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ESTIMATING EFFECT OF R&D SUBSIDIES ON FIRMS' PERFORMANCE

Master Thesis

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Declaration

I hereby declare that I am the sole author of this thesis. I duly marked out all quotations. The used literature and sources are stated in the attached list of references.

Gabriela Čechová

In Prague on August 16, 2019

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Abstrakt

Cílem této práce je prozkoumat dopad dotací na výzkum a vývoj na výkonnost podniků. Indikátory zaměstnanosti, výnosů a produktivity ve společnostech jsou pozorovány na unikátním datovém souboru České republiky na úrovní firem v letech 2013 až 2018. Analýza kauzálního efektu je aplikována pomocí odhadu modelu rozdíl-v-rozdílech kombinovaného s CEM metodou párování. Metodika je dále použita ke sledování jednotlivých let během doby po obdržení dotace a také k porozumění vlivu pro různé velikosti firem. Výsledky značí pozitivní vliv na zaměstnanost a produktivitu pro krátké a střední období. V případě pozorování vlivu během jednotlivých let se výsledky neprokazují jako významné pro první dva následující roku po obdržení dotace. Třetí a čtvrtý rok po obdržení je vliv však významný a pozitivní s rostoucím trendem v případě výnosů firmy a produktivity. Kladný vliv dotace na produktivitu je také nalezen v případě mikro firem a malých firem v porovnání s korporacemi. Výsledky podporují (ačkoliv s vybranými omezeními) hypotézu o pozitivním vlivu dotací na výkonnostní ukazatele firem, hlavně v případě malého a středního podnikání.

Klíčová slova: inovační dotace, CEM, rozdíl-v-rozdílech, výkony firmy, malé a střední podnikání
JEL klasifikace: H25, O38, D23

Abstract

The goal of this thesis is to explore the impact of R&D subsidy on firms' performance. The companies' employment, sales and productivity measures are observed on unique Czech dataset of firm level data for the period 2013 – 2018. The causal effect analysis is applied in form of difference-in-differences model estimation combined with CEM matching method (coarsened exact matching). The methodology is further applied to observe the post treatment years separately and to provide insights on role of firm size. The results indicate positive effect on employment and productivity in both short term and medium term. When observing the yearly post treatment effect, the estimates for first two years are lacking significance, however the third and fourth year estimates show positive and increasing effect on both sales and productivity of the companies. The positive effects of subsidy on productivity performance indicator are also found for the cases of micro and small firms compared to the large enterprises. The findings support (although with reservations) the hypothesis about positive effect of subsidy on firm's performance, especially for micro and small firms.

Keywords: innovation subsidies, CEM, difference-in-differences, firm performance, SME
JEL classification: H25, O38, D23

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Introduction

In most of the EU countries there is an appearance of R&D subsidies provided either by local government or by EU, mostly from both of the institutions (Becker, 2015). These subsidies should provide the sustainable growth and achieve innovations together with unemployment dealing. The economics theory is well established on this topic and builds a framework of market imperfections describing the need of such public financial help, especially for the small and medium enterprises sector. The small and medium enterprises are typically lacking financial resources however exhibits better productivity thanks to their flexibility and low cost of administration. This sector is also recognized by the local governments, paying special attention to it when redistributing the financial resources.

This thesis provides and tests several economic models on firm level Czech data, exploring the effect of such subsidies. Do the subsidies affect the companies in short term or in medium term? Does the SME sector benefit more than the corporate firms in terms of improving its productivity and sales? Such questions are further discussed and elaborated with main results of this study that employment and productivity are affected positively by the subsidies in both short and medium term. Moreover, the productivity increase is significantly higher in case of SME firms during the subsidized year and afterwards.

This study has following structure: The first part is defining the topic from economics point of view. The existing literature is evaluated together with explanation about the main economic challenges connected to the topic. Specifics of the Czech Republic market and description of SME sector is closing the first part of the thesis. Second part is applying causal effect estimation methodology (CEM matching and difference-in-differences) and comes up with results about the effect of receiving a subsidy on selected performance indicators, also in terms of companies' sizes. The end of the second part summarizes the tested hypothesises and suggests further research possibilities.

1. Theoretical part

1.1. Research and Development

1.1.1. Definition of R&D

The known abbreviation of R&D - research and development - encompasses different terms, however the meaning remains the same. OECD (2007) covers three activities under this abbreviation: basic research, applied research, and experimental development. The definition provided by Eurostat (2017) elaborates the description as *"creative work undertaken on a systematic basis in order to increase the stock of knowledge (including knowledge of man, culture and society), and the use of this knowledge to devise new applications."* UNESCO (OECD, 2007) adds to the mentioned the dimension of research fields such as agriculture, medicine, industrial chemistry and distinguishes experimental development based on final product - new device, product or process.

The Czech law covers the topic in the §2 of R&D Public Support Act[1] and interprets the term as research, experimental development and innovation. It categorizes basic research, applied research and experimental development. The research is systematic and broadens the human knowledge with the aim of confirmation, enrichment or disproof. Experimental development is a usage of acquired knowledge and aims to cover production of new or improved products, processes (also organizational innovations are part of the process improvements), and services. Czech Statistical Office (CSO, 2006) adopts this definition and points out that the definition is according to the Frascati Manual (OECD, 2015).

The Frascati Manual recognizes several criteria which shall be fulfilled for the activity to be R&D. It is (1) novel; (2) creative; (3) uncertain; (4) systematic; (5) transferable and / or reproducible. From the economics point of view two of the aspects are especially important and interesting. Firstly, uncertainty gives the R&D a possibility of failure which increases the cost of investment into the activity (Arrow, 1962). Secondly, the activity

[1] The Act No. 130/2002 Coll. On the research and development support from public funds and on the change of some related acts

being reproducible brings risk of the idea replication by the firm's competitors (Cooter & Schäfer, 2012). Both properties will be further discussed.

Multiple authors and definitions are working with the term "innovation" (Gustafsson, Stephan, Hallman, & Karlsson, 2016; Rogers, 1998; Santos, Cincera, Neto, & Serrano, 2016; Tingvall & Videnord, 2018). This term is closely associated with the R&D and the border between their meaning is not always clear. It can be said that an innovation is an extension of R&D into the business (Müllerová, 2007).

"An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (products) or brought into use by the unit (process)." as described by OECD/Eurostat (2018, p. 20). The terms innovation and R&D are commonly used as synonyms in economics literature and this study further uses it in the same matter.

Another commonly associated term is "invention". However, there is an important nuance between *innovation* and *invention*. An invention is understood as a new idea, a new product or a new piece of knowledge in its origin and without the act of application. An innovation is rather the activity of implementing the new product or the new idea into the use and it is the key driver of the capitalist dynamics according to Schumpeter's theory (Gerguri & Ramadani, 2010).

In the world of economics theory, Shy (1995, p. 221) describes the innovation as *"…the search for, and the discovery development, improvement, adoption, and commercialization of new processes, new products and new organizational structures and procedures."* He sees R&D as a tool for *"…creating (or changing) the production functions."* He also points out that two groups of research and development exist - process and product innovations. Both can influence firm's cost functions, and so R&D can also be a cost-reduction method.

1.1.2. History of R&D in economics

The technological progress has been acknowledged by economists together with the economies of scale during the late 19th century. Activities such as learning-by-doing and adopting new techniques had been described as some of the sources of growth (Fagerberg, Srholec, & Verspagen, 2010; Gerguri & Ramadani, 2010). But the commonly accepted first description of innovation and its place in economics comes in the first half of the 20th century from J. A. Schumpeter (Gerguri & Ramadani, 2010; Rogers, 1998).

"The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates" as written by J. A. Schumpeter (1942/1994, p. 83). J. A. Schumpeter connected the process of innovation to capitalism, but from our current perspective, it can be taken as relevant regardless of the economic and political system.

From the microeconomic point of view, industrial organization covers the theory of R&D on a firm level. Jefferson et al. (2003) and Hall (1992) can be examples of such an approach. Those models focus mainly on firm's cost reduction designs, uncertainty concepts, or patent races using game theory during the analysis. In the models of market structures and changes due to technological progress, Arrow (1962) significantly contributed with concepts of resource allocation for innovations.

Macroeconomic complex usage of R&D in economics was delivered by R. Solow in the 1950s (Solow, 1956). In his famous model of economic growth, technological progress has its place. In the model, the potential of economic growth does not solely rely on the accumulation of capital or labor, but also on the "technological progress" created by the R&D activities. Taking the total growth, one can subtract parts of the growth created by labor and capital accumulation and still come up with some growth residual which cannot be explained neither by labor nor capital accumulation. This residual is due to the R&D activities. The technological progress in the model is taken as exogenous and is not however further explained.

Another model contributing to this topic is the endogenous growth theory model brought up by multiple economists, for instance P. Romer (1986) and R. Lucas (1988). The endogenous growth theories build the basis on microeconomics, where the households are maximizing utility and firms are maximizing profit. The technological progress here is understood as capital improvement delivered through education and physical capital enhancement. The investments into the capital improvement (both physical or human) exhibit positive spillovers and society benefits from it. Thus, a society which is investing into the capital improvement grows due to the investment itself and grows even more due to spillovers. This conclusion explains why the poor countries do not grow that fast as rich countries despite the theory of diminishing returns.

1.1.3. Types of R&D

There are multiple ways how the R&D topic can be divided into smaller categories based on the category specific properties.

Basic research, applied research, and development are already discussed in the definition of R&D itself. The Frascati Manual (OECD, 2015) sets that during the basic research the fundamental knowledge and ideas are gained. Applied research is prototyping the idea and trying out a specific usage. The development then leads to a production towards the end user and possible mass production on the market. When considering the output of R&D activities: (a) product; and (b) process innovations can be distinguished (Gerguri & Ramadani, 2010; also Shy, 1995). And we can find (i) drastic; and (ii) non drastic innovations in the special case of process innovation.

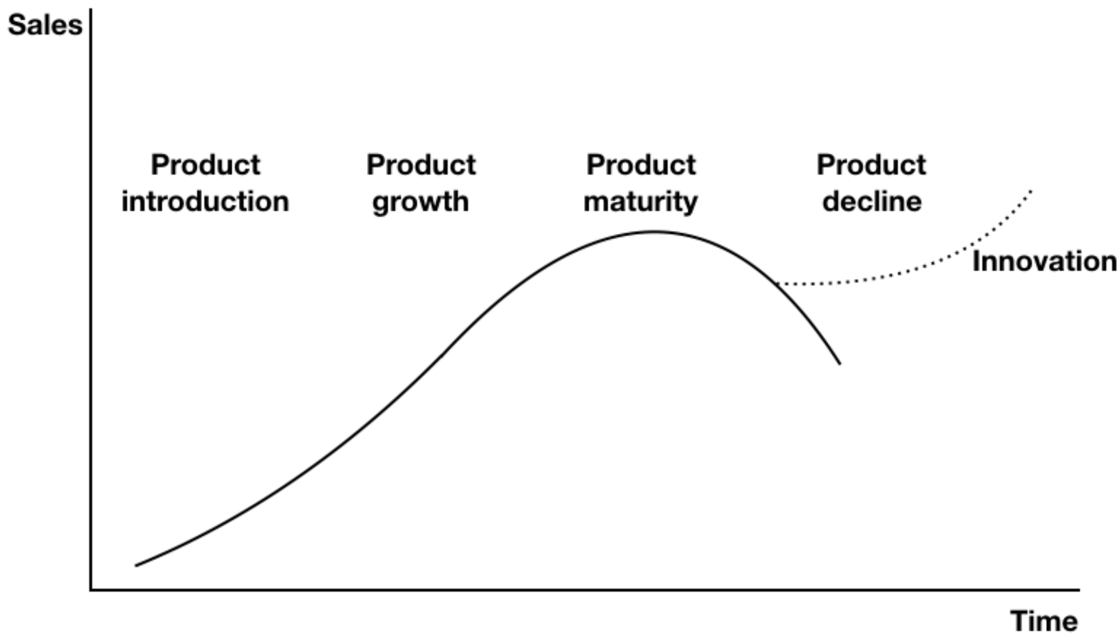
Product innovation

This type of innovation brings either new technologies for new / improved product creation or the new/improved product itself (a good or a service). By introducing new or improved product, one can gain a comparative advantage on the market or enter a brand new market. Figure 1 depicts the life cycle of a product. In case the product does not undergo an innovation, the sales drop off after the product maturity. However, the product innovation can resume the life cycle. This is adopted in exemplary way by the phone manufacturers during the last years. The phone model popularity fades after some time which triggers the manufacturers to release new phone model every year. An example of other product innovation is water resistant but breathable clothes (e.g. Gore-Tex membrane), smartphones and smart homes applications (e.g. Google Nest thermostats, Phillips Hue light bulbs).

Innovating the product does not necessarily mean that the innovation generates additional revenue to the producer. A few studies on the determinants of a success or a failure in product innovation can be for instance found in (Maidique & Zirger, 1984; Martin & Horne, 1993).

As Shy (1995) describes in the theory, the product innovation can be viewed as a tool for firm's cost-reduction. Before the innovation the new product is just potential, and its production costs would go to infinity. By innovating the product, the production costs go to a finite level which is lower.

