Ratio Working Paper No. 289

Regional Effects of Publicly Sponsored R&D Grants on SME Performance

Patrik Gustavsson Tingvall *

Josefin Videnord **

* Södertörn University and The Ratio Institute, P.O. Box 3203, 103 64 Stockholm, Sweden, patrik.tingvall@ratio.se

** Uppsala University and The Ratio Institute, P.O. Box 3203, 103 64 Stockholm, Sweden, josefin.videnord@ratio.se

The Ratio Institute P.O. Box 3203, SE-103 64 Stockholm, Sweden, www.ratio.se

Regional Effects of Publicly Sponsored R&D Grants on SME Performance

Patrik Gustavsson Tingvall *

Josefin Videnord **

Abstract

This paper explores regional variation in the effects of publicly sponsored R&D grants on SME performance. The results suggest that there is no guarantee that the grants will impact firm growth, either positive or negative. Studying the heterogeneity of the results, positive growth effects are most likely to be found for publicly sponsored R&D grants targeting SMEs located in regions abundant with skilled labor, whereas the opposite is found for SMEs located in regions with a limited supply of skilled workers.

Keywords: R&D grants; SME; Economic growth; Regional growth; Selective policies

JEL Codes: H81; O18; O38; O40; R11; R58

* Södertörn University and The Ratio Institute, P.O. Box 3203, SE-103 64 Stockholm, Sweden, patrik.tingvall@ratio.se. Acknowledgements: Financial support from the Swedish competition authority, The Swedish Retail and Wholesale Development Council, and The Foundation for Baltic and Eastern European Studies is gratefully acknowledged.
** Uppsala University and The Ratio Institute, P.O. Box 3203, SE-103 64 Stockholm, Sweden, josefin.videnord@ratio.se

1. Introduction

The importance of innovation as a key driver of long run economic growth is well established. However, although the link between innovation and growth is recognized, there is no consensus regarding the best policy through which to achieve innovation and growth. Interestingly, Veugelers (2015) shows that innovation policies deployed in EU member states seem, to a great extent, to apply similar combinations of instruments, regardless of their innovation capacity. In this vein, direct R&D grants and support through tax incentives are two commonly applied measures. Sweden, however, is somewhat of an outlier in this area, as it has a strong focus on direct government funding through R&D grants and a low reliance on R&D tax-incentives (OECD 2015).

Apart from having innovation and growth as desired outcomes, many growth-oriented government programs tend to focus their efforts on supporting small- and medium-sized enterprises (SMEs). New ventures and innovative SMEs account for a large share of net job-creation and productivity growth. These capabilities are well documented, but due to a lack of financial resources or competitive elements in the industry, many new firms are not able to survive their first year(s) of business (Shane 2009; Nightingale and Coad 2014). As a response to these complications, governments have – in the last couple of decades – been implementing various policies that aim to increase SME survival rates and innovation. One channel through which governments support private enterprises is via 'targeted R&D grants'. However, even though there is a history of targeted R&D grants, surprisingly little is known about the actual effects of such policies (Edler et al. 2013).

In summarizing studies that analyze the impact of various R&D grants and subventions, it is clear that results seem to vary, not only across programs, but, in some cases, also across studies of the same program. Bronzini and Iachini (2014) assessed the effects of receiving an investment grant on R&D in northern Italy. They found that such grants had positive effects on R&D for small enterprises, whereas large companies did not seem to be affected by the grants. Cin et al. (2017) found R&D subsidies to enhance the performance of Korean SMEs. For Finland, Koski and Pajarinen (2013) showed that R&D support seemed to lead to an increase in the number of employees as long as support was given to the firm, but these results did not persist after the funding ended. Similar results were also found by Cappelen et al. (2016) for Norway. Zúñiga-Vicente et al. (2014) summarize the results of 77 studies on different R&D support schemes. They uncovered three fairly stable patters: (i) The amount of crowding-out is closely related to the financial restrictions facing the companies, (ii) the growth effects vary across basic- and applied research, and (iii) the impact of a grant is larger for smaller firms. The finding that the impact of a grant seems to be largest for smaller firms is further supported by Gonzalez et al. (2005). An example of somewhat contradicting results for studies analyzing the same program is given by Vinnova (2014), who performed a self-evaluation of the Swedish R&D subsidy program “Research & Growth”. Vinnova’s analysis was divided into two parts, one qualitative and one quantitative. In the qualitative part, the results suggest positive growth effects, while no such effects could be detected in the subsequent quantitative analysis. The overall conclusion drawn by Vinnova was that the program did contribute to firm growth. However, in a matched differences-in-differences study of the same program, Growth Analysis (2014) concluded that there was no robust evidence of positive effects on employment, productivity, relative demand for skilled labor, or turnover.

A few studies have taken a regional perspective on how subsidies impact firm performance. Banno et al. (2013) and Herrera and Nieto (2008) both found that R&D subsidies had stronger growth effects in central regions than in remote regions. Similar results were found by Piekkola (2007) and Czarnitzki and Licht (2006), whereas Doloreux (2004), in a Canadian study, did not find evidence for a significant difference across regions.

Overall, these results suggest that regional characteristics matter for the impact of R&D subsidies, but the source of the heterogeneity at large remains unknown. We contribute to this literature by explicitly focusing on the role of the local supply of human capital in shaping the impact of R&D grants. This route is partly motivated by the close link between innovation and human capital, as well as by a lack of knowledge of the role of the regional dimension in this area. Using information on the size of the grants, as well as detailed firm and individual characteristics, we can analyze the relationship between R&D grants, firm- and regional characteristics in some detail. One main result of this study is that, in most cases, the R&D grants have no significant impact on firm growth, though the likelihood of finding a positive effect increases as the regional supply of skilled labor increases.

The remainder of this paper is organized as follows. Section 2 presents the earlier literature, and Section 3 discusses the theory. Section 4 provides information about data and matching. The models are described in Section 5, and the results are outlined in Section 6. Finally, Section 7 summarizes the main findings of the paper.

2. Earlier Literature

The impact of various forms of public R&D and innovation support incentives has been analyzed in a series of studies. A striking finding is that the results vary across programs and studies, though some patterns seem to emerge clearly. For example, grants seem to be more beneficial for smaller than for larger firms, and it seems to be more difficult for a support program to generate long lasting growth effects compared to a temporary growth boost in targeted firms (while the grant is being funneled into the firm). Below, the intention is to give a brief overview of this field of research.

The largest and most comprehensive study in this field is probably that of Zúñiga-Vicente et al. (2014), who surveyed 77 different studies investigating the effects of public R&D subsidies to private firms. A general result was that there were mixed and inconclusive results. However, a few common tendencies were revealed. First, the crowding-out effect of a subsidy is affected by the financial restrictions faced by the individual firm. Second, the effect of subsidies differs between basic research and development projects. Third, the effect is most likely larger on smaller R&D projects. Finally, there is a time-lag before the effects kick in. Koski and Pajarinen (2013) argue that the time-lag between the receipt of the grant and subsequent firm growth is somewhere between one and three years. One challenge with determining time lags is that as more time passes, the contamination risk increases, and it becomes harder to separate the effect of the grant or subsidy from other effects that impact the results. However, in a study by Koski and Pajarinens (2013), the positive effect on employment during the time of the subsidy diminished once the subsidy period ended.

In addition to the findings above, two additional tendencies can be observed. First, the effect of a subsidy seems to be larger for smaller firms. In support of this statement, Gonzalez et al. (2005), Bronzini and Iachini (2010) and Criscuolo et al. (2012) all find stronger effects of R&D subsidies in smaller firms; and in Sweden, Heshmati and Lööf (2005) and Gustafsson et al. (2016) reach similar conclusions. There are also indications of start-ups being more innovative than established firms (Acs and Audretsch 1988). Hence, there is reason to believe that R&D subsidies directed at small or newly created firms yield different effects compared to subsidies directed at larger or older firms. Finally, there are indications suggesting that firms benefit from grants during the time when the funds are actually being transmitted to the firm, but that it is more difficult to find evidence for long-lasting post-treatment growth effects (Koski and Pajarinen 2013; Gustafsson et al. 2016).[1] A recent example of positive effects of R&D subsidies is found in Cin et al. (2017) who find positive effects on both R&D expenditures and productivity on a sample of Korean SMEs.

