35	19	0.47	0.56
Gas, water & multiutilities	8	34	16	0.75	0.68
Travel & leisure	9	20	10	0.81	0.73
Beverages	4	10	6	0.43	0.56
Food & drug retailers	5	17	9	0.88	0.85
All	**835**	**13**	**7**	**0.61**	**0.61**

Source: own computation.

Appendix 5. Estimates using production factors with one lagged period.

	(1)	(3)	(4)
log(L_{t-1})	.66 (.02)***	.67 (.02)***	.65 (.02)***
log(C_{t-1})	.24 (.01)***	.24 (.01)***	.24 (.01)***
log(K_{t-1})	.09 (.01)***	.07 (.02)***	.13 (.02)***
log(K_{t-1}) x log(#count)		.01 (.005)**	
log(#countries)		-.07 (.03)***	
log(K_{t-1}) x log(#indus)			-.01 (.01)**
log(#industries)			.08 (.03)**
R-sq	.95	.95	.95
#obs	3486	3468	3421

Dependent variable: log(Y). Sample of 835 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. 'Industries' is the number of 4-digit Nace industries where the firm is active. Estimates conducted without observations above 99th percentile of diversification.

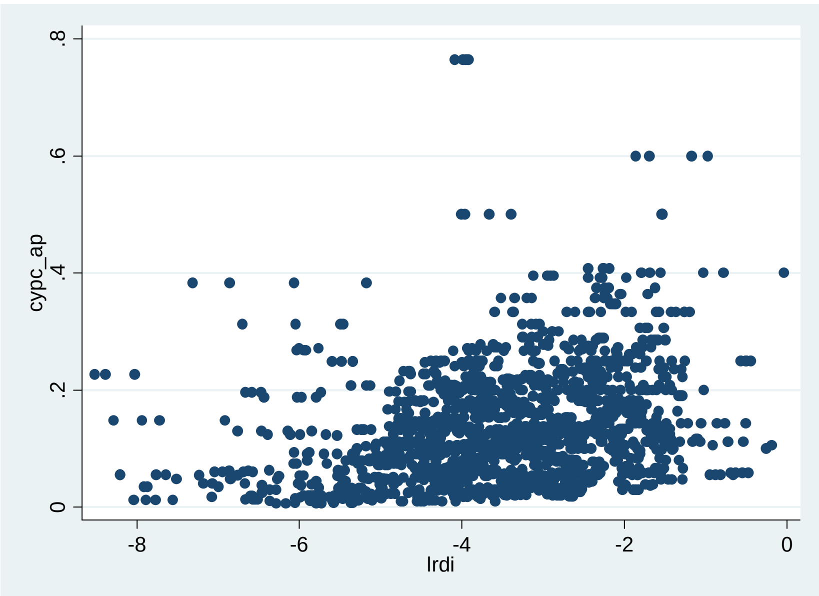
Appendix 6. Estimates over 2006-2008.

	(1)	(3)	(4)
log(L_t)	.63 (.02)***	.63 (.02)***	.61 (.02)***
log(C_t)	.25 (.02)***	.26 (.02)***	.26 (.02)***
log(K_t)	.10 (.01)***	.06 (.02)***	.14 (.03)***
log(K_t) x log(#count)		.02 (.01)**	
log(#countries)		-.09 (.04)***	
log(K_t) x log(#indus)			-.02 (.01)**
log(#industries)			.01 (.05)**
R-sq	.95	.95	.94
#obs	2182	2143	2136

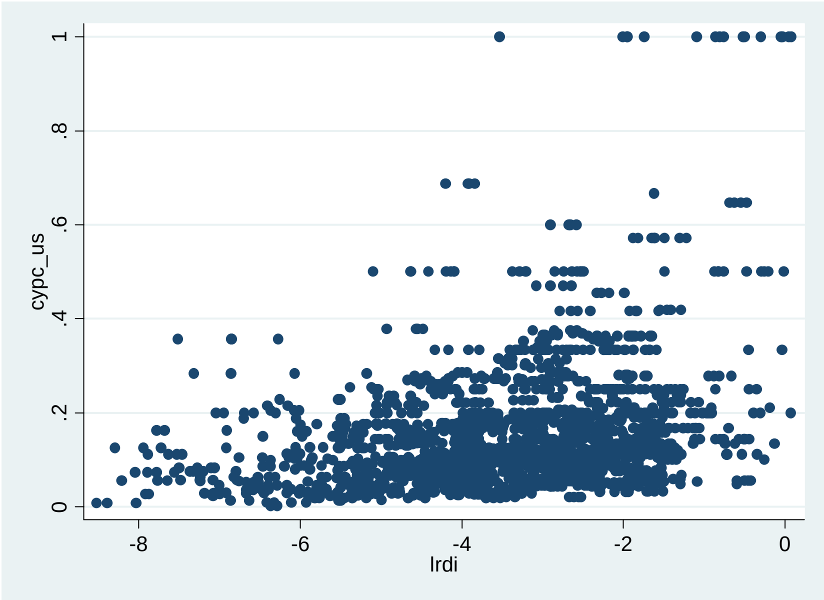
Dependent variable: log(Y). Sample of 835 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. 'Industries' is the number of 4-digit Nace industries where the firm is active. Estimates conducted without observations above 99th percentile of diversification.

