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Chapter 1

General Introduction

"Omnium Rerum Principia Parva Sunt". Cicero stated that all things have small beginnings. In the context of this doctoral dissertation, the "small" would point to innovating firms, small in size and in age and the "things" would point to inventions or new products, encompassing technological progress. Although one should be careful generalizing and it has to be acknowledged in this context that certainly not all important progress flows from small young innovators, some of the major novelties came out of the smallest and youngest firms an economy holds, as Baumol (2002) illustrated and described, "from A to Z, from the Airplane to the Zipper". These not only enabled growth of the firms themselves, but also impacted other firms' activities and social welfare.

Small young innovators as driving forces of technological progress and growth. It is an increasingly embraced point of view in academic literature and in policy guidelines. In this context, several measures towards small young innovators, aimed at facilitating their activities, color the political and economic landscape. This is mainly incorporated in the European strategy 'Europe 2020', the reworked Lisbon Agenda, to increase technological performance and productivity of its member states.

Following the increased attention of policy makers and the recent evolutions in

academic literature, this dissertation looks deeper into the growth opportunities of small young innovators and also assesses the role of targeted subsidies, both with respect to innovative input and output of firms. In addition, as the academic literature has elaborated upon several methods to evaluate policy measures such as targeted subsidies, one of the chapters extends upon existing methodologies.

This introductory chapter gives a broad overview of the dissertation. Sections 1.1 and 1.2 discuss the general literature on which this thesis builds, and section 1.3 provides an introduction to the research questions tackled in the different chapters.

1.1 Firm heterogeneity and economic growth

Amongst all firms in the economy, some specific subsets gained increasing attention over the past decades. An important group of firms in this respect are the ones that are small, young and engaged in innovation activities. They are assumed to contribute both directly and indirectly to technological progress and economic growth. The rationale to consider the combination of these different firm characteristics as crucial determinants or indicators of the possibility of progress is rooted in a long-standing literature discussing the impact of each of these factors individually on technological progress and growth.

A main factor in this respect is innovation, a buzz word of the current era. The view that innovation activities constitute a main driving force of the economic system in terms of welfare, economic competitiveness and sustainable economic growth is not new in itself, see e.g. Schumpeter (1934). However, only since the early 1950s, the growth theory explicitly nullified the view that technological change is exogenous to the economic system and incorporated this as an endogenous factor at the heart of economic growth (Solow, 1956). In later studies, technological change as an endogenous growth factor was supported and further exploited by Romer (1990); Grossman and Helpman (1991*a*,*b*) and Klette and Griliches (1997). In line with this, attention has been increasingly drawn to the

driving forces behind innovation activities of firms, the many different aspects of doing it and the results these generate. The increasing attention of scholars to innovation as a driving force of growth is not only limited to the macro level, but is also investigated empirically especially at the microeconomic, i.e. firm level (see e.g. Geroski and Machin, 1992; Geroski and Toker, 1996 focusing on turnover and profitability and Griliches, 1986; Hall and Mairesse, 1995 on productivity).

The focus on small young firms within the category of innovative firms is rooted in the assumption that these are more likely to behave 'entrepreneurial' and do not refrain from challenging the status quo with their innovation activities.[1] Small young innovators are assumed to induce technological change and growth by enlarging the existing innovation base.[2] On the one hand, these effects lead to expectations on growth of these firms themselves as they might prove to be so-called gazelles or high-growth enterprizes (for a survey of the literature on gazelles, see a.o. Henrekson and Johansson (2010) and Mazzucato and Parris (2014) for a recent contribution). On the other hand, they are assumed to more broadly impact progress by shaping new markets, creating further opportunities and triggering follow-up innovations, thereby potentially creating social value.

Following upon a.o. Schumpeter who introduced the idea that new entrepreneurial innovators play a fundamental role in fostering progress, entailing 'creative destruction'[3] and the increased attention towards subsets of firms such as the broad

[1] A focus on small and / or young firms in general is mainly rooted in the well-established literature trying to understand firm growth dynamics (Gibrat, 1931; Sutton, 1997; Santarelli et al., 2006; Evans, 1987*a*,*b*; Haltiwanger et al., 2013). See also the survey by Van Praag and Versloot (2007) in this context.

[2] Note that they are also acknowledged to thereby disrupt the existing competitive and technological advantages of mature firms ((Malerba and Orsenigo, 1996); also see the well-known Arrow (or replacement) effect, pointing to a low incentive of a monopolist to invest in innovations in contrast to competitive firms (Arrow, 1962)). The disturbance of existing markets might not only create positive externalities but could of course also create negative externalities impacting some of the (less efficient) market participants (Malerba and Orsenigo, 1996).

[3] This, in contrast to the concept of 'creative accumulation' also introduced by Schumpeter and pointing to large industrialized concerns as drivers of innovation and thus economic growth. Note in this context that, although this dissertation focuses mainly on small young innovators, the potential role of large firms in innovation activities is not nullified by doing so (Baumol, 2002, 2004). Next to this, in the context of this dissertation, the potential effects of innovation activities of small young innovators on other actors such as large firms in the economy are acknowledged and suggestions for further research in order to incorporate this are given in chapter 5.

group of Small-and Medium-sized Enterprizes (SME's), several types of firms were defined that explicitly incorporate the characteristics of size, age and innovation. The Arthur D. Little Consulting group, for instance, awakened the interest in the so-called New Technology Based Firms (NTBF) (Little, 1977). The aim of this report was to provide a first attempt to survey the existing stock of young independent firms engaged in innovation activities involving substantial technological risk in Europe (based upon Germany and the UK) and the US, finding evidence that the analyzed European countries were lagging behind in terms of formation and performance of these firms. A lot of work has been done so far confirming the economic potential and importance of similar firms. In this line of research, Westhead and Cowling (1995) and Almus and Nerlinger (1999) found also that NTBFs, defined by them as independent firms in high-tech sectors, showed the highest growth rates.[4] Increasingly, scholars focused on these firms in high-tech sectors as incubators of economic progress (see e.g. Bartelsman et al., 2004; Calvo, 2006; Colombo and Grilli, 2010; Cozza et al., 2012). More recently, Young Innovative Companies (YIC) were defined as an important subgroup of the broader group of Small and Medium-sized enterprizes (SMEs), acknowledging the large heterogeneity in terms of innovation within this broad class of firms (Veugelers, 2008; Schneider and Veugelers, 2010). They are small, young and have as main specificity that they are intensively engaged in innovation activities. They are considered as being the firms which are most likely to be radical innovators (Baumol, 2002; Veugelers, 2009). It is important to note again that attention to these firms is not only based upon their assumed direct growth potential, but also upon the indirect and long-term benefits that breakthrough innovations might bring.

Nevertheless, in spite of the appealing characteristics of these firms and their presumed technological and growth potential, both directly and indirectly, the EU is recognized as lacking small young innovators, which are, if present, less engaged in innovation activities than their US counterparts.[5] Europe is thus considered as

[4]Research on NTBFs often deviates from how the concept was initially introduced either due to data limitations or more general perceived definitional unclarity.

[5]A main explanation for the lower presence is that EU firms face higher barriers to entry, growth and exit as compared to their US counterparts (Bartelsman et al., 2004; Aghion et al., 2008). The US is in that sense acknowledged to be more open to experimentation, which is more likely to lead

benefiting less from both the direct and indirect effects that innovation activities of these firms might bring. In Europe, several scholars argue that the lack of activity of these types of firms might exactly be the reason for the lagging behind of the EU as compared to its main competitors, the United States and Japan, posing an important challenge for Europe (Veugelers, 2009). Figures on R&D spending show that in spite of the target of 3% R&D spending relative to GDP, the EU ratio seems to stagnate at the lower border of 2%, in contrast to the US and Japan, which are at approximately 2.8% and slightly above 3% respectively (OECD, 2013). These findings and both the studies on NTBFs and the findings of Veugelers (2008) were instrumental in highlighting the importance of support infrastructures for the creation and growth of small young innovators in Europe.

1.2 Fostering innovation-induced growth?

Following the increased evidence on their potential role on growth and technological progress as discussed in the previous section, "small young innovators" are increasingly incorporated into policy guidelines around the globe. One aspect of this increased attention is the fostering of innovation activities of these firms (see e.g. the SBIR program in the US (Lerner, 2000; Audretsch, 2003) and the recent guidelines of the EC within the flagship initiative 'Innovation Union' under the 'Europe 2020' targets, the reworked Lisbon Strategy goals (EC-DG Research and Innovation, 2011)).

The justification for policy makers to intervene in fostering innovation activities of firms in order to entail economic growth is rooted in a number of characteristics of R&D activities and market failures related to these activities. For innovating firms in general, it is widely acknowledged that the road both towards and under-

to radical innovations. It has to be noted that this dissertation does not focus on entry and exit of these firms, apart from correcting for a potential survival bias in chapter 2 and the more detailed discussion of market failures related to R&D activities, which are often recognized not only as growth but also as entry barriers, especially for small young firms, and which are one of the main rationales to grant R&D subsidies as certain projects of high value might be foregone (see chapters 3 and 4 below).

taking R&D might be a bumpy one. While the indispensable role of technological progress in firm growth is emphasized in many studies, it is important to take a step back and recognize the fact that R&D activities themselves are often highly uncertain and risky. It is not always straightforward to, first of all, invest in R&D and second, stipulate a successful roadmap that depicts the most efficient way towards a successful innovation. One can never know whether the planned outcome of a new technology will be achieved, and even if this is the case, market success remains uncertain (Arrow, 1962). In addition, once the R&D investment is effectuated, it is to a large extent irreversible, no matter what the outcome is, because R&D investments encompass a large share of sunk costs (Pindyck, 1991; Dixit and Pindyck, 1994). Not only equipment can be highly project-specific, but also the human capital and the tacit knowledge that this entails.

Closely linked to these specific characteristics of R&D activities, innovative firms often face financial constraints for innovation activities. The uncertain and risky nature of R&D investments described above lead to information asymmetries between firms and external suppliers of finance. In addition, the high amount of sunk costs and thus low collateral value could hamper external financing even if information is shared. As a consequence, it might turn out to be difficult for a firm to find external lenders to finance its R&D activities resulting in underinvestment in R&D (Arrow, 1962; Stiglitz and Weiss, 1981).

Another problem, at least from the investing firm's point of view, could emerge, even if a firm was able to finance its projects. The generated knowhow by R&D activities could spill over to competitors, hindering the appropriation of the returns from the initial investment (Schumpeter, 1942; Nelson, 1959; Arrow, 1962). This is rooted in the rationale that knowledge is a non-rival and non-exclusive good.

These characteristics of R&D activities and market failures described above, i.e. uncertainty, lack of appropriability and financial constraints, will lead to an investment level into R&D below what would be done without these problems. It is often posed that this leads to underinvestment into R&D from a social point of view, i.e. social returns to R&D are assumed to be generally higher than private

returns. In this context, it is often posed that a lack of appropriablity by the funded firm could for example lead to positive spillovers and consumer surplus.

While also prevalent for the mature innovators, these issues are found to be more substantial for young and small firms than for larger and more mature firms. As already specified above, small young innovators are assumed to be more likely to invest in radical innovations, which are often more uncertain and risky. When it comes to spillovers, the former are often less able to effectively defend their intellectual property or to extract most of the rents in the product market (Mansfield et al., 1977; Lanjouw and Lerner, 2000; Lerner, 2002). Access to external finance is also found to be more difficult for the young and small firms (see e.g. Himmelberg and Petersen, 1994 and Hall and Lerner, 2010 for a recent survey). Young and small firms usually lack the experience and necessary relationships that could reduce problems of asymmetric information between themselves and potential debtholders. In addition, especially small young firms have limited access to internal funds as they cannot use earlier profit accumulations or a steady cash inflow from a broad and established product portfolio for financing their R&D projects (see e.g. Himmelberg and Petersen, 1994; Carpenter and Petersen, 2002; Cassar, 2004). Research of Berger and Udell (2002) and Müller and Zimmermann (2006) for example suggests that a limited access to finance might be a major reason why there would be lower entrepreneurial activity in Europe than in the US.

Governments can design and implement several policy measures in an attempt to circumvent these issues. One set of policy tools is direct and at the firm level and consists of for example tax credits or public funding of private R&D activity. Another type of policy interventions is indirect. Examples are amongst others patent policies, competition policies or trade policies (Aghion et al., 2005; Veugelers, 2010; Bartelsman et al., 2004; Santarelli and Vivarelli, 2007; Mazzucato and Parris, 2014; Furman et al., 2002). In the context of this dissertation, attention is limited to project-specific innovation subsidies granted to firms. This policy tool is fairly 'narrow' in that it is a selective policy tool.[6] The main argument is to get

[6]Note that, as mentioned in chapter 2 and in chapter 5, this government intervention to overcome financial constraints should be seen next to private venture capital, a topic not explicitly

projects with a high social value initiated that would not have been started as the private value is considered too low by the firm. This type of support can effect both the marginal rate of return (MRR) and marginal cost of capital (MCC) curves of firms. The specificity of selective R&D subsidies is that firms have to go through a selection procedure, they are thus not granted automatically. In general, all selective subsidy schemes evolve along the following lines: after having applied for a subsidy, the government agency decides upon the subsidy to be granted. If a positive decision is made, the government usually funds only a part of the proposed project (see e.g. Jaffe, 2002 for a general description of the subsidy granting process).

Within this framework, several European countries specifically target small young innovators in R&D subsidy programmes. In Germany for example, the 'high-tech strategy 2020' explicitly focuses on small young innovators active in key technologies as being the so-called 'drivers of innovation and the basis for new products, processes and services' (BMBF (Federal Ministry of Education and Research), 2010). Similarly, the Flemish agency in Belgium, IWT, has preferential granting schemes for SMEs and firms active in basic research.

There is a broad literature trying to evaluate the way in which firms make use of these subsidies. In this context, especially the effect on R&D spending of firms has been assessed. This is done as a main concern when granting R&D subsidies is that this might as well entail crowding-out effects. This refers to the situation in which innovation projects are subsidized that would also have been carried out without public subsidies. So far, the main focus in subsidy evaluation literature was on these input additionality effects, i.e. whether R&D subsidies increase investment in R&D of firms (see David et al., 2000; Cerulli, 2010; Zúñiga Vicente et al., 2014 for surveys).

Another, but nevertheless less investigated aspect of R&D subsidies is the ability to create additional output (Czarnitzki and Hussinger, 2004; Czarnitzki and Licht,

tackled in this dissertation (Bottazzi and Da Rin, 2002; Veugelers, 2011; Grilli and Murtinu, 2014)

2006; Hussinger, 2008).[7] It is in general questionable to what extent the induced private R&D investments, if any, stimulate innovative output and thus lead to new technologies at the firm level and if so, do this differently than private R&D (David et al., 2000; Griliches, 1979). In general, research in this field cannot reject an equal productivity of publicly induced R&D as compared to private R&D.

In general, the subsidy evaluation literature calls for a better understanding of subsidy effects on small young innovators, next to some existing studies (Wallsten, 2000; Reinkowski et al., 2010; Colombo et al., 2011; Grilli and Murtinu, 2012). In addition, as the previous paragraph suggests, this field would also benefit from further research assessing both input and output additionality effects.

1.3 Overview of the different thesis chapters

While the above sections provide an overview of the general literature on the growth of small young innovators and the fostering of progress by inducing innovation activities, the sections below will give a brief overview of the contribution of this dissertation to these specific topics. The thesis can be broadly divided into two main parts. The first part investigates the growth of young innovative companies (chapter 2) and the second part extends upon the evaluation of R&D subsidies (chapters 3 and 4). More specifically, the latter two chapters look into input and output additionality effects of subsidies on the firms under consideration. The first of these chapters focuses more specifically on firm heterogeneity in subsidy evaluation while the second one presents a new methodological approach to estimate input and output effects of subsidies.

[7] It is important to note that this dissertation is only concerned with output effects for the subsidized firm itself and abstracts from any positive or negative externalities created by subsidized R&D activities such as e.g. a positive effect consisting of potential spillover effects that subsidies might generate, increasing the performance of other players in the market. For a recent contribution in terms of estimating social value of R&D subsidies, see e.g. Takalo et al. (2013)

1.3.1 Growth

Chapter 2 of this thesis assesses whether 'Young Innovative Companies', as fostered by the European Commission, have the presumed growth potential. The aim of this chapter is thus to critically evaluate whether a current focus on young, small and highly innovative companies is actually warranted and whether YICs may hold the promise of higher growth rates than other firms.

Next to a first-time assessment of the growth of YICs, an important contribution of this study is the explicit analysis of complementarity of the different factors, size, age and innovation activities. This is assessed by comparing YIC growth to growth of other types of small young firms that differ in terms of their intensity of R&D activities. Finally, this chapter also analyzes the potential variability of the growth of YICs over different points of the growth distribution by means of quantile regressions. This is rooted in the premise that one might expect high variability in growth of these firms as there is presumable a high heterogeneity within the class of firms that can be categorized as YICs.

1.3.2 R&D subsidies: firm and method heterogeneity

Firm heterogeneity

As already introduced above, policy makers in Europe did not remain indifferent to the specific constraints faced by small young firms and the presumed beneficial effect of subsidies. Therefore, this chapter analyzes the impact of targeted R&D subsidies to small young innovators. Within this relatively broad class of firms some subsets, such as high-tech and independent firms, are acknowledged to suffer even more from market failures related to innovation activities (Carpenter and Petersen, 2002; Westhead and Storey, 1997; Hoshi et al., 1991; Schaller, 1993). This literature suggests that small young independent high-tech firms are most in need of external funding. In line with these findings and the objectives of the European

Commission to provide less and better general state aid, several governments acknowledge the specificity of specific subsets of small young firms (see e.g. the high-tech strategy 2020 in Germany (BMBF (Federal Ministry of Education and Research), 2010)). However, although the literature suggests a higher need for support by these firms and governments seem to acknowledge this, there is no conclusive evaluation yet on whether firm heterogeneity within broader sets of firms should be a determining factor of policy stipulations.

In order to assess the efficacity of R&D subsidies targeted towards subsets of small young innovators, **Chapter 3** of this dissertation focuses on both input and output additionality effects of subsidies granted to these firms in Germany. Next to the main contribution of this chapter, distinguishing between the effects of subsidies on different subsets of small young innovators, in line with the detailed focus of scholars and policy makers, this chapter also questions the need for evaluating R&D subsidies at a finer-grained level. Most of the subsidy evaluation literature so far focuses on only one (sub)set of firms. However, it might well be important to be more careful when assessing the impact of funding.

Method heterogeneity

The analysis on input additionality in chapter 3 is conducted by the method of matching, a modern micro-econometric technique in order to address selection bias and endogeneity of subsidies (see Heckman et al., 1999; Imbens and Wooldridge, 2009). Research in chapter 3 also adds to the less researched output evaluation by estimating the effect of subsidies in a patent production framework using the estimated treatment effects obtained from matching in order to reflect subsidy induced R&D and the identified counterfactual reflecting private R&D, i.e. what the firm would have invested without receiving subsidies.

Chapter 4 adds to the existing literature by constructing a structural model in which both input and output effects are estimated in a simultaneous equations model, which is not the case in chapter 3. In order to do so, subsidies are for the

first time added to the Crépon, Duguet, Mairesse framework (Crépon et al., 1998), which is essentially a refinement of the traditional knowledge production function framework (Griliches, 1979). Integrating subsidy evaluation in this framework, this setup acknowledges the inextricable nature of input and output stages in the innovation process and presents a new approach for estimating output additionality and assessing whether there is a discount or premium of subsidy induced R&D compared to purely private R&D in terms of output.

1.3.3 Only the beginning of a roadmap

The different chapters of this dissertation raise attention towards studying (subsets of) small young innovators and emphasize the importance of redirecting attention towards these firms both when studying general performance indicators and when assessing the impact of specific policies. In addition, this dissertation shows that not only firm heterogeneity should be taken into account, but also draws attention to the fact that research should be increasingly involved with alternative estimation methods.

Providing more detailed conclusions is beyond the aim of this introductory chapter, but will be given in **Chapter 5**. This last chapter provides an overview of the main results and the key insights of the thesis and provides an overall conclusion. It also identifies and presents limitations of the presented chapters. In addition and following upon the raised limitations, suggestions for further research are also formulated in this concluding section, because after all, this dissertation is only one point in the roadmap towards a deeper understanding of economic realities.

Chapter 2

Young Innovative Companies: the new high-growth firms?

2.1 Introduction

As already touched on in the introductory chapter policy makers and scholars got worried about the emerging gap between the United States and Europe in terms of labor productivity over the past decades. In the mid–nineties, the European Commission identified the 'European Paradox' as a reason for this phenomenon. They stated that Europe plays a leading role in top–level research output around the world, but fails to convert this strength into technological innovation reaching the market. In this view, the 'upstream' production of knowledge and technology is thus considered as being world–class but the corporate sector, the 'downstream' market, is responsible for Europe's productivity slowdown. In the recent past, scholars rebutted this view on the world–class top–level research, finding that the statistics indicating top–level European science were misleading and incomplete (see e.g. Dosi et al., 2006, 2009). According to more intelligent bibliometric and other related measures, European science is by no means world–leading in most

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areas. Nevertheless, a lack of entrepreneurial dynamics of the European corporate sector in comparison to the US has been assumed by multiple scholars. For instance, as Veugelers (2009) argues, EU start–ups face higher entry and growth barriers than their US counterparts. A major reason for this is limited access to finance of European companies (see e.g. Berger and Udell, 2002, Müller and Zimmermann, 2006), such as e.g. the underdeveloped European venture capital market as compared to the US (see e.g. Bottazzi and Da Rin, 2002). This Europe–US disparity has, according to Veugelers (2009) serious consequences for economic growth and therefore, she calls for policy initiatives aiming at young, innovative companies — those which presumably radically innovate and allow reaping the fruit of breakthrough innovations. In contrast to incumbent firms which focus more on incremental innovations in order to protect their current market shares and competencies rather than on developing radically new technologies having the potential to create new markets (Henderson and Clark, 1990; Henderson, 1993), small and young firms are less concerned with safe–guarding their current assets. The view that such firms are more likely to introduce radical innovations and to create new markets is confirmed by Baumol (2002) and Veugelers (2009) who reported that major innovations have been introduced by small US firms during the last century.

Given these stylized facts on limited access to capital, and, as a consequence supposed lacking entrepreneurial dynamics, the European Commission has recently reinforced the policies towards small and medium–sized firms and entrepreneurs by introducing measures to facilitate the creation and growth of these companies. With the revised state–aid rules for innovation support, the European Commission especially reinforces policies towards potential radical innovators by introducing the concept of Young, Innovative Companies (YICs) (see EC-DG ENTR, 2009, for an overview). By the European definition, these companies are less than six years old, have less than 250 employees and are highly R&D intensive, that is, they have an R&D intensity larger than 15% as measured by R&D spending relative to total operating expenses. Despite this increased attention by policy makers and scholars, surprisingly little attention has been paid to the question whether YICs may

actually hold the promise of higher growth than other firms. Therefore, this chapter provides an empirical analysis on the growth potential of the existing YICs. Although YICs are currently a rare species in European economies, it is highly interesting to investigate whether the few existing YICs do actually show superior growth patterns compared to other companies. If not, it would be questionable if the revised state–aid rules for preferred subsidy treatment of these types of companies are justified. If no higher growth could be identified, European policy should rather question other institutional barriers and regulatory burdens.

The remainder of the chapter is organized as follows. The second section reviews some literature on growth of small, young, technology–based companies in order to motivate our specification of the growth equations, section 2.3 discusses the data used and presents descriptive statistics, section 2.4 outlines the econometric methods and presents the empirical results and section 2.5 contains some robustness checks. Finally, a concluding section summarizes the findings and discusses policy implications.

2.2 Theoretical background

2.2.1 The growth of companies

Investigating the growth of firms does not only shed light on the performance of firms in the economy, but also on growth of the economy as a whole. As a consequence, the growth of firms is already intensively investigated, both to evaluate firm performance, and to assess the aggregate economic growth. As the growth of YICs is investigated, incorporating the factors of size, age and innovation, some of the studies that analyzed the influence of each of these factors on growth are discussed.

The earliest contributions focusing on firm growth developed around the law of proportionate effect, more commonly known as Gibrat's Law, and related the size

of the firm to growth. According to this law, the expected value of a firm's growth rate is independent of its current size (see also Sutton, 1997). In general, this law was rejected in empirical studies. However, some of these studies pointed to the fact that the law does hold for the larger firms in the economy but not for the smallest firms (Evans, 1987*a*; Hall, 1987; Dunne and Hughes, 1994; Lotti et al., 2006). For an overview of the literature building upon Gibrat's law, see Sutton, 1997 and Santarelli et al., 2006. Several studies acknowledged the particularity of smaller firms and focused on this type of firms when analyzing growth. Some of these studies found, although often only weakly, an inverse relationship between firm size and firm growth, which was often also weakly confirmed for the larger firms (Mansfield, 1962; Hall, 1987; Evans, 1987*b*; Lotti et al., 2006).

Next to size, age was also considered as an important determinant of company growth. Jovanovic (1982) predicts that firm growth decreases with firm age if firm size is held constant. Fizaine (1968), Evans (1987*a*,*b*), Geroski and Gugler (2004) and Yasuda (2005) for example showed that age has, as predicted, a negative impact on firm growth. In line with this, several scholars found extra variability in firm growth for younger firms (Fizaine, 1968; Evans, 1987*a*,*b*). Many of the authors testing Gibrat's Law, also included age in their regressions, confirming the negative relationship between this latter factor and growth. Evans (1987*a*), Fizaine (1968) and especially more recent evidence of Haltiwanger et al. (2013) even suggested that, if age was taken into account, size lost all of its effects, if any, on firm growth. Haltiwanger et al. (2013) thereby question the main focus on small firms instead of on young firms in literature and policy stipulation.

The quest to the determinants of firm growth came not to an end and several authors extended their scope beyond solely size and age. Geroski (2000), for example, pointed to the unpredictable, stochastic and idiosyncratic nature of growth itself and concluded that this might be owing to the nature of innovation. The outcome of innovations is highly unforeseeable and firm-level innovations could thus be the key determinant of the growth of companies. The attention towards the link between technical progress and growth was already elaborated in the macro-

economic model of Romer (1990). According to this model, higher prosperity of a country is positively related to the resources spent on R&D. Several scholars investigated the influence of innovation on the growth at the company level (for an overview of the theoretical models, see Aghion and Howitt, 1998). Mansfield (1962), Scherer (1965), Geroski and Machin (1992) and Geroski and Toker (1996) for example found a clear positive effect of innovation on growth.

2.2.2 The growth of Young Innovative Companies

The previous section clearly indicates that it is impossible to hold only one company characteristic responsible for the growth pattern of a firm. Instead, as several of the above-mentioned authors showed, it is essential to investigate the combination of several factors in order to explain firm growth. The first scholar that can be considered as explicitly linking two factors, in this case innovation and size, is Schumpeter. Schumpeter's Mark I scenario describes how new entrants are involved in innovation activities in order to gain new market shares in function of a longer survival and a successful growth. Many scholars followed Schumpeter's path and tried to find evidence of an interdependence between size, the share of technological advances in the economy and growth. Mansfield (1962) for example not only limited his research to the sole effect of innovation on growth, but also oriented his attention towards smaller firms. He found that the positive effect of innovation activities on growth was larger for smaller firms. In general, subsequent studies confirmed this finding (Storey, 1994; Roper, 1997; Heunks, 1998; Freel, 2000). Other scholars such as for example Baumol (2002) and Vaona and Pianta (2008) point to the importance of small young firms, being the roots of radical innovation, the source of future growth.

The fact that the individual firm characteristics were found to be complementary in their influence on growth attracted the attention of scholars. As a consequence, as already introduced in chapter 1, new 'firm-type labels' incorporating these characteristics were defined and further investigated. The Arthur D. Little Consulting

group, for example, awakened the interest in the so-called New Technology Based Firms (NTBF), a combination of young and innovative firms (Little, 1977). However, it always remained unclear what the exact definition of a NTBF is. Numerous scholars investigated these firms, defining them as a certain combination of being young and/or active in high-tech sectors (Storey and Tether, 1998; Colombo and Grilli, 2010; Licht and Nerlinger, 1998; Almus and Nerlinger, 1999). In general, the evidence suggests that these firms grow above average.

More recently, the attention shifted to the Young Innovative Companies (YIC) (Veugelers, 2008; Schneider and Veugelers, 2010). These firms combine several characteristics and are small, young and highly intensively engaged in innovation activities. As Veugelers (2008) argues, these YICs are exactly the ones more inclined to exploit a newly found concept, and not the incumbent firms. Incumbent firms mostly introduce incremental innovations because they want to safeguard existing profits and do not want to face the burden of an important restructuring in order to being able to introduce a more radical innovation. YICs on the other hand do not have to care as much as incumbent firms about these issues. Similarly, Baumol (2002) and Vaona and Pianta (2008) argued that firms not concerned with safeguarding existing skills or their market position are more inclined to introduce radical innovations. Consequently, they might grow faster than other firms.[2]

[2]The European governments acknowledged the growth potential of these firms and consequently several of the EU member states introduced special measures in order to facilitate the creation and the growth of this type of firms. Article 35 of the General Block Exemption Regulation (GBER) defines advisory conditions for aid to YICs (European Commission, 2008) by defining specific categories of state aid for which no notification to the Commission is necessary. The support granted to YICs should be compatible with articles 87 and 88 of the EC Treaty, declaring certain categories of aid compatible with the common market.