Earlier studies of the two Swedish R&D subsidy programs analyzed in this paper ("Win Now" and "Research & Growth") have produced mixed results. Some studies have found that they yield growth in employment and sales, while others have found negative outcomes (Söderblom et al. 2015; Bergström 1998; Growth Analysis 2014; Vinnova 2014). Combining information from a series of subsidy programs with a growth focus, Gustafsson et al. (2016) find that the overall average effects of R&D subsidies in Sweden can be described as a short-term sugar rush without any long-lasting effects. Furthermore, they argue that their findings cast some doubt on the belief that firm subsidies can boost firm performance in the long run, indicating that the Swedish R&D subsidy programs may need to be redesigned or, in some cases, fully abandoned. However, the above arguments are based on average effects. In some firms and regions, these programs may work better than in others. Identifying the average effects is a good start when investigating the effectiveness of public R&D subsidies to private firms, but it does not provide us with the whole story. The question is, therefore, are there any regional differences, and if so, what and where?

The aim of this study is to determine whether the effects of innovation grants differ among regions, and if so, what drives these differences? Following this line of reasoning, a number of British studies of R&D subsidies have taken a regional focus (Harris and Robinson 2005; Jones and Wren 2004; Criscuolo et al. 2012; Wren 2005; Harris and Trainor 2005). Among these studies, most find positive effects of subsidies on employment and investment, but in general, they find no effect on productivity (Harris and Robinson 2005; Criscoulo et al. 2012). In addition, Harris and Robinsson (2005) find that the effects of the subsidies are different in different regions. However, they do not investigate which underlying regional factors are driving these regional discrepancies.

Before summarizing the literature on the effects of public R&D subsidies and regional differences, we may note that the regional dimension is of great importance in regard to the creation and production of new innovations. The quality of the regional innovation system affects both the probability of innovation within firms and knowledge transfers across firms (Asheim et al. 2011; Cooke 2004; Doloreux and Parto 2005; Tödtling and Trippl 2005; Srholec 2007). This line of reasoning is consistent with the finding that in Finland, half of all

[1] However, as indicated above, the identification of post-treatment effects is burdened by the problem of increased data contamination over time.

R&D is conducted in the capital city, Helsinki, and that four regions are responsible for almost 80 percent of all R&D. A similar pattern holds true for the US, where ten areas contribute to two-thirds of all R&D activity in the country (Georghiou et al. 2003). It is, therefore, interesting to note that just as R&D activities, innovation subsidies and grants are not distributed evenly across regions, the probability of receiving innovation support is larger for a firm located in a central area compared to a peripheral area (Czarnitzki and Fier 2002; Gonzalez et al. 2005; Herrera and Nieto 2008).

A limited number of studies have investigated regional variations in the effects of innovation subsidies. For Italy, Banno et al. (2013) find that policies intended to stimulate R&D generate larger economic profits in regions that are relatively more internationalized than in remote regions. Similarly, Herrera and Nieto (2008) divide Spain into central and peripheral regions. Their analysis shows that the effects of R&D subsidies are larger in two out of three central regions compared to the rest of the country. Focusing on the importance of knowledge capital, Piekkola (2007) finds that growth from R&D subsidies is concentrated in regions that have a high level of knowledge capital to begin with. Czarnitzki and Licht (2006) also use a regional dimension in their analysis of innovation policies in Germany. Overall, they find a positive effect on both R&D spending and the number of patents. However, the size of these effects varies across regions. Because the regions in their study are divided into two larger areas, the former East and West Germany, the authors mainly use historical arguments to explain the regional differences in effects.

Although it may seem as though regions have a vital impact on the innovative activities of firms, some studies argue against this. One such example is Doloreux (2004), who conducts telephone interviews with small- and medium-sized Canadian firms. The results indicate that the R&D patterns within firms are the same across several Canadian regions. Moreover, most firms stated that they use national and global knowledge sources when innovating, and they downplayed the importance of the regional structure. Isaksen and Onsanger (2010) reach a similar conclusion in their study of Norway, where they find that rural areas and smaller cities have a larger proportion of innovating firms compared to larger cities. This finding contradicts earlier research in this field. To explain their results, Isaksen and Onsanger (2010) stress that innovation subsidies in Norway are aimed at firms in smaller cities and rural areas, as a part of Norway’s overarching policy to develop the whole country.

In short, most empirical evidence indicates that factors within regions matter in regard to the distribution and the effects of R&D subsidies and grants. This suggests that there are reasons to take location into consideration when forming policies around the distribution of selective public R&D subsidies and grants.

3. Theoretical Framework

The belief in R&D-driven growth is grounded in the literature on creative destruction (Schumpeter 1911) and technological progress (Solow,1957), and it is further strengthened by the endogenous growth theory (Romer 1986; Lucas 1988; Aghion and Howitt 1998). The view of R&D as the solution to many pressing challenges related to both economic growth and sustainability has spurred the development of innovation policies wherein public R&D subsidies and grants constitute an important part of the package (OECD 2015). However, although R&D grants are widely used; it is possible to find theoretical arguments both for and against such policies.

Perhaps the argument most commonly used to support the government's innovation subsidies builds on the existence of market failures in the form of imperfect credit markets and positive R&D spillovers. In short, the assumption of imperfect credit markets builds on a moral hazard situation with asymmetric information where the inventor, due to the risk of idea stealing, is unwilling to reveal detailed information about the intended innovation to the financier. The standard outcome of this game is that the market solution leads to a situation in which less credit is given than what is socially optimal. In regard to the risk of being credit constrained, young and innovative firms with short histories and little or no equity are especially likely to be credit constrained (Shane 2009; Nightingale and Coad 2014). In addition to the problem of imperfect credit markets, the problem of an undersupply of financing for R&D is further exacerbated when one considers that innovative activities generate positive knowledge spillovers (Akerlof 1970; Stiglitz and Weiss 1981). With knowledge spillovers, knowledge leaks out from the innovating firm to the surrounding economy, enhancing overall growth but hurting the innovating firm due to lost profit. Hence, given such massive leakage, firms may not carry out innovation projects even if they are motivated from a socioeconomic perspective.

In addition to the classical market failure arguments, a relatively new school of thought is collected under the label "The systems approach". Here, we can find a series of alternative views, which consider knowledge as heterogeneous and context-specific. This line of thinking considers system failures rather than market failures, and it focuses on overcoming co-ordination problems between actors in the innovation system (Warwick 2013). The systems approach stresses that it is more important to develop a common strategy for the government and private firms than to support individual projects or protect-specific industries (Warwick 2013). However, there is no consensus regarding at which level of the system the policy maker should intervene (Edler et al. 2013). The bottom line is that this perspective enables active policies where the government can and should intervene in the market to a larger extent than what is traditionally argued for by neoclassical market failure arguments.

Despite the growing popularity of selective measures, the implementation of such policies is often associated with challenges and unintended side effects (OECD 2015). Two of these challenges are the information problem and rent-seeking behavior. According to Baumol (2002), to correctly distribute grants and selective measures, the government should possess information not available to the market, an assumption that can be difficult to confirm. In addition, with imperfect political markets, there is a risk that, after the intervention, we will end up in a situation that is worse than the initial situation (Baumol 2002; Hayek 1945). With selective measures, there is also the risk of firms adopting rent-seeking behavior moving resources from productive work to applying for subsidies. Rodrik (2008) argues that rent-seeking leads to government subsidies being awarded to firms who are good at seeking subsidies or at influencing politicians, instead of to the most efficient firms.

An additional problem with selective polices is that they can distort competition in the market by favoring selected firms, which can be fatal because a highly competitive environment is of great importance to achieving both growth and innovation (Geroski 1991). Firm subsidies can also delay structural changes and lead to a misallocation of resources when projects within the firm are set aside due to subsidies awarded for other projects (Dasgupta and Stiglitz 1980; Krugman and Obstfeld 2009). Finally, we have the problem of deadweight losses associated with the taxation needed to fund these programs (Feldstein 1999).

The regional dimension

Turning to the regional dimension, Marshall (1920) argued for three factors affecting the localization decision of a firm. In short, Marshall argued for (i) access to labor and a reasonable maximum commuting distance for workers, (ii) input and output links, and (iii) spillovers that are “in the air”.

The first argument is related to both the size of the local labor market and its content. What type of labor is accessible? It is well known that production and the comparative advantage of a region depend on the regional supply of production factors. In regard to innovation and R&D, local access to a well-educated labor force is instrumental (Dosi 1988;

Feldman 1994a; Fujita, Krugman and Venables 1999), suggesting that the geographical distribution of innovative activities is interdependent with the distribution of skilled labor. This line of reasoning is further supported by questionnaires, where the typical result is that one of the most important factors determining firms' localization decisions is access to qualified workers and markets, whereas factors such as wages, taxes and supply of entertainment and culture are found lower down the list (UNCTAD 1997).

The importance of the local environment is further strengthened when we consider the influence of input-output linkages. Today, the interplay between input-output linkages, transportation costs and scale effects as vehicles for clustering and agglomeration is formalized in the new economic geography (Fujita, Krugman and Venables,1999). However, this literature also stresses the upward pressure on wages that follows when firms in the same region compete for the same type of workers, which in turn dampens input-output driven cluster effects (Fujita, Krugman and Venables 1999; Krugman 1991; Audretsch and Lehmann 2006).