Appendix 7. R&D intensity and share of subsidiaries in the main geographic regions

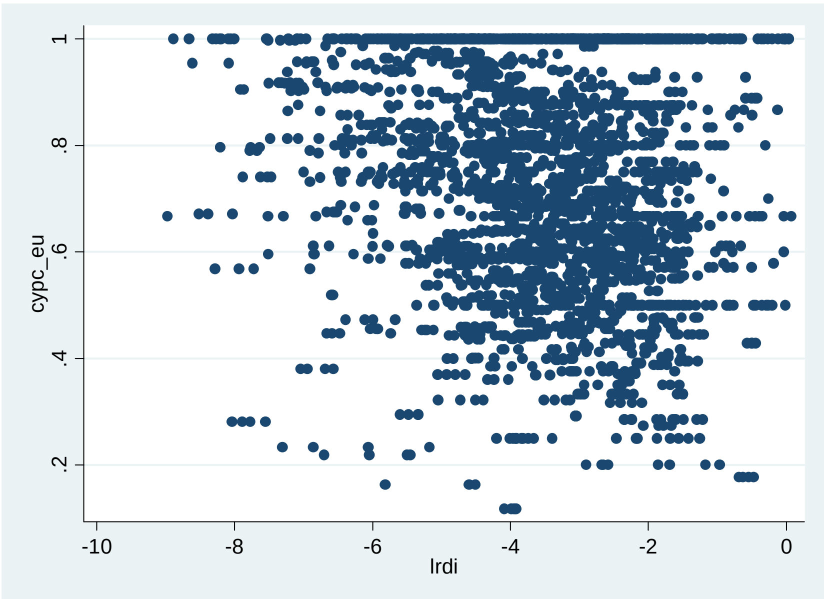
%AP versus log(RD/Y)



%US versus log(RD/Y)



%EU versus log(RD/Y)



Appendix 8. Descriptive statistics by industry (637 EU R&D MNEs)

Industry - ICB	# Firms	# Inventors	% Same	% EU27	% Others
High-tech	**286**	**124179**	74,33%	20,30%	1,78%
Biotechnology	49	2747	67,97%	17,91%	7,03%
Semiconductors	17	6921	61,26%	28,62%	1,50%
Pharmaceuticals	44	10407	45,74%	40,71%	3,53%
Telecommunications equipment	21	9959	33,96%	55,86%	2,73%
Software	25	393	64,63%	21,37%	2,04%
Electronic office equipment	2	822	52,19%	47,20%	0,12%
Electronic equipment	25	3125	78,94%	18,66%	0,64%
Leisure goods	6	7346	70,99%	22,98%	1,21%
Aerospace & defense	20	6252	59,39%	38,79%	1,20%
Computer hardware	5	157	82,17%	15,29%	0,00%
Automobiles & parts	37	47524	88,96%	8,19%	1,16%
Electrical components & equipment	24	28086	82,97%	13,08%	1,87%
Computer services	11	440	60,00%	38,64%	1,14%
Medium-tech	**206**	**75031**	75,56%	14,62%	3,26%
Health care equipment & services	26	2993	71,60%	18,54%	2,91%
Commercial vehicles & trucks	15	2108	85,67%	10,01%	4,17%
Chemicals	40	39479	83,27%	9,52%	2,68%
Alternative energy	3	140	97,14%	0,71%	0,71%
Industrial machinery	63	9676	76,06%	16,57%	4,21%
General industrials	18	4475	75,02%	20,18%	1,72%
Household goods & home construction	18	6317	76,70%	19,46%	1,17%
Media	4	1863	50,99%	18,09%	3,44%
Food producers	19	7980	40,41%	29,69%	7,37%
Low-tech	**145**	**30411**	71,23%	20,23%	2,91%
Personal goods	12	3782	91,01%	4,18%	1,45%
Fixed line telecommunications	10	6417	52,64%	39,18%	1,99%
Support services	12	1179	91,86%	5,17%	2,37%
Tobacco	2	198	36,87%	44,95%	5,05%
Internet	2	73	100,00%	0,00%	0,00%
Other financials	9	684	89,62%	8,77%	1,17%
Mobile telecommunications	3	103	70,87%	24,27%	1,94%
Oil equipment, services & distribution	4	334	65,27%	19,16%	7,78%
Electricity	13	1772	71,84%	24,10%	2,88%
Construction & materials	22	1991	63,69%	26,87%	7,08%
Forestry & paper	6	261	67,05%	31,42%	0,38%
Mining	4	85	22,35%	25,88%	23,53%
Industrial metals & mining	12	2281	75,84%	16,97%	4,73%
Industrial transportation	7	4935	90,54%	2,53%	3,55%
General retailers	5	758	95,91%	1,58%	1,19%
Oil & gas producers	7	4032	46,21%	36,41%	2,55%
Gas, water & multi utilities	6	1323	76,57%	8,24%	1,44%
Travel & leisure	4	140	95,00%	2,86%	0,71%
Beverages	4	29	34,48%	27,59%	0,00%
Food & drug retailers	1	34	91,18%	5,88%	2,94%
All	**637**	**229621**	**74,32%**	**18,43%**	**2,41%**