2.3 Data and descriptive statistics

2.3.1 Data sources

This study investigates growth of YICs in Flanders, the northern part of Belgium. Two different databases are combined: the Flemish part of both the Community Innovation Survey (CIS) and the Eurostat/OECD Research & Development (R&D) survey. The CIS is a survey that is largely harmonized across European member states in order to get a coherent view on innovation inputs and outputs, and is carried out in every odd-numbered year since 2005 (beforehand it was only carried out every fourth year). Similarly to the CIS, the R&D survey collects harmonized information about innovation and R&D activities across OECD member states and is carried out in every even-numbered year. Although the foci of the surveys differ to some extent, we can use the combination of these data to construct a panel covering firms in manufacturing and business services during the period 2001 - 2008.[3] Besides information on R&D activity both surveys also include general information on the respondent firms, such as sales, number of employees, founding year and so forth.

After dropping outliers and missing values in the variables of interest for this study, we end up with an unbalanced panel of 7,888 firms-year observations corresponding to 3,537 different firms.[4] Of these 3,537 different firms, about 45% are only observed once. As a consequence, panel econometric approaches are ruled out as this would significantly reduce the number of observations in our sample.[5]

[3]The CIS mainly collects information about firms' innovation activities in general. The R&D survey focusses in more detail on R&D (and thus the main innovation input) and different dimensions of R&D activities, such as financing, outsourcing etc.

[4]Due to some additional missing values in the sales variable we can only use 6,110 observations when sales are considered as dependent variable.

[5]In addition, about 22% of the firms are observed twice, 16% are observed in three years, 7% in four years, about 4% are observed five times, 2% six times and less than 2% are observed over seven years. Only about 1% of the firms is observed in all years of the analysis.

2.3.2 Variables

As already mentioned above, we measure annual growth both in terms of turnover
$[(TURN_{it+1} - TURN_{it})/TURN_{it} \times 100]$
and employment
$[(EMP_{it+1} - EMP_{it})/EMP_{it} \times 100]$.
The turnover values used in this analysis were adjusted for inflation using a GDP deflator as published by EUROSTAT.[6] The use of both growth measures allows us to shed a clearer light on the growth of the YICs. The literature is in general ambivalent when it comes to determining which growth measure to use.

Employment growth is of high interest for policy makers as job creation is highly important for a society. In addition, the focus on employment growth could be especially relevant in the context of the current study as we focus on small, young, R&D intensive firms. For these types of firms, it is possible that employment grows before any potential sales even occur (Delmar et al., 2003). However, measuring growth in terms of employment also has an important drawback closely related to the previous statement. It is possible that no additional employees are hired as technological progress is often labor-saving (Harrison et al., 2008). As Delmar et al. (2003) remark, a company might grow considerably in output while no employment growth is occurring. For this reason, Coad and Rao (2006), for example, prefer turnover as a growth measure in their empirical analysis. They state that it is reasonable to expect a higher sales growth from successful innovators. Freel (2000) favors turnover growth, as this is often considered as being precisely the reason for increasing the number of employees in a company. Freel (2000) compared studies using turnover and employment as a growth measure for small firms and found that the studies using turnover growth to evaluate small firm innovation were far less ambivalent in their results than the studies using employment growth as a measure.

Delmar et al. (2003) state that one should use several growth measures in the same

[6]Source: 'http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=en'.

explanatory model in order to get a more complete picture of the underlying relationship. Consequently, and as already stated above, we will analyze the influence of YICs on both growth measures in order not to focus on a single growth variable.

Our main independent variable of interest is the dummy indicating whether a company is a YIC or not. We use the European definition as specified in article 35 of the General Block Exemption Regulation (GBER). This latter definition determines YICs as having fewer than 250 employees, being less than 6 years old and spending at least 15% of its operating expenses on R&D. This definition is also used by Schneider and Veugelers (2010), although they do not define R&D intensity in terms of expenditures but in terms of turnover. As the European definition explicitly defines the R&D intensity of YICs in terms of expenditures, we follow the European R&D intensity specification.

For our subsequent analysis, we define a company as a YIC once it meets the criteria for the first time in the period under review. As we are interested in studying how these firms evolve over time, we do not define the YIC dummy on an annual basis but fix it to the value of one once the YIC criteria have been fulfilled for the first time in the sample period. This allows investigating the (long term) growth of YICs compared to other companies even if these YICs exceeded the size threshold of the YIC definition because they conducted business successfully. We will present regression results with alternative YIC definitions as robustness checks in a subsequent section of this chapter.

We include two additional independent variables in order to analyze the decisive influence of being a YIC on growth. We question whether YICs can really be distinguished in terms of growth from small young innovators in general and small, young firms, the latter not having any requirement with respect to innovation activities. Therefore, we create two additional dummy variables, one identifying Small Young Innovators (SYI) and the other indicating small, young firms (SY). The SYI variable is analogous to the YIC-variable except with respect to the intensity of R&D.[7] While a YIC company is highly R&D intensive, the only requirement

[7] In the published version of this chapter, we label SYIs by the more widely-known term 'NTBF'.

we set for a SYI is to have R&D spending above zero. With this SYI variable, we control whether young, small, R&D performing firms grow differently than YICs. The SY companies are small and young, specified according to the YIC definition, but do not have any R&D requirements. We check thus whether it are not solely the size and age requirements that significantly influence the growth of companies. We also adopt the longer-term view for SYIs and SY firms by specifying that, once a company classifies as a SYI or SY, the firm stays a SYI or SY for the rest of the sample period. YICs are defined as a subset of SYIs, which are in turn a subset of SYs. In the regression analysis we code these dummies as mutually exclusive variables (this eases the comparison of growth coefficients in the regression tables):

$$\text{YIC}_{it} = \begin{cases} 1 & \text{if age}_{it} < 6 \;\&\; \text{EMP}_{it} < 250 \;\&\; \text{RDint}_{it} > 15\% \\ 0 & \text{otherwise} \end{cases}$$

$$\text{SYI}_{it} = \begin{cases} 1 & \text{if age}_{it} < 6 \;\&\; \text{EMP}_{it} < 250 \;\&\; \text{RDint}_{it} > 0 \\ 0 & \text{otherwise or if YIC}_{it} = 1 \end{cases}$$

$$\text{SY}_{it} = \begin{cases} 1 & \text{if age}_{it} < 6 \;\&\; \text{EMP}_{it} < 250 \\ 0 & \text{otherwise or if SYI}_{it} = 1 \text{ or if YIC}_{it} = 1 \end{cases}$$

In addition to these variables of main interest, YIC, SYI and SY, we include other control variables commonly used in other studies on firm growth. We control for the influence of innovation on growth by including RDint as a measure for the R&D intensity of the firms. The R&D intensity variable is constructed as used in the YIC definition and measures the R&D intensity as the proportion of R&D expenditures to operating expenditures. RDint is measured in percentages and has thus values between 0 and 100. We allow for a non-linear relationship by including the squared R&D intensity in the regression (RDint^2).

We control for age with the log of age, ln(AGE), and expect to find a negative

We relabeled this in the context of this dissertation as this labeling might be confusing compared to how NTBFs are defined in chapter 3.

effect of the age on growth, as discussed above. Similarly, we use the log of emp, ln(EMP), in order to control for initial size in t-3.

Delmar et al. (2003) point to the potential important, but ambiguous influence of the independence of firms on growth. While firms that are part of a group might have the advantage of getting the necessary support to exploit new opportunities from the parent company, these firms might lack the necessary flexibility to find these new opportunities (see also Eisenhardt and Martin, 2000 and Barney et al., 2001). Consequently, we include a group dummy (GROUP) indicating whether a firm is part of a group. In addition to the group variable, a dummy is added taking the value 1 if the home base of the company is not situated in Belgium (FOREIGN) in order to control whether foreign ownership has an influence on growth.

Another dummy included in the regressions is EXPORT, taking the value 1 if the firm exports to other countries, both within and outside Europe. We expect to find a positive relationship between being an exporter and growth. Exporters might learn from their presence in other markets. On the one hand, spillovers are more likely to occur, which enables the exporting firm to perform better. On the other hand, exporting allows the exploitation of economies of scale. However, the evidence is not unambiguous with respect to this relationship (see Castellani, 2002 for a survey).

In addition, we control for differences in technological opportunities with industry dummies. It is realistic to assume that unique attributes of a certain industry affect the development of the firms in that industry (Delmar et al., 2003). These industry dummies are based on the NACE codes, the Statistical Classification of Economic Activities in the European Community. This classification is a European industry standard classification system. Table A2.1 in the appendix shows the industry structure of our sample. In addition, time dummies are constructed in order to control for business cycle effects and four region dummies control for unobserved heterogeneity across the different Flemish regions.

2.3.3 Descriptive statistics

Table 2.1 shows the descriptive statistics of the different variables used in the regressions for respectively YICs, SYIs, SYs and all other firms that can not be categorized as one of these firm types.[8] The descriptive statistics reveal that YICs grow, on average, more than all other firm types, both when growth is measured in terms of employment and when measured by the change in sales.

In terms of sales growth, SYIs grow, on average, faster than both SY firms and other firms. Similarly, SY firms have, on average, a higher sales growth than the other, non-categorized, firms, which show an average negative sales growth. For employment, results are different and only YICs have, on average, a positive growth in employment. Although YICs grow, on average 3.32% in terms of employment, SYIs face an average loss of 0.44% and SYs even have a negative average growth of 4.26%, which is lower than the average negative employment growth of 3.12% of the other, non categorized, firms.

In line with the definition of the different firms, both YICs, SYIs and SYs are, on average, younger than the other, non-categorized firms. Although the same result holds for size, this difference seems to be less pronounced for SYIs, which are, on average, clearly larger than YICs and SYs.[9] In terms of R&D intensity, results are also in line with expectations, as YICs have an average R&D intensity of 40.02%, more than 35% points higher than the average R&D intensity of SYIs, which have the second largest R&D intensity of the different firm types.

[8] Correlations between the variables are given in Table A2.2.

[9] This result is possible as both YIC, SYI and SY variables do not cover the exact YIC, SYI and SY definition anymore. We specified that once a company classifies as a YIC, it remains a YIC throughout the rest of the sample period.

Table 2.1: Descriptive Statistics

	YIC			SYI			SY			Other firms		
Variables	Mean (StDev)	min	max	Mean (StDev)	min	max	Mean (StDev)	min	max	Mean (StDev)	min	max
# of Observations	180			309			161			5460		
Sales Growth[a]	13.01(43.15)	-76.16	189.91	3.44(30.69)	-68.66	152.17	1.11(35.49)	-77.90	177.31	-0.22(24.31)	-78.07	194.84
# of Observations	245			345			288			7010		
Employment Growth	3.32(24.97)	-66.67	75	-0.44(15.62)	-64.29	62.07	-4.26(21.66)	-65.22	66.67	-3.12(15.67)	-66.67	75
Employment	32.33(49.44)	1	298	117.09(474.22)	2	4862	36.37(49.45)	1	239	170.06(479.57)	1	11485
Age	4.67(2.50)	1	13	4.94(2.60)	1	13	3.95(2.07)	1	10	26.90(18.38)	1	193
R&D intensity	40.02(31.16)	0	99.56	4.77(9.77)	0	89.96	0.56(4.70)	0	62.43	4.05(12.16)	0	100
FOREIGN	0.23(0.42)	0	1	0.29(0.45)	0	1	0.22(0.41)	0	1	0.25(0.43)	0	1
EXPORT	0.27(0.45)	0	1	0.37(0.48)	0	1	0.35(0.48)	0	1	0.38(0.49)	0	1
GROUP	0.43(0.50)	0	1	0.63(0.48)	0	1	0.37(0.48)	0	1	0.52(0.50)	0	1

[a] Due to missing values, the sales growth equation can only be estimated for a subsample.
Note: Region dummies, time dummies and industry dummies are omitted in this table.

2.4 Empirical analysis

2.4.1 The growth of Young Innovative Companies: pooled OLS

To evaluate the growth of YIC companies, pooled OLS regressions are used. We specify the following equation in order to estimate the growth of YICs, SYIs and SYs separately[10]:

$$\begin{aligned} GROWTH_{i,t+1} =& \beta_0 + \beta_1 YIC_{it} + \beta_2 ln(EMP)_{it} + \beta_3 ln(AGE)_{it} + \beta_4 RDint_{it} + \beta_5 RDint_{it}^2 \\ &+ \beta_6 FOREIGN_{it} + \beta_7 EXPORT_{it} + \beta_8 GROUP_{it} + \text{industry dummies} \\ &+ \text{time dummies} + \text{region dummies} + \epsilon_{it} \end{aligned} \quad (1)$$

To control to what extent the growth of the different firm types can be really distinguished, we estimate a similar equation, with dummies of all mutually exclusive firm types included:

$$\begin{aligned} GROWTH_{i,t+1} =& \beta_0 + \beta_1 YIC_{it} + \beta_2 SYI_{it} + \beta_3 SY_{it} + \beta_4 ln(EMP)_{it} + \beta_5 ln(AGE)_{it} \\ &+ \beta_6 RDint_{it} + \beta_7 RDint_{it}^2 + \beta_8 FOREIGN_{it} + \beta_9 EXPORT_{it} \\ &+ \beta_{10} GROUP_{it} + \text{industry dummies} + \text{time dummies} \\ &+ \text{region dummies} + \epsilon_{it} \end{aligned} \quad (2)$$

We use a cluster-robust covariance matrix in order to account for heteroskedasticity and for arbitrary autocorrelation within a firm, as the errors of the same firm observed over multiple years might be correlated.[11]

Table 2.2 presents the regression results. Columns 1 to 4 show the results when employment growth is used as dependent variable and the results for sales growth are presented in columns 5 to 8.

[10] To measure the growth of SYIs and SY firms, the YIC dummy inserted in the equation is replaced by the SYI and SY dummies respectively.

[11] Note that results are robust to regression-to-the-mean effects, in line with the remarks raised by a.o. Davis et al. (1996); Haltiwanger et al. (2013).

We find for both growth measures that YICs grow significantly more than any other type of firm, while both pure SYIs and SYs, so without the YIC category and without the YIC and SYI categories respectively included, have an insignificant or negative coefficient. Column 3 shows that being a YIC increases employment growth with almost 5%, all else equal. Similarly, column 7 indicates that YICs achieve a higher expected sales growth of approximately 7.5%, ceteris paribus. Columns 4 and 8 assess to what extent the growth of YICs can be really differentiated from the growth of firms with the same age and size requirements but with a lower R&D intensity, SYIs, and with no innovation activities, SYs. In other words, is it really the combination of the three factors of size, age and R&D intensity that gives the YICs a higher growth capability or can the same growth pattern be found for firms that do not combine these factors? For both growth measures, we find a positive confirmation of the superior growth of YICs compared to the other firms.

Although the SYI and SY dummies are insignificant in both regressions, the YIC dummy stays positive and significant.

The importance of the combination of different factors in YICs is further confirmed by the results of the inclusion of the individual size, age and R&D intensity variables in the regressions. For both growth measures, size and age have a significant negative effect on growth which is in line with the literature. The estimation results reveal that there is an inverted u-shaped relationship between R&D intensity and sales growth. The estimation results do not reveal a significant effect of R&D intensity on employment growth. This result is in line with the findings of Harrison et al. (2008) who argue that technological progress is often labor-saving. A higher R&D intensity in itself is thus not leading to higher employment if not seen in combination with the factors age and size.

We cannot find a significant relationship between being part of a group and growth, and between foreign ownership and growth. For the export variable, however, we find a negative significant relationship. This implies that an exporting firm would grow less than the other firms. Although this result may seem counterintuitive, similar negative results with the export dummy have been found in productivity

studies. Clerides et al. (1998), Bernard and Jensen (1999) and Bernard and Wagner (1997) studied the influence of export on productivity and find at best an insignificant influence and otherwise a negative impact of export on productivity growth.

Table 2.2: Pooled OLS regressions on employment and sales growth

	Employment Growth				Sales Growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
YIC			4.791**	4.782**			7.414**	7.253**
			(2.101)	(2.130)			(3.552)	(3.562)
SYI		1.125		1.340		-0.252		0.277
		(1.036)		(1.050)		(1.696)		(1.682)
SY	-2.690*			-1.799	-2.997			-2.219
	(1.380)			(1.409)	(2.850)			(2.891)
ln(EMP)[a]	-0.348*	-0.348*	-0.317*	-0.332*	-1.111***	-1.096***	-1.070***	-1.082***
	(0.186)	(0.186)	(0.185)	(0.185)	(0.287)	(0.287)	(0.285)	(0.285)
ln(AGE)	-1.120***	-0.762***	-0.658**	-0.690**	-1.925***	-1.762***	-1.416***	-1.533***
	(0.270)	(0.294)	(0.257)	(0.302)	(0.489)	(0.502)	(0.449)	(0.522)
RDint	0.074	0.085	0.055	0.048	0.186**	0.196**	0.143	0.137
	(0.053)	(0.053)	(0.051)	(0.051)	(0.090)	(0.089)	(0.092)	(0.093)
$RDint^2$	-0.001	-0.001	-0.001	-0.001	-0.003**	-0.003**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FOREIGN	0.796	0.798	0.735	0.766	0.787	0.765	0.686	0.706
	(0.560)	(0.561)	(0.561)	(0.562)	(0.877)	(0.878)	(0.881)	(0.882)
EXPORT	-2.688***	-2.689***	-2.690***	-2.725***	-2.007**	-1.983**	-2.038**	-2.057**
	(0.491)	(0.491)	(0.490)	(0.490)	(0.866)	(0.867)	(0.864)	(0.863)
GROUP	0.623	0.640	0.671	0.624	-0.978	-0.961	-0.904	-0.919
	(0.512)	(0.511)	(0.508)	(0.509)	(0.838)	(0.839)	(0.831)	(0.831)
Constant	-1.239	-2.569*	-2.926**	-2.719*	6.692***	6.007***	4.849**	5.343**
	(1.307)	(1.359)	(1.299)	(1.431)	(2.148)	(2.185)	(2.007)	(2.281)
N	7888	7888	7888	7888	6110	6110	6110	6110
R^2	0.056	0.056	0.057	0.058	0.073	0.073	0.075	0.075
F	17.417***	17.477***	17.326***	16.517***	14.581***	14.555***	14.500***	13.561***
F-test on joint significance of industry dummies	4.39***	4.35***	4.34***	4.41***	8.13***	8.15***	7.99***	7.98***
F-test on joint significance of time dummies	28.80***	29.13***	29.23***	28.69***	39.06***	39.20***	39.33***	39.14***
F-test on joint significance of region dummies	2.06*	2.04*	1.96*	2.04*	0.98	0.91	0.84	0.88

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Cluster-robust standard errors are given in parentheses.
[a]: The results hold when we include the logarithm of turnover as a size measure, instead of the logarithm of employment in the regressions on sales growth

2.4.2 Quantile regressions

Ordinary least squares estimations as used above represent average effects of the covariates, and thus only give a partial insight in the relationship between dependent and independent variables. As the effect of a covariate might be heterogeneous across the distribution of the dependent variable, we also estimated quantile regressions taking the distribution of the underlying dependent variable into account (Buchinsky, 1998; Koenker and Hallock, 2001; Koenker, 2005; Angrist and Pischke, 2009). Quantile regressions shed a more complete picture of the relationship between employment growth and the different regressors at different points of the conditional distribution of the dependent variable, y. Instead of minimizing a sum of squared residuals as in OLS estimations, quantile regressions solve the minimization of a sum of asymmetrically weighted absolute residuals (symmetric at the median). The θth quantile regression solves:

$$\min_{\beta_\theta} \frac{1}{n}\{\sum_{i:y_i \geq x_i^{'}\beta_\theta} \theta|y_i - x_i^{'}\beta_\theta| + \sum_{i:y_i < x_i^{'}\beta_\theta} (1-\theta)|y_i - x_i^{'}\beta_\theta|\} = \min_{\beta} \frac{1}{n}\sum_{i=1}^{n} \rho_\theta(\epsilon_{\theta i}),$$

where $x_i^{'}\beta_\theta$ is the linear prediction and different weights are given to absolute errors, i.e. over- and underpredictions get different penalties. The last term of this equation is just an alternative representation where $\rho_\theta(\epsilon_{\theta i}) = (\theta - I(\epsilon_{\theta i} < 0))\epsilon_{\theta i}$ is a so-called check function with $I(\cdot)$ an indicator function and $\epsilon_{\theta i}$ corresponding to the error term.

Quantile regressions are appealing to analyze the growth of the YICs, as Mansfield (1962) found an, on average, higher but also more variable growth of small firms. Presumably, YICs show the same pattern as found by Mansfield and the higher growth of YICs as compared to the other firms could be even more pronounced in the higher quantiles, whereas the opposite could be true in the lower quantiles. In other words, there is probably a high variation in the growth of YICs over the

distribution and consequently, a difference in the estimated slope parameters at different quantiles of the conditional growth rate distribution. If this is the case, this can be attributed to the high heterogeneity within the class of firms that are categorized as YICs. Scatterplots of size on growth and age on growth give a first indication that it is good to perform quantile regressions (see figure 2.1). Both the youngest and the smallest firms show a high variability in growth, both when growth is measured in terms of employment as when sales growth is measured.

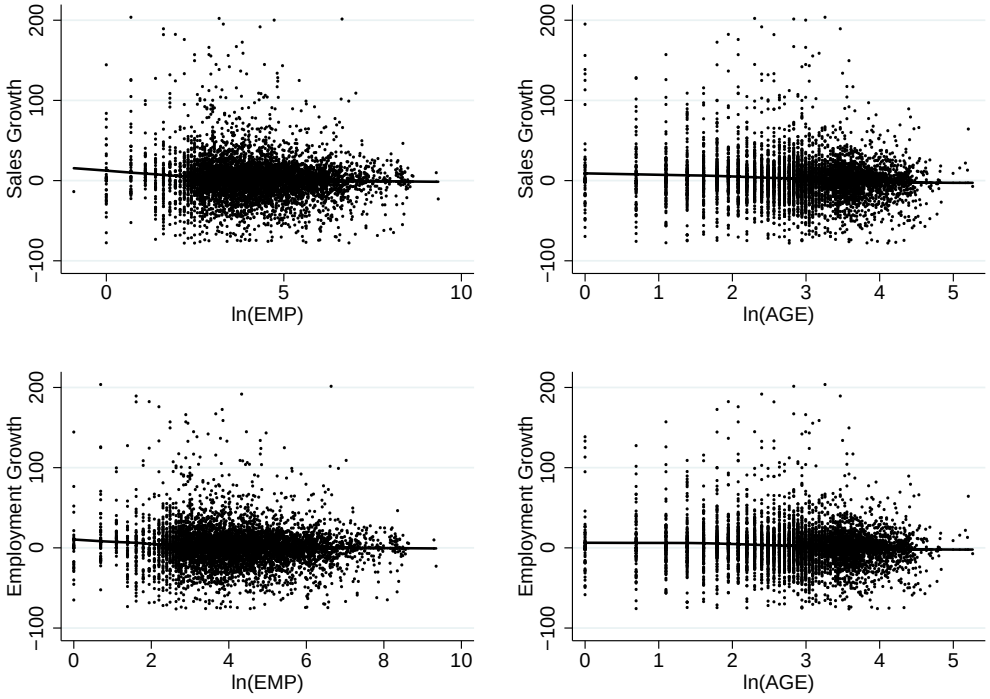


Figure 2.1: Variation of size and age over the growth distribution

We estimate quantile regressions at each decile of the distribution and correct the estimated standard errors for heteroskedasticity by bootstrapping. Bootstrapping is used instead of the calculation of asymptotic standard errors, as this would require the estimation of the conditional density of the error term (Angrist and Pischke, 2009). We use a bootstrapped quantile regression estimation with 500 replications.

Table 2.3 shows the result of the quantile regressions on the sales growth of YICs. The nine different columns refer to nine different deciles for which the quantile regression was performed, with the first decile presented in column 1 and the last

decile presented in column 9. In the first two deciles, the sign of the YIC coefficient is negative but insignificant. Consequently, there is no evidence that YICs would be performing worse than the other firms in the lowest growth quantiles, thus compared to other low performers. Only from the fifth decile onwards, the coefficient for YICs becomes significant and positive. Until the sixth decile, however, the growth rate of YICs remains below the average growth rate found in the OLS regressions. From the seventh decile onwards, the growth rate of YICs surpasses the growth rate that was found in the OLS regressions, evolving from a 15% higher growth rate in the seventh decile to an approximately 30% higher growth rate in the ninth decile, ceteris paribus. Consequently, we find that firms having the YIC characteristics in the higher growth quantiles, show a superior growth as compared to the other categories of firms. The other main finding is that there is no evidence of a slower growth of the YICs in the lowest quantiles. This is remarkable, as one could have expected that YICs that fail perform poorer than the other firms due to their high-risk factor.

The quantile regression results in table 2.3 also show the evolution of the firms that categorize as pure SYIs and SYs over the different quantiles. For SY firms, we find significant results at different points of the distribution. However, the sign of the significant coefficients is always negative. As a consequence, the relevance of the combination of the different factors in YICs is strongly confirmed. The quantile regressions also reveal that size has a positive significant effect on growth in the first two deciles. This indicates that, among the least-growing firms, being a larger firm is beneficial for growth, at least in terms of sales. This result can be related to the result of the SY dummy, indicating that especially small young non-innovating firms grow less than the other least-growing firms. Among the bulk of not or slowly growing firms, it is reasonable to expect that the small young firms, not heavily involved in innovation activities, will grow even less as they might not have built up valuable resources yet.

Table 2.3: Quantile regressions on sales growth (6,110 observations)

	(1) 10%	(2) 20%	(3) 30%	(4) 40%	(5) 50%	(6) 60%	(7) 70%	(8) 80%	(9) 90%
YIC	-12.185	-1.704	2.333	3.553	5.534**	7.172**	14.730***	21.510***	29.445***
	(7.476)	(4.766)	(2.961)	(2.979)	(2.628)	(3.587)	(5.160)	(4.917)	(7.644)
SYI	2.468	0.552	1.014	-0.020	-1.092	-2.039	-1.506	-2.023	0.001
	(2.567)	(1.732)	(1.296)	(1.379)	(1.191)	(1.250)	(1.375)	(2.586)	(4.273)
SY	-7.326*	-6.854**	-2.739	-4.699***	-4.972**	-2.399	-0.568	0.073	8.609
	(4.184)	(3.204)	(2.240)	(1.486)	(2.345)	(2.819)	(2.538)	(3.726)	(10.948)
ln(EMP)	0.837*	0.548*	0.326	-0.004	-0.276	-0.688***	-1.148***	-1.454***	-2.823***
	(0.433)	(0.288)	(0.228)	(0.201)	(0.177)	(0.199)	(0.236)	(0.298)	(0.529)
ln(AGE)	-0.002	-0.598	-0.077	-0.315	-0.682**	-0.997***	-0.852**	-1.567***	-2.298**
	(0.876)	(0.509)	(0.367)	(0.382)	(0.340)	(0.341)	(0.412)	(0.574)	(1.030)
RDint	-0.174	-0.048	0.070	0.104	0.115*	0.134**	0.242***	0.196**	0.440**
	(0.166)	(0.103)	(0.081)	(0.066)	(0.064)	(0.059)	(0.077)	(0.097)	(0.193)
RDint2	0.001	-0.001	-0.002	-0.002*	-0.002**	-0.002***	-0.004***	-0.002	-0.005*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
FOREIGN	3.190**	1.657*	0.770	0.112	0.367	1.039*	0.520	0.815	0.481
	(1.489)	(0.938)	(0.669)	(0.637)	(0.693)	(0.613)	(0.689)	(0.921)	(1.718)
EXPORT	-4.701***	-2.652***	-2.653***	-1.287**	-0.946	-0.752	0.076	-0.414	1.403
	(1.316)	(0.940)	(0.630)	(0.640)	(0.656)	(0.655)	(0.687)	(0.867)	(1.654)
GROUP	-5.226***	-2.841***	-2.421***	-1.660**	-1.261**	-0.972	-0.221	0.241	2.789*
	(1.327)	(0.858)	(0.652)	(0.651)	(0.604)	(0.616)	(0.664)	(0.850)	(1.575)
Constant	-27.157***	-18.552***	-13.609***	-7.417***	-1.243	5.713***	9.539***	18.351***	31.014***
	(3.570)	(2.303)	(1.719)	(1.780)	(1.697)	(1.441)	(1.735)	(2.442)	(3.952)

* p<0.10, ** p<0.05, *** p<0.01

Note: Bootstrapped standard errors are given in parentheses (500 replications). Regressions control for time, region and industry dummies.