Marshall (1920) pointed to "spillovers that are in the air" as a localization factor. Innovative firms are dependent on new knowledge, and most knowledge has a geographical dimension that makes it easier to transport between individuals and firms who are physically close. Dosi (1988) presented "five stylized facts" that help explain why knowledge spillovers are geographically bound. Dosi's arguments have since been further developed by Feldman (1994a, 1994b) and Baptista and Swann (1998). Marjolein (2000) contributes with both theoretical arguments and an empirical overview regarding the local nature of knowledge. Hence, it is widely accepted that knowledge will spread, whether the owner wants it to or not, and that geographical closeness eases knowledge transfers. To conclude, the literature suggests that firms in knowledge-intensive industries benefit from both direct access to skilled labor as well as spillover effects that accompany the local concentration of skilled workers.

The system approach provides us with an additional explanation of why regions matter for innovation. This line of thinking stresses the importance of cooperation and of links between industry, government and academia. The key idea of the system perspective is to promote the creation and diffusion of knowledge via interactions among actors involved in the innovation process. Hence, understanding the concept of the regional innovation system and how its main actors cooperate is of importance for both the efficiency of the local innovation system and the design of R&D-subsidies. Today we lack an exact and commonly agreed upon definition of what a regional innovation system really is, but it can be said to be a collection of organizations, institutions, firms and individuals among whom the creation, use and distribution of new knowledge occur (Cooke 2004). It can also be defined as a micro constitutional order held up by cooperation, trust and mutual exchange (Cooke et al. 1997). Regardless of which definition we choose, the regional innovation system comprises all clusters of firms, as well as the institutional structures and rules that surround them. The system is considered to be of great importance in regard to the creation and production of new innovations (Asheim et al. 2011; Asheim and Gertler 2004; Cooke 2001; Cooke 2004; Doloreux and Parto 2005; Tödtling and Trippl 2005). Within the system perspective, several arguments can be found to support the use of an active innovation policy. Hence, compared to the neoclassical view, within the system perspective, the government assumes a more important position as a coordinator of the different agents. However, the system perspective is not as clear regarding which policies should be promoted (Edler et al. 2013).

With the above discussion as background, it becomes relevant to discuss possible interaction effects between the impact and efficiency of innovation grants and the local environment. We suggest that the likelihood that an R&D grant will generate positive growth effects is positively correlated with the local pool of skilled labor. To determine whether this suggestion is supported by real-world data, we will, in subsequent chapters, perform a difference-in-differences analysis to analyze the linkages between the growth effects of R&D grants and the size of the local labor pool that has tertiary education.

4. Data and Matching

Data

Firm-level data on public grants and subsidies in Sweden is collected and stored in the “MISS database” by the Swedish Agency for Growth Policy Analysis (Growth Analysis). The MISS database comprises information about the grant distributor and receiver, the size of the grant, and when the firm receives the payments. We link these data with register data containing information on firms’ input and output, covering all firms in the economy. Yearly data on firms’ input and output are provided by Statistics Sweden (SCB) and cover all Swedish firms.

In addition to firm data, individual level data on workers’ education, wages, gender, and age is aggregated to the firm level and linked to firm data. Firm-level and aggregated individual-level data contain information on production, sales, employment, value added, investments, physical capital, profits, industry affiliation, educational attainment of the labor force, geographic location, etc., spanning the period 1997-2011. All datasets are linked using unique individual firm-year ID codes.

Out of the two analyzed programs, "Win Now" is the smaller program directed at start-ups, and its funds can be granted to firms that have developed a new product, method or service that has not yet reached the market. The aim is to give start-ups a chance to survive in the market by providing financial aid during the commercialization process, which is intended to attract external capital and make the business successful in the future. Hence, future growth is one of the main purposes of the grant. However, the timeframe for achieving these growth effects is not specified. A total of 1309 firms applied for Win Now, and approximately ten percent received support. Win Now has been granted 125 times during the period under study, and the average grant was 164,847 SEK ($18,458). A firm is only granted the subsidy once, and the maximum amount awarded is 300,000 SEK ($33,592).

The subsidy program "Research & Growth" targets small- and medium-sized innovative firms supporting developing projects, but support may also be awarded to pilot studies. Approximately 20 percent of the applicants are granted support, and the recipients consist mostly of firms that are already on the market. The purpose of Research & Growth is to support and promote innovation-driven growth within the subsidized firms. In all, the program provided 645 grants, with an average grant of 543,321 SEK ($60,836).

The analyzed grants are distributed to firms in cities as well as rural areas. In Table 1, all Swedish regions and municipalities are divided into three different groups: *Big Cities*, *Support Areas A&B* and *Other Areas*. This division is used to provide an overview of the regional division of the grant sums. The first category, *Big Cities*, contains the three largest cities in Sweden: Stockholm, Gothenburg and Malmo. The second category, *Support Areas A&B*, includes particularly vulnerable regions in Sweden. Vulnerable areas are those that have the right to apply for regional support.[2] The third and final group, *Other Areas*, comprises the remaining regions in Sweden.

[2] For information on the Swedish regions eligible to apply for regional support, see: http://www.tillvaxtverket.se

Table 1. Total and average grant sums, by group of regions

	Number of Grants	Total Sum	Average Sum	Sum/employee
Big Cities	218	215 000 000	986 830	36.22
Support areas A&B	45	22 800 000	506 648	11.75
Other Areas	358	288 000 000	803 490	23.89
Total	621	525 800 000	846 340	26.38

As seen in Table 1, both the size of the average grant and funding per employee is largest in the *Big Cities*. There is a tendency to give more grants to firms in large cities compared to other firms, which is consistent with the internationally observed pattern regarding the distribution of R&D grants.

As noted above, the supply of skilled workers is a key component of innovation and growth. To measure the regional supply of high-skilled labor empirically, we construct a regional index. This index-variable is constructed as a revealed comparative advantage index (RCA-index), where a value above one indicates that a region is above the country average, and vice versa. To simplify the interpretation of our regression variables, this index will be centered around zero in our analysis, and thus, a value above (below) zero will indicate that a region is above (below) the country average.[3] The measure of the relative supply of high-skilled labor is as follows:

$$RCA - Skill = \left(\frac{L_r^H}{L_r}\right) / \left(\frac{L_{Swe}^H}{L_{Swe}}\right) \tag{1}$$

where the first term describes the share of high-skilled labor in the region, and the second term describes the share of high-skilled labor in the country.

Table 2. Average RCA-index, by region

	Average RCA skill: Supply of High-Skilled Labor
Big cities	0.22
Support areas A&B	-0.31
Others	-0.04
Total: Sweden	0.00

Note: RCA-index centered around zero.

Table 2 reveals a clear picture of the distribution of skilled labor across regions in Sweden: skilled labor is concentrated in the large cities, whereas the opposite is true for the (rural)

[3] With centralized interaction variables, we can evaluate the direct effect of a grant as what happens when the RCA-index is zero, that is, when we evaluate the effect at the mean.

areas granted regional support measures. The RCA-index and firm-level variables, sources, mean values and standard deviations are described in Table 3 below.

Table 3. Variable description

Variable	Description	Data Source	Mean	Stdv.
ln(L)	Log. of number of employees	IFDB	1.11	1.08
ln(Lp)	Log. of inflation adjusted value added per emp.	IFDB	5.83	0.83
ln(sales)	Log. of sales	IFDB	7.90	1.60
Wage premium	Mean of wage premium for skilled labor, divided by sni5 codes	LISA	1.93	1.68
ln(K)	Log. of physical capital	IFDB	4.95	1.90
RCA skill FA	(Skill FA/Emp FA)/(Skill Swe/Emp Swe)	LISA	0	0.23
Post Treatment	1= period after support, 0= otherwise	MISS, IFDB	0.0004	0.02
Treatment	Annually awarded grant/sales	MISS, IFDB	0.115	0.19
R&D/Ind	Share of researchers by industry	LISA	0.117	1.36
Profit quota	Operating profit/ production value	IFDB	-0.52	69.3
Share of higher educ.	Number of higher educ./total	RAMS	0.26	0.36
R&D int. SSY	Share of researchers by industry/ total number of emp.	LISA	0.01	0.09
ln(value added)	ln(L) in period (t-1)	IFDB	6.97	1.47
ln(W)	Log. of inflation adjusted value added	LISA	5.15	0.79

Notes: Treatment is calculated as grant divided by net sales. Observations where the grant is larger than the net sales, or where repayment transactions are observed, are excluded from the analysis.