Figure 1: Product life cycle with innovation



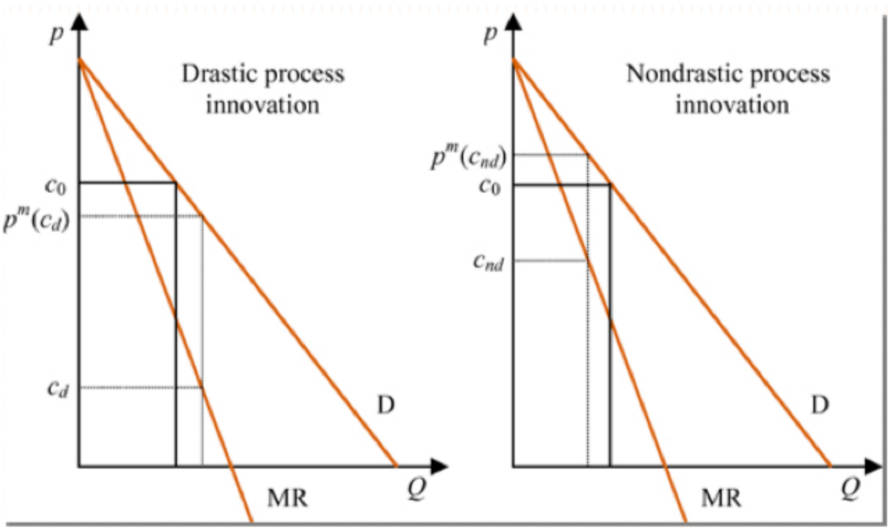
Source: author (based on Polli and Cook (1969))

Process innovation

Process innovation brings new technologies and methods to produce or provide the same product (a good or a service). In other words, the same product can be produced using a less expensive combination of resources or different resources. The example in today's world is an incorporation of information technology into firms' processes. To provide an illustrative example - the Czech company Rossum is selling a system with artificial intelligence to extract and process company's invoice data (Baudis, 2018). Using this product in one's company process, the company cuts costs by not having accountants to pay salary to, being faster when processing the data and being more accurate with less human errors.

In the economic theory, we also define drastic and nondrastic innovation. Suppose that there is a firm in perfect competition, and it is at its equilibrium. Figure 2 presents the situation with cost c_0 in both diagrams. Assume also that there is an equivalent company and it is a monopoly with depicted p^m as its price. A drastic innovation (c_0 drops to c_d) would end up in monopoly selling the product at its equilibrium with *lower* price than a firm in perfect competition without the innovation. On the other side, a nondrastic innovation keeps the monopoly with still higher price than the perfect competition market would otherwise have (Jackson & Smith, 2015; Shy, 1995).

Figure 2: Drastic and nondrastic innovation



Source: Belleflamme and Peitz (2010)

1.2. Schumpeterian environment

In the beginning of 19th century, the political economist J. A. Schumpeter analysed and described the connection between innovation and entrepreneurship. The concept of new combinations, new markets and organizational development has its place in the economic growth. These activities were marked as *innovations* and are brought by the entrepreneurs from within, using the inner business powers. Schumpeter viewed this economic development as circular flow in which the old is crushed and replaced by the new, so called the famous *creative destruction*.

The innovation in entrepreneurship is the core of a successful business as Schumpeter (1942/1994, p. 84) puts it *"...the competition from the new commodity, the new technology, the new source of supply, the new type of organization, ... This kind of competition is as much more effective that the other ..."*

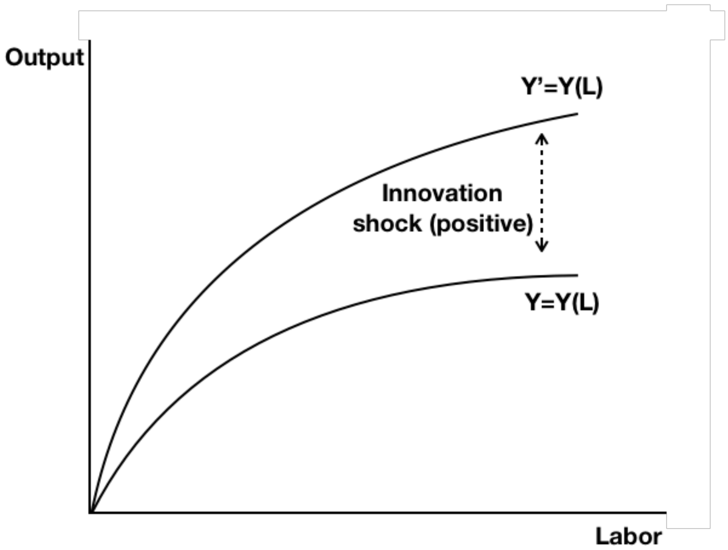
In the Schumpeterian environment the perfect competition concept is disrupted. If the company does not innovate, it will most likely be challenged on the market and the running business shall be destroyed. On the other hand, the successful innovator gains a reward in firm's positive profit, thus the perfect competition breaks, at least in the short run. There are a couple of instruments for the innovator to survive. One can either

- make new product, or
- implement new technology, or
- access new markets, or
- make organization changes, or
- integrate new source of supply.

These instruments serve the final output of the innovation as generally accepted here - the product and the process innovations (previously described in the Types of R&D chapter), pushing the cost down and changing the firm's production function as illustrated in the figure 3. This figure shows that with the same level of workers, the firm can produce more output (an upward shift of production function $Y \rightarrow Y'$ due to the innovation activities).

Besides studying innovation in the economics theory, Schumpeter also looked into the importance of small and medium companies (SME hereinafter) and marked them as the source of innovation (Schumpeter, 1939/1939, 1934/1983). The innovation was described as typical for newly established small companies with out of the box perspective of the market and production.

Figure 3: Change of production function due to innovation



Source: author (based on Solow (1957))

Elaboration of the topic pointed out several reasons why SME might not be the typical sector for R&D (Schumpeter, 1942/1994). The SME sector suffers from underinvestment due to market imperfections that favour large companies and monopolies. The corporations are able: (1) to diversify the risk investments over multiple company's projects; (2) to access the external finance resources easily or to find internal financing possibilities; and (3) to pay-off the investment faster as the production volume is high. None of the mentioned is easy for small companies to achieve. It is more expensive and riskier for the SME companies to undergo an innovation project and it is much easier for them to profit from the spillovers of R&D delivered by large companies.

Number of studies empirically tested the hypothesis of causal effect of firm size on the volume of R&D investments. Scherer (1965) concludes that innovation (measured by patents) grows with firm size, but less than proportionally and is not significantly related to the monopoly market structure. But when industry and other sector characteristics are taken into account, the relationship disappears (Cohen, Levin, & Mowery, 1987; Dosi, 1988). However, the current policies of the EU and of the Czech Republic addresses the hypothesis of Schumpeter with special SME and R&D support which is common among the EU member states lately (Becker, 2015).

1.3. R&D and firm's performance

This chapter aims to describe the main indicators of firm's performance influenced by the R&D activity. It also provides the literature overview on measuring the impact on the indicators and discusses briefly in theory the main variables chosen for the empirical study.

The research and development is considered to be the key driver of economic and productivity growth (Griliches, 1998). As a tool for decreasing the costs and scaling the production function, it also affects the ratio of turnover per input. The ratio, known as productivity, should then grow when an innovation is in place.

Several recent studies on European data discuss the impact of government subsidies with mixed evidence. The studies mostly report positive effect on productivity growth but only in the short term (Becker, 2015; Santos et al., 2016; Sissoko, 2011). Gustafsson et al. (2016) and Decramer and Vanormelingen (2016) also find a positive effect but in case of small companies only. Bernini and Pellegrini (2011) report positive effect on productivity growth in case of subsidized firms but smaller than for the non-subsidized firms. Some argue that productivity growth declines (Karhunen & Huovari, 2015) or the subsidy has no significant effect (Banai, Lang, Nagy, & Stancsics, 2017; Brachert, Dettmann, & Titze, 2018; Čadil, Mirošník, Petkovová, & Mirvald, 2018). In terms of a long run, the majority of studies detect no significant effect of public subsidies in R&D on productivity growth (Bergström, 2000; Brachert et al., 2018; Gustafsson et al., 2016).

Some authors dispute that when a subsidy is granted and the R&D is initiated, companies might need to rellocate resources to get to their production and cost equilibrium again

(Bernini & Pellegrini, 2011; Karhunen & Huovari, 2015). This triggers a short term decline in productivity until they reach the new optimum.

Radicic et al. (2014) and Santos et al. (2016) suggest that innovation policy results can be influenced by “cherry picking” principle. The subsidies are systematically provided to companies that exhibit more innovative activities and are expected to innovate successfully. The aggregate outcome (in terms of productivity growth) is then worse than it would be in case of a random selection of the subsidized companies.

Majority of studies also use firm’s profit (and related variables), and firm’s investment as a performance indicator. The value added as an observed variable is used for instance in studies of Cadil et al. (2018) and Karhunen and Huovari (2015). Other studies as Becker (2015), Karhunen and Huovari (2015) and Brachert et al. (2018) use the turnover as a financial performance indicator instead of profit with results of negative, positive and positive effect irrespectively. Another financial variable commonly used is volume of investments (e.g. Bernini & Pellegrini, 2011; Brachert et al., 2018; Gustafsson et al., 2016). The subsidies have a positive effect on investments in the studies but only in the short and medium term.

The last chosen main indicator of firm’s performance in this study is employment. The employment increase is part of the R&D subsidies programs such as the EU's Horizon 2020. It is expected that a company increases the number of employees as the people are key driver for creating knowledge and implementing innovation. Even though Becker (2015) finds negative yet statistically insignificant impact, other studies report positive effects in short and medium terms (e.g. Bernini & Pellegrini, 2011; Brachert et al., 2018; Karhunen & Huovari, 2015). Evidence in long term remains discussable.

1.4. Challenges and approaches of R&D public support concepts

It has always been a popular topic of discussion among economists whether the government and the public funds should or should not intervene in the market environment. This chapter aims to reiterate chosen concepts in the economic theory connected to the R&D investments and opens a discussion. Do have public subsidies in R&D significant effect in terms of a firm's performance or does the *laissez-faire* approach represent a better set-up?

1.4.1. Market imperfection and uncertainty

The perfect competition is built on several assumptions. Among others, the concept expects homogeneous product, perfect information, known utility and production functions and perfect mobility of the production factors. These chosen properties of perfect competition struggle where innovation plays a role.

The homogeneous product assumption can survive in some cases. If the company innovates its processes, the product itself does not change in core. Rather the price is changing, and the firm is able to compete with its price. But in case of product innovation, the homogeneity is questionable. The aim of the innovation is to bring new or improved product which is in contradiction with the statement. Nevertheless, this does not directly implicate the reason of having a public support.

A cause for public support might be found in the perfect competition market preconditions of perfect information and known functions. These condition consists of: (1) well known consumer's utility functions and; (2) producer's production function and it implicitly restricts uncertainty (Arrow, 1962). As Arrow further discusses, when a company wants to invest in its research and development, the outcome is not always certain and clear. R&D is mainly about producing knowledge and it is hard to create a market for it (due to characteristics such as indivisibility, unknown price, replication, allocation inefficiency, intangibility etc.) and thus there is a struggle for the R&D production inputs (e.g. human talent, "good day", "good place") and the activity bears a risk.

Illustrating on the production function, there are the known commodities on the input together with a "state-of-nature" which brings the unknown part. It can be a needed piece of information, a human talent, or others on the input side of the production. Then, the production function does not always result in a known output and the investors are discouraged. They would rather invest into less risky opportunities in order to maximize profit, assuming there are risk averse agents in capital markets due to scarcity of financial resources. Moreover Akerlof's (1970) informational asymmetry theory supports the financial misallocation as the investors can have biased information set contrary to the firm looking for finances and the risk assessment of the funding target is difficult to perform. All this leads to underinvestment in the free market with perfect competition. A further evidence that the SMEs are often lacking capital can be found in Hall (1992), or Himmelberg and Petersen (1994).

Only limited mitigations and solutions are offered. The firm can insure against the "state-of-nature" but it brings the moral hazard problem and the company would be tempted not to succeed given the fact that the "state-of-nature" has rather an endogenous characteristic here. Another solution is to diversify the risk within the company. This means that the company would run several independent small R&D activities and if one fails, the loss is not fatal to the company. Having said that, this solution could be feasible for rather large companies and corporations.

The mentioned tools describe the market's solution or the company's own solution. However, there is another possible solution - the government intervention. The government can bear part of the risk in the production and informational asymmetry and provide the needed investment for small and medium enterprises where the capital market does not provide enough due to aforementioned risks. In other words, the government could attempt to compensate for the market's failure.

1.4.2. Other frameworks and challenges

Other properties of firm's R&D can create obstacles when it comes to investments. Moreover, in case the public support is introduced it is always with doubts. Following description presents the frameworks and the challenges other than uncertainty widely discussed in connection to the innovation. First four concepts (1) principal-agent; (2) public good; (3) procyclicality; and (4) standard lock-in give some space for government intervention. They describe further reasons of a possible underinvestment into the R&D and time-wise suboptimal resource allocation where public support can be a solution. And in contrast the last three concepts (1) crowding-out and additionality;

(2) public choice theory; and (3) rent-seeking show potential challenges of public support and possible reasons to fail.

Principal-agent problem. The contracting between the company and the R&D investor can display the principal-agent problem. Kaplan and Stromberg (2001) empirically studied the characteristics of principal-agent in venture capital environment. The principal - as the venture capitalist - funds hopeful projects and rising companies, willing to maximise the profit, but has limited control over the activities. The study documents that the principal wants to closely monitor the activity and is significantly worried about the investment and willing to hand over the control to the company only once the performance and outcome rise. This finding shows how expensive investment in venture capital actually is, not only in terms of money but also in terms of time spent monitoring, effort, and others.

Public good. Innovation and knowledge production are sometimes considered as a commodity with externalities to the outside market. An idea itself is a nonrival good. Multiple agents can use the innovation without limiting the others on sources. Also, part of an innovation in a company can be observed outside the company in public (e.g. new product) and cannot be effectively excluded from others. It means that innovation can be partially considered as a public good which brings few issues to the potential investors. As the innovation is expected to bring a positive effect to the company (lowering costs, introducing new product) and a competitive advantage, others might try to replicate it (Cooter & Schäfer, 2012; Gustafsson et al., 2016). By replicating the innovation by others, the first innovator losses the advantage and profit. In the short run this can be partially solved by patents. Similar theory is behind the spillovers to the society and other competitive companies (Arrow, 1962; Gustafsson et al., 2016). The innovation can serve others as a tool for market advantage even though they will not implement the innovation by themselves or use it as a basis for their own innovation activities. Moreover, the society can benefit from bringing competitiveness to the markets. But in these cases, none of the mentioned can be collected by the innovator as a profit nor can be protected by a patent. The fact that innovator cannot exploit the full benefit of his activity does not always repel the investors.