Table 2.4: Quantile regressions on employment growth (7,888 observations)

	(1) 10%	(2) 20%	(3) 30%	(4) 40%	(5) 50%	(6) 60%	(7) 70%	(8) 80%	(9) 90%
YIC	6.683	5.208**	3.637**	2.079**	1.642	4.215**	6.051***	9.722***	11.611***
	(5.105)	(2.445)	(1.851)	(1.059)	(1.033)	(2.092)	(2.189)	(3.091)	(3.408)
SYI	5.232***	1.676	1.672*	0.265	0.205	0.375	0.000	0.224	-0.519
	(1.856)	(1.248)	(0.880)	(0.635)	(0.762)	(0.738)	(0.845)	(1.537)	(2.006)
SY	-6.441*	-4.703**	-3.269**	-1.340	-0.806	-1.023	-0.781	0.087	2.742
	(3.529)	(2.070)	(1.652)	(1.326)	(0.835)	(0.701)	(1.403)	(1.742)	(3.079)
ln(EMP)	1.732***	1.050***	0.461***	0.009	-0.252**	-0.341***	-0.671***	-1.207***	-2.404***
	(0.285)	(0.187)	(0.156)	(0.110)	(0.105)	(0.102)	(0.119)	(0.185)	(0.236)
ln(AGE)	0.985*	-0.118	-0.199	-0.413**	-0.329*	-0.391**	-0.606***	-1.363***	-2.175***
	(0.590)	(0.287)	(0.221)	(0.176)	(0.186)	(0.172)	(0.216)	(0.309)	(0.532)
RDint	-0.260***	-0.194***	-0.035	0.031	0.043	0.060*	0.117**	0.277***	0.306***
	(0.094)	(0.074)	(0.058)	(0.034)	(0.031)	(0.036)	(0.046)	(0.061)	(0.095)
$RDint^2$	0.002	0.001	0.000	-0.000	-0.001*	-0.001**	-0.002***	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
FOREIGN	1.036	1.429**	0.923**	0.487	0.417	0.171	0.269	0.488	0.558
	(0.962)	(0.574)	(0.415)	(0.359)	(0.346)	(0.313)	(0.364)	(0.505)	(0.731)
EXPORT	-2.886***	-3.194***	-2.994***	-3.053***	-2.837***	-2.334***	-1.665***	-2.562***	-2.313***
	(1.043)	(0.645)	(0.437)	(0.442)	(0.361)	(0.370)	(0.393)	(0.473)	(0.834)
GROUP	0.009	0.076	0.213	0.242	0.172	0.165	0.073	-0.054	0.358
	(0.883)	(0.613)	(0.449)	(0.353)	(0.338)	(0.275)	(0.358)	(0.523)	(0.827)
Constant	-34.039***	-18.950***	-11.559***	-5.132***	-1.553	1.586**	4.913***	13.276***	27.074***
	(2.664)	(1.528)	(1.323)	(0.946)	(1.043)	(0.655)	(1.049)	(1.525)	(1.962)

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Bootstrapped standard errors are given in parentheses (500 replications). Regressions include time, region and industry dummies.

Table 2.4 presents quantile regression results for employment growth. These results confirm even more the superior performance of YICs as compared with the other types of firms, having lower innovation intensities, SYIs, or no innovation activities, SYs. Except for the first and fifth decile, the YIC coefficient is positive and significant over all quantiles. Again, we see that the highest significant growth difference between YICs and other companies is situated in the upper quantiles. The growth rate surpasses the average OLS growth rate from the seventh quantile onward.

In the first and third decile, the SYI coefficient is positive and significant. However, in the third decile, the dummy is only weakly significant and the coefficient is far below the positive significant coefficient of YICs. In addition, it is only among the least-growing firms that the SYI coefficient is higher and more significant than the YIC coefficient. When we focus again on the higher quantiles, the fast-growing firms, no significant effect of SYIs can be found. With respect to the other control variables, the results presented for the quantile regressions on employment growth largely confirm the results found for sales growth.

In figure 2.2, we show a graphical representation of the evolution of the YIC coefficient over the distribution of growth as presented in the quantile regressions. The solid line and the gray area present the YIC coefficient of the quantile regressions and its confidence interval. The dashed line represents the OLS coefficient, while the dotted lines below and above present the confidence interval of the OLS estimator.

For sales growth, we see a clear, upward trend of the YIC coefficient over the growth distribution. Although the coefficient is still negative in the first decile, it increases steadily till the last deciles, largely surpassing the OLS estimator and its upper bound of the confidence interval. A test on the differences between the YIC coefficients over the different quantiles shows that they are significantly different from each other, showing that the slope of YICs is indeed different over the different quantiles.

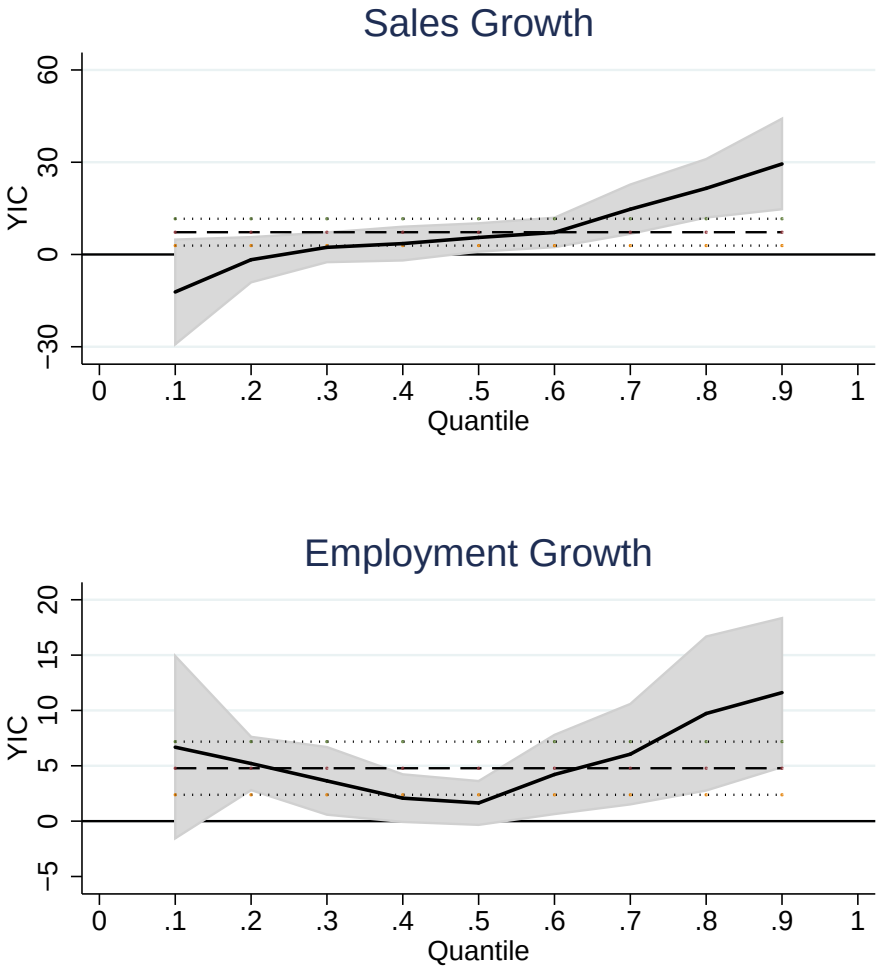


Figure 2.2: Quantile regression representation of the YIC coefficient

For employment growth this trend is, in general, less upward. However, while the coefficient stays close the OLS estimator in the first and middle quantiles, it surpasses the OLS estimator in the last deciles, the deciles of the fast-growing firms. Another finding is that the YIC coefficient never goes below zero. Consequently, although the results are very variable in the first deciles, YICs never perform significantly worse than the other companies at any point of whole growth distribution. Estimates of the difference between the YIC coefficients over the different quantiles show that they are significantly different at the 5% level. When disentangling these differences further, results indicate that these differences are solely driven by the upper quantiles (80% and 90%) which are significantly different from

the lower and middle quantiles.

2.5 Robustness checks

2.5.1 YIC growth in the short and medium term

In the previous section, we investigated the long-term growth of YICs.[12] However, one could question how the growth pattern evolves if shorter time spans are taken into consideration. Therefore, we also investigate the growth of YICs (and of SYIs and SY firms) in the short and medium term. In order to do so, we restrict the time span of the initial definition of YICs, SYIs and SY firms. Instead of considering a YIC, SYI or SY firm as belonging to the respective firm group for the rest of the sample period after the respective criteria have been met once, we set shorter thresholds. To measure short-term growth of YICs, we only allow a firm to be a YIC maximum three years after it had actually fulfilled the criteria of the YIC definition. Medium-term growth is measured by setting this maximum allowed time span to five years. For both short-term growth and medium-term growth, the definitions of SYIs and SY firms are adjusted analogously.

Table 2.5 presents the short-term and medium-term growth rates of the covered firm types as specified above. Columns 1 and 2 reveal that, in the short-term, YICs grow significantly faster than all other firms, both in terms of employment and sales. This superior growth of YICs is also confirmed when measuring medium-term YIC growth. In addition and in line with the previous results, YICs outperform SYIs and SY firms over both alternative time spans considered. In general, the growth measures do not seem to vary a lot depending on the different YIC definitions used. This confirms the high growth capacities of YIC companies in the short, medium and long term.[13]

[12] Closely related to this, table A2.3 in appendix 2.B shows an extension on the 'durability' of growth

[13] An alternative extension would be to vary the YIC definition in terms of its R&D intensity

Table 2.5: Short-term and medium-term YIC growth

	Short-term YIC growth		Medium-term YIC growth	
	(1)	(2)	(3)	(4)
	Emp Growth	Sales Growth	Emp Growth	Sales Growth
YIC	4.348**	7.95**	4.286**	8.051**
	(2.189)	(3.687)	(2.109)	(3.491)
SYI	1.277	1.196	1.148	0.337
	(1.141)	(1.916)	(1.069)	(1.730)
SY	-1.668	-1.212	-1.925	-2.143
	(1.476)	(3.036)	(1.408)	(2.890)
ln(EMP)	-0.336*	-1.080***	-0.334*	-1.079***
	(0.185)	(0.285)	(0.185)	(0.285)
ln(AGE)	-0.718***	-1.352***	-0.746**	-1.490***
	(0.298)	(0.515)	(0.301)	(0.520)
RDint	0.052	0.138	0.051	0.132
	(0.051)	(0.143)	(0.052)	(0.093)
$RDint^2$	-0.001	-0.002**	-0.001	-0.002**
	(0.001)	(0.045)	(0.001)	(0.001)
FOREIGN	0.762	0.691	0.769	0.696
	(0.563)	(0.434)	(0.562)	(0.882)
EXPORT	-2.704***	-2.032**	-2.716***	-2.045**
	(0.490)	(0.864)	(0.490)	(0.864)
GROUP	0.635	-0.898	0.624	-0.915
	(0.510)	(0.830)	(0.510)	(0.830)
Constant	-2.618	4.683**	-2.510*	5.195**
	(1.410)	(2.241)	(1.424)	(2.266)
N	7888	6110	7888	6110
R^2	0.057	0.075	0.058	0.075
F-statistic	16.53***	13.55***	16.528***	13.545***
F-test on joint significance of				
-industry dummies	4.38***	7.97***	4.40***	7.96***
-time dummies	28.84***	39.16***	28.66***	39.12***
-region dummies	2.05*	0.85	2.04*	0.88

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Cluster-robust standard errors are given in parentheses.
Short-term YIC definition: Once a company classifies as a YIC, it is only considered as being a YIC for a maximum of three further years after fulfilling the criteria of the YIC definition.
Medium-term YIC definition: analogous to the short-term definition but the threshold of elapsed years is set to five instead of three.

2.5.2 Controlling for a potential survival bias

As we use survey data to investigate the growth of YICs, our regressions might suffer from a potential survivor bias. If YICs are more likely to exit the market than other firms, we would overestimate their growth rate as the surveys can only account for firms that have survived until the date of the data collection. Therefore, we have tried to control for firm survival by employing a Heckman selection model. First, we estimate the probability of survival using a Probit model with the population of firms as obtained from the 'Belfirst' database[14], or more precisely, for that part of the population where we have information on determinants possibly influencing survival as described below. From the Probit model, we obtained the predicted propensity score of survival that we used to compute Heckman's inverse Mills ratio (see e.g. Heckman, 1979). Then we included the inverse Mills ratio in the growth equations as reported above.

The Belfirst database contained 38,438 observations that could be used for the first stage regression, the survival equation. According to the Belfirst database, about 10% of the 38,438 observations exited the market. The reasons can be summarized as liquidation, bankruptcy and being absorbed in a merger. The latter is not necessarily a "negative exit" as selling the firm to another owner might actually be a highly profitable business strategy and may happen because of doing business successfully. Therefore, we ran different versions of the Probit model. In one version we included all types of exits, and in another we dropped all firms that were absorbed in a merger (2,254 observations, i.e. about 5.9% of the data). This change in sample specification did not have any effect on the conclusion as reported below.

threshold. Appendix 2.B, table A2.4 shows the relevance of this threshold.

[14]The Belfirst database is published by Bureau van Dijk and basically contains accounting data for the population of Belgian firms.

As the Belfirst database provides mainly accounting information, we cannot identify YICs in the first stage regression on survival because of missing R&D information. Therefore, we tried to explain survival by the following determinants: firm size, labor productivity, capital intensity, cash flow, debt ratio, industry, region and time dummies. We also experimented with a number of interaction terms and different functional forms as well as different lag structures and changes in variables rather than using levels. Although the estimated coefficients had largely the expected signs in the survival regressions, it turned out that the explanatory power of these regressions was low. This resulted in the following problem: whenever we estimated the growth equation augmented with the inverse Mills ratio, we only got insignificant results concerning the selection term, and all results we reported earlier in this study persisted. This does, however, not convincingly reject the idea that the growth equations might suffer from a survival bias. It rather turns out that our first stage regression might not fit the data well enough to estimate the possible bias to a satisfactory extent. Our first stage regression never predicted a probability of survival lower than 93%. This owes to the limited availability of regressors having decent explanatory power on future exit. We believe that one would need a more targeted, forward looking measure, such as a credit rating (see e.g. Czarnitzki and Kraft, 2004, 2007), to forecast exits and eventually account for a survival bias convincingly. Unfortunately, we do not have credit ratings or something comparable available for these data. Therefore, our robustness check on a potential survival bias in the growth regression remains somewhat inconclusive.

2.6 Conclusion

In this chapter, the growth of Young Innovative Companies (YICs) is analyzed. Governments seem to have high expectations of these firms. However, we question whether these expectations are, in general, reasonable. In addition, it is not clear to what extent the combination of size, age and R&D intensity is a crucial

combination determining firm growth. We question whether YICs show higher growth rates than firms encompassing only part of the factors that determine YICs. Therefore, we compare YIC growth to the growth of both small, young (SY) firms and small young innovators (SYIs). SYIs have the same size and age requirements as YICs, but their R&D criterion is less strict, as their R&D intensity should just be higher than zero percent. We question whether the R&D requirement matters at all in order to explain growth by comparing YICs to small young firms (SY), only incorporating the size and age requirements of YICs.

In general, we find that YICs grow more than other firms, both when measuring growth in terms of sales and in terms of employment. In addition, our results confirm the relevance of combining the different factors incorporated in YICs. When combined in the regressions, the positive significant growth result of YICs holds, whereas no positive, significant result can be found for SYIs and SY firms. As a consequence, the combination of the factors age, size and R&D intensity seems to be crucial for the superior growth of YICs.

We also analyzed the growth of YICs by means of quantile regressions in order to address the possibly high variation in YICs' growth. We find evidence that there is indeed a high variation in the growth rates of YICs at different points of the growth distribution, that is, the estimated coefficients of the quantile regressions are sometimes significantly different from the coefficient obtained with OLS regressions. However, YICs show a superior growth in the highest growth quantiles indicating that these firms grow even more than the already fast growing firms. Another important finding is that we do not find, at any point of the growth distribution, a negatively significant effect of being a YIC on growth (both when sales growth and employment growth are analyzed). This indicates that the growth of YICs does not vary to that extent that YICs dramatically 'fall harder' as compared to the other slow-growth firms.

In general, this study reveals that the expectations on growth of YICs (mainly put forward by European policy makers) might be justified, as their growth appears to be higher than that of other firms, on average. As a consequence, the reinforce-

ment of state aid programs towards YICs, as defined in the EC's General Block Exemption Regulation (GBER) might foster growth and job creation. Especially the higher growth of YICs compared to SYIs and SY firms may well affirm the relaxed limitations on national state aid by governments in the European Union. Re-directing increased state aid to YIC is also in line with economic arguments on market failure in the context of R&D activities. The literature has suggested that young, highly innovative companies suffer more from financial constraints than other firms (see e.g. Himmelberg and Petersen, 1994, or the recent survey by Hall and Lerner, 2010, for an overview on the financial constraints literature). In addition, both positive sales and employment growth suggest that the innovation activities of YICs are successful to a certain extent at least. In the long-run, other companies are likely to benefit from successful R&D activities of highly innovative companies by building further on promising innovations. Governments should thus not only focus on the growth potential of YICs as isolated cases, but should view the results in a broader context, acknowledging the potential social value of YICs. Note that the 'validity' of any policy recommendation deserves further analysis as this chapter has no prescriptive role in this respect.

In terms of further research, it would be highly interesting to trace YICs over longer periods of time than we could do in this chapter with our data in order to study the possible higher exit rates of YICs when compared to other companies. In addition, the current estimations disregard other firm characteristics that were recognized to determine growth such as for example the already in the introductory chapter discussed financial constraints (in this context, see e.g. Carpenter and Petersen, 2002). Similarly, several scholars found above-average education and skills of founders and employees of these small young innovators. In accordance with competence-based theories, these latter factors are recognized as key determinants of growth (see e.g. Colombo and Grilli, 2005 discussing these determinants in the context of growth of young high-tech firms). In line with this, other factors, such as industry dynamics are also acknowledged as impacting growth dynamics (e.g. Mazzucato and Parris, 2014 for some recent research on the competitive environment as impacting the R&D–growth relationship). Furthermore, it would

have been interesting to derive the macroeconomic potential for job creation. This has unfortunately not been possible in this study, as we cannot identify how many YICs exist in the population because we have to rely on our sample from the surveys for calculating the R&D intensity. It would have been required to have R&D information for the whole population of firms in order to define the YICs also in the population and not only in the sample. Note that more general limitations to this dissertation that also apply to this chapter are discussed in chapter 5.

Chapter 3

R&D subsidies to small young companies: should the independent and high-tech ones be favored?

3.1 Introduction

As already introduced in the previous chapters, expectations on the creation of valuable new knowledge are especially high for small and young firms (Veugelers, 2008; Schneider and Veugelers, 2010; Czarnitzki and Delanote, 2013). Performance effects of these firms have been found to be even more pronounced in high-tech sectors. Audretsch (1995) for example, following upon Dunne et al. (1988) who found differences in growth rates across different industries, touches upon the importance of sectoral differentiation. The small start-ups active in a highly innovative environment seem to perform better than the ones in a low-tech environment. In this line of research, Westhead and Cowling (1995) and Almus and Nerlinger (1999) found also that the new technology based firms (NTBFs), thus independent firms in high-tech sectors showed the highest growth rates. Increasingly, schol-

Joint work with Dirk Czarnitzki

ars focused on these firms in high-tech sectors as incubators of economic progress (see e.g. Bartelsman et al., 2004; Calvo, 2006; Colombo and Grilli, 2010; Cozza et al., 2012).

Before introducing an innovation on the market, these small young firms need to invest in R&D. However, as is widely known, investment in R&D suffers from market failures, as already introduced in chapter 1. These will be briefly recapitulated here. First, firms might be reluctant to invest in R&D as the generated knowhow by R&D activities can spill over to competitors, hindering the appropriation of the returns from the initial investment (Schumpeter, 1942; Nelson, 1959; Arrow, 1962). In addition, innovative firms often face financial constraints for R&D activities. Funding R&D projects is risky, as the outcome of R&D investments is often very unclear and once the R&D investment is effectuated, it is to a large extent irreversible, no matter what the outcome is (Pindyck, 1991; Dixit and Pindyck, 1994) because R&D investments encompass a large share of sunk costs. Not only equipment can be highly project-specific, but also the human capital and the tacit knowledge that this entails. These specific characteristics of R&D investments lead to information asymmetries between firms and external suppliers of finance, resulting in underinvestment in R&D (Arrow, 1962; Stiglitz and Weiss, 1981).

While also prevalent for the mature innovators, these problems are found to be worse for young and small firms than for larger and more mature firms. When it comes to spillovers, the former are often unable to effectively defend their intellectual property or to extract most of the rents in the product market (Mansfield et al., 1977; Lanjouw and Lerner, 2000; Lerner, 1999, 2002). In addition, access to external finance is also found to be more difficult for the young and small firms (see Evans and Jovanovic, 1989; Holtz-Eakin et al., 1994*b*,*a*; Czarnitzki and Hottenrott, 2011 and Hall and Lerner, 2010 for a recent survey). Young and small firms usually lack the experience and necessary relationships that could reduce problems of asymmetric information between themselves and potential debtholders. Himmelberg and Petersen (1994) and Carpenter and Petersen (2002) focus more specif-

ically on independent high-tech small young firms and conclude that these firms are more financially constrained. Westhead and Storey (1997) explicitly compare the extent to which most technologically sophisticated small firms are more financially constrained than less technologically sophisticated ones. They find that the high-tech, technology sophisticated firms were more impeded in growth due to financial constraints than the comparison group. Goodacre and Tonks (1995) state that innovation in high-tech industries is more likely to be of a new sort because of which it is more difficult to evaluate the investment by financiers. Storey and Tether (1998) focus more specifically on NTBFs, corresponding to the class of small young independent high-tech firms in this study and emphasize their higher need of external financing. Based upon this literature, we would expect that the small young independent high-tech firms are most in need of external funding as they are more likely to lack internal financing. In the same vein, most of these scholars focus on independent small young innovators, the rationale being that group firms have the advantage of their parent while the non-group counterparts on the other hand, lack the critical mass and the experience to access funds for their high-risk R&D projects. That independent firms would be more in need of external funding is already suggested multiple times in literature. In general, Hoshi et al. (1991), Schaller (1993) and Czarnitzki and Hottenrott (2011) confirm that large internal capital resources reduce underinvestment problems, suggesting that this is even more true for R&D investments.

Ever since Schumpeter, who emphasized the necessity of temporary monopoly profit for financing of future R&D, economists acknowledged the importance of internal finance for funding R&D investment and further elaborated upon this topic (Schumpeter, 1942). In the context of small young firms, several scholars found a positive relationship between R&D investment and internal finance (Himmelberg and Petersen, 1994; Czarnitzki and Hottenrott, 2011). However, as pointed out at the same time by these scholars, especially small young firms have limited access to internal funds as they cannot use earlier profit accumulations or a steady cash inflow from a broad and established product portfolio for financing their R&D projects (see also e.g. Berger and Udell, 2002; Carpenter and Petersen, 2002; Cas-

sar, 2004).

Policy makers in Europe did not remain indifferent to the specific constraints faced by small young firms and the presumed beneficial effect of subsidies. As a consequence, they are heavily engaged in providing support to innovation activities of this type of firms. The increased attention towards small and young firms fits within the flagship initiative 'Innovation Union' under the 'Europe 2020' targets, the reworked Lisbon Strategy 2010 goals (EC-DG Research and Innovation, 2011).

One of the main objectives of the European Commission is to provide 'less and better' general state aid. Moncada et al. (2010) state that at least size, age, innovativeness and sectoral differentiation should play an important role in the choice of policy measure targets. The authors claim that the granting process of innovation subsidies should be oriented towards small, young, high-tech innovators. The focus on high-tech firms gained increasing attention by some European countries. In Germany for example, the country analyzed in this study, the 'high-tech strategy 2020' explicitly focuses on key technologies as being the so-called 'drivers of innovation and the basis for new products, processes and services' (BMBF (Federal Ministry of Education and Research), 2010).[2] In addition, the European Commission specifies that autonomous SME's should be distinguished from group firms and the focus of different policy measures is on the former group (European Commission, 2008). However, although both the literature suggests a higher lack of financing for these firms and the government seems to acknowledge this, there is no conclusive evaluation yet on whether these firms show higher treatment effects when receiving subsidies.

In order to evaluate whether the subsidy granting process of small, young firms should be determined by independence and sectoral differentiation, we compare the impact of subsidies on small young firms that are either independent or part of a group and active in high-tech or low-tech sectors. In order to do so, we analyze

[2]Some policies are designed and implemented focusing on R&D intensity of firms instead of on sectoral differentiation (see also chapter 2 of this dissertation). In the current setting of Germany however, we follow the stipulations by the BMBF.

the subsidy impact on New Technology Based Firms (NTBF), group NTBFs, Low Technology Based Firms (LTBF) and group LTBFs. NTBFs are, since their introduction by the Arthur D. Little Consulting Group a well-known type of firms (Little, 1977). Several scholars investigated this type of firms and found, in general, a high innovative performance and growth (Storey and Tether, 1998; Colombo and Grilli, 2010; Licht and Nerlinger, 1998; Almus and Nerlinger, 1999). In this study, NTBFs refer to small, young, independent firms active in high-tech sectors. LTBF is a concept coined by us in order to denote the 'counterparts' of NTBFs with respect to sector of activity. While NTBFs are active in high-tech sectors, LTBFs are small, young indepedendent firms active in low-tech sectors. We also evaluate the subsidy impact on firms that have all characteristics of how LTBFs and NTBFs are defined in this study, except for the independence component. In other words, we also evaluate the impact on these so-called group NTBFs and group LTBFs, that are thus part of a group, in order to assess the relevance of current policies to mainly target independent firms. Table 3.1 graphically presents the four groups of firms analyzed in this study and recapitulates the differences between the different types of firms.

We evaluate the impact of direct R&D subsidies granted to companies on several R&D input measures and in a second step on output. In order to evaluate the impact of subsidies on the R&D investment of the different categories of small young firms, we perform caliper matching with replacement. However, it is a priori unclear, if additional R&D due to subsidies is found in the first place, whether this also leads to technological progress of the subsidized firm. Thus, even if no crowding out can be found in the first place, it remains questionable what the technological (and thus economic) benefits of public funding are. In this study, technological performance is measured by patent applications and analyzed in a patent production framework, with the private and publicly induced R&D effort taken from the results of caliper matching in the first step.

The remainder of the chapter is organized as follows: sections 3.2 and 3.3 review

Table 3.1: Overview of the firms studied, embedded in the full sample

<table>
<tr><td>NTBF
Small, young independent firms, active in high-tech sectors</td><td>Group NTBF
Small, young group firms, active in high-tech sectors</td><td rowspan="2">Small Old firms</td></tr>
<tr><td>LTBF
Small, young independent firms, active in low-tech sectors</td><td>Group LTBF
Small, young group firms, active in low-tech sectors</td></tr>
<tr><td colspan="2">Large young firms</td><td>Large old firms</td></tr>
</table>

the evaluation literature and outline the econometric method used for both the input and output analysis, section 3.4 discusses the data used and presents descriptive statistics and section 3.5 presents the empirical results. Finally, a concluding section summarizes the findings and discusses policy implications.

3.2 Subsidy input evaluation

In this study, we first evaluate the impact of direct subsidies on innovation input. It is an empirical question how firms that receive these subsidies react to this support. It is possible that the subsidies are subject to crowding–out effects. This might happen if firms replace their privately financed R&D projects by the publicly subsidized ones. Furthermore, the empirical analysis could reveal heterogeneity in subsidy effects among the different firm types. For instance, many innovation subsidies to young, small firms are oriented towards firms that are not part of a group. If our results, however, would show higher treatment effects for firms associated with groups, it would suggest a current misallocation of public resources.

In order to measure the effect of public support on R&D input, several econometric models were proposed. However, estimating the effect of public subsidies is not that straightforward as subsidies are likely to be endogenous. Firms that receive a subsidy are presumably different from companies that do not receive a subsidy. A first difference already emerges at the application stage as some firms might be more likely to apply for public funding than others. Indeed, some firms might consider the administrative burden or the information sharing conditional upon being subsidized as important reasons to restrain from applying for a subsidy. In addition, there is a possibility that the funding agencies follow a picking-the winner strategy with respect to the firms that applied for a subsidy. In other words, firms might have some characteristics that make them more attractive to governments for funding. As a consequence, funding cannot be considered as a random process and this selection should be accounted for when evaluating subsidy schemes.