Matching

As noted above, the grants have both a specific purpose and are targeting a specific population of firms; hence, grants are not randomly distributed across firms. This, in turn, leads to the question of how to create a control group of similar firms. To handle this selection problem, we use Coarsened Exact Matching (CEM) to create a control group of non-treated firms that, in all relevant aspects, are as similar as possible to the firms receiving grants. For recent applications of this matching method, see Croce et al. (2013), Cumming et al. (2017), and Grilli and Murtinu (2014).

The matching will be based on variables that are relevant for both program participation and program outcomes, and the key idea is that all matching variables should be as similar as possible between the control and treatment groups. Unlike PSM, CEM does not estimate the probability of being treated, but instead it coarsens variables into strata and puts different weights on the control firms depending on how close they are to the treated firms (Iacus et al. 2011, 2012). Because CEM is easy to use and has good statistical properties, it is becoming a commonly used matching method. Detailed descriptions of CEM can be found in Blackwell et al. (2009) and Iacus et al. (2011, 2012). The matching performed in this paper is so-called one-to-one matching, which yields one control firm for each treated firm. Consequently, we do not need to take matching weights into consideration to adjust for differences in the number of observations between the treated and control groups. For each of the treated firms, we match on firm properties one year before the treatment, (*t-1*), with *t* being the year a firm receives a grant.

Results from the matching are presented in Table 4. As noted by Iacus et al. (2011, 2012), the value of the imbalance test is subordinate to the change in imbalance as given by matching. As shown in Table 4, matching reduces the imbalance for all variables, suggesting that matching leads to a control group that is more similar to the treatment group than to the collection of all non-treated firms.

	Matching imbalance		
	Employment	**Labor Productivity**	**Sales**
ln(K)			0.04 (0.29)
Profit quota	0.02 (0.11)	0.03 (0.11)	0.03 (0.11)
ln(value added)	0.04 (0.45)		
ln(W)	0.10 (0.38)		
R&D int. SSY	0.02 (0.22)	0.01 (0.26)	0.01 (0.26)
ln(L)		0.01 (0.35)	0.03 (0.35)
Share of higher educ.	0.02 (0.48)	0.01 (0.49)	0.02 (0.49)
ln(capital intensity)		0.07 (0.24)	
Overall (L1)	0.56	0.46	0.38

Table 4. CEM matching results

Note: Results from 1-1 matching. Matching imbalance, univariate L1 distance between treated and control group, imbalance between treated and all other firms within parentheses (.).

Table 5 displays the matching results when the region of the treated firms is added as an (exact) matching variable, forcing the control firm to be in the same region as the treated firms. Forcing the control firm to be in the same region as the treated firm creates a perfect balance between the treatment group and the control group on this variable. Having the “twin” firm located in the same region as the treated firm removes the possibility that subsequent changes in the development of the treated and control firms is due to location. We may also note that matching results from this matching strategy correspond strongly to the matching results presented in Table 4, where no geographical concern was included in the matching.

	Matching imbalance		
	Employment	**Labor Productivity**	**Sales**
Region	0.00 (0.19)	0.00 (0.17)	0.00 (0.17)
ln(K)			0.08 (0.29)
Profit quota	0.02 (0.11)	0.04 (0.11)	0.04 (0.11)
ln(value added)	0.06 (0.45)		
ln(W)	0.10 (0.38)		
R&D int. SSY	0.04 (0.22)	0.04 (0.26)	0.04 (0.26)
ln(L)		0.08 (0.35)	0.07 (0.35)
Share of higher educ.	0.06 (0.48)	0.17 (0.49)	0.15 (0.49)
ln(capital intensity)		0.14 (0.24)	
Overall (L1)	0.71 (1.00)	0.71 (0.99)	0.66 (0.99)

Table 5. CEM matching results, including region as a matching variable

Note: Matching imbalance, univariate L1 distance between treated and control groups, imbalance between treated and all other firms within parentheses (.).

Finally, Table 6 provides the mean values of our outcome variables – employment, sales, and labor productivity – divided into six categories. The outcome variables are reported for all firms, treated firms, treated firms before treatment, treated firms after treatment, firms in the control group (original match), and firms in the control group when we include region as a matching variable.

Table 6. Mean values for dependent variables

	All	**Subsidized firms**	**Subsidized firms – before treatment**	**Subsidized firms – after treatment**	**Control group (Original match)**	**Control group (Match on regions)**
ln(L)	1.17 (1.09)	2.21 (1.26)	2.19 (1.28)	2.30 (1.20)	1.95 (1.34)	1.84 (1.37)
ln(sales)	8.01 (1.55)	8.91 (2.01)	8.92 (2.01)	8.89 (2.03)	9.03 (1.81)	8.70 (1.71)
ln(Lp)	5.89 (0.77)	6.05 (0.73)	6.04 (0.71)	6.06 (0.81)	6.12 (0.69)	6.21 (0.80)

Note: Standard deviation within parentheses (.).

5. Models

As noted above, a main purpose of the analyzed grants is to promote growth and competitiveness in targeted firms, whereas the type of growth desired is less clear. To tackle this problem, we analyze the effects of the R&D grants on a set of outcome variables capturing various aspects of firm growth and competitiveness. More specifically, we will analyze how the grants impact employment, sales, and labor productivity. In the analysis, we will estimate matched differences-in-differences (DID) regressions and, as a robustness test, we employ fixed-effects (FE) regressions on treated firms only. Hence, while the first method seeks to analyze the performance of the treatment group *vs*. a set of similar firms that did not receive any R&D grants, the latter method seeks to detect trend breaks in firm development at the time of or after receiving the grants. The model specifications are chosen based on the existing literature in each respective area. Because the choice of model is central to the analysis, we will present each model in more detail.

Labor demand

The labor market literature is relatively clear on the specification of the employment model. A firm's demand for labor is derived from the production function where firms, for a given set of factor prices, decide on the combination of input factors that are consistent with profit maximization (Hijzen and Swaim 2008). Furthermore, we allow for the adjustment costs of the labor force. Adjustment costs are handled by including a dynamic lag of the number of employees as an explanatory variable (Cahuc and Zylberberg 2004), thus shifting the analysis toward a dynamic panel data model specification (Angrist and Pischke 2008). To handle the endogeneity problem associated with a lagged dependent variable as an explanatory variable, we apply Han and Phillips' (2010) dynamic panel estimator. Compared to the commonly used GMM-estimators that rely on the absence of second order autocorrelation in the residual and a properly specified instrument matrix (Arrelano and Bond 1991; Blundell and Bond 1998), the Han and Phillips (2010) estimator tackles the endogeneity problem through its differencing design. The Han and Phillips (2010) estimator is known for having good short panel properties and avoiding much of the weak moment condition problem that is known to affect conventional GMM estimation when the autoregressive coefficient is near unity. Thus, to evaluate the effects of public R&D grants on employment, we estimate the following augmented labor demand model:

$$
\begin{aligned}
&ln(L)_{it} = \alpha_i + \beta_l\, ln(L)_{it-1} + \beta_w\, ln(w)_{it} + \beta_y\, ln(y)_{it} + \beta_T(treatment)_{it} + \\
&\beta_p(post)_{it} + \beta_R(\mathrm{RCA})_{rt} + \beta_1[(\mathrm{RCA})_{rt} \bullet (\mathrm{treatment})_{it}] + \beta_2[(\mathrm{RCA})_{rt} \bullet (\mathrm{post})_{it}] + \\
&+\beta_1(\textit{skill-share})_{it} + \beta_2(\pi)_{it} + \upsilon_i + \gamma_t + \varepsilon_{it} \qquad (2)
\end{aligned}
$$

where β_l reflects the effect from the number of employees in the previous period (l_{it-1}) and implicitly depends on the size of the adjustment costs, w_{it} is wage in firm *i* and year *t*, and y

is value added, *treatment* is a dummy for the year the firm receives the grant, whereas *post* captures the post treatment period. Regional differences in the supply of skilled labor are captured by the RCA-index *RCA*, where a value above zero indicates that a region as a relative abundance of skilled labor. Hence, the interaction between the regional supply of skilled labor and the treatment indicators captures asymmetric effects in how the grants impact firm performance in different regions. To control for firm-specific human capital and profitability (variables that may impact innovation, firm performance and the likelihood of receiving support), the model is augmented with firms' profit ratio π and the share of the labor force with tertiary education (*skill-share*); firm- and year fixed effects are captured by υ_i and γ_t, respectively, and finally, ε_{it} is the error term.

