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FACULTY OF ECONOMICS AND BUSINESS

Novel perspectives on public support, firm performance and regional development



Dissertation presented to obtain the degree of Doctor in Business Economics

by

Cem Ermagan

Number 812 2023

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Faculty of Economics and Business



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Daar de proefschriften in de reeks van de Faculteit Economische en Toegepaste Economische Wetenschappen het persoonlijk werk zijn van hun auteurs, zijn alleen deze laatsten daarvoor verantwoordelijk.

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General Introduction

The impact of innovation subsidies to trigger a higher level of Research & Development (R&D) investment in the private sector has been an important research subject in the economic literature[1]. Despite the long history of empirical research performed on this subject to reveal the impact of the subsidies, the interest in new empirical evidence persists. New expectations on how the analyses should be employed empirically, and what new factors should be considered in addition to the work done in the past, constantly add challenges for scholars who are conducting R&D-subsidy program evaluation studies. Both econometric methods applied and data available to address research questions in the field of R&D subsidies have been growing over the decades and both factors may contribute to higher levels of robustness and reliability of the results. Besides more sophisticated methods and more extensive and detailed data also new factors affecting both R&D subsidies and firms have become of increasing interest to policy makers. Examples are the potential impact of subsidy allocation mechanisms or the environment firms operate in.

Examples about the efforts to investigate the potential impact of subsidy allocation mechanisms focus, among others, on the role of different subsidy sources (Blanes and Busom, 2004; Czarnitzki and Lopes-Bento 2014; Busom et al. 2015). Here the interest is on the question whether subsidies received from different sources for the same kind of activities are heterogeneous in their impact or whether the receipt of subsidies from several sources simultaneously (policy mix) leads to diversity in subsidies' impact. The evaluation of subsidy treatment effects are most likely biased in case not all subsidies stemming from different sources are taken into account in the analyses by the researcher; leading possibly to hidden treatment bias (Guerzoni and Raiteri, 2015).

The potential bias can go in both directions negative or positive. If a group of companies with subsidies granted from one source are considered, the impact will be underestimated in case the control group (non-subsidized companies) received

[1] See Zúñiga-Vicente et al. (2014) for a survey of empirical research for the five decades before 2012 about R&D subsidies and R&D investment in the private sector.

subsidies from another source/other sources which is/are not considered or observed by the researcher. In that case underestimation of the measured treatment effect, i.e. the difference of the policy outcome variable between treated and control groups respectively, can be expected. On the other hand, the treatment effect will be overrated if the subsidized companies received simultaneously grants from one or several sources but the additional treatment/s is/are not observed by the researcher and consequently not taken into account in the empirical setting applied. Such bias might have occurred more often in older studies where data availability was less comprehensive than nowadays.

An example for determinants about the firms' environment that ought to be considered in policy evaluation studies is the location of the company. (Montmartin et al., 2018). Other geographically close entities or industry hubs as well as infrastructure (physically such as transportation infrastructure or non-physically such as digital infrastructure) available to the company are further examples. Spatial data availability as well as advanced software packages, such as Geographic Information Systems (GIS), enable researchers more and more to take into account the potential effect of the environment on R&D subsidies' impact.

Based on the new possibilities and challenges by the improvement of data and software availability, this dissertation sets off to develop and discover novel approaches and contents to enrich the economic literature within the R&D subsidy framework. To do that potential effects arising out of different subsidy sources, i.e. the policy mix, as well as environmental differences are considered in three empirical studies.

The first study takes the geographic proximity of the companies to the subsidy granting authority into account for the first time in the literature on R&D subsidies to evaluate the potential effect of geographic proximity on the likelihood of being subsidized. This is done by utilizing detailed data as well as the advanced spatial software package Quantum GIS (QGIS)[2].

The second study focuses on the potential effects of subsidy sources by considering different granting authorities and the policy mix by utilizing recent data that provide

[2] Open source software available on https://qgis.org/en/site/

all innovation subsidy receipts for a representative sample of companies active in the Belgian economy. In addition, by considering the three different Belgian regions, the firm environment's potential effect to create heterogeneity in the subsidies' impact is tested.