Procyclicality. Economic literature suggests that investments into R&D are procyclical. The empirical studies, however, come up with acyclical patterns (Barlevy, 2007). Following reasoning is behind the acyclicality.

1. Let's assume that a firm has finite financing possibilities and it can invest either in producing an output or to producing innovations. Then the opportunity costs of R&D can be described as the firm's forgone output. During the economic recessions the output declines which means that the opportunity costs of R&D decline. In such a case the company is willing to invest more to R&D (Ouyang, 2011).
2. It has been shown that labor productivity falls during recessions (Griliches, 1990). And the major hypothesis in this study says that innovation increases the labor productivity and thus economic growth. If the agents on the market want to improve the labor productivity and help the economy to recover from the recession, support and investments into the R&D will occur. This is the social optimum path.

And yet the study of Barlevy (2007) shows the R&D activities as procyclical in empiria. Firm's profit decreases in recessions and if the company wants to exploit the most from the technology update, it will wait for the economic expansion when the profits grow and firm gets more (Shleifer, 1986). This theory is elaborated by Francois and Lloyd-Ellis (2003) stating that in this case, the company would run the R&D in recessions and save the implementation to the economic expansion. But Barley further argues that due to firm's impatience the intertemporal substitution can be ruled out by the preference of higher profit and R&D investment in recession will not occur. Also the boom during economic expansion can be enlarged due to a spillover effect (Čadil et al., 2018).

Standard lock-in. The R&D has general positive effect for the public and provides spillovers. A company can build further innovation based on knowledge brought by another company. By doing so it can start locking-in on a standard (Cantner & Vannuccini, 2016). But standards might kill other innovations which would exist if the standard was not there. Due to the standardisation these innovations are much more expensive and have higher risk involved. The R&D underinvestment then occurs based on the theory already described above.

Crowding out effect and additionality. What if the public funding puts off the private investments? Does it trigger some additional investments, or does it substitute the private financial resources? The scientific literature provides mixed evidence on the topic of additionality. Meta-analysis on European Union member states shows that public funding does not put off the private investments completely. There is (in the majority of the studies) at least some additionality effects (Becker, 2015). For instance additional 0.28 private Euro for one publicly funded Euro has been observed in the study of Fier and Czarnitzki (2005) in Germany. Gorg and Strobl (2007) and Wallsten (2000) provide evidence that large companies tend to be associated with crowding out effect. On the other side Gorg and Strobl (2007) also argue in nonexistence of the crowding out effect in case of small domestic companies which tend to lack the finances for investments.

Public choice. The government resource redistribution is done by officials and state representatives. These are not paid based on the success of the money redistributed and thus their target might differ from the economic social optimum (Buchanan & Tollison, 1984; Gustafsson et al., 2016). The officials might have other interests such as being re-elected. This gives us a potential misallocation of financial resources to R&D and gives us a possibility of ineffective public support based on incentives (e.g. lobbying) other than economically optimal.

Rent-seeking. From the perspective of the entrepreneurs, some only seek the rent of subsidy money (Tullock, 1967). In case the companies are manipulating the political programs to get financial support, further resource misallocation occurs. The rent-seekers look for a profit but do not compensate with any value added and do not contribute to productivity.

1.5. Public support in the Czech Republic

Companies in the Czech Republic have two fundamental choices for getting public support. It is either to apply for funding from the state budget of the Czech Republic or request European funding (or both). This chapter shall provide a basic overview of the set-up and show some of the facts and statistics.

1.5.1. Institutional foundation

The public support for research, development and innovations has been captured in both Czech national and European legislation. The Czech legislation describes the support in the R&D Public Support Act[2] where among others it distinguishes public tenders, competencies, auditing, public subsidies rules and project definitions. It also sets the institutional coordinators and direct providers of the support to the end recipient. The legislation further contains the Act on the Regulation of Certain Relations[3] adjusting the coordination with European Union as EU widely supports the R&D funding too. The Horizon 2020 is the European biggest R&D program supported by the European parliament and European Commission within the Europe 2020 Strategy, providing public financial resources in addition to the ones invested privately by the companies. During the period 2014 - 2020, the stakeholders plan to invest €80 billion in EU member states. They expect sound GDP growth, increasing employment, more breakthroughs, ideas and other. The budget is known as the European Structural and Investment Fund.

The Czech law also provides specific support platform for non-large companies in the SME's Public Support Act[4] where part of the Act focuses on innovation, R&D investments and competitiveness using wide scale of tools such as direct subsidies, loans or lower interest rates.

1.5.2. State public support schemes

The Czech legislation establishes multiple instruments for a public support (e.g. favourable loans, lower interest rates, guarantees, and deductions) with two main policies widely used: (1) direct subsidies to raise the private marginal rate of return on investments; (2) tax credits to reduce the cost of R&D (David, Hall, & Toole, 2000;

[2] The Act No. 130/2002 Coll. Act on the Research and Development Support from Public Funds and on the Amendment of some Related Acts. Also, the further elaboration in The Act No. 211/2009 Coll.

[3] The Act No. 215/2004 Coll. Act on the Regulation of Certain Relations in the Field of Public Support and on the Amendment of the Act on Support of Research and Development

[4] The Act No. 47/2002 Coll. Act on the Public Support of Small and Medium Enterprises

Liu, 2013). These incentives are also commonly used in multiple other EU countries (Becker, 2015; Liu, 2013).

In 2016, Czech Republic government spent €1.091 billion (which is 0.61% of GDP) from the government budget in R&D investments using the direct subsidies policy (CSO, 2017) and € 93 million using the tax credit (CSO, 2018a). The direct subsidies thus operate with much bigger budget and serve as primary redistribution system. About €100 million out of the direct subsidies budget went to private sector which is less than 10%. The majority of the funding is granted to universities, public research institutions and the Academy of Science (CSO, 2017).

The government budget is distributed among the recipients through dedicated institutional organizations, namely:

- government ministries,
- Academy of Science,
- Czech Science Foundation,
- Technology Agency (TA CR hereinafter),
- regional offices,
- other minor providers.

Each provider has its own operational programs under which it provides bundles of the assigned budget. The aims and dating differ but all are established based on the guidelines described above. In the period of 2014 - 2017, 72 programs were active with total budget of €4.419 billion out of what is €468 million provided to the private sector (CSO, 2017). The programs are subject to public tenders and the tenders are announced in rounds during the active time period.

1.5.3. Current evaluation of subsidy programs

The government of the Czech Republic is regularly provided with a report of the programs' outcomes and their evaluation. The evaluation is mainly built on descriptive statistics (Government of the Czech Republic, 2015).

Examples of the key variables are:

- number of published studies and its quality based on peer reviews and type of publication,
- number of patents, technical designs etc.,
- prototypes,
- difference between the benefits and the costs.

Such an evaluation cannot bring an accurate subsidy efficiency description. The provider does not see the causal effect of the policy, i.e. what would happen if the policy was not there and how the actual policy benefits the society and the recipients considering also the effects of the other relevant variables.

In recent times some of the economists started to elaborate such an analysis using data on Czech Republic with inspiration in studies abroad. Moreover, the dedicated program providers (mainly the aforementioned TA CR) started to work out new methodologies based on the counterfactual analysis where the analysis compares subsidized and non-subsidized companies and their performance over time (Horák, 2016; Potluka & Špaček, 2013).

Sidorkin and Srholec (2017) studied the effect of public subsidies granted within three different programs: (1) "ALFA" managed by TA CR; (2) "TIP" managed by the Ministry of Industry and Trade of the Czech Republic (MIT hereinafter); (3) "IMPULS" from the same ministry. They suggest in the hypothesis that the subsidy programs have a positive impact on the intellectual property registration. As for the methodology the authors used propensity score matching together with conditional difference-in-differences (DiD hereinafter), which is currently the mainstream method for policy evaluation (e.g. Bernini & Pellegrini, 2011; Karhunen & Huovari, 2015; Sissoko, 2011)). The results support the hypothesis in case of programs "TIP" and "ALFA" (with some limitations due to time lag of the data) but only on case of local patent registration in the Czech Republic. It is not proven that abroad effect (i.e. patent registration in other countries than the Czech Republic) statistically differ from zero. Same conclusion is made for the "IMPULS" program both locally and abroad.

The impact of the “ALFA” program is evaluated in another study provided by Horák (2016). The authors observe the effects of the subsidy on firms’ ROA, ROE and ROS. These variables are chosen as the company's performance and competitiveness indicators. Using again the propensity score matching together with DiD, the study shows a positive impact of the subsidy on the ROA and ROS and a negative on ROE due to the own capital increase compared to the profit.

The newest studies on this topic using the same methodology in the Czech Republic come from two scientific groups. Firstly, Čadil et al. (2018) published a study on a program supported by the TA CR running in the 2007-2010 period. The authors conclude that there is a positive impact of the subsidy on intellectual property registrations. On the other side, the effect on value added and productivity lacks significance. Secondly, Dvouletý and Blažková (2019) focused on the subsidies granted to companies in the food industry from the Operational Program Enterprise and Innovation budget running in the period 2007-2013. The results back the hypothesis about the positive impact of the support on the labor productivity but also show a negative impact for total factor productivity.

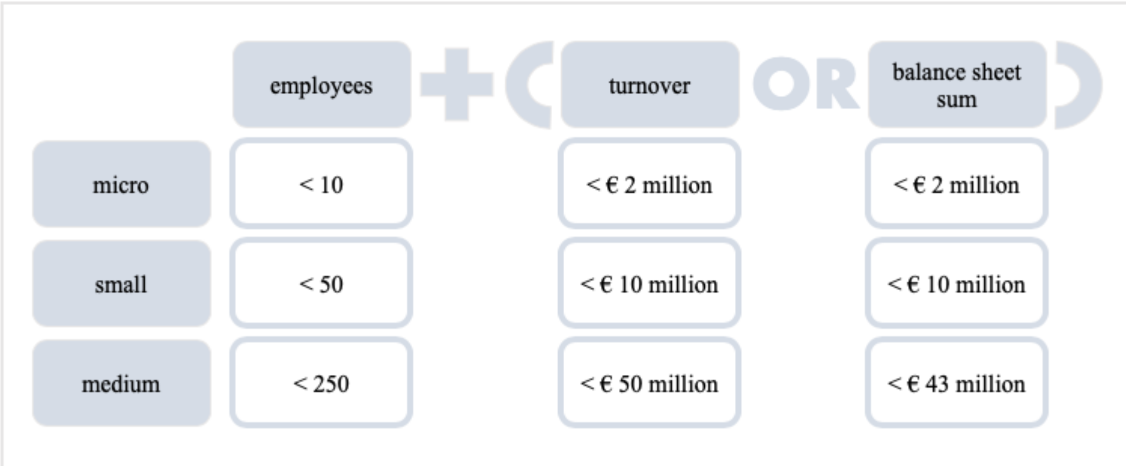
Other studies focused on the R&D subsidies effect in the Czech Republic. Palguta and Srnholec (2016) studied the “ALFA” program (organized by TA CR) using the regression discontinuity methodology. Their results support the additionality impact of the public subsidy to the private investments but to the sample heterogeneity the causality is not proven. Petkovová et al. (2015) also study the program of “ALFA” using simple DiD method. Based on their results the subsidy does not influence the financials of the recipients.

1.6. Introduction to Czech SME Sector

The definition of SME in the Czech Republic corresponds with the EU interpretation (MIT, 2018). Several variables determine if a company belongs to SME sector (EU & Directorate-General for Internal Market, Industry, Entrepreneurship, and SMEs, 2017): (1) number of staff headcount covering all personnel participating in the activities of the company except interns working based on bilateral contract with a school and personnel on parental leave; (2) volume of company’s revenues without any taxation;

(3) balance sheet totals, e.g. sum of actives; (4) outside relations and partnerships evaluating the stakeholders matrix and ownerships. The figure 4 presents the borders for micro, small and medium companies in terms of staff headcount, turnover and balance sheet totals. To comply with SME classification, a company has to have less than 250 staff headcounts, and either turnover shall not exceed €50 million or balance sheet totals is under €43 million. The condition regarding outside relations evaluates the independence level of the company. Generally said in case the company's external relations (defined as equity shares or voting rights) reach 25%, the company is not with sufficient independence level to be considered an SME. External relations meaning owning equity shares (or votes) of other companies or be owned by other companies. The investment companies, universities and research centres are excluded.

Figure 4: SME definition and breakdown

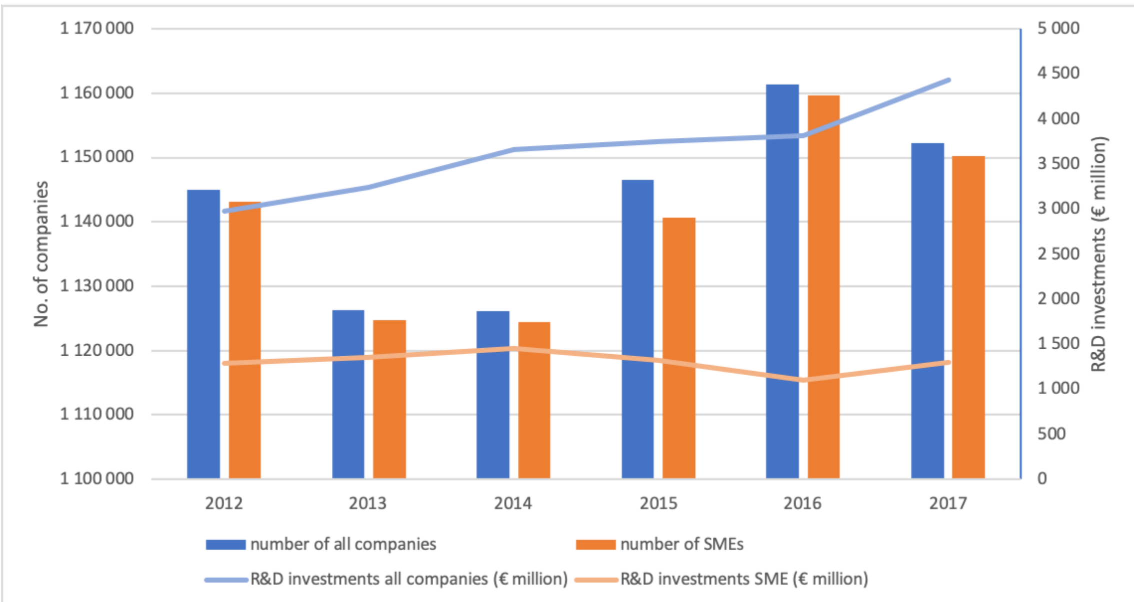


Source: author (based on EU & Directorate-General for Internal Market, Industry, Entrepreneurship, and SMEs (2017) data)

The SMEs have an important place in the Czech economy. The share of SMEs on the total number of entrepreneurs is 99.8% as of 2017. The total number of the SME is about 1.1 million entrepreneurs. The value added by SME reaches 54.6% and the share of employees in the private sector is 58%. The Czech Republic supports the sector together with EU using operational programs specific for SME. The Czech Republic issued The Support Concept for Small and Medium Enterprises in the Period of 2014 - 2020 (MIT, 2013) and part of the support should also be provided to innovations. R&D is marked in this concept as an activity with high value added and with further potential to exploit and is also established by the MIT concept as one of the strategic policy targets. The concept aims (beside others) to support the venture capital, start-up incubators, intellectual property registration and related activities.