Sales

Two commonly used measures when analyzing firm growth are number of employees and sales. Number of employees represents an input variable and a measure of growth in resources, while sales represents an output variable and a measure of the acceptance of the product or service in the market (Delmar et al. 2003). For input variables, it is reasonable to expect positive effects for firms receiving a grant. However, the effect on output variables is unclear (Gustafsson et al. 2016). How sales are affected by the R&D grants can also be influenced by the fact that the subsidy program descriptions state future sales growth as a relevant key variable. Hence, following the commonly applied Cobb-Douglas production function approach, the augmented sales model takes the following form (Filipe and Gerard 2005):

$$ln(S)_{it} = \beta_k\, log\, K_{it} + \beta_l\, ln(L)_{it} + \beta_T (treatment)_{it} + \beta_p (post)_{it} + \beta_R (\text{RCA})_{rt} + \beta_1 [(\text{RCA})_{rt} \bullet (\text{treatment})_{it}] + \beta_2 [(\text{RCA})_{rt} \bullet (\text{post})_{it}] + \beta_1 (\textit{skill-share})_{it} + \beta_2 (\pi)_{it} + \beta_3 (R\&D)_{it} + \upsilon_i + \gamma_t + \varepsilon_{it} \tag{3}$$

where we have the same set of fix-effect, regional- and treatment indicators as in equation (2), but note that the dependent variable here, sales, is represented by S_{it}; K is firm capital stock, L is employment, and finally, *R&D* is firm level R&D-intensity.

Labor productivity

As a complementary measure to employment and sales, we look at labor productivity, which can be seen as a combination of the relative impact of the grants on employment and production. To study labor productivity effects, we follow Griliches (1986) to obtain the following augmented labor productivity (lp) model:

$$ln(lp)_{it} = \beta_{k/l}\, ln(K/L)_{it} \; + +\beta_l\, ln(L)_{it} + \beta_T(treatment)_{it} + \beta_p(post)_{it} + \beta_R(\mathrm{RCA})_{rt} + \beta_1[(\mathrm{RCA})_{rt} \bullet (\mathrm{treatment})_{it}] + \beta_2[(\mathrm{RCA})_{rt} \bullet (\mathrm{post})_{it}] + +\beta_1(\textit{skill-share})_{it} + \beta_2(\pi)_{it} + \beta_3(R\&D)_{it} + \upsilon_i + \gamma_t \; + \varepsilon_{it} \quad (4)$$

where $\beta_{k/l}$ is a measure of the productivity elasticity with respect to the capital intensity in the firm. The coefficient for number of employees, β_l, is a scale indicator; if $\beta_l = 0$, this is a sign of constant returns to scale; $\beta_l > 0$ and ($\beta_l < 0$) signal increasing (decreasing) returns to scale, respectively.[4]

6. Results

Table 7 contains basic results on how the R&D grants impact our three outcome variables: employment, sales, and labor productivity. To be precise, Table 7 shows the effects from both matched differences-in-differences (DID) estimations and fixed-effects (FE) estimations on treated firms only. In this paper, our focus will be on the DID results because these can be considered more precise, but as we will observe, the results from the DID estimations and the more naïve fixed effects estimations are rather similar, which we interpret as a sign of the robustness of the results. We may also note that the first set of CEM matched regression results presented in Table 7 is based on a matching where we are not forcing the "twin" to be located in the same region as the treated firm. Hence, in these first estimates, we cannot exclude the possibility that a part of the treatment effect can be influenced by regional differences in the location of treated and control firms. In subsequent regressions, this matter will be examined in more detail.

Employment

A goal prioritized by the government is to generate new jobs. Hence, employment is one of the analyzed outcome variables. However, as shown in Table 7, there are no statistically significant employment effects of the analyzed grants. That is, we do not find evidence of a

[4] The reason for not using a dynamic model specification is that the non-dynamic formulation is more frequently used when labor productivity is evaluated (Chansarn, 2010).

direct employment effect of the grants at the time of the payment, nor in the post-treatment period. However, the estimated direct effect represents the average effect over all regions. To uncover the potential heterogeneity of the impact of the R&D grants, we turn to the interaction between the received grant and regional characteristics. Studying the regional interaction, the first thing to note is that the estimate is positive but insignificant, suggesting a positive relation between employment that is not significant at the *midpoint* of our sample (RCA-Index=0), as illustrated in Figure 1 and given by the estimates in Table 7.

When interpreting the above result, we may note that the estimated coefficient reflects the mid-point estimate and does not reveal the marginal effect of the grants at the endpoints of the distribution. The full cross-regional variation in the impact of the R&D grants is illustrated in Figure 1, suggesting a varying effect that goes from a negative and significant effect in regions at the low end of the human capital supply ranking to a positive and significant effect in the regions with the most abundant human capital (during the period when the grant is paid out). For the post-treatment effect, however, the estimate never becomes positive and significant as we move toward more skill-abundant regions. This spread in marginal effects is an example of how information can be hidden behind the average effect. We also note that the results discussed here that are based on CEM-matching not are based on a matching where we force the treated and control firm to be located in the same region. Hence, if there are systematic differences in the locations of treated and control firms, not controlling for location may impact the estimates of the treatment effect. In subsequent regressions, we will analyze whether controlling for location upsets the results.

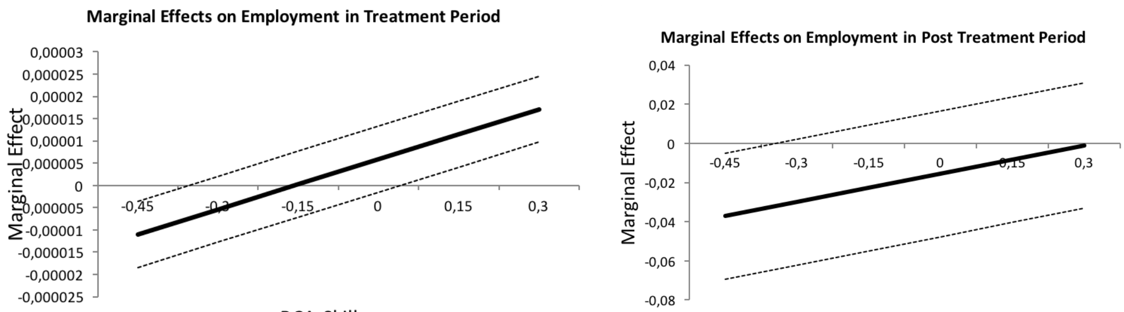

Figure 1. Marginal Effects on Employment
Notes: All figures are constructed with non-clustered standard errors. The confidence intervals regarding the employment effects are only correct for RCA-index = 0.

Sales

Together with employment, sales are a commonly applied indicator of firm growth. If firms are able to increase their efficiency, sales can be increased without a matching increase in the labor force. The results from the sales regressions are given in columns 1 and 4 in Table 7, and the regional distribution of the marginal effect (matched DID estimates) is depicted in Figure 2. Figure 2 reveals a series of interesting observations. First, at the time of the treatment, there is a tendency of a negative drift in sales, and the negative effect is largest in regions with abundant human capital. One possible explanation for this result is that the grant triggers investment, which leads to a temporary reallocation of productive resources from production to investment activities; this effect may be largest in human capital-abundant regions. However, when we move from the period of treatment to the post-treatment period, the picture is reversed. After the treatment period (during which the grant is paid out), we find a negative and significant effect on sales for firms in regions with a relatively small share of high-skilled workers, and a positive but not significant effect for firms in regions with an abundance of high-skilled workers (the post-treatment effect is positive and significant at the ten percent level in the most human capital-abundant regions). We may note that this post-treatment pattern is consistent with the hypothesis that the largest investments take place in firms located in human capital-abundant regions, leading to more positive sales development in subsequent years among those firms.

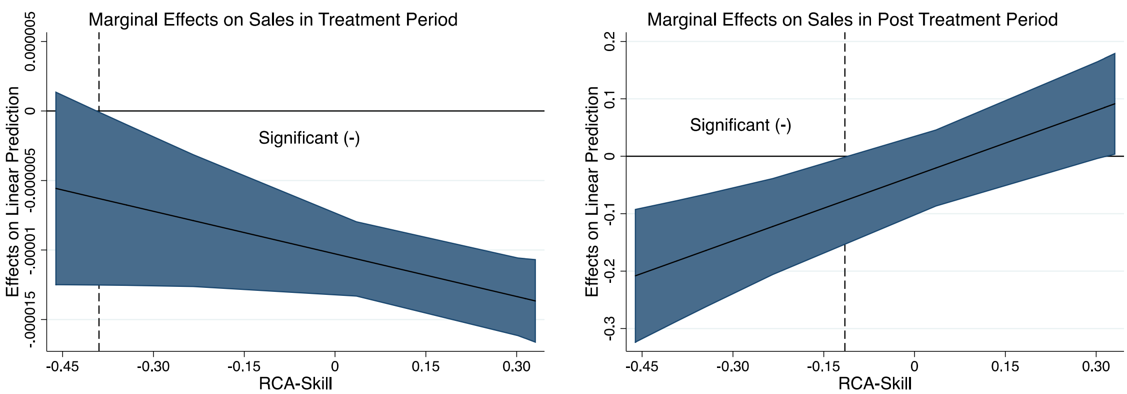

Figure 2. Marginal Effects on Sales
Notes: All figures are constructed with non-clustered standard errors. The figures are based on estimations from Table 7.[5]

Productivity

[5] Due to technical limitations in retrieving marginal effects at different percentiles when using clustered standard errors, estimates, depicted in Figures 2-3, are based on non-clustered standard errors.