Source: Own computation.

% Inventors

Industry - ICB	EU27	US-CA	CN	IN	JP	EUnon27	ROW
High-tech	**94,62%**	**3,60%**	**0,11%**	**0,03%**	**0,39%**	**0,91%**	**0,33%**
Biotechnology	85,88%	7,10%	0,18%	0,00%	1,71%	4,11%	1,02%
Semiconductors	89,89%	8,61%	0,06%	0,09%	0,25%	0,38%	0,74%
Pharmaceuticals	86,45%	10,02%	0,00%	0,21%	1,03%	1,81%	0,48%
Telecommunications equipment	89,82%	7,45%	0,73%	0,00%	0,53%	0,74%	0,72%
Software	86,01%	11,96%	0,00%	0,00%	0,00%	0,00%	2,04%
Electronic office equipment	99,39%	0,49%	0,00%	0,00%	0,00%	0,12%	0,00%
Electronic equipment	97,60%	1,76%	0,13%	0,03%	0,13%	0,29%	0,06%
Leisure goods	93,97%	4,82%	0,22%	0,00%	0,53%	0,25%	0,22%
Aerospace & defense	98,18%	0,62%	0,02%	0,08%	0,14%	0,85%	0,11%
Computer hardware	97,45%	2,55%	0,00%	0,00%	0,00%	0,00%	0,00%
Automobiles & parts	97,15%	1,69%	0,00%	0,02%	0,23%	0,69%	0,22%
Electrical components & equipment	96,05%	2,08%	0,12%	0,00%	0,36%	1,14%	0,26%
Computer services	98,64%	0,23%	0,00%	0,00%	0,23%	0,68%	0,23%
Medium-tech	**90,18%**	**6,56%**	**0,10%**	**0,27%**	**0,94%**	**1,31%**	**0,64%**
Health care equipment & services	90,14%	6,95%	0,00%	0,00%	0,50%	2,31%	0,10%
Commercial vehicles & trucks	95,68%	0,14%	0,00%	0,00%	0,00%	3,94%	0,24%
Chemicals	92,79%	4,53%	0,12%	0,01%	1,40%	0,81%	0,34%
Alternative energy	97,86%	1,43%	0,00%	0,00%	0,00%	0,00%	0,71%
Industrial machinery	92,63%	3,16%	0,00%	0,03%	0,03%	3,89%	0,26%
General industrials	95,20%	3,08%	0,00%	0,00%	0,16%	0,74%	0,83%
Household goods &home construction	96,15%	2,68%	0,03%	0,00%	0,17%	0,44%	0,52%
Media	69,08%	27,48%	1,02%	0,00%	0,32%	0,70%	1,40%
Food producers	70,10%	22,53%	0,03%	2,49%	1,42%	0,75%	2,68%
Low-tech	**91,46%**	**5,62%**	**0,16%**	**0,01%**	**0,93%**	**1,21%**	**0,60%**
Personal goods	95,19%	3,36%	0,00%	0,00%	0,87%	0,50%	0,08%
Fixed line telecommunications	91,82%	6,19%	0,62%	0,02%	0,09%	0,58%	0,69%
Support services	97,03%	0,59%	0,00%	0,00%	0,00%	0,85%	1,53%
Tobacco	81,82%	13,13%	0,00%	0,00%	1,01%	1,01%	3,03%
Internet	100,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Other financials	98,39%	0,44%	0,00%	0,00%	0,00%	1,02%	0,15%
Mobile telecommunications	95,15%	2,91%	0,00%	0,00%	0,00%	0,00%	1,94%
Oil equipment, services & distribution	84,43%	7,78%	0,00%	0,00%	0,00%	6,89%	0,90%
Electricity	95,94%	1,19%	0,00%	0,00%	0,00%	2,82%	0,06%
Construction & materials	90,56%	2,36%	0,00%	0,00%	0,05%	4,92%	2,11%
Forestry & paper	98,47%	1,15%	0,00%	0,00%	0,38%	0,00%	0,00%
Mining	48,24%	28,24%	0,00%	0,00%	0,00%	0,00%	23,53%
Industrial metals & mining	92,81%	2,46%	0,04%	0,00%	4,21%	0,35%	0,13%
Industrial transportation	93,07%	3,38%	0,16%	0,00%	1,90%	1,32%	0,16%
General retailers	97,49%	1,32%	0,00%	0,00%	0,13%	0,53%	0,53%
Oil & gas producers	82,61%	14,83%	0,00%	0,02%	1,22%	0,67%	0,64%
Gas, water & multi utilities	84,81%	13,76%	0,00%	0,08%	0,00%	1,36%	0,00%
Travel & leisure	97,86%	1,43%	0,00%	0,00%	0,00%	0,00%	0,71%
Beverages	62,07%	37,93%	0,00%	0,00%	0,00%	0,00%	0,00%
Food & drug retailers	97,06%	0,00%	0,00%	0,00%	0,00%	2,94%	0,00%
All	**92,75%**	**4,83%**	**0,11%**	**0,11%**	**0,64%**	**1,08%**	**0,47%**