The total investments in R&D in SME sector reached €1.292 billion at the end of the year 2017 as depicted in the figure 5. In 2015 and 2016 there was a brief decline in the investments although the number of companies increased. On the other side the total R&D investments in large companies has increased steadily during the last 5 years and the difference between SMEs' and large companies' investments grows. As for the specifics of venture capital, (OECD, 2018) reports a decreasing trend of venture capital investments in SME since 2008.
The structure of the finance sources does not change dramatically, most of the sources are provided from private investments. The participation of the government on financing R&D in SMEs is about 6% - 13% during the last five years with a slight decreasing trend (CSO, 2018b).

Figure 5: Trends in R&D investments



Source: author (based on CSO (2018) and MIT (2018) data)

Multiple studies focused on evaluating the effect of public innovation subsidies for the SME sector. As for the Czech Republic, Dvouletý and Blažková (2019) targeted program supporting SME as priority and its effect on total factor productivity with inconclusive results. Palguta and Srnholec (2016) studied subsidy program for all companies but found significant positive effect of the subsidy on private investments into R&D for SME sector compared to insignificant effect for large companies.

2. Empirical part

Based on the discussion in the first part, the scientific literature on this topic already exists but only a few of them focus on innovation subsidies and their effect on competitiveness and firm's productivity (Čadil et al., 2018). The aim of this study is to bring another piece of evaluation of direct R&D subsidies in the Czech Republic. The evaluation focuses on the R&D connection to competitiveness and productivity, particularly on the difference in the effects on SME sector and large companies. A unique dataset is used to provide an evaluation of some still ongoing subsidy programs and its interim results. Such an approach can serve the policy makers to review the subsidy assigning strategy and grant criteria.

For empirical evaluation several steps are conducted. Firstly, the dataset is prepared and pre-processed applying relevant filters and using matching technique. Secondly, the impact of the subsidy is measured using difference-in-differences method. Following subchapters describe the details together with the model and observed results.

2.1. Data

2.1.1. Data sources

The information about the recipients of public funds is expected to be transparent and accessible for any citizen. The data have been tracked by the Czech Government office in the Information System of Research, Experimental Development and Innovations so called IS VaVaI. The system was established in 1993 and has been collecting all data regarding publicly funded R&D projects in the Czech Republic. This data source provides only part of the necessary information. It gives us a basic information about the companies which are supported from the public funds - the treated group - and further information about the support itself, e.g. amount of money provided, project documentation, and outcome description.

Other necessary information has been acquired using Albertina database provided by Bisnode. This database maintains data about the entrepreneurs and their financial statements. The data for the control group, such as number of employees, productivity, sales etc., were created using this database. Further information about the treated group is acquired using this database too. For the treated group the company Identification Number (IC) is used to match the records.

2.1.2. Dataset creation and data pre-processing

Applying relevant filters. During the dataset creation several filters are applied to obtain relevant data. Only companies owned privately are taken into account and the firms must be active and must report their financials[5] during the observation time period of years 2013 - 2018. The observed public support itself is ongoing during the 2014 - 2016 time period. Thus, the year 2013 is chosen as prior support observation year, and the years 2017 and 2018 are post treatment observations. It is important to mention that the treatment can happen in one year only (for instance 2014), or in multiple years during the given period (for instance 2014 and 2015). In such cases the post treatment years are adjusted to cover all the years after receiving the subsidy (2015, 2016, 2017, and 2018; 2016, 2017, and 2018 respectively for the mentioned examples).

To avoid bias from other subsidies not directly observed in this study, only companies not receiving a subsidy after the year 2016 and 2 years prior to the observation period are covered in the dataset. Such subsidies can distort the post treatment estimates. Furthermore, the subsidy programs are analysed and filtered. Between 2014 and 2016, 66 programs supporting R&D activities have been financed by the government of the Czech Republic. The aims of the programs are wide, from supporting the tertiary education to applying innovations in the national defence of the Czech Republic. Therefore, only part of the programs is suitable for this study. Following logic is applied to filter out irrelevant programs:

- programs focused on innovation in non-private companies are filtered out (e.g. national defence, government administration),

[5] The company has to have at least 75% of the observed values reported during the years 2013 - 2018.

- programs supporting tertiary education granted to schools or students are filtered out as the connection to a private company where the effect would occur is not known,
- programs backing basic (theoretical) research are filtered out as without implementation the gained knowledge does not have an impact on firms' performance yet.

In other words, only programs encouraging actual execution and application of innovations in the private sector are relevant for the purpose of this study. The final list of the chosen programs consists of 30 programs and can be found in the appendix D.

After obtaining the information about treated group, the control group was further filtered based on 2-digit NACE codes. If a company in the control group has the same 2-digit NACE code as at least one in the treated group, it appears in the dataset. Remaining companies are not further processed.

Combining the two data sources and applying the first round filters a unique dataset of 140 353 firms has been created as the data basis. In total 533 firms in the treated group and 139 820 in the control group as depicted in table 1.

Table 1: Observed firms' volumes

Group	Number of unique firms
Treated (subsidised)	533
SMEs	461
Large enterprises	72
Control (non-subsidized)	139 820
SMEs	138 763
Large enterprises	1 057

Source: author (based on data from Albertina and IS VaVaI databases)

Pre-processing by matching. The assignment of a subsidy consists of several steps. The company has to apply and fulfil the application form. The application is then revised and assessed by the institutional provider and it is decided about the result. Thus, the subsidy allocation is not random, and this brings some issues into the empirical evaluation. Firstly, the firms choose to participate so they self-select. Secondly, the subsidy provider evaluates the applications and decides about the granting. Such matter of fact generates selection bias in the sample and distorts the effect measure. The firms which apply for the subsidy can be systematically different in observable and unobservable variables. The outcomes of the two groups differ due to other reasons than just the treatment. It is then difficult to impossible to detach the effect of subsidy allocation known as selection bias from the effect of the subsidy which is analysed.

The observed treatment effect of the subsidy is presented as (Heckman, 1979):

$$E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0] = E[Y_{1i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0] =$$
$$= \{E[Y_{1i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0]\} + \{E[Y_{0i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0]\} \qquad (1)$$

The first part is the average treatment effect of the subsidy and the second part is selection bias. The aim is to reduce the selection bias to zero to have results of good quality.

To address this issue and reduce the bias, comparable groups (treated and control) of firms need to be created. These comparable groups can be understood as statistical twins. To achieve this the coarsened exact matching (CEM hereinafter) technique is used (Brachert et al., 2018; Gustafsson et al., 2016; Iacus, King, & Porro, 2012; King & Nielsen, 2019; King, Nielsen, Coberley, Pope, & Wells, 2011; Tingvall & Videnord, 2018). This technique helps to design an appropriate control group with similar characteristics to the treated group and outperforms other matching techniques such are propensity score matching and Mhalanobis distance matching (King et al., 2011). For each of the treated observations (a subsidized firm) it matches control observation (a non-subsidized firm) on the chosen control variables, also called covariates. Unlike the propensity score matching CEM does not estimate the probability of being selected. CEM approach matches the similar observations using pre-defined strata. Based on how close the coupled (control and treated) observations are, it gives them a weight.

Table 2: Summary statistics of treatment and control groups

	Mean	Median	Std. Dev.	Observations*
Treatment				
Number of employees	227.0	66.0	660.9	2 655
Wage cost per employee	13.9	12.5	16.8	2 606
Total sales	30 857.6	3 872.2	167 124.2	2 655
Total capital stock	9 330.9	886.7	55 988.4	2 655
Total value added	6 437.5	1078.1	27 007.5	2 655
Total amount of subsidy received	348.9	217.0	1 026.2	533
Control				
Number of employees	24.0	4.0	144.0	643 064
Wage cost per employee	9.7	7.8	28.4	205 248
Total sales	2 720.9	139.9	39 388.0	643 064
Total capital stock	1 252.4	52.9	18 363.4	643 064
Total value added	186.9	23.7	41 348.2	643 064

Note: Monetary values are presented in € thousands. * Observation = combination of firm-year.

Source: author (based on data from Albertina and IS VaVaI databases)

The descriptive statistics from table 2 show that the treated firms are bigger than the non-treated on average and have better access to capital. This outcome does not support the theory discussed in the first part of this study. But such a conclusion should not be made based on descriptive statistics alone as multiple misinterpretations can happen. For instance, the distribution of the values can differ which skews both the average and the median. Also, the groups are not yet matched so the comparability is disputable.

The control variables' observations from the period of 1 year prior to the first subsidy occurrence is used for matching (Tingvall & Videnord, 2018). The timing here is important as the firms can anticipate the subsidy and adjust their decisions and behaviour *ex ante*. The subsidy allocation is known and confirmed prior to the actual investment. This means that the company can undertake steps they would not do if they did not get the subsidy. E.g. the company can hire people or change the structure awaiting the money. This is known as Ashenfelter's dip and if the estimation is not adjusted accordingly, the accuracy of estimated outcome is likely to be compromised and distorted upwards (Gustafsson et al., 2016; Karhunen & Huovari, 2015).

The choice of covariates for matching is inspired by the existing literature to ensure the variables relevancy. The categorical variables are matched exactly (Brachert et al., 2018; Gustafsson et al., 2016). The chosen covariates are listed in table 3.

Table 3: Covariates used for matching

Categorical variables	**Description**
Industry	2-digit NACE code
Region	Czech regions (14)
Continuous variables	
Firm's size	Number of employees
Firm's age	In months until the end of the year 2013 (prior subsidy year)
Capital stock	Natural logarithm of physical (tangible) assets, ln(K)
Value added	Natural logarithm of firm's value added, ln(Va)
Competitiveness (Productivity)	Natural logarithm of labor productivity, ln(Lp), calculated as value added divided by the number of employees

Source: author

To see how imbalanced the dataset is, the $\iota_1$statistics measuring the overall imbalance (Iacus et al. 2008) is calculated. The distance between the treated and control group based on the chosen variables is depicted in L_1column in table 4. The L_1represents the balance of covariates with zero indicating perfect balance (i.e. there is a lack of difference between treated and control observations in the specific category up to the coarsening) and one indicating complete separation. The other columns describe the difference in means and the difference in the distributional quantiles - min, 25th, 50th, 75th, and max irrespectively. To be able to interpret the results, the matching is prepared, and the outcomes are then compared.

Table 4: Imbalance measurement

	L1	Mean	Min	25%	50%	75%	Max
Firm’s size	0.508	178.600	1.000	9.000	59.000	127.000	-2 502.000
Firm’s age	0.269	46.800	3.000	67.000	75.000	37.000	-113.000
ln(K)	0.444	2.425	3.228	2.300	2.832	2.425	-0.656
ln(Va)	0.488	2.148	4.257	2.205	2.199	2.243	-1.607
ln(P)	0.266	0.451	4.339	0.569	0.386	0.228	-2.950

Source: author (based on data from Albertina and IS VaVaI databases)

2.1.3. Matching results

In order to support the matching algorithm with the market characteristics that are not necessarily observable based on data, specific cut points for employment variable are defined respecting the division of micro, small, medium and large enterprises. These cut points help to capture characteristic data groups market wise. The companies will then be matched within the defined interval - i.e. companies with number of employees in the 0 -10 range will be evaluated together if they are a successful match. The other ranges defined are 11-50, 51-250, and 251 and more.

The rest of the data are matched using automated CEM algorithm with industry and region variables matched exactly as mentioned in the methodology description. The final matching results are depicted in table 5.

Table 5: Matching summary

Number of strata		14 924					
Number of matched strata		346					
	0 (control)	1 (treated)					
All	139 820	533					
Matched	7 292	396					
Unmatched	132 528	137					
	L1	**Mean**	**Min**	**25%**	**50%**	**75%**	**Max**
Firm’s size	0.092	1.004	1.000	-2.000	-2.000	-2.000	-53.000
Firm’s age	0.084	2.534	1.000	8.000	9.000	-1.000	-1.000
ln(K)	0.088	0.056	0.105	-0.017	-0.094	0.081	-0.063
ln(Va)	0.071	-0.107	-0.349	-0.028	-0.062	-0.023	-0.098
ln(P)	0.151	0.002	0.036	-0.026	0.007	-0.057	-1.433
Industry	2.2e-16	-5.7e-14	0	0	0	0	0
Region	2.1e-16	-1.4e-14	0	0	0	0	0

Source: author (based on data from Albertina and IS VaVaI databases)

The matching results show that the L_1statistics improved in all the covariates compared to the initial imbalance estimates. This implies that the matching processing is successful, and characteristics of the treated and control group are more similar. There is also a decrease in the mean difference for the covariates. Another outcome of the matching is reduction of the number of observed firms in the sample. From the initial dataset with 533 observed companies, the matching dropped 137 observed companies as the algorithm did not find a suitable candidate from the control group for coupling. Thus, the method provided 396 observed and 7 292 control companies which are better balanced and will be used for further analysis together with the weights which have been assigned to them.