Comparing subsidized and unsubsidized firms based on random samples would thus lead to biased results. In order to evaluate the impact of subsidies on the R&D investment of the different firm types, caliper matching is performed in this study. Doing so, we do not use a random control group, but firms that are actually similar to the subsidy recipients in observed characteristics.

3.2.1 Literature review

The impact of R&D policies on firms' innovation behavior has already been extensively covered in the economic literature. The main focus in the literature is on the input additionality of subsidies. As a consequence, most of the literature addressed the issue of crowding-out effects of subsidized R&D. David et al. (2000) and Cerulli (2010) survey the literature on subsidy effects and find that, in general, the results of the reviewed literature vary a lot and only a limited number of authors effectively tackles the selection bias described above. Zúñiga Vicente et al. (2014) provide the most recent literature survey on the effect of public subsidies on R&D investment.

Busom (2000), for example, applied a selection model and excluded total crowding-out. Lach (2002) and Gonzales et al. (2005) reject total crowding-out by analyzing the effect of subsidies using difference-in-differences and simultaneous equation models with threshold, respectively. A lot of studies applied matching, the method that is also used in this chapter, in order to evaluate the input effect of R&D subsidies. Almus and Czarnitzki (2003), for example, reject crowding out as they find that Eastern German firms that received public R&D subsidies increased their innovation activities. Similarly, Aerts and Czarnitzki (2004); Duguet (2004); Czarnitzki and Hussinger (2004) and Gonzales and Pazo (2008) reject (full) crowding out in Belgium, France, Germany and Spain, respectively. Czarnitzki and Lopes Bento (2010) apply matching in a cross-country comparative evaluation and also reject total crowding out.

In line with policy attention, several scholars shifted their attention towards sub-

sets of firms, by focusing on younger and/or smaller firms when evaluating the effect of public subsidies on R&D input. Wallsten (2000), for example, uses a 3SLS approach in order to evaluate the effect of grants to small firms in the context of the SBIR program. At first sight, he finds crowding–out of firm–financed R&D spending dollar for dollar. However, Wallsten (2000) remarks that this result could be simply due to the fact that firms would have cut back their R&D expenditures in case no public funding was available. In other words, the R&D grants may have allowed firms to continue their R&D at a constant level rather than cutting it back. Reinkowski et al. (2010) apply matching and specifically focus on SMEs. They find that SMEs, and especially the micro firms show an increase in R&D intensity as a result of the subsidies. Reinkowski et al. (2010) also find that subsidies increase the probability of patent application for small and medium sized firms.

While the above studies already focus on subsets of firms, the impact of subsidies on the group of NTBFs and its counterparts has not been discussed extensively in the literature so far. Some studies evaluated the effect of subsidies on output measures. Colombo et al. (2012) for example show that NTBFs grow most after receiving public funds and especially if these are allocated through a selective evaluation process. Colombo et al. (2011) and Grilli and Murtinu (2012) focus more specifically on R&D subsidies and find that TFP growth of NTBFs is only enhanced if subsidies are provided competitively and if they aim at enhancing R&D investments.

Apart from the current study, there are, to our knowledge, no papers that study the effect of innovation subsidies on R&D input of NTBFs. Neither exist studies that investigate the different subsidy effects on NTBFs, Group NTBFs, LTBFs and Group LTBFs, evaluating that way whether the current policy focus towards non-group firms in high-tech sectors is really as fruitful as presumed.

3.2.2 Methodology

In this study, we apply Caliper Matching. The technique of matching has, among others, been discussed by Angrist (1998); Dehejia and Wahba (1999); Heckman et al. (1998); Lechner (2000). In the context of this chapter, matching tries to address the following question: "What is the effect of a subsidy grant on a subsidized firm?". In general, we want to observe the difference between the actual observed R&D of the subsidized firms and the counterfactual situation. The average treatment effect α^{TT} of firms receiving a subsidy, the treated firms, (T) relative to firms receiving no treatment, the counterfactual situation, (C) can be written as:

$$E\left(\alpha^{\mathrm{TT}}\right) = \mathrm{E}\left(\mathrm{Y^T}|\mathrm{S}=1\right) - \mathrm{E}\left(\mathrm{Y^C}|\mathrm{S}=1\right) \tag{1}$$

In this equation, Y^T denotes the outcome of the treated firms and Y^C the outcome of the untreated firms. S takes the value 1 if the firm is subsidized and zero otherwise. However, it is impossible to observe the outcome Y^C in the counterfactual situation because it is impossible to observe the actual behavior of the same firm without treatment. Therefore, this counterfactual outcome of treated firms has to be estimated and is in this context constructed based upon the control group of non-subsidized firms. The idea is to balance the sample of subsidized firms and comparable non-subsidized firms. The remaining differences between the matched firms can then be fully attributed to the received treatment, a subsidy in this case.

It already became clear above that comparing the subsidized and unsubsidized firms based on random samples would lead to biased results because of the possible selection bias. When performing matching, we replicate the conditions of an experiment to the best possible extent. Therefore, we determine a broad set of characteristics, X, that should be equal among the compared firms. In other words, we compare the treated firm with an untreated firm that is identical to the treated firm with respect to the characteristics that we define. This set of characteristics

should be exhaustive. Rubin (1977) introduced this as the Conditional Independence Assumption (CIA), which stipulates that the treatment and the outcome of this treatment are independent for the observations having the same set of exogenous characteristics. If this CIA is satisfied, the following equation is valid:

$$\mathrm{E}\left(\mathrm{Y}^{\mathrm{C}}|\mathrm{S}=1,\mathrm{X}\right)=\mathrm{E}\left(\mathrm{Y}^{\mathrm{C}}|\mathrm{S}=0,\mathrm{X}\right) \tag{2}$$

Based upon this equality, the outcome of the non-subsidized firms can be used to estimate the counterfactual situation of the subsidized firms and the treatment effect can then be written as:

$$\mathrm{E}\left(\alpha^{\mathrm{TT}}\right)=\mathrm{E}\left(\mathrm{Y}^{\mathrm{T}}|\mathrm{S}=1,\mathrm{X}=\mathrm{x}\right)-\mathrm{E}\left(\mathrm{Y}^{\mathrm{C}}|\mathrm{S}=0,\mathrm{X}=\mathrm{x}\right) \tag{3}$$

Usually, X contains many different variables in order to satisfy the Conditional Independence Assumption. This makes it almost impossible to find control variables that exactly fit the characteristics of the subsidized firm. In other words, the so-called curse of dimensionality enters because the more dimensions that are included, the more difficult it becomes to find a good match. Rosenbaum and Rubin (1983) showed that it is possible to reduce X to a single index -the propensity score- and match on this index instead of on all the individual X. The propensity scores are constructed based upon a probit model of treatment, in this case subsidies, on the exogenous variables and then used as matching argument.

It is necessary that the propensity scores of the treatment group and the control group coincide. In some cases, however, this is not the case. This problem is referred to as the 'common support problem'. It is crucial that the sample of unsubsidized firms contains at least one observation similar to each subsidized firm. This requirement is imperative, as, when performing matching, we restrict the sample to firms with common support.

In this study, we evaluate the effect of subsidies by applying caliper matching

with replacement (Cochran and Rubin, 1973). This method is similar to the nearest neighbor matching method but it adds an additional restriction. In this case, treated units are selected to find their closest match in terms of the propensity score, but only if the propensity score of the control is within a certain, pre-specified, distance. Thus, by applying this method, it is possible that a treated observation cannot be matched to a control. The matching routine used in this study is presented in table 3.2. In addition, as an additional restriction, we require the firm observations in the control group to belong to the same year and the same region (Eastern versus Western Germany) as the corresponding firm in the group of subsidized firm observations.

Table 3.2: The matching protocol

Step 1	Specify and estimate a probit model to obtain the propensity scores $\hat{P}(X)$.
Step 2	Restrict the sample to common support: delete all observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. (This step is also performed for other covariates that are possibly used in addition to the propensity score as matching arguments.)
Step 3	Choose one observation from the subsample of treated firms and delete it from that pool
Step 4	Find an observation in the sub-sample of subsidized firms that is as close as possible to the one chosen in step 3 in terms of the propensity scores, but only if the propensity score of the control is within a certain, pre-specified, distance. Closeness is based on the Mahalanobis distance between this firm and all non-subsidized firms in order to find the most similar control observation. MD_{ij}=(Z_j-Z_i) Ω^{-1} (Z_j-Z_i) where Ω is the empirical covariance matrix of the matching arguments based on the sample of potential controls. Do not remove the selected controls from the pool of potential controls, so that it can be ued again
Step 5	repeat steps 3 and 4 for all observations on subsidized firms
Step 6	Compute the estimate of the treatment effects using the results of step 5. This can be done with a t–test on mean differences between treated firms and selected controls.
Step 7	As we perform sampling with replacement to estimate the counterfactual situation, an ordinary t-statistic on mean differences is biased, because it does not take the appearance of repeated observations into account. Therefore, we have to correct the standard errors in order to draw conclusions on statistical inference. We follow Lechner (2001) and calculate his estimator for an asymptotic approximation of the standard errors.

3.3 Subsidy output evaluation: the patent production function

Even if we can reject crowding-out, this does not imply that public efforts lead to new technologies of the subsidized firm itself.[3] The projects that were not carried out yet might be associated with a higher chance of failure and/or lower expected revenues (going down the MRR curve) and might thus also not be the most promising projects in terms of technological output (David et al., 2000). However, if the additionally induced projects do not have lower chances to succeed, but could not be started due to a lack of financing, there is a likelihood that the project leads to positive technological output. Another consideration with respect to the question whether output additionality can be expected is closely linked to the rationale to look at input additonality at the level of R&D employees (see below) (Goolsbee, 1998; Howells, 2008). Suppose that the additional money is redirected to increase wages of the existing staff, this will then presumably also not be translated in output (unless staff becomes more productive). This is another reason why a focus on R&D employment is crucial. Another argument is related to the peer review process. Assuming the selection process is fully efficient, the most promising, high quality projects might have been selected, which would increase the expectations that an effect on technological performance is found due to this subsidized R&D. In addition, this process might also entail a possible monitoring process effect, i.e. management of projects, potentially increasing the likelihood of successful R&D (Lerner, 1999; David et al., 2000; Barney et al., 2001; Colombo and Grilli, 2005; Teece and Pisano, 1994). The subsidy grant might also serve as a signal to potential investors and clients (certification effect), which might on itself increase the likelihood that the technological output of firms increases (Lerner,

[3]The focus in this chapter is only on technological performance of the subsidized firm itself. This cannot account for any effects subsidies might have on technological performance of other firms via potential spillover effects that occur between the subsidized firm and other firms in the economy. It might well be the case that some additional R&D of the firm will thus not lead to beneficial private effects, but will impact other firms' innovation activities and thus maybe lead to beneficial social effects via these other market players (or negative if this has a negative effect on too many efficient competitors).

1999).

In order to assess the effect of both private and publicly induced R&D on technological performance, we estimate their effect on patent applications. Patents are already extensively discussed and acknowledged as an indicator of technological performance (see Pakes and Griliches, 1984; Griliches, 1990, 1998 or OECD, 1994). More specifically, they point to immediate output of the R&D process, i.e. point to successful R&D.

In order to estimate the patent production function, count data models are usually used and in this study, a QMLE (Quasi-Maximum Likelihood Estimator) Poisson model is estimated in order to to analyze the impact of R&D on the number of patent applications.[4] In this setting, R&D is split into two components, purely private R&D (the counterfactual situation) and publicly induced R&D (referring to both the effect of subsidies and the increase in private R&D due to subsidies). Unfortunately, one cannot observe this breakdown based upon the datasets at hand. Therefore, we construct these measures based upon the previous matching procedure by disentangling the R&D input into the research engagement of the firm in the absence of a treatment, $R\&D_i^C$, and the additionally induced R&D by the subsidy (including the subsidy itself), α_i^{TT}. Note that the observed $R\&D_i$ is thus decomposed according to eq. 3: $R\&D_i = R\&D_i^C + \alpha_i^{TT}$. Thus, the second equation to be estimated can be written as

$$\text{PATENT}_\text{i} = \text{f}\left(\text{R\&D}_\text{i}^\text{C}, \alpha_i^\text{TT}, \text{other firm characteristics}\right) \tag{4}$$

If subsidies have a positive effect on technological performance of the firm under consideration, α_i^{TT} should positively influence the patent outcome.[5]

[4] An assumption of the poisson model is $E(Y_i|x_i) = Var(Y_i|x_i)$ (Wooldridge, 2002). If the latter is not the case, there is over- or underdispersion. Implementing a statistical test of overdispersion in line with Cameron and Trivedi (1990, 2005) shows that there is overdispersion in the model. As a consequence, QMLE poisson is implemented which has no specific requirements about the functional form of overdispersion, but corrects for wrong SE in a poisson model by using robust SE (Wooldridge, 1997).

[5] Note that contemporaneous R&D is inserted in this equation as this has been found to have

Although, as shown above, several scholars already investigated input additionality effects, not that many studies tried to establish an explicit link between a certain (government) intervention and patenting behavior. Branstetter and Sakakibara (2002) do not focus on government subsidies as in the current chapter, but on the effect of being a member in a subsidized research consortium. They find that being member of such a consortium has a positive effect on patenting. Czarnitzki et al. (2007) focus on the effect of subsidies and collaboration on patent outcome, but as an output variable in the matching routine, thus not disentangling the counterfactual and publicly induced R&D. In line with the current study, but focusing on all types of firms in the economy, Czarnitzki and Hussinger (2004) implement a matching estimator in order to estimate innovation input additionality and output additionality based upon the matching estimators in a second step.

3.4 Data, variables and descriptive statistics

3.4.1 Data sources

The data used in this chapter stem from the Mannheim Innovation Panel (MIP), the German part of the Community Innovation Survey. Next to information on general firm-level characteristics, this database contains specific information on innovation activities and the receipt of subsidies. Our database is a pooled cross–section including the following years of observations (these years of the MIP data include information on subsidies): 1994, 1996, 1998, 2000, 2002, 2003, 2004 and 2006. Patent data are taken from the German Patent and Trade Mark Office (GPTO). Our version of the database contains information on all patent applications in Germany from 1979 to 2005. Patent and firm data were linked using a computer-supported text search algorithm and potential matches were checked manually.

Our sample includes NTBFs, Group NTBFs, LTBFs and Group LTBFs. All these

the strongest effect on patenting (Hall et al., 1986; Pakes and Griliches, 1984).

firm classes have less than 250 employees and are less than 10 years old. In addition, all the firms in the sample are innovative and have thus introduced at least one new or significantly improved product or process, or have ongoing or abandoned innovation projects over the period covered in the survey. While NTBFs and LTBFs are not part of a group, their Group counterparts are. NTBFs and Group NTBFs belong to the high-tech or key-tech technologies as defined in the high-tech strategy (BMBF (Federal Ministry of Education and Research), 2010), while LTBFs and Group LTBFs belong to medium low-tech and low-tech sectors (for an overview of the industry classification, see table A3.1 in appendix).[6] Table 3.3 presents the sizes of the different samples before and after matching. As can be derived from the table, the sample initially consists of 1228 NTBFs, 609 Group NTBFs, 965 LTBFs and 470 Group LTBFs. Each time, a part of the firms are subsidized and a part not. All non-subsidized firms can potentially serve as controls for matching. Table 3.3 shows that, in line with expectations, a larger share of NTBFs receive subsidies than LTBFs. After matching, the sample of subsidized firms is slightly reduced to 605 subsidized NTBFs, 262 subsidized Group NTBFs, 283 subsidized LTBFs and 95 subsidized Group LTBFs, to which an equal number of non-subsidized firms were matched.

Unfortunately, we can use the data only as pooled cross-sections, but not as a panel: of the total initial sample of 3,272 observations, corresponding to 2,399 different firms, about 72% of the firms are only observed once. As a consequence, panel econometric approaches are ruled out as this would significantly reduce the number of observations in our sample.

[6] this distinction between high-tech and low-tech industries coincides with distinguishing between the most and least R&D intensive sectors in the German economy, based upon the survey data.

Table 3.3: The samples further unfolded

<table>
<tr>
<td>
NTBF
subsidized 649
potential controls 579
Matched subsidized firms: 605
</td>
<td>
Group NTBF
subsidized 306
potential controls 303
Matched subsidized firms: 262
</td>
<td rowspan="2">
Old firms ($<$ 250 employees, $\geq$ 10 years old)
6432 obs
</td>
</tr>
<tr>
<td>
LTBF
subsidized 328
potential controls 637
Matched subsidized firms: 283
</td>
<td>
Group LTBF
subsidized 120
potential controls 350
Matched subsidized firms: 95
</td>
</tr>
<tr>
<td colspan="2">
Large firms ($\geq$ 250 employees, $<$ 10 years old)
695 obs
</td>
<td>
Large and Old firms ($\geq$ 250 employees, $\geq$ 10 years old)
2936 obs
</td>
</tr>
</table>

3.4.2 Variables

This study investigates the influence of subsidies on various outcome variables. The receipt of subsidies over the covered survey period is denoted by a dummy variable SUB. The subsidy dummy covers subsidies from the national or regional governments and from the EU. In order to evaluate the effect of subsidies on the innovative behavior of firms, we investigate the impact on R&D intensity of these firms, RDint. This variable is constructed as the ratio of internal R&D expenditures to turnover (multiplied by 100). Next to the R&D intensity, we also evaluate the subsidy effect on R&D expenditures (R&D).

A large part of R&D spending consists of salary payments for R&D employment. If companies increase their R&D expenditures after receiving R&D subsidies, a large fraction of these increased spending might be distributed towards hiring new

R&D employees, enlarging that way the inventive capacity. However, as Goolsbee (1998) and also more recently Howells (2008) states, R&D labor supply might be quite inelastic and thus the increased spending might be redirected to higher wages for the existing staff instead of resulting in new human capital, which is not the direct aim of government subsidies. Similarly, Hall and Lerner (2010) emphasize that R&D employees form a real resource base with high adjustment costs. In order to evaluate the impact of innovation subsidies on R&D employment, we investigate the impact of R&D subsidies both on the number of R&D employees (RDemp) and on the R&D employment intensity (RDEint), measured as the number of R&D employees over the total number of employees (multiplied by 100).

In the second stage, we disentangle R&DEint into the counterfactual situation $RDEint_i^C$ and the additionally induced R&D employment intensity, $\alpha_{TT,i}$ for all four firm groups. The dependent variable in this stage is the number of patent applications (PAT).

We use a number of control variables: a first variable that is included is size. Although we are already focusing on small firms, there might still be differences between the larger and smaller firms in this subset. We measure size by total employment both in its logarithmic form (ln(EMP)) and as a square of this logarithm ($\ln(EMP)^2$) in order to capture possible nonlinearities. Similarly, although we are already focusing on the smallest firms of the economy, we include the logarithm of age (ln(AGE)) in the analysis in order to capture differences between start–ups and older firms.

Firms that export to other countries might be more innovative than other companies. The chance that they apply for innovation subsidies is thus also higher. As a consequence, a dummy indicating whether a firm is an exporter or not, EXPORTER, is included in the analysis. Another variable that is assumed to be positively correlated with subsidy receipt is capital intensity (CAPINT). Capital intensive firms supposedly rely more heavily on innovation activities than the less capital intensive ones (fixed assets/EMP).

Another variable that is included is the price-cost margin (PCM). Firms with a higher price-cost margin are more likely to have financial resources for internal funding of R&D projects, which is positive in light of financial constraints as discussed above. As a consequence, they might apply less for subsidies. On the other hand, a high price-cost margin might be the result of successful past innovation activities and the likelihood to receive subsidies might thus increase. The price-cost margin is constructed as suggested by Collins and Preston (1969) and Ravenscraft (1983): ((sales - staff cost - material costs)/sales).

The history of (successful) R&D activities is likely to strongly influence both the probability to receive subsidies, R&D expenditures and R&D employment. If a firm already has a lot of experience in R&D activities, this firm is more likely to know how to apply for subsidies and to invest more in new R&D activities. In addition, governments often adopt a picking-the-winner strategy and firms with previous successful innovations might thus be favored in the granting process. In order to capture the influence of past R&D, we include the patent stock in our regression as patent stock per employee (PS/EMP). We divide by employees in order to reduce potential multicollinearity with firm size. Patent stock is defined as

$$\mathrm{PS}_{it} = (1 - \delta)\,\mathrm{PS}_{i,t-1} + \mathrm{PA}_{it},$$

where PS is the patent stock of firm i in period t and t-1 respectively, PA is the number of patent applications filed in period t. The patent stock in period t-1 is depreciated at a constant rate, with δ set to 0.15 (see e.g. Jaffe, 1986; Hall, 1990; Griliches and Mairesse, 1984).

As already elaborated upon above, credit constraints might also have an influence on subsidy receipt and the outcome variables. In order to capture the access a firm has to external capital, we use the firm's credit rating, RATING, lagged one period.

The credit rating is obtained from Creditreform which is the largest German rating agency. The rating is an index ranging from 100 to 600, where 600 is the worst and essentially corresponds to bankruptcy of the firm.

The dummy variable EAST indicates firms that are located in Eastern Germany. Eastern Germany is still in transition from a planned to a market economy, and firm behavior may thus be different. In addition, Eastern German firms are preferred in the policy incentive schemes, and special schemes have been launched exclusively for these firms in order to accelerate the catching up process in this region.

In addition, we control for differences in technological opportunities with industry dummies. The complete industry structure for the medium high-tech and high-tech industries on the one hand and the medium low-tech and low-tech industries is presented in table A3.1 in appendix. These industry dummies are based on the NACE codes, the Statistical Classification of Economic Activities in the European Community. This classification is a European industry standard classification system. Finally, seven time dummies are constructed in order to control for business cycle effects.

For the variables PCM, CAPINT and RATING, we have some missing values. In order to account for these missing values, we construct dummy variables equal to 1 if the values are missing (D(PCM), D(CAPINT) and D(RATING)). In addition, we set the missing values in the original variables to zero. Including both the dummy variable and the adjusted original variables in the analysis corrects for missing values and avoids the imputation of unknown values. Also note that all time-varying variables enter the regression as lagged values to avoid simultaneity bias. The only exception is AGE, as we consider this as truly exogenous.

3.4.3 Descriptive statistics

Table 3.4 displays the descriptive statistics of the variables used in order to evaluate subsidies for the four different firm classes. The t-tests reveal that there are some significant differences between the group of subsidized firms and the potential control group. The subsidized firms are, on average, more export-oriented, are more often situated in Eastern Germany and have more patents per employee. Some average differences are only significant for specific firm types. For example, only the independent subsidized firms have, on average, significant more employees than the non-subsidized independent firms. Similarly, only the class of high-tech firms has, on average, a significant lower credit rating (thus higher values of the RATING variable) for subsidized firms than for the potential control group.

Next to the summary statistics of the control variables, table 3.4 reports the summary statistics and t-tests on mean differences between the outcome variables. In general, these variables have the highest values for both NTBFs and Group NTBFs. In addition, all outcome variables differ significantly between subsidized firms and the control group. In all cases, the subsidized firms have higher intensities and more R&D expenditures and employees. From the descriptive statistics, it is unclear whether these differences can be attributed to the receipt of subsidies. We will apply a matching estimator, as outlined in the previous section, in order to unravel this question.

Table 3.4: Descriptive statistics[a]

	Strict NTBFs					**Group NTBFs**				
	subsidized firms N_1=649		potential control group N_1=579		p-value of two-sided t-test on	subsidized firms N_1=306		potential control group N_1=303		p-value of two-sided t-test on
	Mean	Std. Dev.	Mean	Std. Dev.	mean equality	Mean	Std. Dev.	Mean	Std. Dev.	mean equality
EMP	42.515	52.871	36.546	48.737	p=0.041	80.330	72.048	90.185	159.540	p=0.326
AGE	6.131	2.034	6.195	2.112	p=0.588	6.075	2.086	6.092	2.129	p=0.920
EXPORTER	0.629	0.484	0.390	0.488	p < 0.0001	0.752	0.433	0.581	0.494	p < 0.0001
CAPINT*	0.042	0.095	0.063	0.884	p=0.553	0.178	1.422	0.035	0.083	p=0.082
PCM*	-0.442	11.900	-0.160	6.911	p=0.618	-0.107	1.863	-0.052	2.170	p=0.738
EAST	0.678	0.468	0.427	0.495	p < 0.0001	0.663	0.473	0.294	0.456	p < 0.0001
PS/EMP	0.040	0.078	0.013	0.045	p < 0.0001	0.038	0.069	0.019	0.052	p < 0.0001
RATING*	233.156	85.019	221.838	84.462	p=0.020	214.899	80.098	194.677	95.928	p=0.005
$\hat{P}$(X)	0.635	0.209	0.408	0.203	p < 0.0001	0.628	0.222	0.376	0.211	p < 0.0001
RDint	19.573	29.217	3.568	11.419	p < 0.0001	16.808	28.774	4.510	15.550	p < 0.0001
RDEint	32.568	29.865	9.639	18.113	p < 0.0001	25.734	27.599	9.082	18.382	p < 0.0001
R&D	1.013	4.945	0.147	0.579	p < 0.0001	1.804	4.770	0.868	2.515	p=0.003
R&Demp	8.957	14.786	1.875	3.913	p < 0.0001	15.779	25.637	6.344	17.444	p < 0.0001
PAT[b]	0.444	1.253	0.128	1.224	p < 0.0001	0.682	1.805	0.244	1.191	p < 0.0001

	Low-Tech NTBFs					**Low-Tech Group NTBFs**				
	subsidized firms N_1=328		potential control group N_1=637		p-value of two-sided t-test on	subsidized firms N_1=120		potential control group N_1=350		p-value of two-sided t-test on
	Mean	Std. Dev.	Mean	Std. Dev.	mean equality	Mean	Std. Dev.	Mean	Std. Dev.	mean equality
EMP	57.845	55.165	43.848	46.898	p < 0.0001	87.533	62.246	78.140	68.088	p=0.183
AGE	6.290	2.133	6.055	2.118	p=0.104	6.400	2.056	6.040	2.162	p=0.112
EXPORTER	0.506	0.501	0.273	0.446	p < 0.0001	0.567	0.498	0.423	0.495	p=0.006
CAPINT*	0.074	0.147	0.049	0.130	p=0.007	0.099	0.354	0.152	0.677	p=0.414
PCM*	0.111	0.626	-0.468	14.669	p=0.476	0.115	0.601	0.115	0.646	p=1.000
EAST	0.872	0.335	0.641	0.480	p < 0.0001	0.742	0.440	0.414	0.493	p < 0.0001
PS/EMP	0.015	0.054	0.004	0.025	p < 0.0001	0.016	0.051	0.003	0.017	p < 0.0001
RATING*	224.262	76.796	220.476	90.811	p=0.519	207.125	77.667	199.136	100.240	p=0.427
$\hat{P}$(X)	0.506	0.224	0.256	0.188	p < 0.0001	0.426	0.224	0.200	0.161	p < 0.0001
RDint	4.620	11.313	0.668	1.625	p < 0.0001	3.492	6.903	1.178	5.226	p < 0.0001
RDEint	11.232	17.374	3.693	10.809	p < 0.0001	6.894	12.046	3.439	9.309	p=0.001
R&D	0.195	0.348	0.074	0.634	p=0.001	0.471	1.028	0.224	1.144	p=0.036
R&Demp	3.768	5.796	1.001	2.513	p < 0.0001	3.938	5.851	1.797	6.135	p=0.001
PAT[b]	0.121	0.528	0.029	0.227	p < 0.0001	0.581	2.372	0.120	1.120	p=0.006

[a]: Industry dummies and time dummies not reported

[b]: Patent descriptives only shown for observations for which this variable is available

*: For the variables Capint, PCM and Credit rating, the descriptive statistics are based on the actual observed observations. The observations for which the dummy was set to 1 and the missings to zero are thus not included.

3.5 Estimation and results

3.5.1 Subsidy effect on small young firms

When applying a matching estimator, we estimate in first instance a probit model on the receipt of subsidies. This probit model is estimated in order to obtain the propensity score. Table 3.5 presents the results of this estimation in columns 2, 3, 4 and 5 of this table for the different firm categories. The first column estimates the likelihood of receiving subsidies for the full sample, introducing the different firm class dummies, with NTBF as reference category, in the estimation. This reveals that NTBFs are most likely to receive subsidies as compared to all other firm categories defined. In addition, when testing the equality of the coefficients of the other firm categories, we find that high-tech firms in general are more likely to receive subsidies. Within each broader group of high-tech and low-tech firms, the independent ones also seem to be more likely to receive subsidies.

The other results obtained from the probit estimation are in line with the results from the descriptive statistics. We find that companies located in East-Germany have a higher probability to receive subsidies. In addition, the results also confirm the higher probability of receiving subsidies if the patent stock is larger. Except for Group LTBFs, being an exporter has a positive effect on subsidy receipt. Other average significant differences in the descriptive statistics however are not apparent anymore in the probit estimation.