The impact of the grants on productivity can be seen as a weighted employment and sales effect. As noted above, the effect of the grants on employment and sales was negative during the treatment period, although not significant for employment. Hence, expectations for labor productivity are not obvious. Looking at the DID results in Table 7, the direct effect of the grants is negative but not significant, both during and after the treatment.

The regional spread in labor productivity effects is illustrated in Figure 3, which indicates no significant treatment effects in any region during the treatment. However, for the post-treatment effect, we note that, in line with the findings for sales and employment, a more positive (or less negative) productivity effect is found in regions with an abundance of high-skilled workers. To be precise, as we move from the least to the most skill-abundant region, the post-treatment effect on labor productivity goes from negative and significant to barely positive and significant in the most skill-abundant regions. Hence, the probability of a positive post-treatment effect on sales, employment and productivity is highest in skill-abundant regions. These results are, to some extent, consistent with earlier studies that found the most positive effects of similar grants in central rather than rural regions (Banno et al. 2013; Herrera and Nieto 2008; Piekkola 2007; Czarnitzki and Licht 2006). This result allows us to speculate whether it may be the lack of high-skilled workers that puts growth restrictions on innovative SMEs in regions with a low RCA-Skill index. However, because firm location is not included as a matching variable, we cannot rule out the possibility that these results may be driven by a systematic difference in location between treated firms and the control group. In the subsequent section, we will take a closer look at the robustness of these results when controlling for firm location.

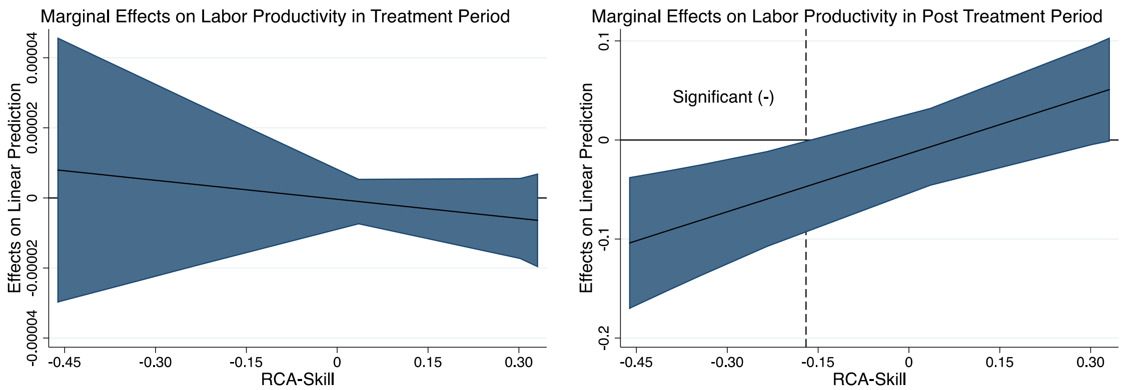

Figure 3. Marginal Effects on Labor Productivity
Notes: All figures are constructed with non-clustered standard errors. The figures are based on estimations from Table 7.

Table 7. The effect of R&D grants: Basic regression results

	CEM-matching not controlling for regional location			**Treated firms only**		
	DID *ln(*sales)	DID Han-Philips *ln*(L)	DID *ln*(Lp)	FE *ln*(sales)	FE Han-Philips *ln*(L)	FE *ln*(Lp)
ln(K)	0.0921 (0.0292)***		0.0760 (0.0135)***	0.0921 (0.0318)***		0.0764 (0.0147)***
ln(L)	0.7901 (0.0609)***		-0.0119 (0.0325)	0.7867 (0.0666)***		0.0014 (0.0337)
RCA Skill	-0.3412 (0.5826)	-0.0721 (0.1036)	-0.1866 (0.2226)	-0.3595 (0.6580)	0.0470 (0.1588)	-0.1561 (0.2440)
RCA Skill* Treatment	-0.00001 (9.94e-06)	3.75e-05 (2.89e-05)	-1.81e-05 (3.04e-05)	-1.2e-05 (9.01e-06)	3.62e-05 (3.04e-05)	-1.47e-05 (2.6e-05)
RCA Skill* Post-Treat	0.3782 (0.1715)**	0.0480 (0.0643)	0.1954 (0.0817)**	0.3805 (0.1727)**	0.0400 (0.0700)	0.1871 (0.0818)**
Treatment	-0.00001 (2.49e-06)***	-5.88e-06 (3.79e-06)	-3.99e-07 (3.99e-06)	-9.9e-06 (2.3e-06)***	-5.77e-06 (3.99e-06)	-1.40e-06 (3.45e-06)
Post-Treat	-0.0338 (0.0512)	-0.0157 (0.0163)	-0.0138 (0.0266)	-0.0558 (0.0559)	-0.0035 (0.0186)	-0.0164 (0.0287)
Profit ratio	0.0021 (0.0003)***		1.4099 (0.1887)***	0.0021 (0.0003)***		1.6463 (0.1273)***
Share of higher educ.	-0.4073 (0.1593)**		-0.1052 (0.0875)	-0.4566 (0.1781)**		-0.0834 (0.0976)
R&D int.	0.0842 (0.2753)		0.0701 (0.1150)	0.1183 (0.3048)		0.0381 (0.1272)
ln(L (t-1))		0.8539 (0.0446)***			0.8977 (0.0658)***	
ln(y)		0.2363 (0.0063)***			0.2374 (0.0089)***	
ln(w)		-0.2800 (0.0097)***			-0.2771 (0.0144)***	
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,439	7,761	6,868	3,745	3,669	3,330

Notes: *,**,***, indicates significance at the 10, 5, and 1 percent levels, respectively. Clustered standard errors within parentheses (.). The matching method is 1-1 coarsened exact matching. Only firms receiving R&D grants are included in the FE-estimations. Both treated firms and matched twins are included in the difference-in-differences estimations. The employment model is estimated with the Han-Philips (2010) linear dynamic panel data regression.

6.1 Robustness: Matching by labor market region

The analysis above does not guarantee a complete separation of the effect of being localized in a specific labor market region from the effect of the grant. To rule out the possibility of location-driven bias, we redo our matching and include regions as a matching variable, forcing the control firm to be localized in the same labor market region as the treated firm. Hence, any differences in results between Table 8 and Table 7 signal a locational selection bias in Table 7.

Studying the results in Table 8, we find that these are quite similar to the results found in Table 7; when there is a significant effect in Table 8, we always find a corresponding effect in Table 7 in both sign and (approximately) size. Consequently, forcing the control firm to be located in the same local labor market region as the subsidized firm does not significantly alter the results. These observations lead us to two noteworthy results.

First, matching on location does not impact the overall instantaneous and post-treatment effect. The grants have, considered over all regions, no significant post-treatment effect on employment, sales or productivity. However, an instantaneous dip in sales and labor productivity can be found.

Secondly, turning to the regional dimension, starting with the regional distribution of the instantaneous effect, we find no significant interaction effects. For the post-treatment period, however, we find a positive interaction between the regional supply of skilled labor and the receipt of a grant on sales and productivity. This significant interaction suggests that grants have a more positive impact on firms located in human capital abundant regions than in other regions. Given that the treated and control firms are located in the same region, this asymmetry can occur if the agency administrating the grants is systematically targeting more successful firms in human capital-abundant regions compared to other regions. We may also consider the possibility that receiving a grant generates a temporary competitive advantage. Given that the prospects of growth for innovative SMEs are better in human capital-abundant regions than in other regions, the marginal return is likely to be higher in human capital-abundant regions. Hence, given that we ignore distributional issues and potential distortions caused by the grants and focus on growth in targeted firms, the results suggest that if firm growth is the primary goal of the program, R&D grants focused on innovative SMEs tend to generate the largest growth effects when they are given to firms located in human capital-abundant regions.