The third study builds on the advancement in data which recently became publicly available and contain information about the EU's public support programme called European Structural and Investment Fund (ESIF). The aim is to evaluate the potential impact of ESIF on economic regional development. This is of particular interest as one main policy goal of ESIF is to smooth out economic disparities within the EU's regions. The data comprehend the entire territory of the EU and are combined with detailed regional information providing a more comprehensive set of covariates utilized in the empirical analysis than prior literature. In the following a short description of the three chapters is provided.

The studies reported within this dissertation focus mainly on direct R&D grants which are in many industrialized countries the most important policy instrument for subsidizing R&D. Within the first two chapters also R&D tax credits are implicitly considered[3] while further indirect channels to subsidize R&D such as demand-side policies (innovative public procurement and other policies) are not the subject of the empirical analyses applied.

Outline of the dissertation

Chapter 1 – Examining the relation between subsidy receipt likelihood and geographic proximity

Geographic proximity has been considered as an important determinant for a variety of economic research subjects after the starting signal hinting on the relevance has been set by Jaffe et al. (1993). They showed empirically that knowledge spillovers' strength depends on the level of geographic proximity between the parties of knowledge exchange. Ponds et al. (2007) found empirical evidence for the positive effect of higher geographic proximity on the likelihood of researchers collaboration

[3] Innovation subsidies sourced by the Belgian Federal Government are mainly R&D tax credits.

for R&D activities which has been confirmed by a number of examinations addressing the same research subject (Hoekman et al., 2009, 2010, 2013; Singh and Marx, 2013; Kabo et al., 2014; Morescalchi et al., 2015). Other empirical work conducted found among others evidence for the impact of geographic proximity on the performance of merged companies (McCarthy and Aalbers, 2016), on managements' success to increase the productivity in conglomerates (Giroud, 2013), or decreasing the information asymmetry between venture capital providers and startups (Kolympiris et al., 2018).

The possible impact of geographic proximity within the subsidy framework is a new aspect that has not been the subject of an empirical examination yet where my coauthor Prof. Dr. Peter Teirlinck and I decided to step in. Following the idea to do research on the possible impact of geographic proximity, it is examined whether the physical distance between subsidy seeking companies and subsidy granting authorities is statistically and significantly related to the likelihood of being granted with innovation subsidies. The possible mechanism hereby is that the companies physically located closer (higher geographic proximity) to the authorities will face lower transaction costs to get and stay in touch with the authorities' personnel. Thus, they will suffer under a lower level of information asymmetry about the expectations and goals of the authority. Since lobbying and networking activities are the main channels through companies get and stay in touch with the authorities, geographic proximity measured as physical distance serves as a proxy for the costs of these activities. The expected outcome of the examination is that in case of higher geographic proximity the transaction costs of lobbying and networking will be lower and in turn lead to higher likelihood of being subsidized.

Based on a representative sample of companies in Flanders, adjacent region to the subsidy granting authorities, the hypothesis of higher likelihood to be granted with innovation subsidies in case of a higher geographic proximity is tested. The subsidy granting authorities taken into account are all innovation subsidy granting authorities located in the city of Brussels; European, Belgian Federal Government, and Flemish Regional Government authorities respectively. The empirical evidence of the analyses performed shows that the geographic proximity indeed plays a statistical significant role when innovation subsidies sourced by the EU are considered while for both of the

other authorities the same effect is not evident. This finding is in line with expectations since while EU authorities are heavily ensnared by different groups through lobbying and networking, the other authorities are not expected to be the subject of interest groups as intense as the EU authorities.

Chapter 2 – Revealing the importance of policy mix, hidden treatment, and regional heterogeneity on subsidies' impact

While the economic literature about innovation subsidies' impact on private R&D investments is well developed (Zúñiga-Vicente et al., 2014), there are still avenues open to examine further on different aspects which have not been considered yet. Few researchers recently conducted research on the subject by involving new factors which are found to play a role in variability of subsidies' impact and opened new perspectives for future subsidy evaluations.