Table 6: Mean values for dependent variables

Dependent variable	All	Subsidized firms	Matched control firms	Matched subsidized firms
Employment	25.0 (155.1)	227.0 (660.9)	26.2 (130.5)	134.9 (438.0)
Sales	2 862.9 (41 091.9)	30 857.6 (167 124.2)	4 912.0 (34 299.2)	16 349.8 (82 733.6)
Productivity	22.6 (63.7)	27.1 (23.7)	27.2 (46.7)	25.5 (21.9)

Note: Monetary values are presented in € thousands. Standard deviation is shown in parenthesis.

Source: author (based on data from Albertina and IS VaVaI databases)

The comparison of mean values of the outcome variables is presented in table 6. For each of the variable - employment, sales, and productivity I compare means of 4 different categories. In the first two columns I observe all the firms and subsidized firms only before undergoing the matching. The last two columns show means of control group and treated group after the matching. The means of matched groups are closer than the mean of groups before matching. This indicates that the treated and control groups are more similar and more suitable for measuring the actual subsidy effects. Also, the measured standard deviations lowered. This can indicate that matching has dropped out the extreme observations.

2.2. Estimation method, model, and hypothesis

2.2.1. Estimation method

For the empirical evaluation itself the difference-in-differences method is applied. This method estimates the causal relationship between the R&D subsidy and observed variable, in this case productivity, employment and sales. It enables to quantify the effect of subsidy itself compared to a situation in which the subsidy is not hypothetically granted. By comparing the outcomes of companies with and without subsidy, before and after it is granted, other effects such as time trends and institutional changes are eliminated. Using this method, the average difference between treated and control group over the year of treatment can be estimated. The DiD is widely used and recommended for policy evaluations (Bergström, 2000; Bernini & Pellegrini, 2011; Brachert et al., 2018; Čadil et al., 2018; Callaway & Sant'Anna, 2018; Gustafsson et al., 2016; Karhunen & Huovari, 2015; Sissoko, 2011). Together with the used matching method the endogeneity related to selection bias is reduced and the result estimates are expected to be accurate.

2.2.2. Model

For the effect's estimation the following general model is suggested:

$$y_{it} = \alpha + \beta X'_{it} + \gamma Treatment_{it} + \lambda PostTreatment_{it} + \rho_r + \nu_n + \theta_t + \varepsilon_{it} \quad (2)$$

The model is estimated for each outcome variable *y*, for firm $i = 1, \dots N$, in time $t = 1, \dots T$. On the explanatory side of the formula, $\beta X'_{it}$ stands for a vector of control variables, ρ_r are 2-digit industry control dummy variables, ν_n are regional control dummy variables, θ_t are year dummy variables, and ε_{it} stand for an error term.

The effect of treatment itself is captured in $\gamma Treatment_{it}$ term where *Treatment* is dummy variable for *t* year(s) where the subsidy took place in a firm *i*. The consecutive effect is captured in the $\lambda PostTreatment_{it}$ with *PostTreatment* defined as a dummy variable for *t* year(s) after the treatment took place in a firm *i*.

The description of exogenous and endogenous variables can be found in table 7. The capital stock describes the firm's access to capital and stands on the input side of the production function. The wage costs are also part of the firm's input and provide information about labor quality. In the model estimation this variable stands as a proxy for skilled labor. If company has access to subsidy and hires more skilled employees, this variable is expected to rise (Gustafsson et al. 2016). Firm's age describes the maturity of the firm and is covered in the model as a proxy to catch effectiveness of the firm due to "learning-by-doing". Majority of the variables is used in their natural logarithm to provide the outcomes as marginal effects in percentage form. The logarithm form also provides smoother distribution of the variables meaning there will be a reduction in impact of the observation outliers. This is convenient given the nature of the data.

Table 7: List of variables

Variable	Description
Employment	Natural logarithm of number of employees
Sales	Natural logarithm of total revenues
Productivity	Natural logarithm of value added per total labor (employee)
Capital stock	Natural logarithm of physical (tangible) assets
Wage	Natural logarithm of average monthly wage rate per employee
Industry	Dummy variable for 2-digit NACE code
Region	Dummy variable for region
Year	Dummy variable for years

Source: Author

Additional two models are also estimated to analyse the effects of subsidy closer.

Following model explores the effect of subsidy in separate years after receiving the subsidy:

$$y_{it} = \alpha + \beta X'_{it} + \gamma Treatment_{it} + \sum_{r}^{4} \lambda_r \, PostTreatment_{itr} + \rho_r + \nu_n + \theta_t + \varepsilon_{it} \quad (3)$$

The term $\sum_r^4 \lambda_r \, PostTreatment_{itr}$ captures the post treatment effect year by year. Maximum number of post treatment years is four and that is for companies receiving subsidy only in 2014. The post treatment years are therefore 2015, 2016, 2017, and 2018.

And the last model evaluates the impact of subsidies specifically for SMEs:

$$y_{it} = \alpha + \beta X'_{it} + \sum_{n}^{4} \gamma_n \, Treatment_{it}\eta_{itn} + \sum_{n}^{4} \lambda_n \, PostTreatment_{it}\eta_{itn} +$$
$$+\rho_r + \nu_n + \theta_t + \varepsilon_{it} \quad (4)$$

In this model the η_{itn} as a dummy variable is introduced. This variable distinguishes whether the observation belongs to a group of micro, small, medium, or large companies as defined in the first part of this study. This model is firstly estimated for each of the groups and later on for two groups – SME and large companies (omitted dummy).

2.2.3. Hypothesis

As discussed in the first part of this thesis, there are three areas to focus on when evaluating the effect of R&D on firm's performance. Based on the theoretical discussion following specific variables are chosen: (1) employment; (2) sales; and (3) productivity per labour cost. Employment serves as an input variable and describes the resources growth. Sales show the output performance, and product (or market) achievements. Together with productivity per labor cost these variables capture firm's competitiveness and illustrate well the company's growth (Delmar, Davidsson, & Gartner, 2003; Tingvall & Videnord, 2018). There is an estimated model for each of the observed variables.

Employment. People are the key resources for innovation production, from having an idea up to implementing the idea into practise.

In the beginning of the innovation process (i.e. short term) a positive impact of R&D on employment is assumed (Bernini & Pellegrini, 2011; Brachert et al., 2018; Karhunen & Huovari, 2015; Tingvall & Videnord, 2018).

The employees create the idea, test the idea and then apply it to the company's business. But after the innovation implementation the effect is not clear (Becker, 2015; Tingvall & Videnord, 2018). The reason behind can be the *cost-structure-changing* property of R&D. If an innovation is *cost-cutting* and focuses on automatization, the impact on the number of employees is clearly negative. On the other hand, if an innovation creates new product or helps the company to enter new markets, the expected effect on employment is positive. Therefore, the long term impact is unclear.

Sales. The firm's performance is commonly measured by sales or value added (Becker, 2015; Brachert et al., 2018; Čadil et al., 2018; Tingvall & Videnord, 2018). Firms' sales as another performance indicator is used in the models.

The effect of a R&D subsidy on firm's sales is expected to be positive as the subsidised R&D brings new opportunities towards the company increasing the company's revenues (Brachert et al., 2018; Karhunen & Huovari, 2015; Park, Lee, Moon, Kim, & Kwon, 2018).

The new opportunities consist of: (1) entering new markets, and introducing new products directly increasing the number of sold units; (2) using new technologies, integrating new source of supply, alternating input structure, and increasing production efficiency giving the company better space to produce on its optimum and adjust the price (based on the firm's supply elasticity) to increase its revenues.

Productivity. The main firms' performance measure in this study is adjusted labor productivity (Bergström, 2000; Brachert et al., 2018; Čadil et al., 2018; Gustafsson et al., 2016; Karhunen & Huovari, 2015; Tingvall & Videnord, 2018). This indicator covers the measurement of competitiveness and is directly influenced by innovation activities. If an innovation changes cost structure and scales the production, productivity must change as a consequence as it is the ratio of sales to costs. For the purpose of this study productivity defined as value added per labor (i.e. number of employees) is used (Tingvall and Videnord 2018).

A firm's productivity is assumed to be positively affected by R&D subsidies granted to the firm in the medium term (Becker, 2015; Gustafsson et al., 2016; Sissoko, 2011). Short term effect is assumed to be negative as the company needs to optimize new mix of resources and as a consequence of reorganisation, the productivity shortly falls (Bernini & Pellegrini, 2011; Karhunen & Huovari, 2015).

The studies of Gustafsson et al. (2016) and Decramer and Vanormelingen (2016) backs the hypothesis also for the specific case of SME sector.

2.3. Results and discussion

2.3.1. Overview of the results

The treatment and post treatment effects for each of the dependent variables in the first model are depicted in tables 8 - 10. The models are estimated for two types of datasets: (1) full population data; and (2) matched dataset using CEM method. When using the dataset of CEM matched data, the CEM weights are covered in the regression. The actual estimated coefficients for full population should be rather biased (as discussed in the data pre-processing chapter) but will serve as a robustness check to the coefficients estimated for matched dataset. Same trends (positive / negative) in the coefficients demonstrate that the results are appropriate and intuitive.

All the coefficients of treatment and post treatment are consistently lower in case of CEM matched dataset compared to the full population for all the models. This indicates that the selection bias has really been lowered by the pre-processing techniques and the coefficients are more accurate in case of CEM matched data. Moreover, the average treatment and post treatment effects for this dataset are statistically significant (beside one). Only the treatment effect on sales occurs insignificant.

The coefficients of the two additional models are presented in tables 11 and 12. These subsequent models are estimated using CEM matched data and provide further insights about post treatment yearly effect and about specific effects on firms belonging to different firm sizes (i.e. micro, small, medium, and large).

The number of observations differ for each of the dependent variables model. This is due to missing some of the data and it is expected given the nature of the data. Despite missing some of the data, the affected observation is still suitable for analysis. Adjusted R^2 also meet the expectations as the models are handling micro level data. The models' overall F-statistics are significant for all the estimated models and the details are present in the appendix A, B, and C. The t-statistics for each of the coefficients are present in the table with results together with *p* values in brackets.

2.3.2. Results of the general model

Employment. For the estimation of subsidy effect on employment, the wage is used as a control variable. The coefficient is estimated to be negative meaning that with increasing wage the company has fewer employees. Such an outcome is understandable, company hires less people if the price is higher due to the substitute effect (i.e. company exchange the expensive labor with comparatively less expensive capital), or the income effect (i.e. higher wages with the same budget implicates hiring less people).

Table 8: Dependent variable: Ln Employment

	CEM matched		**Full population**	
	Coefficient (std. error)	T stat (P > |t|)	Coefficient (std. error)	T stat (P > |t|)
Treatment effect	0.1247120 (0.0168773)	7.39 (0.000)	0.1938712 (0.0125376)	15.46 (0.000)
Post treatment	0.1498256 (0.0279923)	5.35 (0.000)	0.2087563 (0.0200574)	10.41 (0.000)
Ln Wage	-0.5968634 (0.0703128)	-8.49 (0.000)	-0.4365545 (0.0063962)	-68.25 (0.000)
Constant	4.1340480 (0.0105740)	390.96 (0.000)	2.3103110 (0.0025964)	889.81 (0.000)
Number of observations		17 565		183 109
Adjusted R^2		0.1189		0.1035

Note: Firm, year, regional, and industry fixed effects are included. Cluster (on a firm level) robust standard errors and *p*-value are shown in parenthesis.

Source: author (based on data from Albertina and IS VaVaI databases)

The effect of receiving a subsidy on the level of employment is positive and significant. This is according to the hypothesis. One of the goals for the R&D subsidies set by the government is generating vacancies and new job positions. The coefficient shows this tendency of direct employment effect. Moreover, the effect does not lower during the post treatment period and it becomes actually slightly higher during the consecutive years. This is interpreted as the firm's ability to create potentially sustainable job positions, meaning that they are not only hiring temporary employees or consultants. This will be further explored in the model estimating effects for each of the subsidy consecutive years.

Sales. The coefficient of treatment effect on sales is estimated to be negative meaning that during the year of receiving a subsidy, subsidized firms tend to have lower sales than the firms in the control group. This is a different outcome than hypothesized, but yet appears statistically insignificant. On the other hand, the post treatment effect is positive and can be interpreted as significant influence of the subsidy during the post treatment years on firm's sales compared to the control group. Possible explanation of these effects is that companies with lower revenues tend to have less internal financial resources and are thus the targets for receiving a subsidy.

The capital stock and labor force are chosen as the control variables of estimated model for sales. Both estimated with positive impact on sales and both significant. The more people and the more capital available for the company, the higher the revenue is. This is without question; the company reaches higher revenue with more inputs.

Productivity. The control variables for labor productivity model are the ratio of capital stock and employment, and the employment itself (Tingvall and Videnord 2018). Both variables have expected effect, with increasing labor the number of employees rises, and this impacts productivity that is decreasing. Similar explanation exists for the ratio, where the ratio increases with decreasing employment (in the denominator). This positively impacts the productivity.

The direct effect of subsidy is positive and significant. The firm's effectiveness thus rises with getting the subsidy therefore firms receiving public subsidy indicate better competitiveness that firms without it. Similar effect is observed for the post treatment period where the coefficient is also positive, and slightly higher with remained significance.

Table 9: Dependent variable: Ln Sales

	CEM matched		Full population	
	Coefficient (std. error)	T stat (P > |t|)	Coefficient (std. error)	T stat (P > |t|)
Treatment effect	-0.0290881 (0.0214479)	-1.36 (0.175)	-0.0379635 (0.0193718)	-1.96 (0.050)
Post treatment	0.0265203 (0.0040508)	6.55 (0.000)	0.0289978 (0.0249580)	1.16 (0.245)
Ln Employment	0.2491249 (0.0325062)	7.66 (0.000)	0.2116396 (0.0059694)	35.45 (0.000)
Ln Capital stock	0.0729361 (0.0137942)	5.29 (0.000)	0.0668358 (0.0030733)	21.75 (0.000)
Constant	6.6365030 (0.1511950)	43.89 (0.000)	5.3274190 (0.0180581)	295.02 (0.000)
Number of observations		26 691		274 668
Adjusted R^2		0.5541		0.6001

Note: Firm, year, regional, and industry fixed effects are included. Cluster (on a firm level) robust standard errors and p-value are shown in parenthesis.