Source: Own computation.

Appendix 9. Estimates of Specification 1 (CN, IN, JP, EU non 27 and ROW)

Geo	Dependent Variable	Industrial Technology Cluster			
		All	High	Medium	Low
CN		1	2	3	4
	Log(*L*)	.688(.016)***	.660 (.028)***	.682 (.026)***	.744 (.024)***
	Log(*C*)	.224(.012)***	.161 (.021)***	.219 (.024)***	.274 (.019)***
	Log(*K*)	.094(.011)***	.188 (.020)***	.091 (.015)***	-.001 (.018)
	Z_{CN}	-79.1(11.18)***	-99.7 (46.6)**	-5.14 (15.3)	801.8 (206.3)***
	Z_{CN}***Log(*K*)**	9.38 (1.89) ***	14.1 (5.48)***	-2.66 (3.01)	-103.4 (25.7)***
IN		5	6	7	8
	Log(*L*)	.688(.016)***	.662 (.028)***	.676 (.026)***	.747 (.024)***
	Log(*C*)	.224(.012)***	.157 (.021)***	.221 (.024)***	.271 (.019)***
	Log(*K*)	.098 (.012)***	.195 (.020)***	.091 (.015)***	-.009 (.019)
	Z_{IN}	4.65 (5.61)	-.0582 (6.64)	-23.5 (11.4)**	-110.5 (310.2)
	Z_{IN}***Log(*K*)**	-.665 (.863)	1.43 (1.43)	2.37 (1.48)	31.1 (69.8)
JP		9	10	11	12
	Log(*L*)	.686(.016)***	.664 (.028)***	.672 (.026)***	.749 (.024)***
	Log(*C*)	.224(.012)***	.157 (.021)***	.221 (.025)***	.271 (.019)***
	Log(*K*)	.099 (.012)***	.191 (.020)***	.094 (.015)***	-.009 (.019)
	Z_{JP}	1.46 (.654)**	-4.74 (1.11)***	-.152 (1.23)	5.95 (5.57)
	Z_{JP}***Log(*K*)**	-.288 (.128)**	1.18 (.270)***	-.025 (.224)	-.417 (1.15)
EU non 27		13	14	15	16
	Log(*L*)	.688(.016)***	.665 (.028)***	.672 (.026)***	.744 (.024)***
	Log(*C*)	.224(.012)***	.157 (.021)***	.224 (.024)***	.276 (.019)***
	Log(*K*)	.100 (.012)***	.198 (.020)***	.095 (.015)***	-.012 (.020)
	$Z_{EUnon27}$	.685 (.338)**	1.40 (.759)*	.905 (.464)*	-1.51 (1.38)
	$Z_{EUnon27}$***Log(*K*)**	-.178 (.071)**	-.378 (.173)**	-.158 (.091)*	.276 (.252)
ROW		17	18	19	20
	Log(*L*)	.689(.016)***	.665 (.028)***	.670 (.026)***	.751 (.024)***
	Log(*C*)	.222(.012)***	.154 (.021)***	.227 (.024)***	.270 (.019)***
	Log(*K*)	.096 (.012)***	.193 (.020)***	.089 (.015)***	-.018 (.019)
	Z_{ROW}	.-544 (632)	-2.94 (3.39)	-.692 (.854)	-5.58 (1.61)***
	Z_{ROW}***Log(*K*)**	.205 (.147)	.818 (.551)	.310 (.331)	1.33 (.353)***
	R-Squared	.95	.95	.95	.95
	# Observations	3492	1468	1178	846