Blanes and Busom (2004) provided empirical evidence for an effect of subsidies' source besides the subsidy payments. They focused on the subsidized companies attributes in Spain and found that these differ depending on the subsidy granting authority and thus base on different populations of companies. This implies that different subsidy allocation mechanisms or processes applied by the subsidy granting authorities are expected to play a role besides the actual subsidy payment since the companies granted by each authority can differ systematically from each other.

Following up on this idea several researchers conducted empirical examinations considering subsidies' source. Czarnitzki and Lopes-Bento (2014) find that subsidies impact in Germany differ depending on whether sourced by the EU authorities or national authorities. Busom et al. (2015) reveal differences in subsidies' impact depending on subsidies' mode (direct vs. indirect subsidies) and emphasize that the populations of companies receiving public support through different subsidy modes systematically differ. Based on a similar work, Dumont (2017) draws the attention on possibly biased results in subsidy impact evaluations if different subsidy sources are not taken into account.

Other researchers point on that simultaneous receipt of subsidies (policy mix) from one or more sources can also result in differences by creating a hidden treatment effect (Guerzoni and Raiteri, 2015) if not accounted for. Guellec and Van Pottelsberghe De La Potterie (2003) focus on interaction effects of different subsidy modes in OECD member countries and find evidence that direct subsidies and tax incentives (indirect subsidies) are substitutes and thus receipt of one lowers the effect of the other if received simultaneously. Dumont (2017) also find similar evidence hinting on the substitute character of public support in case of different subsidy modes. In contrast, Hægeland and Møen (2007) and Czarnitzki and Lopes-Bento (2014) find evidence for complementarity of subsidies in case of policy mix in case of receiving public support from different sources or receiving public support in form of different modes.

Another perspective is taken by Montmartin et al. (2018) who takes into account subsidy recipients' geographic environment as a factor besides the public support received. They emphasize that regional differences are expected to make a difference in the performance of the subsidized companies since knowledge spillover flows or regional competition faced are also expected to be different in different regions. They find evidence for effects of local economic structure, locally designed support schemes, and local legal framework.

Taking into account potential variation of subsidy impact through different subsidy sources and regional factors the second chapter of this dissertation, coauthored with Prof. Dr. Teirlinck, performs an empirical evaluation based on a representative sample of all companies in Belgium. Different sources are all major innovation subsidy providers in Brussels; EU, Belgian Federal Government, and Flemish government respectively. Doing that also allows to distinguish a possible effect arising out of different subsidy modes as the Belgian Federal Government only grants public support through indirect subsidies (tax benefits[4]) to the private sector, while both of the other sources provide only direct subsidies. Furthermore, regional differences are accounted for also in interaction with different types of subsidy sources. Thus, the

[4] According to Bloom et al. (2019; see Table 2 in the article for an overview of the comparison of different innovation policies) R&D tax credits bear higher net benefits for the economy and unfold their impact in a shorter time period compared with direct R&D grants.

empirical setting allows for both distinction of the impact of subsidies and regions as well as their combinations.

The evidence obtained shows an overall positive effect of innovation subsidies on the input additionality whereat combination of regional subsidies with EU subsidies and combination of being located in Brussels-Capital region and receiving Federal Government subsidies (tax benefits) are related with stronger positive subsidy impact. Thus, complementarity is present by combination of certain subsidies as well as by combination of a certain region and subsidy mode.

Chapter 3 – New evidence on the impact of EU's public support scheme European Structural and Investment Fund (ESIF)

Regional Development Funds was created already 1975 in its first form[5] to strengthen the economic and social cohesion within the European Union (EU). In the course of the years it was adapted and extended several times. The budget foreseen increased in order to respond to new challenges that arose such as the EU enlargements or needs in specific industries. In its most recent version, European Structural and Investment Funds (ESIF)[6], it comprehends five different programmes to follow up on different targets by allocating public support according to the policy goals. The programmes contribute mainly to trigger economic development in poor and rural regions, improve human capital management (labor market/employment measures), manage natural sources sustainably, as well as increase research and innovation activities within the EU.