Having obtained a propensity score based on the estimation results of the probit estimation on subsidy receipt for each of the firm categories, we restrict the sample to common support.[7] In the previous section, we already stated that the matching

[7]The propensity scores based upon the different samples allow for more flexibility in the estimation as it might be the case that the coefficients of the different probit estimations have different effects for the different samples. A test on the equality of the main explanatory variables over the different probit regressions shows that the equality of coefficients is rejected. The results of matching based upon the propensity score of the full sample are nevertheless shown in appendix A3.3 and show that results remain stable even when matching is based upon the propensity score of the full sample. All further results presented in this chapter are also confirmed.

Table 3.5: Probit estimation on subsidy (SUB)

	(1) full sample	(2) NTBF	(3) Group NTBF	(4) LTBF	(5) Group LTBF
ln(AGE)	-0.084	-0.128	-0.262*	-0.135	0.215
	(0.063)	(0.099)	(0.143)	(0.121)	(0.190)
EXPORTER	0.407***	0.547***	0.416***	0.394***	-0.028
	(0.059)	(0.089)	(0.143)	(0.105)	(0.162)
ln(EMP)	0.037	0.022	-0.055	0.028	0.329
	(0.116)	(0.170)	(0.280)	(0.211)	(0.391)
$\ln(EMP)^2$	0.001	0.004	-0.001	0.015	-0.036
	(0.017)	(0.026)	(0.038)	(0.031)	(0.053)
D(CAPINT)	-0.281***	-0.169	-0.220	-0.315*	-0.416
	(0.092)	(0.144)	(0.226)	(0.185)	(0.268)
CAPINT	-0.010	-0.148	0.879	0.396	-0.179
	(0.036)	(0.342)	(0.902)	(0.357)	(0.217)
PCM	0.003	0.000	-0.008	0.009	-0.074
	(0.002)	(0.003)	(0.032)	(0.013)	(0.078)
D(PCM)	-0.161*	-0.190	-0.117	-0.356*	0.124
	(0.093)	(0.147)	(0.206)	(0.198)	(0.261)
EAST	0.965***	1.003***	1.092***	1.053***	0.966***
	(0.065)	(0.092)	(0.132)	(0.134)	(0.174)
PS/EMP	3.948***	3.406***	3.565***	5.362***	8.982***
	(0.584)	(0.729)	(1.258)	(1.290)	(2.808)
RATING	-0.000	0.000	-0.001	-0.002*	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
D(RATING)	-0.203	0.208	-0.637	-0.443	-0.555
	(0.169)	(0.259)	(0.448)	(0.315)	(0.504)
GNTBF	-0.175**				
	(0.080)				
LTBF	-0.465***				
	(0.166)				
GLTBF	-0.650***				
	(0.170)				
Constant	-0.276	-0.091	-0.120	-0.537	-3.075**
	(0.303)	(0.424)	(0.777)	(0.678)	(1.243)
Test on joint significance of					
-industry dummies	$\chi^2(11) = 37.80$***	$\chi^2(4) = 6.49$	$\chi^2(4) = 5.84$	$\chi^2(8) = 25.25$***	$\chi^2(8) = 13.06$
-time dummies	$\chi^2(7) = 47.55$***	$\chi^2(7) = 47.59$***	$\chi^2(7) = 4.66$	$\chi^2(7) = 24.30$***	$\chi^2(7) = 7.81$
test: GNTBF = LTBF = GLTBF	$\chi^2(2) = 9.73$***				
test: GNTBF = LTBF	$\chi^2(1) = 2.87$*				
test: GNTBF = GLTBF	$\chi^2(1) = 7.69$***				
test: LTBF = GLTBF	$\chi^2(1) = 4.37$**				
N	3272	1228	609	965	470
Log-Likelihood	-1788.480	-696.468	-337.828	-490.201	-212.636
Pseudo R^2	0.20	0.18	0.20	0.21	0.20

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

estimator is non applicable if the overlap between the different subsamples is too small in terms of the characteristics controlled for. Table 3.6 shows how many observations have to be dropped for each firm class in order to assure a sufficient overlap between the treated and untreated firms under consideration. Next to the restriction to common support, we also impose a caliper threshold as we apply caliper matching. This caliper threshold of 0.05 serves as a maximum distance between treated and untreated firms. The third column of table 3.6 presents the number of observations that are lost after setting this threshold. The last column of that table shows how many treated observations can be successfully matched.

Table 3.6: Loss of subsidized observations due to a lack of common support and due to caliper threshold

sample	Initial sample size of subsidized firms	lack of common support	out of caliper threshold 0.05	final sample size of subsidized firms
NTBF	649	-2	-42	605
Group NTBF	306	-11	-33	262
LTBF	328	-7	-38	283
Group LTBF	120	-8	-18	95

After setting the different thresholds, we pick the nearest neighbor out of the control group to find the best match for the treated firms. After matching, there are no statistically significant differences in the exogenous variables anymore. In line with this, the propensity score is also not significantly different between subsidized and non-subsidized firms for all groups of firms (results not shown here). Table 3.7 shows the outcome of the tests on overall model significance of the probit models on subsidy receipt after matching. As can be seen in the table, the null hypothesis that all coefficients in the regressions are jointly zero cannot not rejected for any type of firm, as expected in case of successful matching.

Table 3.8 presents the treatment effects on the outcome variables after matching by propensity score. As can be seen, almost all treatment effects are positive and significant. After matching, these significant results can be attributed to the receipt of subsidies. As a consequence, full crowding-out with regard to public funding can be rejected for all firm types studied. Nevertheless, the treatment effects

Table 3.7: Significance of probit regressions after matching

sample	# obs	Wald $\chi^2(23)$	p-value
NTBFs	1210	5.56	0.9999
Group NTBFs	524	5.38	0.9999
Low-tech NTBFs	566	12.71[a]	0.9910
Group low-tech NTBFs	190	15.99[a]	0.9531

[a]: Due to different industry classification of low-tech NTBFs: Wald $\chi^2(27)$

differ between the different groups of firms. While crowding-out can be rejected for NTBFs, the effect of subsidies on R&D expenditures is insignificant for Group NTBFs. In addition, while for LTBFs, the treatment effects are at least significant at the 5% level, the treatment effect on R&D intensity for Group LTBFs is only significant at the 10% level and only the treatment effect on R&D employment is highly significant for these firms.

Table 3.8: Treatment effects after matching

NTBF		**Group NTBF**		**Small Old firms**
Matched subsidized firms: 605		Matched subsidized firms: 262		
R&Dint	15.361***	R&Dint	7.267**	
R&DEint	21.231***	R&DEint	11.775***	
R&D	0.717***	R&D	0.365	
R&D emp	5.428***	R&D emp	8.258***	
LTBF		**Group LTBF**		
Matched subsidized firms: 283		Matched subsidized firms: 95		
R&Dint	3.087***	R&Dint	1.628*	
R&DEint	3.558*	R&DEint	3.934***	
R&D	0.093***	R&D	0.205**	
R&D emp	1.519***	R&D emp	1.897**	
Large young firms				**Large old firms**

This table would suggest that high-tech small young firms make more effective use of subsidies than low-tech small young firms, whether they are independent or part of a group. Within the group of high-tech firms, the independent ones, NTBFs, seem to have higher treatment effects, except for R&D employment, which increases slightly more for Group NTBFs after subsidy receipt.[8] The difference between independent and group firms in high-tech sectors cannot be found within the group of low-tech firms. While R&D intensity seems to be slightly higher after receiving subsidies for LTBFs, the other treatment effects are higher for Group LTBFs. This suggests that the factor being independent or being part of a group has different effects for high-tech and low-tech firms. However, especially for the latter firms, these differences are only small and it is questionable whether they are also significant.

The main conclusion that can be drawn from table 3.8 is that R&D subsidies seem to trigger input into R&D for all types of firms studied. At first sight there is thus no rationale for governments to restrict funding to one of the firm types under consideration. Nevertheless, the table also shows that the treatment effects differ over the different firm categories. However, solely based upon these treatment effects at 'face value', it is highly questionable whether these differences are also significant and whether it is thus correct to pose that high-tech firms and especially NTBFs make more efficient use of subsidies than other small young firms. The next section will elaborate upon this question.

3.5.2 Further evaluation of the treatment effects

As already stated above, the results shown above give an overview of the treatment effects for the different firm classes. However, it remains unclear whether the differences are also significant across firm types. This can be assessed by regressing the individual treatment effects ($\alpha_{TT,i}$), reflecting subsidy induced R&D,

[8] However, one has to be careful as we can only assess the effect of R&D subsidies on the firm itself and not on its group members. It might be the case that spillovers occur between subsidized group members and other group members, which would underestimate the effect of subsidies on group firms in our study.

on dummies referring to the different firm types, with NTBF as the reference group for all firms that received subsidies.

$$\alpha_{TT,i} = \beta_0 + \beta_1 \text{GroupNTBF}_i + \beta_2 \text{LTBF}_i + \beta_3 \text{GroupLTBF}_i + \epsilon_i \quad (5)$$

The constant term β_0 then reflects the treatment effect for NTBFs and the other coefficients show the difference in treatment effects relative to NTBFs. In order to evaluate the differences of the treatment effects with respect to other firm types, we perform F-tests on the equality of the different coefficients of the firm types we want to compare.

While simply regressing the treatment effect on the different firm type dummies indicates to what extent the differences in treatment effects are significant, this does not account for other effects that might influence these differences. In order to control for other effects and thus to assess whether the differences in treatment effects are really the result of subsidies, we include extra control variables, X_i, in the regressions on the treatment effects.

$$\alpha_{TT,i} = \beta_0 + \beta_1 \text{GroupNTBF}_i + \beta_2 \text{LTBF}_i + \beta_3 \text{GroupLTBF}_i + \beta_X \text{X}_i + \epsilon_i \quad (6)$$

As already shown above, high-tech small young firms seem to be more likely to receive subsidies. If these firms thus get funding from multiple sources, it might actually explain why they seem to have higher treatment effects than low-tech firms. All firms included in the estimation of the treatment effect are subsidized firms, having received funding from at least one source. However, it is possible that some firms included in the sample received subsidies from both the European Union, the federal government and local governments. Similarly, some firms might have been subsidized by two different funding sources. Czarnitzki and Lopes Bento (2011) differentiate between firms having received national funding, European funding and funding at both the national and the European level and find that, in terms

of input, getting funding from both sources yields the highest impact. As a consequence, we should control for these multiple sources of subsidies. We do so by including two dummies 2SUB and 3SUB, referring to firms that received subsidies from 2 funding sources and all 3 funding sources respectively, with firms that received funding from only one source as the reference group (based upon national, regional and EU funding).

Another factor, very specific to the German case is the difference between Eastern and Western Germany. Czarnitzki and Licht (2006) found that input additionality has been more pronounced in Eastern Germany during the transition period than in Western Germany. In addition, Eastern German firms were preferred in several subsidy schemes in order to accelerate the transition process since the German re-unification in 1991. It is thus possible that the differences between treatment effects between different firm types can be attributed to the fact that the firm type with higher treatment effects is mainly present in Eastern Germany. In order to control for potential different location effects, we include a dummy EAST in the regressions.

Although we already focus on small firms, we still control for heterogeneity in total employment. Next to controlling for size, we also control for age by including age in the estimation. Finally, we include time dummies in the estimation in order to control for business cycle effects. [9]

[9]Information on the different subsidy sources is not available for all years in the analysis. As a consequence, we had to drop one year (1996) because of missing information on the subsidy sources.

Table 3.9: Comparison

	RDint		RDEint		R&D		R&D employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Group_NTBF	-8.094***	-7.484**	-9.457***	-6.431**	-0.352	-1.061***	2.830	-1.119
	(2.713)	(3.041)	(2.487)	(2.571)	(0.342)	(0.409)	(2.117)	(2.033)
LTBF	-12.274***	-8.210***	-17.674***	-14.984***	-0.623***	-0.685***	-3.909***	-5.437***
	(1.506)	(1.660)	(2.060)	(2.373)	(0.196)	(0.225)	(0.798)	(1.024)
Group_LTBF	-13.733***	-10.051***	-17.298***	-10.530***	-0.511**	-0.893**	-3.531***	-5.840***
	(1.484)	(1.820)	(2.003)	(2.391)	(0.214)	(0.346)	(0.940)	(1.488)
EAST		-1.722		0.091		0.612		2.068
		(2.295)		(2.610)		(0.396)		(1.639)
2SUB		8.912***		7.458***		0.327		2.404**
		(1.912)		(2.135)		(0.249)		(1.214)
3SUB		14.372***		17.240***		2.175*		11.412***
		(4.128)		(3.762)		(1.239)		(2.987)
EMP		-0.061***		-0.103***		0.014***		0.083***
		(0.015)		(0.015)		(0.005)		(0.019)
ln(AGE)		-4.334*		-3.595		-0.617		-1.700
		(2.271)		(2.291)		(0.438)		(1.430)
Constant	15.361***	22.630***	21.231***	26.528***	0.717***	-0.198	5.428***	-0.322
	(1.326)	(4.959)	(1.566)	(4.366)	(0.194)	(0.432)	(0.653)	(2.620)
N	1245	1038	1245	1038	1245	1038	1245	1038
F-test joint sign time dummies		1.08		3.21***		0.69		2.04*
test equality Group NTBF and LTBF	2.79*	0.07	11.17***	9.74***	0.52	1.38	10.09***	4.44**
test equality Group NTBF and Group LTBF	5.13**	0.92	11.04***	2.58	0.17	0.26	8.47***	4.42**
test equality LTBF and Group LTBF	2.23	1.40	0.04	3.00*	1.47	0.76	0.22	0.08
test equality 2sub and 3sub		1.54		6.11**		2.01		8.53***

Clustered standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 3.9 presents the results of the treatment effect regressions on R&D intensity, R&D employment intensity, R&D expenditures and R&D employment. For each treatment effect, both the basic regression without additional control variables and the extended regression are presented. Note that all standard errors are clustered at the firm level. The table reveals that the differences between high-tech and low-tech small, young firms in table 3.8 are only confirmed for independent firms. NTBFs always have a higher input additionality than both LTBFs and Group LTBFs, even after including the control variables in the regressions. For Group NTBFs, we initially also find significant differences compared to LTBFs and Group LTBFs for all treatment effects. However, after including the additional control variables in the regression framework, these results change. First, the significant higher increase in R&D intensity that was found for Group NTBFs compared to LTBFs and Group LTBFs after receiving subsidies becomes insignificant. Similarly, the higher treatment effect for RDEint when comparing Group NTBFs and Group LTBFs becomes insignificant. Only the subsidy induced increase in R&D employment remains significantly higher when comparing Group NTBFs to all low-tech firm categories.

When focusing solely on low-tech firms, we find at most a very weak significant difference between effects of subsidies on independent and group firms (see tests on differences in coefficients at the bottom of table 3.9). As a consequence, for low-tech firms, a policy focus on independent small young firms does not seem to be warranted. For high-tech small young firms, on the other hand, the differentiation between independent firms and group firms seems to matter, although not for all treatment effects. In the basic regressions, the differences are only significant for the treatment effects on the intensity measures (see coefficient of Group NTBF, indicating the relative difference in treatment effects to the reference category of NTBFs, in columns 1 and 3 of Table 3.9). In the extended regressions, the difference between the R&D expenditures' treatment effect also become significant (see column 6 of table 3.9). The results also reveal that the lower treatment effect that was found on R&D employment for NTBFs as compared to Group NTBFs is insignificant in the basic regression (see column 7). This suggests that Group NTBFs

do not make more effective use of R&D subsidies in terms of R&D employment, as was initially indicated by the treatment effects. [10]

In general, the above findings suggest that high-tech firms and especially the independent ones within this category have higher treatment effects. These findings are re-assuring, as policy makers often target small, young independent firms when selecting subsidy recipients. Here it is also revealed that it might be relevant to base this decision in a first stage on sector of activity. Only when the focus shifts to high-tech firms, results suggest that NTBFs make more effective use of subsidies than Group NTBFs. However, this latter result should be interpreted with caution as spillovers to other group members could not be taken into account. In addition, table 3.8 revealed that full crowding out could be rejected for all firm types studied. As a consequence, although results suggest that high-tech firms increase their R&D inputs more after receiving subsidies, none of these groups seem to merely replace their private R&D inputs by public money or seem to simply give higher wages to existing staff without increasing current R&D employment.

3.5.3 The effect on technological progress

Above, we have shown that full crowding-out can be rejected for all firm types studied. A regression of the individual treatment effects on the different firm categories showed that it are especially the high-tech and independent firms that seem to increase their R&D inputs most after receiving subsidies. We now turn to the second major research question in this chapter, that is, if additionally induced R&D input leads to technological progress. As already explained above, it is not because R&D inputs increase that this unambiguously leads to technological progress of the firm. We measure technological progress or performance as

[10] It has to be noted that the differences between group and independent firms have to be interpreted with caution, as we can only assess the effect of subsidies on the firm surveyed, independent of its other group members. It might well be the case that the effect of subsidies reaches beyond the single group member surveyed and also has an effect on R&D input of other group members. It is very difficult to evaluate this, however, as we do not have complete information on all other group affiliates. In addition, spillover effects are difficult to tackle in input additionality studies and they might as well flow from independent firms to others.

the patent activity at the firm level, i.e. the number of patent applications per year (PAT). In this setting, we use R&D employment intensity as an input factor for the patent production function.

The R&D employment intensity input factors are based upon the estimated treatment and counterfactual from the matching procedure. $RDEint_i^C$ represents the part of the total R&D employment intensity that the firms would have held anyway, that is, in absence of subsidies. This component of R&D employment intensity is just equal to the total R&D employment intensity for the non-recipient firms. In addition, the treatment effect on the treated α_i^{TT} is the additionally induced R&D employment intensity, as was already introduced in section 3.5.2. For the non-subsidized firms this variable straightforwardly takes the value zero by construction. Although a patent production function usually does not contain a lot of variables next to R&D, in addition to these two R&D-related variables, we control for industry differences in patenting behavior, and also include time dummies. In addition, we include the log of lagged employment, log(EMP), and log of age, log(AGE), to take possible size and age effects into account. The dummy variable EAST is also inserted in this framework in order to take into account that patenting activity in the still developing Eastern German region might be lower.

In addition to a pooled cross-sectional QMLE Poisson model, we also estimate the so-called pre-sample mean QMLE poisson model (henceforth PSM) (Blundell et al., 1995, 2002). Unlike in the R&D input equation where we cannot control for firm-specific effects due to the cross-sectional nature of our database, we can do so when the patents are considered, as we were able to collect information on firms' pre-sample patenting activity. One can control for unobserved time-invariant firm-heterogeneity if pre-sample information on the dependent variable is available. Blundell et al. (1995, 2002) showed that the unobserved heterogeneity can be approximated by implementing the pre-sample mean of the dependent variable as an additional regressor. This basically amounts to controlling for 'quasi fixed effects'. The pre-sample mean patenting is denoted by PSM in table 3.10.

Table 3.10 shows the results of this estimation. Note that we lose some observa-

tions due to the fact that we currently only have access to the patent data until 2005. Columns 1-2 show results when not differentiating between different firm categories and columns 3-4 show results when measures of the counterfactual and treatment are inserted separately for the different firm categories. We present bootstrapped standard errors as the R&D measures of the treated firms are estimated. We used 200 replications of the procedure to estimate the bootstrap standard errors.

When first focusing on the broad results in columns 1-2, a similar picture as in previous studies emerges (Czarnitzki and Hussinger, 2004). Counterfactual and treatment effect are both significantly positive, both for QMLE poisson and PSM QMLE Poisson estimation. Nevertheless, results in the current paper indicate that the counterfactual is slightly more productive than the treatment, although this result is only weakly significant under the PSM QMLE poisson estimation as shown by the χ^2's from a likelihood ratio (LR) test.

In columns 3-4, we make a distinction between the four different firm categories as introduced above by introducing the treatment and counterfactuals for all firms separately. We find that except for the category of Group LTBFs, both the R&D employment intensity in the counterfactual situation (all c'vars') and the treatment effects (all a'vars') show a statistically significant and positive impact on the number of patent applications. Tests show that the hypothesis of equal coefficients of counterfactual and treatment can in general not be rejected within the different firm groups except for a weakly significant lower productivity of treatment of the NTBF firms under QMLE poisson estimations. In general, results nevertheless point to an equal importance, i.e. productivity, of private and publicly induced innovation input in terms of R&D employment. In addition, the treatment effect of NTBFs is not significantly different from the at first sight higher treatment effect of independent LTBFs, neither from the treatment effect of group LTBFs. With respect to group NTBFs, results show that the treatment effect of independent NTBFs is significantly higher than the one from group NTBFs. As a consequence and as the treatment effect was shown to be higher for high-tech firms and especially for

Table 3.10: Estimation of the patent equation for all firm groups (N=2296)

	(1)	(2)	(3)	(4)
α_i^{TT}	0.021***	0.021***		
	(0.001)	(0.001)		
$RDEint_i^C$	0.025***	0.025***		
	(0.001)	(0.001)		
α_i^{TT} NTBF			0.023***	0.023***
			(0.001)	(0.001)
α_i^{TT} Group_NTBF			0.016***	0.016***
			(0.001)	(0.001)
α_i^{TT} LTBF			0.033***	0.034***
			(0.002)	(0.002)
α_i^{TT} Group_LTBF			0.023	0.022
			(0.018)	(0.018)
$RDEint_i^C$ NTBF			0.029***	0.027***
			(0.003)	(0.003)
$RDEint_i^C$ Group_NTBF			0.016***	0.017***
			(0.001)	(0.001)
$RDEint_i^C$ LTBF			0.039***	0.039***
			(0.001)	(0.001)
$RDEint_i^C$ Group_LTBF			0.040***	0.038***
			(0.014)	(0.015)
EAST	-0.614***	-0.648***	-0.603***	-0.634***
	(0.118)	(0.119)	(0.120)	(0.121)
ln(EMP)	0.675***	0.646***	0.745***	0.707***
	(0.018)	(0.022)	(0.024)	(0.027)
ln(AGE)	0.088	0.009	0.092	0.015
	(0.153)	(0.159)	(0.147)	(0.154)
PSM		0.232		0.220
		(0.161)		(0.174)
Constant	-3.930***	-3.650***	-4.103***	-3.779***
	(0.287)	(0.311)	(0.306)	(0.333)
χ^2 test on joint significance of time dummies	43.86***	69.42***	44.70***	68.07***
χ^2 test on joint significance of industry dummies	172.46***	145.57***	177.13***	153.33***
χ^2 LR test: $\alpha_i^{TT} = RDEint_i^C$	4.24**	3.40*		
χ^2 LR test: $RDEint_i^C NTBF = \alpha_i^{TT} NTBF$			3.35*	1.57
χ^2 LR test: $RDEint_i^C Group_NTBF = \alpha_i^{TT} Group_NTBF$			0.01	0.01
χ^2 LR test: $RDEint_i^C LTBF = \alpha_i^{TT} LTBF$			0.88	0.63
χ^2 LR test: $RDEint_i^C Group_LTBF = \alpha_i^{TT} Group_LTBF$			0.14	0.13

NTBFs (see tables 3.8 and 3.9), the total effect on patents will also be higher for these firms.[11] In general, these results suggest that the evaluation of public subsidies should happen at a more fine-grained level.

3.6 Conclusion

Governments acknowledge the fact that small young firms are in need of R&D subsidies. However, in light of the 'Europe 2020' strategy, they increasingly focus on 'less and better' state aid, thereby trying to target small, young firms that will most effectively make use of their grants. Frequently firms in high-tech sectors are preferred in public schemes. Furthermore, the European Commission since recently also emphasizes that especially small, young, stand-alone high-tech firms make possibly the most effective use of public funds. Thus, firms associated with groups of firms have less access to subsidies than in the past. While these policies thus give a clear preference to a certain type of firms, it is surprising that so far no systematic impact evaluation of such policies exists. Consequently, in this study, we compare the effect of innovation subsidies on New Technology Based Firms (NTBF), Low Technology Based Firms (LTBFs) and their group counterparts for a sample of German firms. NTBFs are small young independent high-tech firms, while LTBFs are small young independent firms active in low-tech sectors. We denote their group counterparts by Group NTBFs and Group LTBFs.

In a first stage, we estimate the input additionality effects for each of these firm types, i.e. we analyze the policy impact on firms' R&D intensity, R&D expenditures, R&D employment intensity and R&D employment numbers. Considering these firm types separately in our empirical analysis also enables us to compare the estimated treatment effects among these groups. In a second stage we turn to the effect subsidies have on innovation output as measured by patents.

[11] As already noted multiple times throughout this paper, we abstain from drawing any conclusions on the potential spillover effects generated by subsidized firms.

In order to evaluate the impact of innovation subsidies on the innovation input of NTBFs, Group NTBFs, LTBFs and Group LTBFs, caliper matching with replacement is applied in order to correct for a potential selection bias. In general, our results reveal that full crowding-out with regard to public funding can be rejected for all firm types studied.

In order to assess the potential differences in subsidy effects, we compare the treatment effects of the different firm types by regressing the individual treatment effects on the different firm types and additional control variables. Our results reveal that the treatment effects on independent NTBFs are actually highest, as presumed by policy makers. Thus our empirical study does not only support the currently common choice to give a preferential treatment to small, young and independent firms active in high-tech sectors, but also provides evidence that previous estimations of innovation policy impacts might have been partly misleading and/or too broad as usually no distinction between preferential firm profiles in policy schemes have been made.

In a second step, we carry the results of the treatment effects analysis over to the estimation of a patent production function, where R&D employment intensity is disentangled into two components: on the one hand, the purely privately R&D employment intensity in the absence of subsidies and, on the other hand, the additionally induced R&D employment intensity that is stimulated by the subsidy. Results of this estimation reveal that we do not have to reject the expectations of the different policy initiatives, especially for small young independent high-tech innovators, as the regression analysis reveals that even the publicly stimulated additional R&D leads to an increased patenting activity, especially for the independent NTBFs.

Of course, our study has a number of caveats that remain for further research. We will introduce some of them here but limitations of all chapters are mainly discussed in the concluding chapter, chapter 5. We were only able to assess whether a firm received a subsidy or not, without being able to assess potential heterogeneities in the grants. With respect to the patent production function, while

patent indicators are a broadly accepted concept to measure technological development, it is a narrow measure of innovative output. Nevertheless, considering other indicators that are effected by R&D further in the future would ideally require longer time series of data than we have currently available for our study. In general, panel data would allow us to draw more robust conclusions on the treatment effects found as unobservables could then also be taken into account in the matching routine and subsequent regressions. Another important limit is the lack of detailed information on group firms, as already touched upon several times throughout this chapter. Next to assessing spillover effects, it would be very informative to know what the 'group' entails. If this would be known, this information would allow us to draw more refined conclusions about the effect of group membership depending on the type of integration or on the group size.

Chapter 4

Incorporating innovation subsidies in the CDM framework: empirical evidence from Belgium

4.1 Introduction

Throughout this dissertation, it has already been broadly introduced that the beneficial effect of business R&D efforts on technological change and growth has been widely acknowledged by scholars and policy makers (Romer, 1990; Mansfield, 1988, 1962; Aghion and Howitt, 1998; Scherer, 1965; Geroski and Toker, 1996). The previous chapter for example redirected attention to the support of R&D activities of subsets of firms, mainly justified by the will to overcome presumed market failures (Nelson, 1959; Arrow, 1962; Stiglitz and Weiss, 1981).

Based upon policy and academic interest towards this topic, evaluating the effects of such policy instruments has a long tradition in empirical innovation research (see David et al., 2000; Cerulli, 2010; Zúñiga Vicente et al., 2014 for surveys). So far, the main focus in literature was on input additionality of R&D subsidies, while

Joint work with Dirk Czarnitzki

only some studies assess the impact on output (see also chapter 3 of this dissertation). Usually, as is also the case in chapter 3, the inextricable nature of these input and output stages is not acknowledged and they are thus not estimated in a simultaneous equation model. Adding to this lack in the evaluation literature, this chapter takes a structural approach in order to integrate both stages in one model. This is done by a new setup in which innovation subsidies are integrated in the Crépon Duguet Mairesse (CDM) framework (Crépon et al., 1998). The resulting model allows to estimate input and output additionality effects of subsidies and whether a firms' subsidized projects generate a discount or premium in terms of innovation outcome when compared to the non-subsidized projects. In addition, both the setup and data allow the inclusion of detailed subsidy data, i.e. the actual amounts, instead of the commonly used dichotomous variable as also used in chapter 3 (nevertheless, recent work increasingly exploits more detailed subsidy information, see e.g. the recent contribution of Takalo et al., 2013).

As already posed in the introductory chapter, this part of the dissertation has mainly a methodological focus and cannot add, in its current set-up, to the research on small young innovators. That being said, it directs attention to an equally important topic in the innovation literature, namely the possibilities and opportunities in which subsidies can be evaluated in order to add evidence to current research and set the stage for further possibilities in this line of studies.