Table 8. The effect of R&D grants: Regions included in matching

	Treated and CEM matched firms CEM-matching with control for regional location					
	DID *ln*(sales)	DID Han-Philips *ln*(L)	DID *ln*(Lp)	DID *ln*(sales)	DID Han-Philips *ln*(L)	DID *ln*(Lp)
RCA Skill				-0.3644 (0.6413)	0.0751 (0.1230)	-0.1482 (0.228)
RCA Skill* Treatment				-0.00001 (9.98e-06)	4.21e-05 (3.06e-05)	-0.00002 (0.00003)
RCA Skill* Post-Treat				0.3789 (0.1724)**	0.0583 (0.0663)	0.1988 (0.0812)**
Treatment	-0.00001 (2.0e-06)***	-1.13e-06 (8.16e-07)	-3.30e-06 (4.5e-07)***	-0.00001 (2.5e-06)***	-6.54e-06 (4.01e-06)	-1.31e-06 (3.51e-06)
Post-Treat	-0.0379 (0.0542)	-0.0093 (0.0171)	-0.0106 (0.0286)	-0.0497 (0.0538)	-0.0110 (0.0172)	-0.0146 (0.0277)
Full Model	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,962	6,392	4,477	4,962	6,392	4,477

Notes: *,**,***, indicates significance at the 10, 5, and 1 percent levels, respectively. Clustered standard errors within parentheses (.). The matching method is 1-1 coarsened exact matching. Both treated firms and matched twins are included in the difference-in-differences estimations. See Table 7 and the description of the model for the full model, control variables, etc. The employment model is estimated with the Han-Philips (2010) linear dynamic panel data regression.

7. Conclusions

The central question discussed in this paper is whether the effects of public innovation grants to private firms vary depending on firm location and the surrounding environment. Why regions matter for the success of different industries has been discussed by, for example, Marshall (1920), Asheim et al. (2011), Cooke (2001), and Tödtling and Trippl (2005). A common feature of these studies is that they all agree that regional context matters for firm location and growth; i.e., there is interdependence between firm performance and the surrounding environment. In this vein, it is well known that access to skilled labor is crucial for the innovation and development of innovative SMEs, or, as noted by Kunz (2014) regarding the US situation: "*A common complaint from 21st century manufacturers is having access to a skilled workforce.,,,. Currently, nine out of ten manufacturers are having difficulty finding skilled workers, and they say this is directly hurting the bottom line*".

This paper analyzes one dimension of how the regional supply of skilled labor influences the prospects of firm growth by examining local abundance of skilled labor and regional variation in relation to the impact of public R&D grants targeting innovative SMEs. Specifically, the effects of two R&D subsidy programs on employment, sales and labor productivity are studied. The main findings are summarized in the following bullet points:

- During the treatment period, we (on average) find a significant and negative effect on sales and non-significant effects on employment and labor productivity.
- After the treatment period has ended, there is no evidence of any direct (average) growth effects.
- Adding a regional dimension, we find that the effect differs across regions, both during the treatment period and in the post-treatment period.
    - During the *treatment period*, the employment effect goes from negative and significant to positive and significant as we move from the least- to the most skill-abundant labor market region. For sales and labor productivity, however, there is a negative trend as we move from the least to the most skill-abundant labor market region.
    - In the *post-treatment period*, the pattern is clear: for sales, productivity and employment we find a positive drift wherein they all shift from a negative and significant effect toward a positive and significant effect as we move from the least to the most skill-abundant labor market region. For labor productivity and sales, the post-treatment effect becomes positive and significant in the most skill-abundant regions.

In conclusion, the treatment effect can be negative for firms in some regions, insignificant in others, and significantly positive for firms in the most human capital-abundant regions. Overall, the findings of this paper indicate that the better regional surroundings a firm faces in terms of human capital-abundance, the higher is the probability that the recipient of an R&D grant will show positive growth effects. Accordingly, these results yield a clear policy implication. Given that the aim is to maximize the growth effects of public R&D grants, it can be counterproductive to distribute the grants too evenly across regions. To maximize the growth effect in targeted firms, R&D grants should instead be concentrated on firms located in regions abundant with human capital. These conclusions make intuitive sense and are consistent with the findings of earlier literature, which state that R&D grants generate larger effects in central rather than rural regions (Banno et al. 2013; Herrera and Nieto 2008; Piekkola 2007; Czarnitzki and Licht 2006).

References

Acs, Z.J., & Audretsch, D.B. (1988). Innovation in large and small firms: an empirical analysis. *American Economic Review*, 78, 678–690.

Aghion, P., & Howitt, P. (1998). *Endogenous Growth Theory*. Cambridge, MA: MIT Press.

Akerlof, G.A. (1970). The market for ‘‘lemons’’: quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84, 488–500.

Angrist, J.D., & Pischke, J-S. (2008). *Mostly harmless econometrics: an empiricist's companion*. Princeton University Press, Princeton.

Arrelano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Econometric Studies*, 58, 277-297.

Asheim, B.T., & Gertler, M. (2004). *Regional systems of innovation*. In: Fagerberg, J., Mowery, D.C., & Nelson, R. (Eds). The Oxford Handbook of Innovation, 291-317. Oxford: Oxford University Press.

Asheim, B.T., Lawton Smith, H., & Oughton, C. (2011). Regional Innovation Systems: Theory, Empirics and Policy. *Regional Studies*, 45(7), 875-891.

Audretsch, D., & Lehmann, E. (2006). The Role of Clusters in Knowledge Creation and Diffusion: An Institutional Perspective. *Clusters and Regional Development: Critical Reflections and Explorations*, edited by Asheim, B., Cooke, P., & Martin, R., 188-198. New York: Routledge.

Banno, M., Morandi, V., & Amorim, C. (2013). Public Policy for Innovation and Internationalization: are they worth it? *Applied Economic Letters*, 20 (10), 927-930.

Baptista, R., & Swann, P. (1998). Do Firms in Clusters Innovate More? *Research Policy*, 27, 525-540.

Baumol, W.J. (2002). Entrepreneurship, Innovation and Growth: The David-Goliath Symbiosis. *Journal of Entrepreneurial Finance and Business Ventures*, 7(2), 1-10.

Bergström, F. (1998). Capital subsidies and the performance of firms. *SSE/EFI Working Paper Series in Economics and Finance*, No. 285. Stockholm School of Economics.

Blackwell, M., Iacus, S.M., King, G., & Porro, G. (2009). CEM: Coarsened exact matching Stata. *Stata Journal*, 9(4), 524.546.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87: 11-143.

Bronzini, R., & Iachini, E. (2010). Are incentives for R&D effective? Evidence from a regression discontinuity approach. *Mimeo Bank of Italy*, No 791.

Cahuc, P., & Zylberberg, A. (2004). *Labour Economics.* MIT-press.

Cappelen, Å., Fjærli, E., Iancu, D-C., Klemetsen, M., Moxnes, A., Nilsen, Ø.A., Rakneru, A., & Rybalka, M. (2016). *Innovasjons- og verdiskapningseffekter av utvalgte naeringpolitiske virkemidler*, Report 2016/12, Statistics Norway.

Chansarn, S. (2010). Labor Productivity Growth, Education, Health and Technological Progress: A Cross-Country Analysis. *Economic Analysis & Policy*, 40(2), 249-261.

Cin, B.C., Kim, Y.J., & Vonortas, N.S. (2017). The impact of public R&D subsidy on small firm productivity: evidence from Korean SMEs. *Small Business Economics*, 48, 345-360.

Cooke, P., Etxebarria, G., & Gomez Uranga, M. (1997). Regional Innovation Systems: Institutional and Organisational Dimensions. *Research Policy,* 26, 475-491.

Cooke, P. (2001). Regional Innovation Systems, Clusters, and the Knowledge Economy. *Industrial and Corporate Change,* 10(4), 945-974.

Cooke, P. (2004). *Evolution of regional innovation systems: emergence, theory, challenge for action*. In: Cooke, P., Heidenreich, M., Braczyk, H-J (Eds) (2004). Regional Innovation Systems: the role of governances in a globalized world, 1–18. London: Routledge.

Criscuolo, C., Martin, F., Overman, H., & Van Reenen, J. (2012). The Causal Effects of an Industrial Policy. *IZA DP,* No. 6323.

Croce, A., Marti, J., & Murtinu, S. (2013). The impact of venture capital on the productivity growth of European entrepreneurial firms: 'Screening' or 'value added' effect? *Journal of Business Venturing*, 28 (4), 489-510.

Cumming, D., Grilli, L., & Murtinu, S. (2017), Governmental and independent venture capital investments in Europe: A firm-level analysis. *Journal of Corporate Finance,* 42, 439-459.

Czarnitzki, D., & Fier, A. (2002). Do Innovation Subsidies Crowd Out Private Investment? Evidence from the German Sevice Sector. *ZEW Discussion Papers*, No. 02-04.

Czarnitzki, D., & Licht, G. (2006). Additionality of Public R&D Grants in a Transition Economy – The case of Eastern Germany. *Economics of Transition*, 14 (1), 101-131.

Dasgupta, P., & Stiglitz, J.E. (1980). Uncertainty, Industrial Structure, and the Speed of R&D. *Bell Journal of Economics*, 11(1), 1-28.