Dependent variable: log(*Y*). Sample of 637 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. Dummies are jointly tested for significance level.

Appendix 10. Estimates of Specification 1 (Same and otherEU27)

Geo	Variable	Industrial Technology Cluster			
		All	High	Medium	Low
Same country		**1**	**2**	**3**	**4**
	Log(*L*)	.685(.016)***	.664 (.028)***	.663 (.026)***	.747 (.024)***
	Log(*C*)	.224(.012)***	.157 (.021)***	.226 (.024)***	.276 (.019)***
	Log(*K*)	.098(.016)***	.197 (.025)***	.072 (.018)***	-.023 (.032)
	$Z_{same\ country}$	-.038 (.078)	.029 (.119)	-.281 (.093)***	-.150 (.186)
	$Z_{same\ country}$***Log(*K*)**	-.0002 (.015)	-.001 (.022)	.029 (.019)	.013 (.036)
Other EU27		**5**	**6**	**7**	**8**
	Log(*L*)	.684(.016)***	.665 (.028)***	.662 (.026)***	.750 (.024)***
	Log(*C*)	.224(.012)***	.157 (.021)***	.227 (.024)***	.273 (.019)***
	Log(*K*)	.096(.012)***	.199 (.021)***	.097 (.015)***	-.020 (.019)
	$Z_{otherEU27}$	-.035 (.083)	.042 (.123)	.241 (.103)**	-.264 (.168)
	$Z_{otherEU27}$***Log(*K*)**	.013 (.163)	-.013 (.023)	-.011 (.021)	.044 (.035)
	Country dummies	Yes***	Yes***	Yes***	Yes***
	Industry dummies	Yes***	Yes***	Yes***	Yes***
	Time dummies	Yes***	Yes***	Yes***	Yes***
	R-Squared	.95	.95	.95	.95
	# Observations	3492	1468	1178	846

Dependent variable: log(*Y*). Sample of 637 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. Dummies are jointly tested for significance level.

Appendix 11. Additional estimates for Specification 2

Variables	Industrial Technology Cluster			
	All	High	Medium	Low
Log(*L*)	.692(.012)***	.663(.019)***	.683(.021)***	.762(.022)***
Log(*C*)	.221(.011)***	.160(.018)***	.212(.019)***	.271(.019)***
Z_{EU27}***Log(*K*)**	.096(.009)***	.184(.015)***	.099(.015)***	-.018(.017)
Z_{USC}***Log(*K*)**	.109(.014)***	.199(.023)***	.067(.028)**	.055(.030)*
Z_{CN}***Log(*K*)**	-.770(.642)	2.568(1.04)**	-3.395(.852)***	-4.386(1.80)**
Z_{IN}***Log(*K*)**	-.107(.558)	1.564(1.11)	-.509(.585)	5.644(4.89)
Z_{JP}***Log(*K*)**	.116(.033)***	.224(.048)***	.035(.041)	.746(.332)**
$Z_{EUunon27}$***Log(*K*)**	.060(.021)***	.121(.038)***	.111(.027)***	.002(.079)
Z_{row}***Log(*K*)**	.170(.043)***	.448(.166)***	.238(.089)***	.056(.055)
Country dummies	Yes***	Yes***	Yes***	Yes***
Industry dummies	Yes***	Yes***	Yes***	Yes***
Time dummies	Yes***	Yes***	Yes***	Yes***
R-Squared	.959	.958	.951	.954
# Observations	3492	1468	1178	846

Dependent variable: log(*Y*). Sample of 637 EU R&D companies. ***, **, * mean statistically significant at the 1%, 5%, 10% levels, respectively. Pooled OLS estimates including sets of industry (ICB classification), country and time dummies. Heteroskedastically-consistent standard errors in brackets. Dummies are jointly tested for significance level.