The empirical study is carried out using Flemish innovation survey data coupled with detailed data on subsidy grants. Our results largely confirm insights of the recent literature, i.e. public subsides complement private R&D investment. Furthermore, it is found that an increase in R&D inputs, both purely private R&D and subsidy induced R&D, is generally associated with a higher innovation performance in subsequent years. The model also suggests that it cannot be rejected that subsidized R&D projects are not less productive in terms of generating sales due to new products than purely privately financed R&D.

The remainder of the chapter is organized as follows: the next section sketches the framework to which we add in this chapter, both conceptually and method-

ologically. The third section presents the model used in this chapter. Data and variables used are discussed in section 4.4 and section 4.5 discusses the empirical implementation and results before concluding.

4.2 Background

4.2.1 Conceptual background

All of the literature acknowledges that it is undeniable that R&D is a driving factor of growth in industrialized economies (see e.g. Romer, 1990), but what is the actual outcome of spurring innovation by means of R&D subsidies? What is the eventual firm-level use of these important budgets devoted to subsidies?

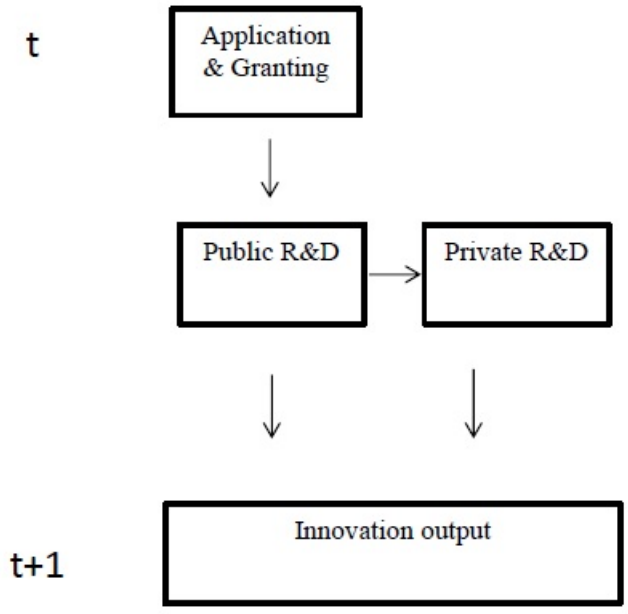


Figure 4.1: subsidy-extension of CDM framework

Figure 4.1 gives a simple representation of how subsidies impact the input and output stages of R&D. In a first stage, a firm can apply for a subsidy. In a second stage, if a firm applied for a subsidy, the agency makes a decision on the subsidy rate, i.e. the share of the R&D investment that will be covered by the agency (which can also be 0 if a project was rejected by the agency). When learning about

the subsidy decision, the firm will choose its R&D investment. R&D subsidies are assumed to spur R&D spending of firms and thereby foster technological change. However, it cannot be taken for granted that these effects are attained. In a first step, when looking at R&D spending of firms, it is not always clear how firms that receive these subsidies react to this support. It is possible that the subsidies are completely inefficiently spent if no extra R&D is undertaken. This might happen if firms simply replace their privately sponsored R&D projects by the publicly subsidized ones. This phenomenon is denoted as crowding-out, and refers to the situation in which innovation projects are subsidized that would also have been carried out without public subsidies.

In a next step, R&D input could to lead to innovative output. As already explained in chapter 3, it is not straightforward that public efforts lead to innovative output for the subsidized firm itself. In addition, it is questionable, if *some* additional output is generated, to what extent the subsidy induced projects are stimulating innovative output more or less than purely private R&D. In this chapter, we focus on progress made by the firm itself and abstain thus from any effect a potential increase in R&D spending might have on activities of other market players or on society. Related to this, projects are assumed to be mainly selected based upon their expected positive social value. There is thus no clear reason why publicly subsidized R&D would entail an innovation premium over purely private R&D at the firm-level. This is nevertheless an important question to be answered for the firm receiving subsidies. In addition, not knowing how much social value is actually created by subsidies, finding that subsidies are not less productive for the recipient firm itself would at least already be reassuring in terms of how public money is spent. Next to the fact that creating a premium in terms of firm-level profits is not a main reason in itself to grant subsidies, there are other arguments on why we would not necessarily expect subsidized R&D to entail a premium over private R&D. For example, as already introduced before, going down the marginal revenue (MR) curve, projects might be associated with lower expected revenues and higher risks of failure (David et al., 2000). The additional conducted projects would in this line of reasoning thus be less productive than the projects

done privately. Another argument that rather suggests a productivity discount of publicly induced R&D is related to wages of researchers. As Goolsbee (1998) argues, the granted subsidies might be redirected to higher wages of researchers instead of hiring new staff and/or investing this money in other research-related assets. Another important factor that could influence the eventual effect of public R&D spending is the peer review process. The subsidies analyzed in this study are selective, i.e. they are not automatically granted but are assessed by government experts who make the granting decision. On the one hand, as suggested by a.o. Lerner (1999) and David et al. (2000), government officials might be selecting firms out of personal interest. This could imply that they do not necessarily select projects that would have very high productivity prospects. On the other hand, if the selection procedure is done correctly, one might expect that it are actually the most promising, high quality project proposals that are accepted. In addition, after being selected, these projects might be closely followed and monitored by the granting agency, which implies that there might be a better management of the subsidized R&D projects and this might have a beneficial impact on the innovative output (Barney et al., 2001; Colombo and Grilli, 2005; Teece and Pisano, 1994). Another argument favoring a potential output premium of subsidized R&D over private R&D is the fact that R&D subsidies might act as a signal to potential investors and clients of the firm by implicitly signaling about its quality (Lerner, 1999).

4.2.2 Previous literature

The first quantitative evaluation of R&D policies has been carried out as early as 1957 by Blank and Stigler. After the US R&D budget was significantly raised during the 1950s Blank and Stigler (1957) questioned the relationship between publicly funded and private R&D. With a large sample of firms they tried to test for a complementary or substitutive relationship between public and private R&D investment. Since then, the literature on quantitative evaluation became vast, especially after the year 2000 when surveys about the current state of the art were

published in a special issue of Research Policy (see the surveys by David et al., 2000; Klette et al., 2000). The survey authors critically reviewed the literature and identified methodological shortcomings in existing studies. In particular, selection bias and endogeneity of subsidies in an R&D investment equation had not been adequately modeled in many early empirical studies.[2] Since then, the literature on the evaluation of innovation subsidies was revived and many papers using modern micro-econometric techniques were published (see Cerulli, 2010; Zúñiga Vicente et al., 2014 for surveys).

The main focus so far in literature has been on input additionality of subsidies, mainly based upon a dichotomous subsidy variable (see e.g. Aerts and Czarnitzki, 2004; Busom, 2000; Lach, 2002; Gonzales et al., 2005; Almus and Czarnitzki, 2003; Duguet, 2004; Gonzales and Pazo, 2008; Czarnitzki and Lopes Bento, 2010). Only a few focus on the effect of R&D subsidies on R&D output. Czarnitzki and Hussinger (2004); Czarnitzki and Licht (2006); Hussinger (2008) and also the research presented in chapter 3 for example, use the estimated private and treatment effect obtained from a matching estimator or other selection model in an output equation in order to measure the effect of private and public R&D on innovation output. In contrast to these papers, the main contribution of this study is the integration of both input and output additionality estimations in one framework. Thereby, this chapter not only adds to the subsidy evaluation literature, but also to the models based upon the framework developed by Crépon et al. (1998). In addition, the presented framework allows making use of detailed subsidy information instead of a dichotomous variable as was mainly used so far in a matching framework, either due to data limitations or a non-exploitation of the richer subsidy information.

[2]Firms that receive a subsidy might be different from companies that do not receive a subsidy. A first difference already emerges at the application stage as some firms might be more likely to apply for public funding than others. Some firms might consider the administrative burden or the information sharing conditional upon being subsidized as important reasons to restrain from applying for a subsidy. In addition, there is a possibility that the funding agencies follow a picking-the winner strategy with respect to the firms that applied for a subsidy. In other words, firms might have some characteristics that make them more attractive to governments for funding. As a consequence, funding cannot be considered as a random process and this selection should be accounted for when evaluating subsidies.

4.3 Extending the CDM model: assessing output additionality of subsidies

In order to integrate R&D input and output equations in a subsidy evaluation framework, this study extends the Crépon Duguet Mairesse (CDM) model. The CDM model introduced by Crépon, Duguet and Mairesse in 1998 (Crépon et al., 1998) is essentially a refinement of the traditional knowledge production function framework (Griliches, 1979). It does so by analyzing the different stages of the innovation process: the innovation choice, R&D intensity, innovation output and/or labor productivity. The set-up of this model is one of the first ones to explicitly acknowledge that all the innovation stages are inextricably connected. The most basic representation of this model incorporates the R&D input ($R\&D$) and output ($Output$) stages.

$$\begin{aligned} R\&D &= z_2'\omega + \varepsilon_2 \\ &\searrow \\ Output &= \beta_1 R\&D + z_1'\theta + \varepsilon_1 \end{aligned}$$

where z_1' and z_2' refer to explanatory variables of interest and z_2' includes an exclusion restriction, as it is unlikely that R&D is exogenous in the output equation.[3] ε_1 and ε_2 are the error terms.

Several extensions of this model have already been proposed, by e.g. explicitly incorporating ICT investments next to innovation inputs (Hall et al., 2013), adding competition conditions (Castellacci, 2011) or, more in line with the original model, adding profitability next to productivity (Jefferson et al., 2006) to give some exam-

[3]See also table A4.4 in appendix, presenting an OLS regression of the output equation without tackling the endogeneity of the R&D input (columns 1 and 4). Columns 1 and 3 in table A4.3 in appendix present IV regressions taking into account the endogeneity of R&D input, but not the heterogeneity of the R&D input variable itself.

ples.

The main contribution of this chapter to both the strand of subsidy evaluation papers and papers implementing the CDM model is the incorporation of R&D subsidies as an important determinant of the different innovation stages.[4]

In this study, we are mainly interested in the last step, the R&D output equation,

$$Output = \beta_1 R\&D + z_1'\theta + \varepsilon_1 \tag{1}$$

$R\&D$ in this equation captures the full amount invested in R&D, i.e. both subsidies and privately financed R&D. In this context however we are interested in the effect of the components of this full R&D input, publicly induced R&D and the counterfactual or purely private R&D.

In order to estimate the output additionality of subsidies, the current literature is dominated by ad–hoc approaches instead of a more structural approach as suggested in this paper. Before turning to the structural approach using the CDM framework, we briefly discuss ad-hoc approaches which help to motivate our model.

- Approach 1: Dummy variable approach
  One intuitive starting point for estimating output additionality is a dummy variable approach, where an (innovation) output measure is simply regressed on R&D input and a dummy variable, $DSUB$ indicating wether a firm received a subsidy, as well as the interaction of the subsidy dummy and R&D inputs.

[4] In spite of the appealing setting and the lack of attention in the literature (see nevertheless e.g. Takalo et al., 2013), the application and granting processes can unfortunately not be incorporated in the estimation framework as a subsidy granted in the beginning period is distributed to the firm over subsequent years. Dependent upon applying, the granting agency will make a decision on the total subsidies and thus subsidy rate granted to a firm. However, it is the yearly amount of subsidies that will eventually have an effect on yearly innovation input and output of firms. Nevertheless, results of these application and granting estimations are shown in appendix 4.B as these inform us on the underlying process of applying by the firm and granting by the agency and thus also on which variables can be used as an exclusion restriction in the subsidy equation.

$$Output = \beta_1 R\&D + \beta_2 DSUB + \beta_3 DSUB \times R\&D + z_1'\theta + \varepsilon_1 \qquad (2)$$

This approach is sometimes considered as allowing to conclude that a premium (discount) is present if β_3 would turn out to be positive (negative), that is, the subsidy would affect the marginal productivity of R&D upwards (downwards). However, the dummy variable approach neglects that subsidies are not constant across firms, and also that $R\&D$ is itself a function of the subsidy. As subsidies are usually varying in terms of the absolute monetary amount granted, this approach can in fact not allow to conclude whether subsidized R&D is more or less productive then privately financed projects.[5]

- Approach 2: Separate R&D input from subsidized amount
  Another intuition for estimating output additionality could be to subtract the subsidies from the R&D input and to estimate two separate coefficients.

$$Output = \beta_1 (R\&D - SUB) + \beta_2 SUB + z_1'\theta + \varepsilon_1 \qquad (3)$$

where $R\&D$ denotes the amount of R&D input and SUB the amount of subsidies received. This specification would, on first sight, allow to conclude whether *any* output additionality is present, that is, if β_2 is larger than zero, and, moreover, if the subsidized R&D is, for instance, more productive than the purely privately financed one if $\beta_2 > \beta_1$, and also vice versa. However, this approach still neglects that even the term $(R\&D - SUB)$ is a function of the subsidy as the whole literature about treatment effects revolves around the question to what extent additional private investment is stimulated by granting subsidies, especially as subsidies are typically distributed as 'matching grants', that is, the government pays only a share of the total cost of a project. [6]

[5] Columns 2 and 5 in table A4.4 in appendix present a 'naive' OLS estimation of equation 2 applied to the data and sample used in this chapter.

[6] Columns 3 and 6 in table A4.4 in appendix present a 'naive' OLS estimation of equation 3

In order to account for the existing treatment effects debate the estimation equation has thus to be modified further. Therefore we suggest to estimate following output equation

$$Output = \beta_1(R\&D - \alpha SUB) + \beta_2 \alpha SUB + z_1'\theta + \varepsilon_1 \tag{4}$$

where αSUB corresponds to a firm-specific treatment effect or subsidy induced R&D spending, i.e. the amount received by the funding agency ánd the additional spending, if we find evidence for this at all, due to this subsidy. The α is estimated in a previous equation by specifying that

$$R\&D = \alpha SUB + z_2'\omega + \varepsilon_2. \tag{5}$$

In order to account for the literature on treatment effects estimation, it has to be taken into account that SUB may itself be an endogenous regressor in the R&D input equation and therefore, one would need to instrument this variable. Thus, the final model is a recursive system of three equations, where the first equation could be written as follows:

$$SUB = z_3'\delta + \varepsilon_3. \tag{6}$$

4.3.1 Econometric implementation

If the error terms, ε_1, ε_2 and ε_3 were not correlated with each other, this recursive system of equations could be estimated sequentially by independent OLS regressions. As this is unlikely to hold, though, consistent estimation requires an instrumental variable approach, i.e. it is required that $z_1 \neq z_2 \neq z_3$ or in other words, z_3 must contain instruments that are not in z_2 and both z_3 and z_2 must contain

applied to the data and sample used in this chapter.

instruments that are not part of z_1 for model identification. Then this system of equations could be estimated using limited information estimator, such as 2SLS, where each equation is estimated separately using the appropriate instruments.

Because of the recursive nature of the system, we opt here for the so-called control function approach (which is in its base form identical to IV). We estimate the first equation by OLS and obtain $\hat{\varepsilon_3}$. This is then used to estimate the 2nd equation including the first stage residuals with OLS:

$$R\&D = \alpha SUB + z_2'\omega + \rho_1\hat{\varepsilon_3} + \varepsilon_2. \tag{7}$$

In order to estimate the 3rd equation, we have to plug in the residuals of both preceding stages, and we also re-arrange as follows:

$$\begin{aligned}
Output &= \beta_1(R\&D - \alpha SUB) + \beta_2\alpha SUB + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (8)\\
&= \beta_1 R\&D - \beta_1\alpha SUB + \beta_2\alpha SUB + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (9)\\
&= \beta_1 R\&D + (\beta_2 - \beta_1)\alpha SUB + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (10)\\
&= \beta_1 R\&D + \pi SUB + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (11)
\end{aligned}$$

where $\pi = (\beta_2 - \beta_1)\alpha$, and consequently the coefficient β_2, pointing to *any* output additionality is $\beta_2 = \beta_1 + \frac{\pi}{\alpha}$. For testing whether subsidies generate a premium over privately financed R&D, it needs to be tested whether $\beta_2 > \beta_1$, and vice versa. The premium/discount component itself can be straightforwardly presented in line with Griliches (1986) who allowed different weighting of the different components of R&D.[7] β_2 would then be equal to a premium/discount component, let's say $(1 + \gamma_2)$ in which γ_2 represents the actual amount of the pre-

[7]Griliches allowed to look at the effect of different components of R&D by weighting one of the terms (say $R\&D_2$) differently than the other, labeled as $R\&D_1$ in this example. The full R&D term can then be decomposed as follows: $R\&D* = R\&D_1 + (1 + \delta)R\&D_2$, where δ corresponds to a premium or discount of this second R&D term.

mium/discount, times the slope of the private R&D, $(R\&D - \alpha SUB)$, β_1 (corresponding to : $\beta_2 = (1 + \gamma_2) \times \beta_1$). Starting again from equation 8:

$$\begin{aligned} Output &= \beta_1(R\&D - \alpha SUB) + \beta_2 \alpha SUB + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (12)\\ &= \beta_1((R\&D - \alpha SUB) + (1+\gamma_2)\alpha SUB) + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (13)\\ &= \beta_1 R\&D + \gamma_2\beta_1\alpha SUB + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (14)\\ &= \beta_1 R\&D + \pi SUB + z_1'\theta + \rho_3\hat{\varepsilon_3} + \rho_2\hat{\varepsilon_2} + \varepsilon_1 && (15) \end{aligned}$$

This last equation 15 is exactly the same as equation 11. The γ_2 can then be backed out as follows: $\frac{\pi}{\beta_1\alpha}$. It is easy to see that this premium/discount component equals $\frac{\beta_2}{\beta_1} - 1$, as $\beta_2 = \beta_1 + \frac{\pi}{\alpha}$.

The model estimated by means of the control function approach will produce biased standard errors and as the coefficient α is only identified in the 2nd equation where R&D inputs are a function of the subsidies, the standard errors in the sequence of innovation input and output equations will thus be computed via bootstrapping, based upon 200 bootstrap replications.[8]

4.4 Data, variables and descriptive statistics

4.4.1 Data sources

The data used in this chapter combines firm-level data with detailed subsidy data. The firm-level data consists of the Flemish Community Innovation Survey (CIS) provided by the Centre for R&D Monitoring (ECOOM) from KU Leuven and additional firm-level data obtained from the Belfirst database published by Bureau van Dijk. The CIS is a survey that is largely harmonized across the different Euro-

[8]Simulations were performed in order to test the presented model and confirmed its validity.

pean member states in order to get a coherent view on innovation inputs and outputs. Next to information on the innovative activity of the companies, the CIS data also provide general information on the companies, such as sales, number of employees, founding year and so forth. The CIS data over the years 2004-2010 were updated and complemented with the Belfirst database which basically contains accounting data for the population of Belgian firms. As Belfirst does not contain information on R&D activities of firms, our sample is limited to firms questioned in the CIS survey.

These firm-level data have then been merged with detailed subsidy information obtained from the agency 'Innovatie door Wetenschap en Technologie' (IWT).[9] All subsidy information is assembled in the ICAROS database providing detailed information on subsidy grants for the population of Flemish firms. For all firms with a successful application process and thus eventual subsidy decision, we know the amount of subsidies granted and the duration of the funded projects.[10]

As only the CIS dataset contains detailed information on innovation inputs and outputs, we base our analysis on this sample, restricted to innovators, i.e. firms that have (a history of) innovation activities and/or (a history of) subsidy applications. After dropping outliers in relevant variables and missing data points in all variables, we end up with an unbalanced panel of 2,472 firms corresponding to 1,521 different firms.

[9]The key organization for support and promotion of R&D and innovation in Flanders is IWT (Innovatie door Wetenschap en Technologie). R&D subsidies in Flanders are granted and administered through this agency for Innovation by Science and Technology. The scope of its existing funding programs is quite broad as it supports a wide range of activities of small as well as large companies, universities, third level education institutions and other Flemish innovative organizations, individually or collectively.

[10]Some more information on the granting process can be found in appendix 4B. More ample background information on the agency and its activities can be found on the website of the agency, www.iwt.be, as well as in Larosse (2004)

4.4.2 Variables

This study integrates innovation input and output additionality estimation of subsidies in one framework. Innovation output is examined based upon a variable reflecting the percentage of sales due to new products, TURNNEW, and thus corresponding to ($\frac{\text{turnover new products}}{\text{turnover}} \times 100$) in a later time period than the R&D input measures.

The main determinants are R&D intensity measures. The CIS data give the opportunity to exploit different R&D input measures. On the one hand, it is possible to focus solely on internal R&D expenditures. On the other hand, one can look at total R&D expenditures of firms, so including both internal and external R&D. While the main focus of input additionality studies is on private R&D expenditures, the measure of total R&D expenditures is also included in this analysis as there is in principle no restriction specified by the granting agency that subsidies should only be used to fund internal R&D. Based upon both innovation input measures, intensity measures can be calculated which will be used in the regression framework. RDint and RDtot reflect intensities in % on turnover of both internal R&D expenditures and total R&D expenditures respectively (corresponding to $\frac{\text{R\&D expenditures}}{\text{turnover}} \times 100$).

Another important component in determining input and output is of course the subsidy variable. As we have detailed information on the starting period of the subsidization, the end period and the total amount granted, we can calculate yearly subsidies, IWTSUB.[11] Based upon this latter variable, subsidy intensity can be calculated, similar to the output measure and R&D input intensity measures, so relative to turnover of the firm (x 100, thus in %) (IWTSUBINT).

As outlined above in the methodology section, exclusion restrictions will have to be defined for both the subsidy and R&D input equations. In order to tackle

[11]The yearly amount of subsidies is calculated based upon a monthly redistribution of the total subsidy grant. E.g. if a firm starts a subsidized project in April 2012 that ends in December 2013, 9/21 of the total amount will be allotted to 2012 and 12/21 to 2013.

the endogeneity of subsidies, several relevant variables to be included in the exclusion restriction are defined. One of these variables is the stock of past project applications a firm has filed scaled by employment (APPSTOCK). This variable is constructed using the perpetual inventory method applying a 15% discount rate.[12] This variable accounts for the firm's experience with the Flemish subsidy system. In general, a firm that has applied before for a subsidy might be more likely to apply again as that firm is acquainted with the application procedure. As a consequence, its chances of getting a subsidy are in general higher than for a firm that does not have a history of applying. In the same vein, SRATE_FIRM reflects the stock of success rates of previous applications (also using a 15% rate of obsolescence). This variable reflects to what extent a firm had a successful interaction with the granting agency. SRATE_OTHER is a similar variable to SRATE_FIRM but captures the previous success of application of all other firms within the same industry, region and size group, the latter being defined by whether a firm can be categorized as an SME or not. This variable is supposed to capture the effect competitors might have on the application process of a firm. At the same time, this variable reflects to what extent the firm is situated in a class of firms that are more likely to get funding. The presented variables are all supposed to influence the subsidy variable but not the firm's investment decision or outcome.

In addition, as already touched upon above, exclusion restrictions will also be inserted in the R&D input equation, reflecting variables that are assumed to have an impact on R&D input but that do not determine R&D output. Variables reflecting the financial distress of a firm will likely influence the propensity to invest in R&D, but will not determine the eventual innovative output of firms. Therefore, the firm's debt ratio (DEBT) (relative to capital and reserves) is included in the input equations, but not in the output equations. Another exclusion restriction inserted in the R&D input equation is the past patent stock (PSold), thus the patent stock of more than 5 years old, and its square PSold2. These will presumably determine R&D investments of firms, but will not, in later time periods, directly impact

[12]The perpetual inventory method calculates the stock of a specific variable (VAR_t) in time t, let's name this $STOCK_t$ as follows: $STOCK_t = (1-\delta) \times STOCK_{t-1} + VAR_t$, where δ refers to the applied discount rate.

innovation output. In general, the patent stock reflects the history of innovation activities or more specifically is an indicator of at least the engagement in innovation activities which leads to some technological opportunity (independent of the value of the latter). This involvement in innovation is likely to strongly influence both the probability to receive subsidies and R&D expenditures. However, there is no rationale why a firm with a larger *history* of R&D activities would have a higher output in later periods. In line with this view, it has already often been argued that a large fraction of patents are "worthless" or become it in a short period of time (Griliches, 1998). The old patent stock is thus considered to at most influence R&D input in a later period but not the output further in time. Nevertheless, while sales with new products should not depend on old patents as these are supposed to just secure sales of older products, newer patents might impact the output induced by new products. Therefore, we insert PSnew and its square (PSnew2) in all equations, referring to the part of the patent stock less than 5 years old. The patent stock variables are constructed based upon the PATSTAT database, scaled by employment and constructed using the perpetual inventory method applying a 15% rate of obsolescence of knowledge.

Of course, other explanatory variables are included in all of the regressions. A first set of variables reflects size and age. Firm size is measured by the log of employment (lnEMP). In order to control for the firm's age, the logarithm of this variable is included in all estimations (lnAGE). As also argued in the other chapters, firms of different age might have different innovation input and output effects.

The GP dummy indicates whether a firm is part of a group. As already introduced in the previous chapter, group firms might be different from independent firms when it comes to innovation input but also innovation output as they are integrated in a broader group of firms and network effects might lead to higher investments and output. At the same time however, this depends on the integration of the firm in the group and its flexibility. When it comes to subsidies, the previous chapter extensively elaborated upon the fact that group firms might actually be less likely to receive subsidies. On the other hand, their probability of

applying might be higher due to network effects. Group firms with foreign headquarters should be viewed independent of national groups as they are also present on foreign territory, therefore a dummy FOREIGN is included (for a discussion on multinationals and innovation see e.g. Castellani and Zanfei, 2006). In addition, the dummy EXPORT reflects whether a firm is exporting in order to capture international presence, which might be an indicator of innovativeness due to the engagement in foreign markets.

Finally a set of province dummies captures location effects, industry dummies account for other non-observed differences among industries and time dummies capture business cycle effects.[13] Note that all time-varying variables enter the regression as lagged values to avoid simultaneity bias.

4.4.3 Descriptive statistics

Table 4.1 shows some descriptive statistics for the firms included in this study, split by whether a firm received a subsidy or not.[14]

Column 3 presents the significance levels of two-sided t-tests of differences between mean values of the variables between subsidized and unsubsidized firms. As can be seen, subsidized firms are, on average larger, more likely to be exporters and part of a group. They are also more likely to have a history of innovation, reflected by a larger patent stock. In line with expectations, the summary statistics also show that subsidized firms have a larger stock of both past project applications and application success rates. On average, the subsidized firms are also more likely to be part of a group of firms, defined as being within the same size class, industry, region and year as the observed firm, which have in general higher application success rates. With respect to the outcome variables, subsidized firms seem to have higher R&D intensities as well as a larger innovation output.

[13] An overview of the industry structure is given in table A4.1 in appendix

[14] The IWTSUBINT variable is thus 0 for all unsubsidized firms by construction.

Table 4.1: Descriptive Statistics

	(1)				(2)				(3)
	Unsubsidized firms (n = 2154)				Subsidized firms (n = 318)				t-test, H0: mean (1) = mean (2)
Variable	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	
DEBT	3.537	5.533	0	67.690	3.116	5.280	0	67.970	
EMP	136.997	285.310	1	5820	383.261	808.290	1	5116	***
PSnew	0.002	0.018	0	0.586	0.012	0.048	0	0.600	***
PSold	0.002	0.015	0	0.320	0.012	0.037	0	0.400	***
EXPORT	0.754	0.431	0	1	0.912	0.284	0	1	***
GP	0.573	0.495	0	1	0.642	0.480	0	1	**
FOREIGN	0.308	0.462	0	1	0.267	0.443	0	1	
AGE	27.788	20.451	1	225	27.420	23.588	2	147	
APPSTOCK	0.007	0.049	0	1.445	0.044	0.094	0	0.680	***
SRATE_OTHER	0.561	0.443	0	1	0.687	0.392	0	1	***
SRATE_FIRM	0.002	0.053	0	1.85	0.255	0.574	0	1.85	***
IWTSUBINT	*0*	*0*	*0*	*0*	0.971	2.267	0.001	19.555	NA
RDint	1.080	3.876	0	50	5.162	8.760	0	49.862	***
RDtot	1.239	4.188	0	50	5.960	9.818	0	49.862	***
TURNNEW	8.146	18.941	0	100	18.108	24.136	0	100	***

* p<0.10, ** p<0.05, *** p<0.01

4.5 Empirical implementation and results

4.5.1 Innovation inputs

In this section we focus on input additionality effects of subsidies on the innovation input decisions of firms.