Delmar, F., Davidsson, P., & Gartner, W. (2003). Arriving at the high-growth firm. *Journal of Business Venturing,* 18(2), 189-216.

Doloreux, D. (2004). Regional Innovation Systems in Canada: A Comparative Study. *Regional Studies*, 38(5), 479-492.

Doloreux, D., & Parto, S. (2005). Regional innovation systems: Current discourse and unresolved issues. *Technology in Society,* 27, 133-153.

Dosi, G. (1988). *The Nature of the Innovative Process*, in Dosi, G., *et al* (eds). Technical Change and Economic Theory. London: Pinter Publishers.

Edler, J., Cunningham, P., Gök, A., & Shapira, P. (2013). Impacts of Innovation Policy: Synthesis and Conclusions - Compendium of Evidence on the Effectiveness of Innovation Policy Intervention Project. Nesta, 2013, June. UK.

Eliasson, K., Kroksgård, A., & Widerstedt, B. (2012). In Swedish: Mikrodatabas över statligt stöd till näringslivet: Ett verktyg för att följa upp och utvärdera tillväxtpolitiska insatser i enskilda företag. Swedish Agency for Growth Policy Analysis: Östersund.

Feldman, M.P. (1994a). *The Geography of Innovation.* Boston: Kluwer Academic Press.

Feldman, M.P. (1994b). Knowledge Complementarity and Innovation. *Small Business Economics,* 6, 363-372.

Feldstein, M. (1999). Tax avoidance and the deadweight loss of the income tax. *The Review of Economics Statistics*, 81(4):674–680.

Filipe, J., & Gerard Adams, F. (2005). The Estimation of the Cobb-Douglas Function: A Retrospective View. *Eastern Economic Journal*, 31(3), 427–445.

Fujita, M., Krugman, P., & Venables, A.J. (1999). *The Spatial Economy, Cities, Region and International Trade*. Cambridge, Massachusetts: MIT Press.

Georghiou, L., Smith, K., Tojvanen, O., & Ylä-Anttila, P. (2003). Evaluation of the Finnish Innovation Support System. 5/2013. Ministry of Trade and Industry: Helsinki.

Geroski, P.A. (1991). *Market Dynamics and Entry*. Oxford: Basil Blackwell.

Gonzalez, X., Jaumandreu, J., & Pazo, C. (2005). Barriers to Innovation and Subsidy Effectiveness. *RAND Journal of Economics*, 36(4), 930-949.

Griliches, Z. (1986). Productivity, R&D and Basic Research at the Firm Level. *American Economic Review*, 76(1), 141-167.

Grilli, L., & Murtinu, S. (2014). Government, venture capital and the growth of European high-tech entrepreneurial firms. *Research Policy*, 43(9), 1523-1543.

Growth Analysis. (2014). In Swedish: Företagsstöd till innovativa små och medelstora företag – En kontrafaktisk effektutvärdering. PM 2014:16. Swedish Agency for Growth Policy Analysis: Östersund.

Gustafsson, A., Hallman, A., Karlsson, N., & Stephan, A. (2016). The “sugar rush” from innovation subsidies: a robust political economy perspective. *Empirica*, 43(4), 729-756.

Han, C., & Phillips, P.C.B. (2010). GMM estimation for dynamic panels with fixed effects and strong instruments at unity. *Econometric Theory*, 26, 119–151.

Harris, R., & Robinson, C. (2005). The Impact of Regional Selective Assistance on Sources of Productivity Growth: Plant Level Evidence from UK Manufacturing 1990-1998. *Regional Studies*, 39(6), 751-765.

Harris, R., & Trainor, M. (2005). Capital Subsidies and Their Impact on Total Factor Productivity: Firm-level Evidence From Northern Ireland. *Journal of Regional Science*, 45(1), 49-74.

Hayek, F.A. (1945). The use of knowledge in society. *American Economic Review*, 35(4), 519-530.

Herrera, L., & Nieto, M. (2008). The National Innovation Policy Effect According to Firm Location. *Technovation*, 28, 540-550.

Heshmati, A., & Lööf, H. (2005). The Impact of Public Funds on Private R&D Investment: New Evidence from a Firm Level Innovation Study. *Discussion Papers 11862*. MTT Agrifood Research: Finland.

Hijzen, A., & Swaim, P. (2008). Offshoring, Labour Market Institutions and the Elasticity of Labour Demand. The University of Nottingham, Research paper series, No. 2008/05.

Iacus, S.M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Associations*, 106(493), 345-361.

Iacus, S.M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political analysis*, 20(1), 1-24.

Isaksen, A., & Onsager, K. (2010). Regions, Networks and Innovatiove Performance: The Case of Knowledge-intensive Industries in Norway. *European Urban and Regional Studies,* 17(3), 227-243.

Jones, J., & Wren, C. (2004). Inward Foreign Direct Investment and Employment: A Project-Based Analysis in North-East England. *Journal of Economic Geography*, 4(5), 517-44.

Koski, H., & Pajarinen, M. (2013). The role of business subsidies in job creation of start-ups, gazelles and incumbents.. *Small Business Economics*, 41(1), 195-214.

Krugman, P. (1991). *Geography and Trade*. Cambridge, Massachusetts: MIT Press.

Krugman, P., & Obstfeld, M. (2009). *International Economics: Theory and Policy*, Seventh Edition. Pearson-Addison Wesley.

Kunz, J. (2014). SME Speaks: Lack of Skilled Workers Challenges Manufactures. *Manufacturing Engineering Magazine*, Aug 2014, 17-18.

Leamer, E.E. (1995). *The Heckscher–Ohlin Model in Theory and Practice*. Princeton Studies in International Finance 77. Princeton, NJ: Princeton University Press.

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

Marjolein, C.J.C. (2000). *Knowledge Spillovers and Economic Growth*. Edward Elgar: Cheltenham, UK. Northampton, MA, USA.

Marshall, A. (1920). *Principles of Economics*. London: Macmillan (8th ed.).

Nightingale, P., & Coad, A. (2014). Muppets and gazelles: political and methodological bias in entrepreneurship research. *Industrial and Corporate Change*, 23(1), 113-143.

OECD, *Organisation for Economic Co-operation and Development* (2015). *Evaluation of Industrial Policy: Methodological Issues and Policy Lessons.* DSTI/IND(2014)3/Final. OECD, Paris.

Ohlin, B. (1967). *Interregional and International Trade*. Harvard Economic Studies 39. Cambridge, MA: Harvard University Press.

Piekkola, H. (2007). Public Funding of R&D and Growth: Firm-Level Evidence from Finland. *Economics of Innovation and New Technology,* 16(3), 195-210.

Rodrik, D. (2008). *Normalizing industrial policy*. International Bank for Reconstruction and Development/ The World Bank.

Romer, P.M. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy*, 94, 1002–1037.

Schumpeter, J. (1911). Theorie der wirtschaftlichen Entwicklung, Redvers Opie (1934). The Theory of Economic Development. Harvard University Press, Cambridge MA.

Shane, S. (2009). Why encouraging more people to become entrepreneurs is bad public policy. Small Business Economics, 33(2), 141-149.

Solow, R.M. (1957). Technical Change and the Aggregate Production Function. *Review of Economics* *and Statistics* ,39(3), 312–320.

Srholec, M. (2007). A Multilevel Approach to Geography of Innovation. *TIK Working Papers on Innovation Studies,* 2007.

Stiglitz, J., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71(3), 393–410.

Söderblom, A. Samuelsson, M. Wiklund, J., & Sandberg, R. (2015). Inside the black box of outcome additionality: effects of early-stage government subsidies on resource accumulation and new venture performance. *Research Policy*, 44(8), 1501–1512

Tödtling, F., & Trippl, M. (2005). One size fits all? Towards a differentiated regional innovation policy approach. *Research Policy*, *34*(8), 1203-1219.

UNCTAD. (1997). Invest in France mission: DATARand Artur Andersen. *International Investment: Toward the year 2001*. OECD, Paris 1997.

Veugelers, R. (2015). Mixing and Matching Research and Innovation Policies in EU countries. Bruegel Working Paper 2015/16, Dec 2015.

Vinnova. (2014). In Swedish: Effektanalys av Vinnovas finansiering av Innovativa SMF.

Warwick, K. (2013). Beyond Industrial Policy: emerging issues and new trends. *OECD Publishing*, 2.

Wren, C. (2005). Regional Grants. Are They Wort It? *Fiscal Studies,* 26(2) 245-275.

Zúñiga-Vicente J.A., Alonso-Borrego, C., Forcadell, F.J., & Galán-Zazo J.I. (2014). Assessing the Effect of Public Subsidies on Firm R&D Investment: A Survey. *Journal of Economic Surveys*, 28(1), 36–67.