Source: author (based on data from Albertina and IS VaVaI databases)

Table 10: Dependent variable: Ln Productivity

	CEM matched		Full population	
	Coefficient (std. error)	T stat (P > |t|)	Coefficient (std. error)	T stat (P > |t|)
Treatment effect	0.0631881 (0.0268499)	2.35 (0.019)	0.1038778 (0.0218132)	4.76 (0.000)
Post treatment	0.0722448 (0.0364642)	1.98 (0.048)	0.0967824 (0.0262087)	3.69 (0.000)
Ln $\frac{Capital\ stock}{Employment}$	0.0840566 (0.0162481)	5.17 (0.000)	0.0571779 (0.0035479)	16.12 (0.000)
Ln employment	-0.5946616 (0.0331050)	-17.96 (0.000)	-0.5973248 (0.0087429)	-68.32 (0.000)
Constant	5.1194360 (0.1439284)	35.57 (0.000)	3.9038800 (0.0247314)	157.85 (0.000)
Number of observations		23 954		239 867
Adjusted R^2		0.5930		0.2060

Note: Firm, year, regional, and industry fixed effects are included. Cluster (on a firm level) robust standard errors and p-value are shown in parenthesis.

Source: author (based on data from Albertina and IS VaVaI databases)

2.3.3. Further models result

Yearly effects. The results for the separate post treatment years are presented in table 11. Each of the firms have different treatment period and this model measures the impact of subsidy in the consecutive years after the treatment, e.g. 1, 2, 3, and maximum of 4 years after receiving the subsidy. Since the observed treatment periods are 2014, 2015, and 2016, the earliest first post treatment period is 2015 (for companies receiving subsidies in 2014 only) and the latest first post treatment period is 2017 (for companies receiving subsidies in 2016). This means that the estimates cover between 2 - 4 consecutive years.

Regarding the effect on employment, all the coefficients are significant, unlike for sales where only fourth consecutive year is measured with significance. In the case of productivity, the third and fourth year after receiving subsidy appear significant. All the coefficients are positive demonstrating that after receiving the subsidy the receivers perform better than the control group.

Table 11: Yearly differences during the post treatment period

	Post year 1 Coefficient (std. error)	Post year 2 Coefficient (std. error)	Post year 3 Coefficient (std. error)	Post year 4 Coefficient (std. error)
Ln Employment	0.1888487 (0.0357379)	0.1287730 (0.0290582)	0.1706740 (0.0335573)	0.2588939 (0.0343348)
Ln Sales	0.0286920 (0.0368475)	0.3661130 (0.0371807)	0.0479310 (0.0340798)	0.1006450 (0.0052933)
Ln Productivity	0.0522798 (0.0523818)	0.0540210 (0.0413096)	0.0844495 (0.0433997)	0.1893492 (0.0120073)

Note: Firm, year, regional, and industry fixed effects are included. Cluster (on a firm level) robust standard errors and *p*-value are shown in parenthesis.

Source: author (based on data from Albertina and IS VaVaI databases)

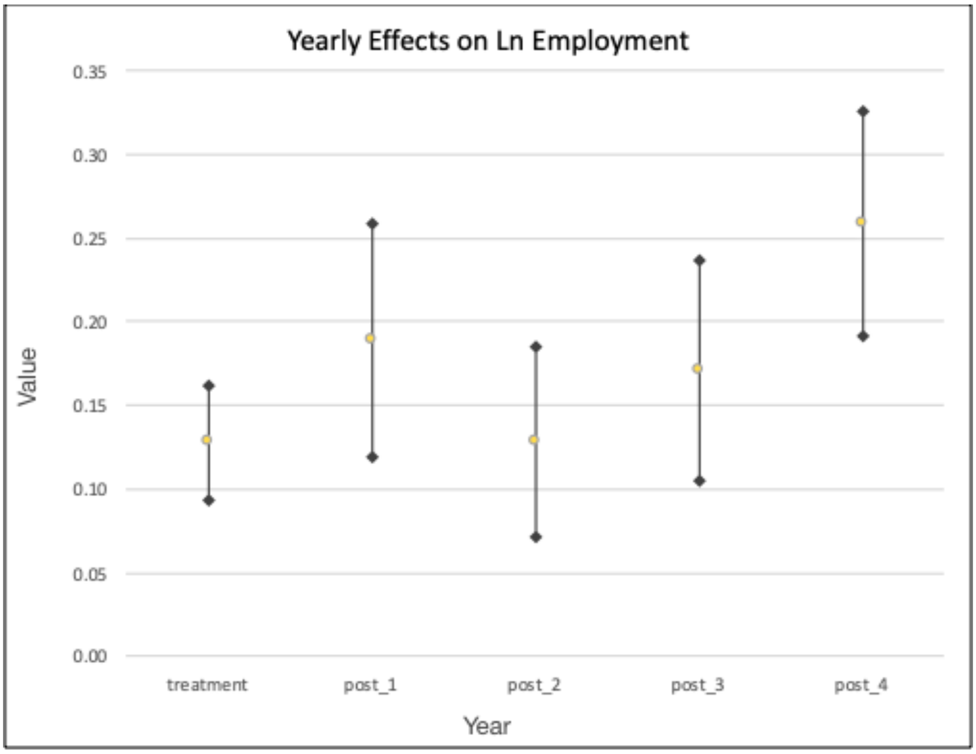
The results are also presented in figures 6 – 8. The coefficients are plotted with their 95% confidence interval.

In figure 6, positive effect can be seen in the year of receiving subsidy and this effect continues in the following years. This can be interpreted as persistent effect in the medium term. The companies are hiring more people and the subsidies have a direct impact on employment. A local peak is observed in the first year, second year is still positive but with smaller coefficient compared to the first year, and the following years there is an increasing tendency. In the beginning of innovation activities financed from the subsidies, the firm hires more people to start the projects and organize next steps. This can explain the higher increase right after getting money from the government.

The figure 7 shows impact on sales. The coefficients are all positive with increasing trend. However, only the fourth year effect is significant.

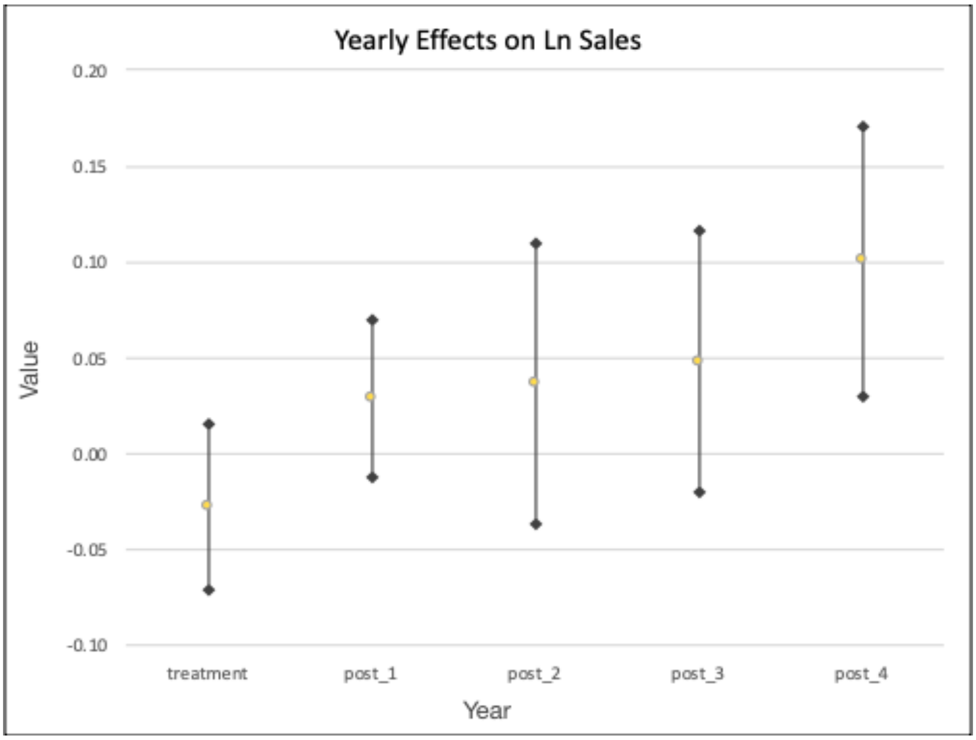
The last figure, figure 8 describes the impact on productivity. First and second years after treatment have positive coefficient of influence, however not significant. The third and fourth years show positive and increasing trend. This indicates that the initial investment of a subsidy starts to bring its fruit and the firm starts to prosper from the innovations and becomes more effective than the firms from control group.

Figure 6: Post treatment yearly effects on employment



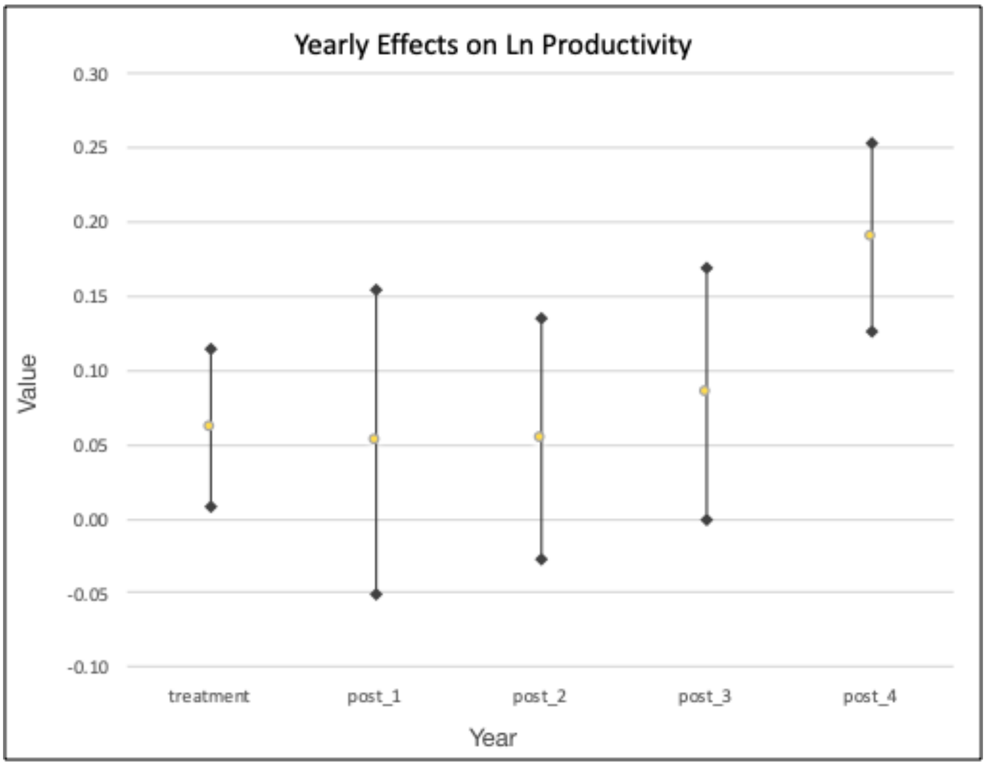
Source: author (based on data from Albertina and IS VaVaI databases)

Figure 7: Post treatment yearly effects on sales



Source: author (based on data from Albertina and IS VaVaI databases)

Figure 8: Post treatment yearly effects on productivity



Source: author (based on data from Albertina and IS VaVaI databases)

Effects on SMEs. The findings from the second alternative model estimation are presented in table 12. This model is estimated for dependent variables productivity and sales, using CEM matched data.

The results exhibit both positive and negative effects, most of them insignificant. The only significant coefficients are in case of micro and small firms and the effect of subsidy on productivity. For the micro firms, the positive effect shows that subsidized micro firms have higher productivity compared to the large companies during the year of subsidy. This can be interpreted as better ability of micro firms to adapt and quickly implement innovations. At least quicker than large companies. For small firms, the significant positive coefficient indicates that during the post treatment years, small subsidized firms perform with higher productivity than the large ones.

To further research the effect on non-large companies one additional dummy is created covering all the micro, small and medium companies and the model is estimated for productivity using the updated variable. Both treatment year and post treatment years prove to be statistically significant. The SMEs appear to be more effective (in terms of productivity) than the large corporates during the treatment year and after the treatment as well. This result prompts that the SME firms can adjust faster that the large firms and are capable of changing their optimal resource mix sooner.

Table 12: Third differences for company size effect

	Micro firms		Small firms		Medium firms		All SME (micro incl.) firms	
	Treatment Coefficient (std. error)	Post treatment Coefficient (std. error)	Treatment Coefficient (std. error)	Post treatment Coefficient (std. error)	Treatment Coefficient (std. error)	Post treatment Coefficient (std. error)	Treatment Coefficient (std. error)	Post treatment Coefficient (std. error)
Ln Sales	-0.1163723 (0.0898752)	-0.1760758 (0.1352242)	0.0122697 (0.0528923)	0.0881578 (0.0630052)	-0.0337291 (0.0490365)	-0.0240114 (0.0448248)	-	-
Ln Productivity	**0.0507054 (0.1097016)**	0.3201439 (0.1944489)	0.0749314 (0.0537533)	**0.1475556 (0.0647593)**	0.0524486 (0.0542495)	0.0628310 (0.055067)	**0.2102623 (0.0790394)**	**0.1585454 (0.0667107)**

Note: Firm, year, regional, and industry fixed effects are included. Cluster (on a firm level) robust standard errors and *p*-value are shown in parenthesis. Bold results are statistically significant on at least 10% level.