Table 4.2 presents the impact of yearly IWT subsidies as measured by subsidy intensity on internal R&D intensity, RDint in column 1 and total R&D intensity, RDtot, consisting of both internal and external R&D investment relative to turnover

Table 4.2: Innovation input equations

	(1) RDint	(2) RDtot
IWTSUBINT	2.569***	3.046***
	(0.402)	(0.593)
DEBT	-0.038***	-0.038**
	(0.012)	(0.016)
lnEMP	0.198***	0.238***
	(0.073)	(0.087)
PSnew	25.267**	28.960**
	(10.950)	(11.965)
PSnew2	-55.502***	-74.175***
	(21.160)	(23.633)
PSold	20.972*	34.118*
	(11.726)	(18.100)
PSold2	-95.165**	-131.593**
	(38.265)	(54.596)
EXPORT	0.636***	0.678***
	(0.219)	(0.236)
GP	0.329	0.394*
	(0.206)	(0.227)
FOREIGN	-0.301	-0.226
	(0.274)	(0.309)
lnAGE	-0.317***	-0.346***
	(0.115)	(0.131)
Constant	0.180	0.103
	(0.484)	(0.554)
N	2472	2472
residfirst	-0.779*	-1.156*
	(0.460)	(0.683)
Test on joint significance of		
-Industry	$\chi^2(11) = 110.31$***	$\chi^2(11) = 111.64$***
-Time	$\chi^2(2) = 1.94$	$\chi^2(2) = 1.59$
-Region	$\chi^2(4) = 3.86$	$\chi^2(4) = 3.91$
F test of excluded instruments	12.74***	12.74***
Test on joint significance of exclusion restriction	17.79***	12.94***

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

in column 2.[15]

In general, the results shown in table 4.2 confirm that subsidy intensity has a positive significant impact on innovation input both when this latter is measured by internal R&D intensity and total R&D intensity. Full crowding out can thus be rejected as subsidies do seem to stimulate the increase of innovation expenditures. However, as there is always only a part of the projects subsidized (SR), it could be the case that this estimated increase due to subsidies reflects a lower increase than what would be expected if firms undertake the full project for which the subsidy application was filed. In other words, we expect the R&D intensity to increase at least to the extent that the initially proposed projects are undertaken. We can assess this by comparing the coefficient for IWTSUBINT with the inverse of the subsidy rate variable (1/SR). This subsidy rate variable can be constructed as we have detailed information on the total project costs and the granted amount in the subsidy database of IWT. The average subsidy rate in our framework is 43.395%, implying that total R&D investment should be at least 2.304 times higher than subsidies received. The results presented in table 4.2 suggest that this is indeed the case. However, the IWTSUBINT coefficients are not significantly higher than this 'private investment factor'. Nevertheless, based upon these results, we cannot reject that firms would not invest that extra amount in R&D after receiving subsidies.

The coefficients of the other control variables are, in general, in line with expectations. Patent stock, both old and new, seems to have a curvilinear effect on innovation inputs. Larger firms seem to have a higher innovation input and in line with expectations on their international presence, exporters invest more in innovation

[15]This step of the system of equations can be estimated by instrumental variables (IV) regressions as the control function approach and IV regressions are identical in this setting in which one endogenous variable enters linearly. Estimating this equation via IV and not via the control function approach show that the instruments pass the over-identification test (Hansen J-test). As a consequence, considering this and the significance of the instruments in the subsidy equation (see bottom rows of table 4.2), the proposed instruments can be considered as valid, at least in terms of statistical requirements. The first stage of the IV regression, namely the OLS regression of IWTSUBINT on the excluded instruments and all other control variables that are also included in the regression on the R&D intensity measures is shown in table A4.2 in appendix (note that the first stage coincides for both RDint and RDtot input equations).

activities. In addition, the older the firm, the less it invests in innovation activities on average. Group firms in general seem to have a slightly higher total R&D intensity.

In general, this section has shown that crowding-out can be rejected on average, i.e. subsidies granted by the government do seem to trigger private R&D investment. In the next section, the output stage, which is the focal point of this chapter, will be discussed.

4.5.2 Innovation outputs

The innovation output stage will be estimated based upon the control function approach, by including the residuals from the subsidy and R&D input stage in this last stage, correcting standard errors by means of bootstrapping based upon 200 replications.[16] Doing so, this section assesses the impact of private R&D inputs on output and analyzes to what extent a premium or discount can be found of the subsidized projects with respect to innovation output at the firm level.

Table 4.3 presents the results of this estimation. The first column presents results when the calculation of the R&D variables is based upon internal R&D intensity (RDint) and column 2 when this is based upon total R&D intensity (RDtot). Results show that the private part of both total R&D expenditures and internal R&D expenditures has a positive significant effect on innovation output as reflected by the coefficient of RDint and RDtot respectively. IWTSUBINT is not significant. However, as extensively introduced before, this coefficient should not be evaluated 'as is'. Instead, in a first step, the structural parameter, β_2, referring to the coefficient of subsidy induced R&D, can be calculated as introduced above: $\beta_2 = \beta_1 + \frac{\pi}{\alpha}$. Re-

[16] While the control function approach and IV estimations coincide for the second stage, the R&D input equation, this is not the case for the output stage. IV estimations of the output stage also insert the exclusion restriction of the subsidy equation in the R&D input equation, letting these variables thus directly impact both stages. It would nevertheless be a robustness check to see whether results are robust to estimation by IV. Table A4.3 in appendix (columns 2 and 4) shows results for this estimation, confirming the results found for the output equation estimated by the control function approach shown below. The similarity of IV and the control function approach for this output equation was also confirmed in the simulations.

Table 4.3: Innovation output equations

	Output Equation (1)	Output Equation (2)
RDint	3.559**	
	(1.641)	
RDtot		3.410**
		(1.571)
IWTSUBINT	-3.883	-5.212
	(4.449)	(4.566)
lnEMP	0.878	0.757
	(0.593)	(0.622)
PSnew	-17.320	-39.239
	(76.823)	(78.217)
PSnew2	-11.087	59.380
	(194.907)	(230.117)
EXPORT	2.574*	2.506
	(1.551)	(1.588)
GP	-1.526	-1.752
	(1.200)	(1.361)
FOREIGN	-1.072	-1.315
	(1.477)	(1.521)
lnAGE	-0.832	-0.798
	(0.794)	(0.873)
Constant	3.853	4.273
	(3.363)	(3.394)
N	2472	2472
Bootstrap replications	200	
β_2	2.048**	1.699**
	(0.960)	(0.772)
γ_2 (=discount/premium)	-0.425	-0.502
	(1.992)	(0.660)
residfirst	-0.623	0.632
	(2.521)	(2.617)
residsecond	-2.801*	-2.765*
	(1.638)	(1.569)
Test on joint significance of		
- Industry	$\chi^2(11) = 44.32$***	$\chi^2(11) = 45.50$***
- Time	$\chi^2(2) = 3.08$	$\chi^2(2) = 2.92$
- Region	$\chi^2(4) = 3.29$	$\chi^2(4) = 3.32$

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

sults in table 4.3 show that the subsidy induced R&D investment has a positive significant effect on output. Both parts of total R&D seem thus to stimulate sales due to new products.

A major question in this study is whether this at first sight lower coefficient of subsidized R&D reflects a lower productivity of this latter R&D component compared to the privately invested R&D in terms of output. Therefore, we are interested in the structural parameter capturing the discount of subsidy induced R&D spending, which has to be calculated as presented above in section 4.3 ($\gamma_2 = \frac{\pi}{\beta_1 \alpha} = \frac{\beta_2}{\beta_1} - 1$).

For the output equation with R&D input measured as RDint, we find $\gamma_2 = (\frac{-3.883}{3.559 * 2.569}) = 0.425$, suggesting thus a discount of subsidized R&D of 42.5% with respect to internal R&D intensity in terms of innovative output. Similarly, a discount of 50.2% is suggested with respect to total R&D intensity ($\gamma_2 = (\frac{-5.212}{3.410 * 3.046})$). Nevertheless, as shown in table 4.3, these coefficients are insignificant, indicating that in fact, no loss in productivity can be observed due to subsidized R&D.

In sum, results point to a positive significant effect on output of both purely private and subsidy induced R&D. Furthermore, we do not find evidence of a lower productivity or higher profitability of this latter component compared to private R&D in terms of generated sales due to new products. There is thus no conclusive evidence supporting either one of the arguments outlined above, in favor of expecting a discount or suggesting a premium of subsidy induced R&D relative to private R&D in terms of innovative output. [17]

[17] A general problem in subsidy evaluation studies is the lack of a reliable control group. In the above section, as in most of the subsidy evaluation studies, the control group consists of all firms that did not get a subsidy in the period under consideration. However, Brown et al. (1995) suggest that the control group of firms that received subsidies should only consist of firms with rejected applications as they might, although not random, come as close to a reliable control group as one might get. As we have information on all subsidy applications from 1984 onwards, our setting would enable us to exploit a similar alternative control group. Instead of having all firms that did not receive a subsidy in the period under consideration as controls, we could only keep those that ever applied for a subsidy between 1984 and the year under consideration. Doing so however reduces the number of observations in the sample to that extent that it is impossible to estimate the model consistently. When more data becomes available over time, allowing a larger sample size with various control groups, this could nevertheless be a viable extension.

4.6 Conclusion

Taking a methodological approach instead of focusing on the literature on small young innovators as in the previous chapters presented in this dissertation, this chapter models input and output additionality in a structural framework. It extends the Crépon Duguet Mairesse (CDM) framework by incorporating subsidies as a determinant of both the input and output equations. Thereby, this study adds to the CDM framework and to the widely spread input additionality literature and the less investigated output additionality strand of research. Doing so, this chapter allows to investigate in more detail both input additionality and output additionality by explicitly modeling the inextricable nature of this process. This latter factor was mostly neglected by previous literature. In addition, the availability of detailed subsidy data enables us to take a step back from the commonly used dichotomous indicator of public subsidies.

The empirical study is carried out using Flemish Innovation Survey data coupled with detailed subsidy data. In line with a lot of the prevalent literature, the empirical analysis finds evidence for input additionality of subsidies. In general, crowding out can thus be rejected and public incentive schemes seem to accelerate R&D spending.

Implementing the method described in this chapter in order to investigate output additionality, this analysis reveals that, in general, an increase in private R&D inputs leads to higher innovative performance in subsequent years. In addition, subsidy induced R&D, encompassing both the subsidy and the additional R&D investment due to this subsidy, also increases sales due to new products. Furthermore, in spite of the at first sight lower output effect of subsidies, results do not show any evidence of a lower profitability of subsidy induced R&D spending, suggesting that both subsidy induced R&D spending and private R&D spending have similar effects on output. There is thus no evidence suggesting that either policy makers select projects with potential lower private value or that firms would get

subsidies for projects with lower outcome expectations.

Of course, our study has a number of caveats that remain for further research and these will be mainly discussed in the concluding chapter 5. A specific shortcoming of this chapter is that application and granting decision stages could not be incorporated in the framework. In addition, it is worth mentioning that, in context of this dissertation and the importance attributed to firm heterogeneity in the previous chapters, it would be valuable if further research could incorporate this latter aspect in the more structural set-ups like the one presented here as well.[18]

[18]While it is beyond the scope of this chapter to insert firm heterogeneity in the model in its current set-up, tables A4.6 and A4.7 in 'Appendix 4.B' show results for a subset of small young firms, confirming all results presented below.

Chapter 5

General Conclusion

In brief terms, this doctoral dissertation elaborated upon the understanding of the growth potential of small young innovators and looked into an important policy tool, selective R&D subsidies that are often used to trigger innovation activities of firms. A focus on small young innovators is not only relevant in terms of evaluating the current policy stipulations of the European Commission (EC), but also adds to the academic literature that in general increasingly emphasizes the importance of these firms in terms of technological performance and economic growth. As measuring policy impacts remains challenging, the importance of evaluation methods was also considered by dedicating a separate chapter to an alternative methodology to analyze subsidy effects. The findings of the individual chapters are briefly summarized before formulating a more general conclusion to this dissertation. This chapter also extends upon the different limitations to this work and formulates opportunities for further research.

In line with the increased focus on specific subsets of innovators, **Chapter 2** of this dissertation looked into the growth opportunities of small young innovators, and more specifically of the "Young Innovative Companies", the so-called YICs, as fostered by the EC. This analysis shows evidence that these firms, being small, young and intensively engaged in innovation activities grow more than other firms, both in terms of employment and in terms of sales. In addition, the study presented in

chapter 2 confirms the complementarity of the factors size, age and R&D intensity as incorporated in the YIC definition as the latter grow more than other subsets of firms that have less strict innovation criteria. In general, these results confirm the expectations on growth of YICs. The additional findings on complementarity point to the importance of carefully defining subsets of firms. Furthermore, as a main goal of policies is to foster growth, this study also seems to support the reinforcement of state aid programs toward YICs.

Although the growth figures are supportive for YICs, one might wonder how YICs perform over the growth distribution. Analyzing this by means of quantile regressions shows that YICs grow especially faster than other, already fast-growing firms. This result is fully in line with expectations on these firms. However, expectations are also that these firms would, on the other end of the tail, perform much worse than the other slow growers in the economy due to the presumed heterogeneity within this class of firms. Nevertheless, this study showed that, although YIC growth is variable over different quantiles, YICs do not seem to perform significantly worse than other firms at any point of the distribution of firm growth. This suggests that they are on the one hand high performers and on the other hand, do not 'fall harder' than other players in the economy.

Following upon this, **Chapter 3** assessed to what extent the recent orientation of R&D subsidies towards small young, stand-alone high-tech firms (NTBFs) is warranted by assessing both input and output additionality effects of subsidies on these firms. This chapter not only analyzed these effects for NTBFs but compared the effects on these firms to the effect on other small young innovators by defining some additional firm categories, i.e. LTBFs (small young independent low-tech firms) and their group, i.e. non-independent, counterparts. Matching results revealed that full crowding-out with regard to public funding can be rejected for all firm types studied, suggesting that public funding seems to attain its goals in terms of innovation input. However, comparing the treatment effects of the different firm types in a regression framework suggested that treatment effects of NTBFs are actually highest. The latter finding is in line with stipulations of policy mak-

ers. Nevertheless, this also suggests that previous estimations of innovation policy impacts might have been partly misleading as in general, no distinction between preferential firm profiles in policy schemes have been made.

Next to an assessment of the additional input in R&D triggered by subsidies, this study looked into the ability of subsidized firms to generate additional output. The analysis showed that for nearly all firm categories, both private R&D and subsidy induced R&D lead to new patent applications. In addition, comparing the effects of publicly induced R&D and private R&D does not point to a lower or higher productivity of subsidy induced R&D as compared to private R&D. These findings further suggest that, at least from the viewpoint of the subsidized firm itself, subsidies are not inefficiently spent.

Building upon these subsidy evaluation studies, **chapter 4** presented an entirely new extension to both the CDM model and the subsidy evaluation literature by incorporating subsidy evaluation in the CDM framework. The integration of input and output additionality in one framework acknowledges the inextricable nature of this process and thereby provides a new method to assess output additionality and to estimate whether subsidies entail a premium over private R&D or a discount in terms of innovative output. In addition, in contrast to the majority of subsidy evaluation studies using propensity score matching, this set-up allows to make use of more detailed subsidy data allowing to take a step back from the commonly used dichotomous indicator of public subsidies. By adding to existing models in several ways, this chapter mainly draws attention to both the possibilities but also the further need to follow up upon different existing frameworks as these might be highly instrumental in follow-up research tackling new research questions.

Results of this chapter indicate that, in line with the prevailing literature, subsidies trigger private R&D investment and crowding-out can thus in general be rejected. In a next step, output additionality was assessed. Findings suggest that, in general, both purely private R&D investment and subsidy induced R&D, the latter encompassing both the subsidy received and the additional R&D investment triggered

by the subsidy, contribute to innovation performance at the firm level. Furthermore, the publicly induced R&D does not entail a significant discount or premium relative to private R&D investments in terms of innovative performance. An equal productivity of publicly induced and purely private R&D can thus not be rejected.

In sum, the different chapters presented in this dissertation add to the innovation literature in different ways, extending upon the specific literature focusing on small young innovators, and adding to the more general subsidy evaluation literature and the papers building upon the framework set up by Crépon, Duguet and Mairesse.

In terms of the literature focusing on subsets of innovators, results confirm that a refined focus might be warranted as the specific subset of YICs seems to stimulate growth and job creation, more than other firms. Building upon this, this dissertation also suggests that the reinforcement of state aid programs towards specific subsets of small young innovators might be beneficial and might help these firms to overcome some of the market failures related to innovation activities, which are acknowledged to be especially hindering the innovation activities of these firms. At least, granting R&D subsidies to specific subsets of firms does seem to attain its goal in terms of fostering both innovation input and output. The inclusion of subsets in this context also has implications for policy recommendations; the increasingly postulated view that an entrepreneurial state should be built at least to some extent by specific and more refined intervention of public institutions can thus not be rejected. In addition, although fostering innovation activities directly as assessed in this dissertation is acknowledged to be a main instrument, the creative destruction mechanism is presumably embedded in a wider set of instruments that allow entry, growth, but also easy exit of firms engaged in these activities. The EU-US gap for example might not solely be solved by subsidizing innovation activities of these firms, but is probably rooted in deeper structural problems hampering dynamics of these firms in the EU both related to regulations (some examples are entry and exit regulations, competition policy, labor market regulations, financial market regulations,...), as well as more cultural specificities of the

economic environment.

Next to adding evidence to the literature assessing the importance of small young innovators, this work suggests that the innovation literature, more broadly, should increasingly incorporate firm heterogeneity in its analysis as some general effects found might differ between different firm types. In the context of this dissertation for example, the majority of the subsidy evaluation literature has focused on very broad sets of firms, while only some incorporated different subsets of firms, as done in this work.

Next to adding to the literature on small young innovators and the general innovation literature, this dissertation also adds to the methodologies used to evaluate policy instruments. By adding to these existing methodologies, this thesis does not only present possibilities to extend research in this respect, but also points to further opportunities to incorporate existing methods in new settings or elaborate upon new methods in order to validate (or question) existing findings in the innovation literature.

As afore mentioned, it has to be acknowledged that this dissertation is only a building block in the broader research field. In this context, it is important to acknowledge that this work is definitely not without limitations. While most of the chapter-specific limitations are discussed in the relevant chapters themselves, below are some limitations listed that apply more generally to some or all of the chapters incorporated in this doctoral dissertation. Nevertheless, some of the limitations raised for this work not only lead to a critical reflection and a further acknowledgement of the broader setting in which this dissertation should be embedded, but also set the stage for further research, on which some suggestions will be given in this concluding chapter.

All chapters suffer from inevitable data-limitations. One of the most obvious problems with the variables used in this doctoral dissertation that are based upon survey data is that the credibility of the responses reaches as far as the interpretation of the responding agent. The responses are thus always subjective to some

extent. Next to this, the analysis of chapters 2, 3 and 4 is only based upon one country and/or one region (the survey data used in chapters 2 (CIS and OECD R&D survey) and 4 (CIS) only cover the Flemish region in Belgium, while chapter 3 only focuses on German CIS data, based upon the Mannheim Innovation Panel (MIP)). In the different chapters, these countries are assumed to be representative for other countries within the European Community. However, it needs no explanation that within the EU, it might be incorrect to extrapolate results obtained for individual countries to the more global European level. In addition, even if it could be assumed that results would be representative for the EU, it would be interesting to further investigate (policies towards) small young innovators in other regions and especially the less researched less-developed regions in line with e.g. Goedhuys and Sleuwaegen (2010) and Sleuwaegen and Goedhuys (2002) as other environments and confounding factors might impact their growth and technological progress. Related to this latter remark on confounding factors and as already mentioned also in chapter 2, it has to be acknowledged that also within the context of the current work, other confounding factors, not taken into account in this dissertation, might impact the (technological) performance of small young innovators (Carpenter and Petersen, 2002; Colombo and Grilli, 2005).

Next to this, the CIS, the R&D OECD survey and the MIP can only be used as pooled cross-sections. In other words, panel data analysis is unfortunately impossible as the same firm is not necessarily observed in several consecutive waves of the surveys. One major advantage of panel data is the possibility to control for time-constant fixed effects. In addition, although the cross-sections contain answers to questions that cover different years, the use of a panel would further enable us to elaborate a lag structure. Without a sufficient time-lag, it might be hazardous to pose any statement on causality. In addition, some effects, e.g. on innovation output and growth, might show a large variability in terms of timing. It would thus be highly interesting to trace the path of young innovative companies over longer periods than what has currently been done in this dissertation. This does not only apply to growth in chapter 2 but also to the output variables presented in the other chapters. Closely related to this, chapter 2 already suggested

another opportunity of having extended data, namely to study in more detail the survival of for example YICs when compared to other companies and assess confounding factors to this in order to understand the exit dynamics because after all, exits are also important vehicles of more general market dynamics (Bartelsman et al., 2004; Haltiwanger, 2012). The latter could in a first step already be implemented with the population information on Flemish firms taken from Belfirst, containing detailed information on exit and the reason thereof. This opportunity for further research is closely related to a limitation of our research setting that could only be taken into account in chapter 2, but eventually applies to all chapters. All results presented in the different chapters are conditional upon survival, meaning that only firms that survived up till the survey period were included in the sample. In chapter 2, the data could be merged with information on the full population of Flemish firms in order to correct for this bias based upon a heckman selection model. Nevertheless, although the selection term, the Mills ratio, was insignificant, this might rather point to difficulties in estimating the selection equation rather than to a lack of survival bias. Together with a more detailed understanding of survival of these firms, both the entry and post-entry dynamics also deserve further attention (for a recent survey on firm entry, growth and exit dynamics, see Santarelli and Vivarelli (2007) and see Fackler et al. (2013) for a recent empirical contribution). In general, these suggestions for further research reveal the need for theoretical models and empirical analysis to focus on the dynamics of these small young innovators in order to add to the broader array of policy designs, apart from the suggestions on innovation policy that could be raised in this dissertation (see also further comments below).

In addition, as already mentioned multiple times throughout this dissertation, potential indirect effects generated by small young innovators were not taken into account. In this context it would for example be valuable to assess to what extent small young innovators create, as often postulated, beneficial effects in terms of creating new markets that might incite research in other firms in the economy (next to or in addition to the other stream of literature discussing the knowledge spillover theory of entrepreneurship, explaining how entrepreneurial opportuni-

ties themselves are shaped through other firms (Acs et al., 2009; Block et al., 2013)). In line with this, collaboration activities of small young innovators are also a valuable avenue for further research: firms' heterogeneity of collaborations (i.e. partner type, asymmetric collaborations), and the effects on output of both the collaborating small young innovators and the other firms (Hagedoorn et al., 2000; Belderbos et al., 2004; Veugelers, 1998; Veugelers and Kesteloot, 1996; Alvarez and Barney, 2001). Related to this, as also already mentioned in chapter 3, research on group participation of small young innovators would also be interesting to be extended, both in context of the general spillover and subsidy evaluation literature. The broader collaboration setting can also be linked to the wide literature on markets for technologies, which suggests an important role of small young technology suppliers in the innovation system (Arora and Gambardella, 2010). Thus, although this dissertation focuses in chapters 2 and 3 only on small young innovators, this should not be interpreted as denying the importance of other (more mature) firms in the economy. Baumol (2002) for example stressed that society can only benefit fully if it has an innovation system that effectively links small and large firms, with the latter following-up and improving the breakthrough innovations of the former. In line with these suggestions, it would also be informative to assess the extent to which research subsidies granted create spillovers and have the presumed additional social welfare effects. Next to exploiting patent data, which in spite of its valuable contributions nevertheless generates limited measures in this respect as at most spillovers to other firms can be measured, a road for further research within that setting consists of focusing more on different structural modeling types in line with e.g. Takalo et al. (2013). This setting aims at estimating broader spillovers, capturing both positive externalities from subsidized R&D (e.g. consumer surplus, technological spillovers to other firms) but also potential negative effects (e.g. cost duplication, business stealing (Aghion and Howitt, 1992; Segerstrom, 1998)).

In addition, as already touched upon in the introduction, this dissertation only focuses on one type of innovation-fostering policies, selective R&D subsidies. It is straightforward that complementary effects or substitution effects could emerge

between different policy measures. It would be interesting to consider the whole pallet of policy measures and the effect each of them has on economic growth. In this context for example, attention has already been directed towards the combination of patent protection, often considered as important for small young firms (de Rassenfosse, 2012), and public R&D subsidies. Scotchmer (2004) e.g. questioned the relevance of 'blending' patent protection with public subsidies as this might simply cause society to pay twice. In addition, further research could look into complementarity of specific subsidies and the private venture capital market in Europe, which is on itself acknowledged to be underdeveloped but often raised as important fosterer of small young innovators (Bottazzi and Da Rin, 2002; Veugelers, 2011; Da Rin et al., 2011; Grilli and Murtinu, 2014). It has to be kept in mind that next to these innovation-related policies, as already mentioned in this dissertation, other policies might also have a more indirect impact on innovation. In this context it was already noted that competition policy, labor market regulations, the education system and other institutional and cultural factors might have an important impact on innovation activities, the creative destruction process and growth (Aghion et al., 2005; Veugelers, 2010; Bartelsman et al., 2004; Meyer and Peng, 2005; Peng, 2003; Santarelli and Vivarelli, 2007; Mazzucato and Parris, 2014; Furman et al., 2002).

Another array for further research lays in the methodologies used to evaluate subsidies. While chapter 4 already extends chapter 3 in important ways, by integrating input and output stages in a structural framework and using a more detailed subsidy measure, it is not that straightforward to incorporate for example firm heterogeneity, as done in chapter 3, into this framework. Further research could build upon this. Also note that not only firm heterogeneity might play an important role, but also subsidy heterogeneity itself. While some attempts have been made to incorporate different types of subsidies (e.g. basic, applied) in a matching approach, it would be valuable to also assess a more refined subsidy impact in this setting (not based upon a dummy variable and assessing both input and output effects). This suggestion could pave the way for an extension of the presented CDM framework in chapter 4, but could also build further upon the structural framework of

e.g. Takalo et al. (2013). In addition, future frameworks should, like the latter one, incorporate the application and granting process in the analysis.

Next to this, all research in this dissertation is conducted at the firm level. It would be valuable to have more detailed project-level information, especially in the setting of subsidy evaluation, both with respect to input and output variables. All data sources used in this dissertation were only available or could only be used at the firm level. The fact that all studies are conducted at the firm level limits to some extent the interpretation of results. Information at the project-level would enable a more fine-grained approach towards subsidy effects. In the current setting, several subsidized projects might have been merged and only the effect on the total R&D spending of the firm can be assessed. This might be partly misleading. Finding that there is no crowding-out at the general firm level for example does not give any information on the exact use of the subsidies within the firm as well as on the effect this might have on other projects. Chapter 4 already found a first indication that it cannot be rejected that firms raise their firm-level R&D spending at least with the amount as postulated in case of subsidy receipt. Nevertheless, this does not shed any light on the distribution of projects over the firm's portfolio. Even if there would be evidence of (partial) crowding-out effects, it could be that what is less invested, is invested in better projects. Takalo et al. (2013) for example do focus at the project-level but cannot assess the full project portfolio of the firm in their setting.

The paragraphs preceding this last one elaborated not only upon several limitations, but also set the thesis in a broader context while adding on avenues for further research. Wrapping up this thesis, it is important to acknowledge that the limitations to the research presented in this dissertation should never serve as a discouraging finding. They only point out the array of possibilities in which research could be extended. Realizing this is very important and should serve as an incentive to keep on going on the sometimes bumpy road of research, never stop wondering and tackle new challenges on the way!

Appendices

Overview of the different firm-types discussed in the dissertation

Below, an overview is given of the different firm types discussed in this thesis. They are presented per chapter and the firm-types that are fostered by policy makers and / or are part of the academic literature are briefly discussed. While none of the chapters specifically discusses SMEs as a single firm category, this firm type is also briefly introduced here due to its importance as overarching firm category based upon which the attention towards subsets of firms increased (e.g. YICs).

SME — Small- and Medium-sized Enterprizes. In its broadest applied form, this term refers to firms having less than a specific number of employees, usually limited to 250. The European definition applied by European policy makers defines this as "enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding 50 million euro, and/or an annual balance sheet total not exceeding 43 million euro" (EC-DG ENTR, 2006).

Chapter 2

YIC — Young Innovative Companies. With the revised state–aid rules for innovation support, the European Commission especially reinforces policies towards potential radical innovators by introducing the concept of Young, Innovative Companies (YICs) (see EC-DG ENTR, 2009, for an overview). By the European definition, these companies are less than six years old, have less than 250 employees and are highly R&D intensive, that is, have an R&D intensity larger than 15% as measured by R&D spending relative to total operating expenses. Article 35 of the General Block Exemption Regulation (GBER) defines advisory conditions for aid to YICs (European Commission, 2008) by defining specific categories of state aid for which no notification to the Commission is necessary. The support granted to YICs should be compatible with articles 87 and 88 of the EC Treaty, declaring certain categories of aid compatible with the common market.

SYI — Small Young Innovators. A firm type introduced by the author to designate firms having all characteristics of YICs, except for the R&D intensity threshold, which should only be above 0.

SY — Small Young firms. A firm type introduced by the author to designate firms having the same size and age criteria as YICs, but should not be R&D active.