In the economic literature a number of evaluations about the impact of ESIF (most work employed focuses on Structural Funds (SF) which comprehends ERDF and ESF) are available. Among others Becker et al. (2010, 2012, 2018) find empirical evidence for a positive impact whereat the distribution along the regions is found to be suboptimal high for some regions and suboptimal low for others. Esposti and Bussoletti (2008) report a limited positive impact allover but negative impact for some

[5] https://ec.europa.eu/regional_policy/en/policy/what/history/

[6] https://ec.europa.eu/info/funding-tenders/funding-opportunities/funding-programmes/overview-funding-programmes/european-structural-and-investment-funds_en

regions while Dall'Erba and Le Gallo (2008) do not find evidence for a statistically significant effect of the funds. Unfortunately, the empirical work performed relies on “planned” expenditures for activities supported by ESIF, i.e. there is a deviation between what is planned at the beginning of a subsidy programme period and what is realized on the field.

Data about the real expenditures on the ground are not available since the management of a big part of the EU public support (around 80%) is administered by national authorities. This makes it difficult to collect the data but efforts on the side of the European Commission (EC) led to a dataset which was published mid-2018. The dataset does not offer the real expenditures on the ground but as an improvement the real amounts as transferred by EC per year and per NUTS 2 regions are available.

The third examination of this dissertation utilizes the new data to conduct an evaluation on the impact of ESIF. By doing that, not only parts of ESIF are considered, as it is often the case in the available literature, but all transfers through the funds that really took place. The empirical setting accounts for the fact that a large share of the funds were directed to economically weak EU regions (Objective 1/Convergence regions) to trigger economic catch up. A rich set of covariates are gathered from different sources and utilized as covariates in an advanced econometric panel method to account for endogeneity of the GDP (dependent variable) and covariates. The results deliver a statistically significant effect of the public support through ESIF on the economic growth of the regions in general whereat additional economic growth is observed in Objective 1 regions.

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Chapter 1 Geographic proximity to the European Commission and the likelihood to be granted with a subsidy from the EU[7]

1.1 Introduction

In the economic literature the likelihood of being subsidized is often modelled as a function of observable firm, industry and regional characteristics (see e.g. the survey by Zúñiga-Vicente et al., 2014). From political economy literature, it is however also well known that companies' representatives are involved in networking as well as formal and informal lobbying activities (see e.g. Bennett (1999) for firms´ choice of lobbying channel) in order to access tacit knowledge and try to influence the decisive authorities to their advantage. Van Schendelen (2013, p. 59) emphasizes the omnipresence of lobbying by the sentence: "*Lobbying takes place at all times and all places, when and where somebody wants to get something from a power-holder and to minimize the risks of a refusal*."

Networking and lobbying activities and the costs related to these activities are often unobserved to the researcher. However, geographic proximity to the decisive authority might approximate the intensity of lobbying as well as networking activities. Geographic proximity can be conducive for business success whenever the transfer of tacit knowledge and thus the frequency and the intensity of personal face to face contact between economic agents is an important factor (Harrison, 1992; Howells, 2002). In case of EU authorities, which are usually not business partners (except for procurement contracts) but providers of funding and are known to be the subject of lobbying parties, one could expect an effect of networking and lobbying efforts. In the "Transparency Register" of the EU where lobbying organizations and individuals can register on a voluntarily basis there are more than 11,000 registrants reported (Joint Transparency Register Secretariat, 2017). As the registration is voluntary the real number of lobbying parties is probably higher. The Guardian[8] reports in an article from

[7] This study is coauthored by Prof. Dr. Peter Teirlinck.

[8] https://www.theguardian.com/world/2014/may/08/lobbyists-european-parliament-brussels-corporate (accessed last on 29.07.2019)

2014 about lobbying activities in Brussels and points on the estimated number of lobbyists[9] (30.000) that matches nearly the number of European Commission staff.