Source: author (based on data from Albertina and IS VaVaI databases

2.3.4. Discussion

Three major hypotheses are set to research in this study. The hypotheses are built based on the current economic theory and literature and are reviewed in this chapter based on the presented empirical results.

Impact of subsidy on employment. Employment is significantly impacted through the whole empirical part of this study. All models estimate positive coefficients, and the yearly estimation shows that the impact persists in short and medium term.

The economic literature suggests that in the beginning of an innovation process, the employment rises as people are the key resources (Karhunen and Huovari 2015; Tingvall and Videnord 2018). This seems likely the case for the analysed dataset. The number of employees is significantly higher the year after receiving public funds compared to the companies without public funding. Therefore, this hypothesis is not rejected for the used dataset.

Effect on sales. Sales is commonly accepted as companies' performance indicator. The effect of receiving public support on sales is considered to be positive from the economics point of view. Yet, the direct effect of receiving subsidy on sales is not supported by the data during the year of treatment (negative sign) and closely following years. The outcome remains insignificant. Neither the specific cases of micro, small and medium firms prove to be significant in the estimation.

The post treatment period shows an impact, especially in the fourth year after getting support. During this year, subsidized companies have significantly higher sales than the companies without subsidy.

Economic explanation may be that when receiving the subsidy, companies temporarily shift their focus and their investments to the beginning innovation. This leads to reduction in revenues. Once the innovation is finished or in some advanced stage, the company begins to benefit from it.

To conclude on this hypothesis, based on the data the hypothesis should be neither rejected nor approved in the short term due to insignificance of the model. For the long term, the hypothesis holds, and rejection cannot be done.

Subsidy influence on productivity. The built hypothesis for effect on productivity states that in the short term the effect should be rather negative as the companies are working on the new optimal resource mix, and during the long run productivity will be higher than in the control group of firms.

The data partially back this hypothesis. The estimated effect of treatment (getting a subsidy) is positive and significant as well as the post treatment effect. This means that the companies performed with higher productivity in the treatment year already. This conclusion is seconded by the specific case of micro firms. The smallest firms are able to significantly increase their productivity just when getting the grant.

The closely following years are not estimated significantly, however third and fourth year are. The increasing trend in these years shows that the companies find their new resource mix and achieve higher productivity and become more competitive. This is again also supported in specific case of SME firms compared to large enterprises. Thus, this hypothesis partially holds with the mentioned reservations.

2.3.5. Further research

To further research this topic, several discussion points arises from the analysis. First of all, there is always possibility to improve the dataset. This analysis works with data describing the whole firms' population in the country. Such an approach brings a potential of selection bias and can be improved by covering the control group from the pool of R&D grants refused applications. The companies applying for the grant may have specific characteristics (e.g. proactive management) which can also determine the observed performance indicators and are not controlled for in this study.

Secondly, the employees' qualification has its share on the outcome of an innovation and on the company's performance. The models can be improved by covering the share of high-skilled employees and researchers. These data are, however, very hard to get if even possible.

And lastly, it is not known how much the companies actually invest into their R&D and what is the portfolio of innovations. Some may be aimed on revenues, some on productivity. This opens a possibility to further research on complementarity of public support and private support, and on the clearer effect on sales and productivity for specific types of innovation.

Other model improvements can be done using different matching technique. Propensity scoring is for instance very commonly used and consists of estimating the probability of getting a subsidy for each of the company based on multiple chosen criteria.

Conclusion

Public support is common phenomenon in EU countries, especially the support for research and development. The European Union itself supports R&D from specific budgets to provoke creation of innovations. Moreover, the local governments support the R&D in addition. Without the supplementary financial motivation, the innovations may not be originated at all. This thesis explored the theoretical background in economics regarding this topic, coming up with market failures and challengers' concepts. The companies may not have sufficient financial resources to trigger the innovations themselves. Thus, the subsidy would help them in the implementation. The remaining question was whether the companies utilize the subsidies effectively.

For the empirical analysis, a unique dataset of 7 688 companies in the Czech Republic have been put together. The observed years were set from 2013 to 2018 with subsidy allocation in years 2014, 2015, and 2016. The analysis discovered that the public subsidies have positive impact on firms' employment and productivity, partially on sales as well. The subsidized companies performed better in these indicators that the companies without any subsidy. Another outcome of this study is that the effect on sales and productivity was significant only for the later years (fourth consecutive year for sales, third and fourth consecutive years for productivity). This suggests that the companies firstly need to restructure their resource mixes and after some time the performance increase occurs. And lastly the effect of subsidy on productivity was significantly higher in case of SME companies compared to large enterprises in both treatment and post treatment periods indicating the higher flexibility for adjustments in case of smaller firms.

This analysis can be further significantly improved by getting advanced data about rejected grant applicants and about the high-skilled labor ratio in the companies. However, the thesis also has implications as is and suggests positive effects of public R&D subsidies. This is actually nice finding in the current world of shadowed money redistribution.

List of abbreviations

Abbreviation	Definition
CEM	Coarsened Exact Matching
CSO	Czech Statistical Office
DiD	Difference-in-Differences
EU	European Union
GDP	Gross Domestic Product
IC	(a company's) Identification Number
IS VaVaI	Information System of Research, Experimental Development and Innovations
MIT	Ministry of Industry and Trade
NACE	Statistical Classification of Economic Activities in the European Community
OECD	Organisation for Economic Co-operation and Development
R&D	Research and Development
RD	Regression Discontinuity
ROA	Return on Assets
ROE	Return on Equity
ROS	Return on Sales
SME	Small and Medium Enterprises
TA CR	Technology Agency in Czech Republic
UNESCO	United Nations Educational, Scientific and Cultural Organization

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Appendix

A – Regression results for general model

Table 13: Regression results Ln Employment

CEM MATCHED						
Fixed-effects (within) regression					F(8,4991)	21.07
Dependent variable		Ln Employment			Prob > F	0.000
					sigma_u	0.3139559
Number of obs	17 565				sigma_e	0.4291375
Adjusted R-sq	0.119				rho	0.3486338
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnwage	-0.5968634	0.0703128	-8.49	0.000	-0.7347074	-0.4590193
treated_year	0.1247120	0.0168773	7.39	0.000	0.0916250	0.1577990
post_treated_year	0.1498256	0.0279923	5.35	0.000	0.0949484	0.2047028
y2	0.0427186	0.0056019	7.63	0.000	0.0317364	0.0537008
y3	0.0805874	0.0109941	7.33	0.000	0.0590342	0.1021406
y4	0.0987556	0.0192821	5.12	0.000	0.0609542	0.1365571
y5	0.1380490	0.0237057	5.82	0.000	0.0915755	0.1845225
y6	0.1087796	0.0234471	4.64	0.000	0.0628129	0.1547463
_cons	4.1340480	0.0105740	390.96	0.000	4.1133190	4.1547780
FULL POP						
Fixed-effects (within) regression					F(8,57493)	5 694.22
Dependent variable		Ln Employment			Prob > F	0.000
					sigma_u	0.2952113
Number of obs	183 109				sigma_e	0.3221983
Adjusted R-sq	0.103				rho	0.4563733
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnwage	-0.4365545	0.0063962	-68.25	0.000	-0.4490911	-0.4240180
treated_year	0.1938712	0.0125376	15.46	0.000	0.1692975	0.2184450
post_treated_year	0.2087563	0.0200574	10.41	0.000	0.1694437	0.2480689
y2	-0.1212008	0.0009467	-128	0.000	-0.1230563	-0.1193453
y3	-0.0944571	0.0019688	-47.98	0.000	-0.0983159	-0.0905983
y4	-0.0923637	0.0030308	-30.48	0.000	-0.0983040	-0.0864234
y5	-0.0402012	0.0037435	-10.74	0.000	-0.0475386	-0.0328639
y6	-0.1484889	0.0836836	-1.77	0.076	-0.3125092	0.0155314
_cons	2.3103110	0.0025964	889.81	0.000	2.3052220	2.3154000

Table 14: Regression results Ln Sales

CEM MATCHED						
Fixed-effects (within) regression					F(9,7248)	431.44
Dependent variable		Ln Sales			Prob > F	0.000
					sigma_u	0.2506125
Number of obs	26 691				sigma_e	0.2619365
Adjusted R-sq	0.554				rho	0.4779173
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.2491249	0.0325062	7.66	0.000	0.1854033	0.3128465
lmcapital_stock	0.0729361	0.0137942	5.29	0.000	0.0458954	0.0999768
treated_year	-0.0290881	0.0214479	-1.36	0.175	-0.0711322	0.0129560
post_treated_year	0.0265203	0.0040508	6.55	0.000	-0.0823041	0.1353447
y2	0.0380567	0.0020346	18.7	0.000	0.0340683	0.0420451
y3	0.0879234	0.0092938	9.46	0.000	0.0697047	0.1061420
y4	0.0798926	0.0134936	5.92	0.000	0.0534412	0.1063440
y5	0.1429081	0.0168165	8.5	0.000	0.1099429	0.1758734
y6	-0.7983177	0.0429679	-18.6	0.000	-0.8825473	-0.7140881
_cons	6.6365030	0.1511950	43.89	0.000	6.3401160	6.9328890
FULL POP						
Fixed-effects (within) regression					F(9,80127)	12 435.24
Dependent variable		Ln Sales			Prob > F	0.000
					sigma_u	0.2798082
Number of obs	274 668				sigma_e	0.2432175
Adjusted R-sq	0.600				rho	0.5696189
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.0668358	0.0030733	21.75	0.000	0.0608121	0.0728595
lmcapital_stock	0.2116396	0.0059694	35.45	0.000	0.1999396	0.2233395
treated_year	-0.0379635	0.0193718	-1.96	0.050	-0.0759321	0.0000051
post_treated_year	0.0289978	0.0249580	1.16	0.245	-0.0199198	0.0779153
y2	0.0694493	0.0011315	61.38	0.000	0.0672314	0.0716671
y3	0.1160643	0.0026537	43.74	0.000	0.1108630	0.1212656
y4	0.1250319	0.0033732	37.07	0.000	0.1184205	0.1316432
y5	0.1840716	0.0040094	45.91	0.000	0.1762132	0.1919300
y6	-0.6645493	0.3665410	-1.81	0.070	-1.3829670	0.0538687
_cons	5.3274190	0.0180581	295	0.000	5.2920260	5.3628130

Source: author (based on data from Albertina and IS VaVaI databases)

Table 15: Regression results Ln Productivity

CEM MATCHED							
Fixed-effects (within) regression						F(9,6879)	96.26
Dependent variable		Ln Productivity				Prob > F	0.000
						sigma_u	0.1539430
Number of obs	23 954					sigma_e	0.2143821
Adjusted R-sq	0.593					rho	0.3402108
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval		
lnratio	0.0840566	0.0162481	5.17	0.000	0.0522053	0.1159078	
lnemployment	-0.5946616	0.0331050	-17.96	0.000	-0.6595577	-0.5297654	
treated_year	0.0631881	0.0268499	2.35	0.019	0.0105540	0.1158221	
post_treated_year	0.0722448	0.0364642	1.98	0.048	0.0007638	0.1437258	
y2	-0.0082688	0.0032365	-2.55	0.011	-0.0146132	-0.0019243	
y3	0.0516195	0.0144490	3.57	0.000	0.0232951	0.0799439	
y4	0.0895177	0.0186303	4.8	0.000	0.0529965	0.1260389	
y5	0.1272424	0.0242651	5.24	0.000	0.0796753	0.1748095	
y6	-1.5208810	0.1143395	-13.3	0.000	-1.7450220	-1.2967410	
_cons	5.1194360	0.1439284	35.57	0.000	4.8372920	5.4015800	
FULL POP							
Fixed-effects (within) regression						F(9,74088)	1 347.00
Dependent variable		Ln Productivity				Prob > F	0.000
						sigma_u	0.1912343
Number of obs	239 867					sigma_e	0.2289312
Adjusted R-sq	0.206					rho	0.4109973
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval		
lnratio	0.0571779	0.0035479	16.12	0.000	0.0502240	0.0641319	
lnemployment	-0.5973248	0.0087429	-68.32	0.000	-0.6144609	-0.5801887	
treated_year	0.1038778	0.0218132	4.76	0.000	0.0611241	0.1466315	
post_treated_year	0.0967824	0.0262087	3.69	0.000	0.0454134	0.1481514	
y2	-0.0922280	0.0014296	-64.51	0.000	-0.0950300	-0.0894261	
y3	-0.0175541	0.0031238	-5.62	0.000	-0.0236768	-0.0114315	
y4	0.0265203	0.0040508	6.55	0.000	0.0185807	0.0344598	
y5	0.1166067	0.0045653	25.54	0.000	0.1076587	0.1255546	
y6	-0.2308421	0.2771823	-0.83	0.405	-0.7741184	0.3124341	
_cons	3.9038800	0.0247314	157.9	0.000	3.8554060	3.9523530	

Source: author (based on data from Albertina and IS VaVaI databases)

B – Regression results for yearly differences

Table 16: Yearly differences for Ln Employment

Fixed-effects (within) regression					F(11,4991)	375.28
Dependent variable		Ln Employment			Prob > F	0.000
					sigma_u	0.3895273
Number of obs	17871				sigma_e	0.4900552
Adjusted R-sq	0.1135				rho	0.3871831
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
ln(wage)	-0.5982717	0.0695962	-8.6	0.000	-0.7347108	-0.4618326
treated_year	0.1280239	0.0173497	7.38	0.000	0.0940109	0.1620369
post_1	0.1888487	0.0357379	5.28	0.000	0.1187867	0.2589107
post_2	0.1287730	0.0290582	4.43	0.000	0.0718062	0.1857399
post_3	0.1706740	0.0335573	5.09	0.000	0.1048870	0.2364611
post_4	0.2588939	0.0343348	7.54	0.000	0.1915826	0.3262051
y2	0.0427061	0.0055578	7.68	0.000	0.0318104	0.0536019
y3	0.0800839	0.0108939	7.35	0.000	0.0587271	0.1014406
y4	0.0999374	0.0192469	5.19	0.000	0.0622050	0.1376697
y5	0.1367746	0.0236358	5.79	0.000	0.0904380	0.1831112
y6	0.1088287	0.0233434	4.66	0.000	0.0630653	0.1545921
_cons	4.1316290	0.0105892	390.18	0.000	4.1108690	4.1523880