Chapter 3

NTBF	New Technology Based Firms. This concept was initially introduced by the Arthur D. Little consulting group (Little, 1977) and points to young independent firms engaged in innovation activities involving substantial technological risk. Although these firms are often discussed in academic literature, there is no univocal definition of this concept (Storey and Tether, 1998). Chapter 3 defines these firms as small ($<$ 250 employees), young ($<$ 10 years old), independent firms active in high-tech sectors.
GNTBF	Group New Technology Based Firms. The group, i.e. non-independent, counterparts of NTBFs.
LTBF	Low Technology Based Firms. The low-tech counterparts of NTBFs.
GLTBF	Group Low Technology Based firms. The group and low-tech counterparts of NTBFs.

Appendix to chapter 2

Appendix 2.A

Table A2.1: Industry structure

Industry	Description	# obs in the sample
1	Manufacture of food products, beverages and tobacco	935
2	Manufacture of textiles	555
3	Manufacture of wood and wood products; manufacture of pulp, paper and paper products; publishing and printing;	530
4	Manufacture of coke, refined petroleum products and nuclear fuel; Manufacture of chemicals, chemical products and man-made fibres; Manufacture of rubber and plastic products	982
5	Manufacture of basic metals and fabricated metal products	964
6	Manufacture of machinery and equipment n.e.c.; Manufacture of transport equipment	1070
7	Manufacture of electrical and optical equipment	693
8	Manufacture of other non-metallic mineral products; Manufacturing n.e.c.	607
9	Research & Development; other business services	1078
10	ICT and related services	474
	Total number of Observations: 7888	

Table A2.2: Table of correlations

	Emp Growth	YIC	SYI	SY	EMP	AGE	RDint	FOREIGN	EXPORT
Emp Growth	1.0000								
YIC	0.0676	1.0000							
SYI	0.0315	-0.0383	1.0000						
SY	-0.0169	-0.0349	-0.0416	1.0000					
EMP	-0.0210	-0.0487	-0.0191	-0.0512	1.0000				
AGE	-0.0559	-0.1871	-0.2227	-0.2130	0.1880	1.0000			
RDint	0.0314	0.4360	-0.0045	-0.0612	-0.0346	-0.1458	1.0000		
FOREIGN	0.0242	-0.0076	0.0213	-0.0127	0.2220	0.0392	-0.0128	1.0000	
EXPORT	-0.1444	-0.0377	-0.0045	-0.0099	0.0035	0.0804	-0.0504	0.0557	1.0000
GROUP	0.0214	-0.0300	0.0511	-0.0562	0.2365	0.0532	-0.0178	0.5586	0.0276

Appendix 2.B: Extensions

Two year lead of the growth variable

In chapter 2, we analyzed the growth of the Young Innovative Companies in t+1. However, we can question whether we can still find a superior growth in t+2. In other words, we question the durability of the growth of YICs. Coad and Rao (2006) state that it is difficult to specify a correct time lag, especially for sales growth to be visible. As a consequence, a wider time horizon could capture the effects on sales growth better. Unfortunately, a larger time horizon than 2 years was impossible to implement due to data limitations. In order to evaluate the growth in a later time period, we adjust the growth definition of both sales and employment in the following way: $[(TURN(EMP)_{it+2} - TURN(EMP)_{it})/TURN(EMP)_{it} \times 100]$. Subsequently, we estimate the growth equations again, with the adjusted growth variable.

Table A2.3 presents the results of these adjusted estimations. Columns 1 and 3 present the growth results when only the YIC dummy is included, while columns 2 and 4 show the results with SYIs and SY firms included in the regression. We find that sales growth approximately doubles over a two-year period when compared to annual growth. This indicates that the growth of YICs, at least in terms of turnover, is persistent. For employment growth, we also almost find a doubling of the coefficient of the YIC dummy. Consequently, the growth of Young Innovative Companies also seems to be persistent in terms of employment.

The inclusion of the SYI and SY dummies in the sales and employment growth equations does not change the results of the YIC dummy. In addition, both the SYI and SY dummies remain insignificant. The results for the other control variables also hold in general. The only difference is that being an exporter has an insignificant effect on sales growth over a two-year period, while we found a negative significant effect on sales growth over a one-year period.

Table A2.3: The 2-year growth of the Young Innovative Companies

Variables	(1) Sales Growth		(2) Sales Growth		(3) Emp Growth		(4) Emp Growth	
YIC	18.554	**	18.244	**	7.929	*	8.408	**
	(7.693)		(7.758)		(4.063)		(4.108)	
SYI			0.303				2.121	
			(2.946)				(1.904)	
SY			-4.437				0.311	
			(4.048)				(2.443)	
ln(EMP)	-1.319	**	-1.334	**	-1.196	***	-1.206	***
	(0.544)		(0.545)		(0.342)		(0.342)	
ln(AGE)	-1.644	**	-1.846	**	-1.590	***	-1.323	***
	(0.722)		(0.890)		(0.428)		(0.506)	
RDint	0.266		0.256		0.126		0.125	
	(0.163)		(0.163)		(0.085)		(0.085)	
$RDint^2$	-0.004	**	-0.004	**	-0.001		-0.001	
	(0.002)		(0.002)		(0.001)		(0.001)	
FOREIGN	1.108		1.128		0.825		0.849	
	(1.526)		(1.525)		(0.969)		(0.969)	
EXPORT	0.080		0.016		-2.554	***	-2.597	***
	(1.565)		(1.564)		(0.821)		(0.819)	
GP	-1.362		-1.395		0.698		0.664	
	(1.496)		(1.497)		(0.855)		(0.854)	
Constant	11.149	***	12.087	***	0.368		-0.538	
	(3.850)		(4.369)		(2.235)		(2.531)	
R2	0.09		0.09		0.07		0.07	
N	4821		4821		6409		6409	
F statistic	14.687	***	13.721	***	13.334	***	12.525	***
F-test on joint significance of								
- industry dummies	8.19	***	8.21	***	4.72	***	4.76	***
- time dummies	36.07	***	36.04	***	22.21	***	22.22	***
- region dummies	0.83		0.77		0.76		0.79	

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Cluster-robust standard errors are given in parentheses.

Thresholds of R&D intensity in the YIC definition

The definition of YICs used in this dissertation is based upon the official definition provided in article 35 of the General Block Exemption Regulation (GBER), i.e. firms being less than 6 years old, having less than 250 employees and with an R&D intensity of more than 15%. It would be interesting to assess to what extent results are sensitive to the R&D intensity threshold in the definition. This is examined by lowering the R&D intensity threshold to 10% and 5% respectively in order to assess the sensitivity of R&D intensity in the YIC definition and the effect on growth.

Table A2.4 shows robustness checks on this. Columns 1 and 2 show results when the R&D intensity threshold is lowered to 10%, both for employment growth in the first column and sales growth in column 2. Columns 3 and 4 show the growth equations for employment and sales growth respectively when the R&D intensity threshold in the YIC definition is lowered to 5%. Results show that when this threshold is gradually lowered, results become less significant. This confirms the relevance of this threshold, next to the evidence on complementarity effects with respect to SYI and SY shown in chapter 2 itself.

Table A2.4: Thresholds of R&D intensity in the YIC definition

	(1) emp10	(2) sales10	(3) emp5	(4) sales5
YIC	4.467**	6.288*	3.197**	3.391
	(1.959)	(3.255)	(1.540)	(2.557)
SYI	1.284	0.382	1.779	1.613
	(1.065)	(1.727)	(1.215)	(1.861)
SY	-1.788	-2.179	-1.753	-2.069
	(1.410)	(2.891)	(1.410)	(2.892)
ln(EMP)	-0.332*	-1.085***	-0.343*	-1.104***
	(0.185)	(0.285)	(0.185)	(0.286)
ln(AGE)	-0.682**	-1.512***	-0.667**	-1.471***
	(0.302)	(0.524)	(0.303)	(0.526)
RDint	0.047	0.139	0.055	0.162*
	(0.051)	(0.094)	(0.052)	(0.093)
$RDint^2$	-0.001	-0.002**	-0.001	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
FOREIGN	0.776	0.744	0.800	0.791
	(0.561)	(0.880)	(0.561)	(0.880)
EXPORT	-2.724***	-2.046**	-2.730***	-2.052**
	(0.490)	(0.864)	(0.490)	(0.864)
GROUP	0.608	-0.968	0.597	-0.992
	(0.509)	(0.832)	(0.511)	(0.836)
Constant	-2.750*	5.267**	-2.792*	5.105**
	(1.434)	(2.286)	(1.437)	(2.292)
N	7888	6110	7888	6110

Cluster-robust standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$
Note: Regressions include time, industry and region dummies.

Appendix to chapter 3

Appendix 3.A

Table A3.1: Industry structure

Industry	Description	NTBF	group NTBF
1	Manufacture of chemicals and chemical products ;Manufacture of pharmaceuticals, medicinal chemicals and botanical products	88	61
2	Manufacture of machinery and equipment n.e.c.; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment; Building and repairing of ships and boats ; Manufacture of aircraft and spacecraft;	235	132
3	Manufacture of office machinery and computers; Manufacture of electrical machinery and apparatus n.e.c.; Manufacture of radio, television and communication equipment and apparatus; Manufacture of medical, precision and optical instruments, watches and clocks;	272	141
4	Research and development; Other Business activities	465	179
5	Computer and related activities	168	96
	Total number of Observations:	1288	609
		LTBF	Group LTBF
6	Manufacture of food products, beverages and tobacco	42	23
7	Manufacture of textiles	61	21
8	Manufacture of wood and wood products; manufacture of pulp, paper and paper products; publishing and printing;	65	35
9	Manufacture of coke, refined petroleum products and nuclear fuel; Manufacture of rubber and plastic products	89	48
10	Manufacture of basic metals and fabricated metal products	179	59
11	Fishing; mining and quarrying; Mineral products; Furniture; other industries; Waste collection, treatment and disposal activities; materials recovery; Other services	243	132
12	Wholesale and retail trade and repair of motor vehicles and motorcycles	133	50
13	Transportation, storage ; Financial and insurance activities	137	89
14	Communication services	16	13
	Total number of Observations:	965	470

Appendix 3.B: Extensions

Table A3.2 presents some descriptive regression results on financial constraints. As introduced in chapter 3, the literature suggests that independent and high-tech small young firms are more financially constrained than those that belong to a group or are active in less technology-advanced areas. In one of the survey waves, MIP 2005, there is an explicit distinction made between the extent to which on the one hand internal (intcon) and on the other hand external (extcon) financing sources constrain innovation activities of firms. These two dummies serve as dependent variables in a probit regression on the dummies referring to the different firm types (with GLTBF as reference category) next to additional control variables such as size, age and region. These results suggest that high-tech small young firms in general are more financially constrained than the low-tech firms. Within the group of high-tech firms, the difference between group and independent firms is not that obvious. Note that we present these results solely for descriptive reasons, and do not claim to prove any causal relationship.

Table A3.2: Financial constraints

	(1) Intcon	(2) Extcon
NTBF	0.729***	0.981***
	(0.245)	(0.279)
GNTBF	0.721***	0.949***
	(0.230)	(0.268)
LTBF	0.069	0.539*
	(0.252)	(0.281)
ln(EMP)	-0.044	-0.150**
	(0.071)	(0.076)
EAST	0.053	0.047
	(0.176)	(0.184)
ln(AGE)	-0.127	-0.205
	(0.185)	(0.193)
Constant	-0.615	-0.607
	(0.413)	(0.434)
N	279	279
test on equality of NTBF, GNTBF and LTBF	9.98***	17.19***

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

Table A3.3: Treatment effects after matching with propensity score based upon full sample probit

NTBF		**Group NTBF**		**Small Old firms**
Matched subsidized firms: 583		Matched subsidized firms: 260		
R&Dint	13.449***	R&Dint	8.278**	
R&DEint	19.774***	R&DEint	13.426***	
R&D	0.521***	R&D	0.450	
R&D emp	5.448***	R&D emp	8.586***	
LTBF		**Group LTBF**		
Matched subsidized firms: 302		Matched subsidized firms: 99		
R&Dint	3.087***	R&Dint	0.743	
R&DEint	4.079**	R&DEint	2.243*	
R&D	0.073**	R&D	0.036	
R&D emp	1.637***	R&D emp	1.413**	
Large young firms				**Large old firms**

Appendix to chapter 4

Appendix 4.A

Table A4.1: Industry structure

Industry	Description	♯OBS
1	Manufacture of food products, beverages and tobacco	245
2	Manufacture of textiles	109
3	Manufacture of wood and wood products; manufacture of pulp, paper and paper products; publishing and printing;	105
4	Manufacture of coke, refined petroleum products and nuclear fuel; Manufacture of chemicals, chemical products and man-made fibres; Manufacture of rubber and plastic products	263
5	Manufacture of basic metals and fabricated metal products	231
6	Manufacture of machinery and equipment n.e.c.; Manufacture of transport equipment	311
7	Manufacture of electrical and optical equipment	127
8	Fishing; mining and quarrying; Mineral products; Furniture; other industries; Waste collection, treatment and disposal activities; materials recovery; Other services	254
9	Wholesale and retail trade; repair of motor vehicles and motorcycles	320
10	Transportation, storage	175
11	Research & Development; other business services	182
12	ICT and related services	150
	Total Number of Observations: 2,472	

Table A4.2: First stage : Subsidy regression

	(1) IWTSUBINT
APPSTOCK	4.669**
	(2.304)
SRATE_OTHER	0.105***
	(0.033)
SRATE_FIRM	0.864***
	(0.256)
DEBT	0.004
	(0.003)
lnEMP	-0.018
	(0.015)
PSnew	-0.566
	(3.340)
PSnew2	13.893*
	(8.426)
PSold	-3.698
	(4.130)
PSold2	23.002
	(20.562)
EXPORT	0.044
	(0.039)
GP	-0.058
	(0.037)
FOREIGN	0.073*
	(0.039)
lnAGE	-0.028
	(0.019)
Constant	0.014
	(0.082)
N	2472
Test on joint significance of	
Industry	$\chi^2(11) = 45.12$***
Time	$\chi^2(2) = 1.99$
Region	$\chi^2(4) = 18.14$***

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

Table A4.3: CDM innovation output equations: IV estimations

	RDint		RDtot	
	(1)	(2)	(3)	(4)
RDint	2.323***	3.715***		
	(0.642)	(1.303)		
RDtot			1.998***	3.553**
			(0.541)	(1.567)
IWTSUBINT		-3.860		-5.105
		(3.288)		(4.501)
lnEMP	1.158***	0.864*	1.142***	0.744
	(0.410)	(0.518)	(0.418)	(0.607)
PSnew	18.071	-23.282	11.899	-46.294
	(48.781)	(58.735)	(48.207)	(63.799)
PSnew2	-94.094	-5.890	-69.059	65.873
	(82.541)	(108.496)	(81.490)	(124.500)
EXPORT	3.283***	2.433*	3.376***	2.353
	(1.048)	(1.320)	(1.013)	(1.489)
GP	-1.089	-1.570	-1.136	-1.800
	(1.066)	(1.222)	(1.064)	(1.372)
FOREIGN	-1.482	-1.031	-1.704	-1.288
	(1.148)	(1.388)	(1.141)	(1.487)
lnAGE	-1.131*	-0.765	-1.166*	-0.723
	(0.632)	(0.722)	(0.633)	(0.843)
Constant	3.538	3.779	3.715	4.188
	(2.664)	(2.937)	(2.669)	(3.048)
N	2472	2472	2472	2472
Hansen J statistic	$\chi^2(6) = 6.709$	$\chi^2(5) = 6.346$	$\chi^2(6) = 5.670$	$\chi^2(5) = 4.250$
- p-value	0.349	0.274	0.461	0.514
Test on joint significance of				
- Industry	$\chi^2(11) = 42.90$***	$\chi^2(11) = 37.86$***	$\chi^2(11) = 42.89$***	$\chi^2(11) = 35.35$***
- Time	$\chi^2(2) = 3.10$	$\chi^2(2) = 2.28$	$\chi^2(2) = 3.14$	$\chi^2(2) = 1.99$
- Region	$\chi^2(4) = 2.35$	$\chi^2(4) = 1.87$	$\chi^2(4) = 2.40$	$\chi^2(4) = 1.79$

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

Appendix 4.B: Extensions

'Naive' OLS estimations

Table A4.4 in this appendix elaborates upon what could be labeled as 'naive' estimations, representing OLS regressions of the output equation.

Columns 1 and 4 of this table show OLS results for the output equation when RDint and RDtot respectively are inserted in the output equation without tackling the endogeneity of this component. Results show that both R&D input measures are significantly positive in the output equation. The same exercise could be done, but now taking into account the heterogeneity of the R&D input itself. Columns 2 and 5 show results for the output equation when a dummy variable indicating whether a firm received subsidies or not (DSUB) is added to the output equation, as well as its interaction with the R&D input terms (RDintDSUB and RDtotDSUB). Results show that the interaction term is negative, which would be in line with the findings of the CDM output equations presented in chapter 4, the latter nevertheless presenting an insignificant discount. Columns 3 and 6 present another 'naive' estimation which inserts (RDintnosub = RDint - IWTSUBINT) and (RDtotnosub = RDtot - IWTSUBINT) respectively next to IWTSUBINT in the output equations. This estimation, next to disregarding any endogeneity, also disregards the fact that a part of the 'private' R&D might be induced by subsidies (matching grants). Results show that while the simplified private R&D is positive and significant, the subsidy variable does not seem to have an effect on output.

Application and granting stage

In this section, the application and granting equations will be outlined. As already mentioned in the main text, it is impossible to integrate these estimations in the sequential stages. Nevertheless, it is informative to show results from these estimations as they add to our understanding on how firms apply and how agencies

Table A4.4: 'Naive' OLS innovation output equations

	RDint			RDtot		
	(1)	(2)	(3)	(4)	(5)	(6)
RDint	0.841***	0.985***				
	(0.128)	(0.197)				
RDintnosub			0.782***			
			(0.143)			
RDtot				0.732***	0.868***	
				(0.114)	(0.179)	
RDtotnosub						0.673***
						(0.128)
IWTSUBINT			1.739			1.720
			(1.077)			(1.061)
DSUB		6.252***			6.275***	
		(1.590)			(1.591)	
RDintDSUB		-0.499**				
		(0.247)				
RDtotDSUB					-0.452**	
					(0.222)	
lnEMP	1.299***	1.105***	1.345***	1.293***	1.103***	1.344***
	(0.388)	(0.396)	(0.389)	(0.390)	(0.397)	(0.391)
PSnew	74.257*	57.176	73.662*	71.650*	56.034	71.303*
	(41.736)	(42.594)	(41.587)	(42.124)	(42.881)	(41.897)
PSnew2	-145.870**	-108.381	-157.744**	-136.385*	-103.402	-150.224**
	(73.335)	(75.245)	(73.093)	(74.614)	(76.141)	(74.070)
EXPORT	4.608***	4.300***	4.564***	4.634***	4.325***	4.585***
	(0.858)	(0.863)	(0.857)	(0.857)	(0.862)	(0.857)
GP	-0.665	-0.708	-0.627	-0.685	-0.742	-0.641
	(1.011)	(1.011)	(1.012)	(1.012)	(1.012)	(1.012)
FOREIGN	-1.885*	-1.567	-1.919*	-1.963*	-1.640	-1.995*
	(1.075)	(1.080)	(1.069)	(1.076)	(1.081)	(1.070)
lnAGE	-1.761***	-1.702***	-1.730***	-1.770***	-1.700***	-1.736***
	(0.563)	(0.564)	(0.562)	(0.566)	(0.566)	(0.565)
Constant	4.199*	4.612*	4.012	4.260*	4.612*	4.051
	(2.537)	(2.533)	(2.547)	(2.543)	(2.535)	(2.553)
N	2472	2472	2472	2472	2472	2472
Test on joint significance of						
-Industry F(11)	4.74***	4.53***	4.75***	4.78***	4.56***	4.80***
-Time F(2)	1.47	1.79	1.61	1.49	1.77	1.63
-Region F(4)	1.44	1.48	1.32	1.44	1.47	1.31

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

grant subsidies.

In a first step, the application decision of firms is analyzed. This is based upon a dichotomous variable indicating whether a firm filed an application at IWT, the granting agency, or not (DAPPLIED). This variable is fairly unique in subsidy evaluation studies as the IWT Icaros database covers all firms that ever applied for a subsidy, independent of the eventual outcome (positive or negative granting decision).

Conditional upon applying, IWT evaluates the projects and decides upon the subsidy. The subsidy amount and duration of the project is determined at the granting stage. One of the subsidy outcome variables used in the model is the logarithm of the amount of subsidies granted at the starting period of the project in thousands of euros, denoted by ln(IWTSUBTOTSTART). The granting agency always allocates a grant relative to the firm's proposed budget for a project. Next to the info on and the eventual amount granted, the Icaros dataset also contains detailed information on the proposed budget by the firm based upon which the subsidy rate can be constructed. This subsidy rate can vary depending upon several project characteristics but can never exceed 70%. This subsidy rate is measured by the variable SR (the amount of subsidies granted relative to the requested budget of a specific firm in a specific year).

Most of the variables inserted in the models are also presented in the 'Variables' section in the main text. Some variables are introduced here as they only determine the subsidy granting decision. In order to encourage smaller firms to perform R&D, a special program for SMEs has been put in place (the "KMO programma"). In order to assess the impact of this program, a dummy, dKMO is constructed in order to reflect whether the IWT allocated the specific to a KMO program or not. Furthermore, IWT classifies its projects according to whether it is research (dBASIC) of development (dPROTO). A last category is dMIXED, a category that is rather difficult to define, but reflects projects that cannot be classified as either research or development. Note that these dummies are not mutually exclusive at the firm level as a single firm can have multiple project applications in a single

year.

Only for firms that did apply for a subsidy, we can observe whether there were any subsidies granted to the firm and the amount of subsidies granted. Therefore, the system of the application and granting equations is estimated by the maximum likelihood Heckman selection model (Heckman, 1979). The results of this estimation are presented in table A4.5 for different outcome variables, granting rate (SR) and the log of starting subsidy amount ln(IWTSUBTOTSTART) in columns 2 and 3 respectively. The selection equation is always based upon a dummy indicating whether a firm applied for a subsidy or not and results of this equation are presented in column 1.

Column 1 presents results for the application decision. The patent stock has an inverted U-shaped relationship to the probability of applying, indicating that having a larger patent history only increases the probability of applying up to a certain point. The stock of former applications and former successful applications of the firm positively influences the probability of applying again, just like the lagged success rate of all other firms within the same industry, region, year and size class. The larger firms are also more likely to apply, as well as exporters, rooted in the premise that firms exporting to other countries might be more innovative than other companies and are thus more likely to apply for a subsidy. Foreign owned firms, on the other hand, are less likely to apply. It is often expected that both group firms and foreign-owned subsidiaries might have a lower incentive to apply for subsidies as they usually do not qualify for the larger subsidy rate programs of the granting agency, irrespective of the incentives of the agency who could actually have high expectations of group firms in terms of knowledge generation and spreading.

The remaining columns, 2 and 3 present the subsidy granting outcomes conditional upon applying. The dummies pointing to whether at least one of the requested projects is categorized by the agency as basic, mixed or applied are positive and significant in all equations. The effect seems to be higher for mixed and basic projects compared to prototype projects in the subsidy rate equation, which

is in line with expectations. This is also confirmed by the test on the equality of these coefficients, revealing that only the differences between either basic and prototype or mixed and prototype are significant ($\chi^2(1) = 19.11^{***}$ and $\chi^2(1) = 24.24^{***}$ respectively). In the case of the log of the amount of subsidies granted in the beginning period, a different picture emerges. In that case, it are especially the firms with prototype and mixed projects that receive more subsidies (only the differences between either basic and mixed and basic and proto are significant: $\chi^2(1) = 17.83^{***}$ and $\chi^2(1) = 22.20^{***}$ respectively). Thus, while the more basic projects do get more subsidies relative to the requested budgets, in line with agency policies, the actual amount received is higher for firms having prototype projects. Similarly, the subsidy rate is higher for firms that have projects under the KMO program, but this is not reflected in significant higher amount of subsidies, suggesting that the KMO projects are the smaller projects. The other general economic indicators are not influencing the agency decision to a large extent. This coincides with the fact that the main focus of the agency is on project characteristics.

Table A4.5: Application and Granting estimations

	(1) Dapplied		(2) SR		(3) ln(IWTSUBTOTSTART)	
APPSTOCK	2.264	***				
	(0.826)					
PS	8.257	***				
	(1.979)					
PS2	-14.768	**				
	(6.678)					
SRATE_FIRM	0.597	***				
	(0.138)					
SRATE_OTHER	-0.245	**				
	(0.103)					
SME	-0.01					
	(0.155)					
dBASIS			0.21	***	1.558	***
			(0.030)		(0.374)	
dMIXED			0.245	***	3.478	***
			(0.028)		(0.417)	
dPROTO			0.088	***	2.873	***
			(0.026)		(0.354)	
dKMO			0.155	***	-0.332	
			(0.034)		(0.363)	
lnEMP	0.174	***	-0.015		-0.029	
	(0.054)		(0.010)		(0.123)	
EXPORT	0.312	***	0.06	*	0.571	
	(0.115)		(0.035)		(0.442)	
GP	-0.025		-0.034		-0.141	
	(0.102)		(0.027)		(0.269)	
FOREIGN	-0.338	***	0.041		0.501	
	(0.108)		(0.027)		(0.397)	
lnAGE	-0.146	***	0.004		-0.003	
	(0.056)		(0.013)		(0.166)	
DEBT	-0.003		0.001		0.022	
	(0.009)		(0.001)		(0.013)	
Constant	-2.003	***	0.054		1.552	
	(0.370)		(0.108)		(1.615)	
N	2472		2472		2472	
uncensored N[a]			221		221	
ρ			0.180		-0.197	
			(0.205)		(0.350)	
Test on joint significance of						
- Industry	$\chi^2(11) = 32.22$***		$\chi^2(11) = 7.28$***		$\chi^2(11) = 2.72$	
- Time	$\chi^2(2) = 10.27$***		$\chi^2(2) = 23.30$***		$\chi^2(2) = 12.62$***	
- Region	$\chi^2(4) = 8.25$		$\chi^2(4) = 2.91$		$\chi^2(4) = 4.22$	

* p<0.10, ** p<0.05, *** p<0.01

[a]: Note that the number of subsidized firms is lower than the number suggested in chapter 4. This is entirely due to the fact that this estimation can only take into account the beginning period of the subsidy granting.

SME's

In the context of this dissertation, it is also interesting to restrict the sample to young small and medium sized enterprizes (SME's). Restricting the sample to firms which have less than 250 employees and that are at most 20 years old, we are left with 1,135 firms in our sample. Re-estimating the whole subsidy-topped CDM model for these firms shows that results also hold for this subset of firms. When solely looking at input additionality results in table A4.6, results on input additionality for the whole sample are confirmed.

Table A4.6: Innovation input equations

	(1) RDINT	(2) RDTOT
IWTSUBINT	2.391*** (0.425)	2.851*** (0.619)
N	1135	1135

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

note: This table only presents the coefficient for IWTSUBINT, but all other coefficients as inserted in the basic input equation are also inserted here but not shown. Both the magnitude and the sign of the other coefficients are in line with results found for the basic model, i.e. with the full sample of firms.

As can be seen in table A4.7 , the discount of subsidized R&D would be 58% with respect to private total R&D intensity in terms of innovative output. With respect to private internal R&D intensity, the discount is suggested to be 48%. However, these discounts are again insignificant and there is thus no evidence that there would be a productivity loss due to subsidized R&D. These results are in line with what was found for the full sample of firms.

Table A4.7: Innovation output equations for sample of SME's

	Output Equation (1)	Output Equation (2)
RDint	3.788**	
	(1.787)	
RDtot		3.810**
		(1.926)
IWTSUBINT	-4.384	-6.307
	(4.037)	(4.674)
residfirst	-0.694	1.014
	(2.980)	(3.009)
residsecond	-3.058*	-3.202*
	(1.798)	(1.930)
lnEMP	-1.281	-1.624
	(0.963)	(1.138)
PSnew	-4.487	-39.654
	(112.546)	(114.342)
PSnew2	-31.068	69.087
	(403.465)	(432.732)
EXPORT	1.181	0.367
	(2.572)	(2.942)
GP	-2.100	-2.517
	(1.946)	(2.187)
FOREIGN	-1.800	-2.149
	(2.656)	(2.721)
lnAGE	0.430	0.852
	(1.699)	(1.935)
Constant	7.560	8.383
	(5.721)	(6.023)
N	1135	1135
Bootstrap replications	200	
β_2	1.954**	1.599**
	(0.987)	(0.729)
γ_2 (=discount/premium)	-0.484	-0.580
	(3.149)	(3.922)
Test on joint significance of		
- Industry	$\chi^2(11) = 29.45$***	$\chi^2(11) = 31.17$***
- Time	$\chi^2(2) = 1.06$	$\chi^2(2) = 0.52$
- Region	$\chi^2(4) = 9.56$**	$\chi^2(4) = 8.03$*

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

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