For the representatives of lobbying/networking parties it will be less time and cost intensive to get together formally or informally with the authorities' personnel, participate in events related to their activity scope, and to monitor new trends or relevant policy discussions if they are located closer to the authorities. This will in turn lead to an advanced information status about the ideas and intentions of the authorities and possibly also give the chance to influence authorities' decision making processes. Thus the closer the lobbying/networking activity performing companies are geographically to the authorities the lower the transaction costs to carry out their lobbying/networking activities and the more successful they may be in achieving their goals. Bouwen (2002, p. 374) points to the importance of costs in the context of lobbying the EU with the following words: "*The cost factor becomes even more important when the complex multi-level structure of the EU is taken into account*".

As one of the goals for lobbying/networking companies might be to increase their likelihood to receive subsidies, geographic proximity could be a significant factor playing a role in the likelihood of being granted. However, in the study of subsidies, this factor largely is ignored (Broekel et al., 2015). Based on data for the period 2006-2014 for innovation active companies in Flanders, a region adjacent to the EC in Brussels, we contribute to filling this gap in the literature by showing empirically that the geographic proximity to the European Authorities in Brussels is significantly related to the likelihood of receiving subsidies for innovation. Besides the relevance for policy makers and companies' managers satisfying the need for quantification of lobbying and networking effects in Brussels, our analysis is also useful for future studies investigating the impact of subsidies since – besides observable firm, industry and region characteristics (Zúñiga-Vicente et al., 2014) – geographic proximity to the administrators of the public funding source can be a relevant factor that should be taken into account when modelling the propensity of subsidy receipt.

[9] Estimated by the Corporate Europe Observatory (CEO), a non-profit organization watching lobbying activities on the European policy making. https://corporateeurope.org/

The next section of the paper revises the literature on geographic proximity, its relation with networking and lobbying, and its relevance for EU funding for innovation. Section 3 provides insights about the dataset and econometric models relied upon for the empirical analysis. Results are presented in Section 4 and Section 5 provides the main policy conclusions and implications for future research.

1.2 Literature

1.2.1 Geographic proximity

Definition of geographic proximity and why it matters

Boschma (2005), building on the work that has been employed on proximity before (e.g. by Kirat and Lung, 1999; Shaw and Gilly, 2000), defines geographic proximity as the spatial or physical distance between economic actors and warns not to mingle it with other types of proximity; social, institutional, organizational, and cognitive proximity respectively. On the one hand, Boschma (2005) states that geographic proximity is neither a necessary nor a sufficient condition for spillovers between economic agents and might be substituted by other forms of proximities. He points on that at least cognitive proximity, which is the similarity level of the common knowledge base of the interacting agents paving the way to understand each other, must be present besides geographic proximity in order to enable knowledge transfer. On the other hand, geographic proximity might be conducive to build up and strengthen cognitive proximity as well as other proximity types (Howells, 2002) and thus it may serve as an indirect force by stimulating the other types of proximity for successful knowledge sharing.

Geographic proximity is not a necessary condition for interaction, but it is widely acknowledged that it is easier to get and stay in touch if the physical distance between parties is low. Furthermore, over short distance the transfer of tacit knowledge and formation of informal ties are more likely whereas with increasing distance more and more barriers arise (Morescalchi, 2015). Personal and face to face contact help to establish and keep alive informal relationships for instance via participating in social

events like professional conferences or activities off the job. This in turn simplifies building up trust and common institutions which are conducive to reduce the information asymmetry and risks stemming from opportunistic behavior between interacting economic actors (Harrison, 1992; Audretsch and Stephan 1996; Agrawal et al. 2006). Since the seminal work of Jaffe et al. (1993) proving the strength of localized knowledge transfer, geographic proximity was considered by scientists for a wide variety of economic examinations in different research fields and turned out to be an important factor to be taken into account whenever interaction between economic agents play a substantial role for the research subject in focus. After reviewing the literature on the role of proximity on collaborative innovation, Frenken et al. (2009) conclude that there is strong empirical evidence for the effect of geographic proximity on scientific interaction patterns.