Source: author (based on data from Albertina and IS VaVaI databases)

Table 17: Yearly differences for Ln Sales

Fixed-effects (within) regression					F(12,7248)	7594.52
Dependent variable		Ln Sales			Prob > F	0.000
					sigma_u	0.5892342
Number of obs	26995				sigma_e	0.4990912
Adjusted R-sq	0.5591				rho	0.5822629
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
ln(employment)	0.2559188	0.0322844	7.93	0.000	0.192632	0.319206
ln(capital stock)	0.0740902	0.0138495	5.35	0.000	0.046941	0.101239
treated_year	-0.0276335	0.0218777	-1.26	0.207	-0.070520	0.015253
post_1	0.0286921	0.0368475	0.78	0.501	-0.011979	0.069363
post_2	0.0366113	0.0371807	0.98	0.325	-0.036274	0.109496
post_3	0.0479310	0.0340798	1.41	0.185	-0.020132	0.115994
post_4	0.1006456	0.0052934	19.01	0.000	0.030269	0.171022
y2	0.0375789	0.0020224	18.58	0.000	0.033614	0.041543
y3	0.0875636	0.0093175	9.4	0.000	0.069299	0.105829
y4	0.0821439	0.0134440	6.11	0.000	0.055790	0.108498
y5	0.1415618	0.0169652	8.34	0.000	0.108305	0.174819
y6	0.7981809	0.0430390	18.55	0.000	0.713812	0.882550
_cons	6.6089780	0.1513542	43.67	0.000	6.312279	6.905676

Source: author (based on data from Albertina and IS VaVaI databases)

Table 18: Yearly differences for Ln Productivity

Fixed-effects (within) regression					F(12,6879)	1107.36
Dependent variable		Ln Productivity			Prob > F	0.000
					sigma_u	0.4289733
Number of obs	24236				sigma_e	0.4986231
Adjusted R-sq	0.597				rho	0.4253346
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
ln(cap_stock/empl)	0.0854352	0.0166748	5.12	0.000	0.0527474	0.1181231
ln(employment)	-0.5919415	0.0330754	-17.9	0.000	-0.6567795	-0.5271035
treated_year	0.0615685	0.0270534	2.28	0.023	0.0085355	0.1146015
post_1	0.0522798	0.0523818	1	0.318	-0.0504047	0.1549644
post_2	0.0540210	0.0413096	1.31	0.191	-0.0269585	0.1350005
post_3	0.0844495	0.0433997	1.95	0.052	-0.0006273	0.1695263
post_4	0.1893492	0.0120073	15.77	0.000	0.1258111	0.2528873
y2	-0.0101231	0.0028904	-3.5	0.000	-0.0157893	-0.0044569
y3	0.0497193	0.0144478	3.44	0.001	0.0213971	0.0780415
y4	0.0900939	0.0186104	4.84	0.000	0.0536117	0.1265761
y5	0.1242190	0.0251503	4.94	0.000	0.0749165	0.1735214
y6	1.5222150	0.1143226	13.32	0.000	1.2981080	1.7463230
_cons	5.1101190	0.1440618	35.47	0.000	4.8277130	5.3925250

Source: author (based on data from Albertina and IS VaVaI databases)

C – Regression results for SME

Table 19: Effects on micro firms

Sales						
Fixed-effects (within) regression					F(11,7242)	452.05
Dependent variable		Ln Sales			Prob > F	0.000
					sigma_u	0.5789743
Number of obs	26 995				sigma_e	0.5902347
Adjusted R-sq	0.565				rho	0.4903701
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.2244916	0.0281517	7.97	0.000	0.1693061	0.2796772
lmcapital_stock	0.0734459	0.0136376	5.39	0.000	0.0467123	0.1001796
treated_year#micro	-0.1163723	0.0898752	-1.29	0.195	-0.2925538	0.0598092
post_year#micro	-0.1760758	0.1352242	-1.3	0.193	-0.4411547	0.0890031
y2	0.0368963	0.0020541	17.96	0.000	0.0328695	0.0409230
y3	0.08885	0.0092954	9.56	0.000	0.0706283	0.1070717
y4	0.0822129	0.0132652	6.2	0.000	0.0562092	0.1082167
y5	0.1442978	0.0163216	8.84	0.000	0.1123027	0.1762929
y6	0.2137355	0.0229092	9.33	0.000	0.1688267	0.2586442
_cons	6.75301	0.1252030	53.94	0.000	6.5075760	6.9984450
Productivity						
Fixed-effects (within) regression					F(11,6879)	62.74
Dependent variable		Ln Productivity			Prob > F	0.000
					sigma_u	0.4786523
Number of obs	24 236				sigma_e	0.5978962
Adjusted R-sq	0.583				rho	0.3905775
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.085013	0.0165749	5.13	0.000	0.0525210	0.1175050
lmcapital_stock	-0.6075084	0.0341471	-17.8	0.000	-0.6744472	-0.5405696
treated_year#micro	0.0507054	0.1097016	0.46	0.644	-0.1643436	0.2657543
post_year#micro	0.3201439	0.1944489	1.64	0.240	-0.0492797	0.6895700
y2	-0.0104109	0.0029290	-3.55	0.000	-0.0161527	-0.0046691
y3	0.0501582	0.0144394	3.47	0.001	0.0218525	0.0784639
y4	0.0897479	0.0185285	4.84	0.000	0.0534263	0.1260695
y5	0.1257195	0.0248228	5.06	0.000	0.0770591	0.1743800
y6	0.2749116	0.0380932	7.22	0.000	0.2002371	0.3495861
_cons	5.180681	0.1476628	35.08	0.000	4.8912170	5.4701460

Table 20: Effects on small firms

Sales						
Fixed-effects (within) regression					F(11,7247)	368.58
Dependent variable		Ln Sales			Prob > F	0.000
					sigma_u	0.5697123
Number of obs	26 995				sigma_e	0.5891238
Adjusted R-sq	0.565				rho	0.4832538
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.2521888	0.0305800	8.25	0.000	0.1922431	0.3121344
lmcapital_stock	0.0735148	0.0136991	5.37	0.000	0.0466605	0.1003691
treated_year#small	0.0122697	0.0528923	0.23	0.817	-0.0914145	0.1159539
post_year#small	0.0881578	0.0630052	1.4	0.162	-0.0353508	0.2116663
y2	0.0376018	0.0020108	18.7	0.000	0.0336600	0.0415436
y3	0.0888739	0.0093002	9.56	0.000	0.0706429	0.1071050
y4	0.0814319	0.0133552	6.1	0.000	0.0552518	0.1076120
y5	0.1435585	0.0164817	8.71	0.000	0.1112496	0.1758674
y6	0.2124673	0.0231175	9.19	0.000	0.1671502	0.2577844
_cons	6.598519	0.1531469	43.09	0.000	6.2983070	6.8987320
Productivity						
Fixed-effects (within) regression					F(11,6879)	62.92
Dependent variable		Ln Productivity			Prob > F	0.000
					sigma_u	0.4771124
Number of obs	24 236				sigma_e	0.5989112
Adjusted R-sq	0.587				rho	0.3882385
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.0850333	0.0166092	5.12	0.000	0.0524741	0.1175924
lmcapital_stock	-0.5931819	0.0326642	-18.2	0.000	-0.6572139	-0.5291499
treated_year#small	0.0749314	0.0537533	1.39	0.163	-0.0304417	0.1803045
post_year#small	0.1475556	0.0647593	2.28	0.023	0.0206075	0.2745038
y2	-0.0100991	0.0028793	-3.51	0.000	-0.0157435	-0.0044548
y3	0.0502038	0.0144335	3.48	0.001	0.0219097	0.0784979
y4	0.0892546	0.0185510	4.81	0.000	0.0528889	0.1256203
y5	0.1254344	0.0248393	5.05	0.000	0.0767417	0.1741271
y6	0.2747195	0.0380408	7.22	0.000	0.2001478	0.3492913
_cons	5.098983	0.1439558	35.42	0.000	4.8167850	5.3811810

Source: author (based on data from Albertina and IS VaVaI databases)

Table 21: Effect on medium firms

Sales						
Fixed-effects (within) regression					F(11,7247)	360.80
Dependent variable		Ln Sales			Prob > F	0.000
					sigma_u	0.4900560
Number of obs	26 995				sigma_e	0.5801222
Adjusted R-sq	0.558				rho	0.4164319
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.2554155	0.0327883	7.79	0.000	0.1911409	0.3196900
lmcapital_stock	0.0740778	0.0138415	5.35	0.000	0.0469445	0.1012111
treated_year#medium	-0.0337291	0.0490365	-0.69	0.492	-0.1298550	0.0623968
post_year#medium	-0.0240114	0.0448248	-0.54	0.592	-0.1118811	0.0638583
y2	0.0375774	0.0020308	18.5	0.000	0.0335964	0.0415584
y3	0.0876111	0.0093100	9.41	0.000	0.0693608	0.1058613
y4	0.0812475	0.0134094	6.06	0.000	0.0549612	0.1075337
y5	0.1421010	0.0167620	8.48	0.000	0.1092427	0.1749593
y6	0.2110266	0.0233220	9.05	0.000	0.1653087	0.2567445
_cons	6.6062540	0.1507015	43.84	0.000	6.3108350	6.9016730
Productivity						
Fixed-effects (within) regression					F(11,6879)	62.01
Dependent variable		Ln Productivity			Prob > F	0.000
					sigma_u	0.4717643
Number of obs	24 236				sigma_e	0.5815689
Adjusted R-sq	0.598				rho	0.3968758
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lnemployment	0.0854014	0.0166674	5.12	0.000	0.0527282	0.1180746
lmcapital_stock	-0.5924404	0.0330877	-17.9	0.000	-0.6573024	-0.5275783
treated_year#medium	0.0524486	0.0542495	0.97	0.334	-0.0538972	0.1587944
post_year#medium	0.0628310	0.0550670	1.14	0.254	-0.0451173	0.1707793
y2	-0.0101180	0.0028799	-3.51	0.000	-0.0157636	-0.0044724
y3	0.0494151	0.0144020	3.43	0.001	0.0211827	0.0776476
y4	0.0892211	0.0185499	4.81	0.000	0.0528576	0.1255846
y5	0.1246056	0.0248079	5.02	0.000	0.0759745	0.1732367
y6	0.2736786	0.0380447	7.19	0.000	0.1990992	0.3482580
_cons	5.1063350	0.1441555	35.42	0.000	4.8237460	5.3889250

Source: author (based on data from Albertina and IS VaVaI databases)

Table 22: Effect for SME

Fixed-effects (within) regression					F(11,6879)	65.50
Dependent variable		Ln Productivity			Prob > F	0.000
					sigma_u	0.1728235
Number of obs	24 236				sigma_e	0.2293246
Adjusted R-sq	0.593				rho	0.3622215
	Coef.	Std. Err.	t	P>|t|	95% Conf. Interval	
lncapital_stock	0.0853208	0.0166729	5.12	0.000	0.0526367	0.1180049
lnemployment	-0.5853639	0.0340676	-17.18	0.000	-0.6521469	-0.5185810
treated_year#sme	0.2102623	0.0790394	2.66	0.008	0.0553206	0.3652039
post_treated_year#sme	0.1585454	0.0667107	2.38	0.017	0.0277719	0.2893188
y2	-0.0099441	0.0028900	-3.44	0.001	-0.0156094	-0.0042789
y3	0.0497726	0.0144030	3.46	0.001	0.0215383	0.0780070
y4	0.0895211	0.0185326	4.83	0.000	0.0531915	0.1258508
y5	0.1252056	0.0247877	5.05	0.000	0.0766141	0.1737972
y6	0.2760579	0.0381561	7.23	0.000	0.2012602	0.3508557
_cons	5.021306	0.1673810	30	0.000	4.6931880	5.3494250

Source: author (based on data from Albertina and IS VaVaI databases)

D – Covered Operational Programmes

CODE	DESCRIPTION
EE	Operační program Vzdělávání pro konkurenceschopnost
7B	Program Společenství pro zachování, popis, sběr a využití genetických zdrojů v zemědělství
7A	Rámcový program Evr. spol. pro výzkum, technický rozvoj a demonstrační činnosti
7E	Podpora projektů sedmého rámcového programu Evropského společenství pro výzkum, technologický rozvoj a demonstrace
ED	Operační program Výzkum a vývoj pro inovace
7H	Společné technologické iniciativy
7C	Výzkumný program Výzkumného fondu pro uhlí a ocel
7D	Eurostars
QI	Výzkum v agrárním sektoru
FR	TIP
NT	Resortní program výzkumu a vývoje Ministerstva zdravotnictví III
LM	Projekty velkých infrastruktur pro VaVaI
LD	COST CZ
LF	EUREKA CZ
TA	Program na podporu aplikovaného výzkumu a experimentálního vývoje ALFA
UD	Regionální inovační program Dotačního fondu Libereckého kraje
TD	Program na podporu apl. spol. výzkumu a experimentálního vývoje OMEGA
QJ	Komplexní udržitelné systémy v zemědělství
UE	Program rozvoje konkurenceschopnosti Karlovarského kraje - Inovační vouchery
LR	Informace - základ výzkumu
LO	Národní program udržitelnosti I
TF	Program podpory aplikovaného výzkumu a experimentálního vývoje DELTA
TG	Program aplikovaného výzkumu, experimentálního vývoje a inovací GAMA
EG	Operační program Podnikání a inovace pro konkurenceschopnost
EF	Operační program výzkum, vývoj, vzdělávání
8C	Horizont 2020 - rámcový program pro výzkum a inovace
8A	Společná technologická iniciativa ECSEL
8B	Evropský metrologický program pro inovace a výzkum
TH	Program na podporu aplikovaného výzkumu a experimentálního vývoje EPSILON
FV	TRIO