Empirical evidence

Jaffe et al. (1993) were among the first to provide evidence for the geographical locatedness of knowledge spillovers by examining patent citations and showing that patents tend to be cited with a higher likelihood by other physically close located economic agents. A number of empirical studies examining the networks of innovators deliver evidence for a negative effect of physical distance for R&D collaboration likelihood (Ponds et al., 2007; Hoekman et al., 2009, 2010, 2013; Singh and Marx, 2013; Kabo et al., 2014; Morescalchi et al., 2015). Some of those investigations show even an increase of the negative effect of physical distance over time whereat the evidence is robust under country as well as at different regional levels of nomenclature of territorial units for statistics (NUTS 1, 2, and 3 levels). As reasons for an effect of geographic proximity Morescalchi et al. (2015) refer to tacit knowledge transfer that happens more easily while having personal face to face contact and innovators being attracted by central regions with large innovation “hubs” where social networks serve as accelerating platforms for knowledge exchange.

McCarthy and Aalbers (2016) point out that the literature on the performance of technological mergers and acquisitions did not pay attention to the impact of geographic proximity and implicitly assumes that firms exist in an “aspatial world”

(Howells and Bessant, 2012). They cover the gap by providing evidence that the post-acquisition innovative performance of the newly created (merged) company decreases with higher physical distance between the acquirer and acquired companies. The argument why geographic proximity plays a role here lies in transaction costs which occur before, during, and after the merging process. The lower the physical distance between merging companies, the lower are the transportation, integration, as well as monitoring costs and thus the information asymmetry, i.e. the acquirer is informed better about closer located target companies (Grote and Umber, 2006; Böckerman and Lehto, 2006). Similarly, Kolympiris et al. (2018) find that information asymmetry between venture capital providers and their target firms is lower if the geographic proximity between the parties is higher since tacit knowledge is transferred with a higher rate of success between them.

Potential diminishing effect of geographic proximity

Some researchers point on the potential weakening of geographic proximity effects owed to new information and communication technologies as well as improved transportation means. Such a development is expected to come along with the ease and speed of electronic communication and information services as well as modern and frequent transportation infrastructure that enable people to work and act together more efficiently setting aside the constraints arising out of physical distance to each other (Castells, 1996; Cairncross, 1997).

Giroud (2013) provides empirical evidence for the effect of improved transportation. According to his examination, decreased travel time due to the introduction of direct flights between headquarters and plants leads to higher geographic proximity and this in turn leads to higher investment in plants as well as an increase in productivity, since headquarters can monitor plants at a lower cost and consequently suffer less under information asymmetry. On the contrary, Howells (2002) emphasizes that tacit knowledge, which is not as easy to grasp and transfer, is often necessary to understand and utilize codified knowledge and thus might be a limiting factor on the weakening effect of new technologies and transportation on the importance of geographic proximity.

Jaffe et al. (1993) investigate whether the localization of knowledge spillovers holds permanently. They conclude that it lasts over longer time periods but with a slow decreasing impact of geographic proximity. More recent studies show a stable or even increasing effect of geographic proximity, suggesting that it can be important to take the potential impact arising out of geographic proximity into account (Ponds et al., 2007; Picci, 2010; Hoekman et al., 2010; Singh and Marx, 2013; Morescalchi et al., 2015).

1.2.2 Networking and lobbying

Being embedded in a network and thus staying in touch closely with third parties, e.g. for the purpose of lobbying, can reduce the level of information asymmetry and, in turn, improve one's own position compared to competitors which suffer under a higher level of information asymmetry. Among other factors, geographic proximity can be a significant factor determining the costs of involvement in networking and lobbying activities.

Besides formally established entities like companies or non-governmental organizations also semi-formal and informal networks can act as interest groups (Van Schendelen, 2013, p. 205). The effect of being embedded within a network, which unfolds its effect among others through enhanced information exchange and access, is investigated in a variety of different research fields and is also important in subjects related to innovation.

Teplitskiy et al. (2018) investigate whether network connections between authors and evaluators of scientific work lead to a bias of the evaluators' judgements. Their findings suggest that evaluators decide in favor of authors who work within their own network. Gonzalez-Brambila et al. (2013) examine the effect of network embeddedness on researchers scientific output and impact. By distinguishing different dimensions of embeddedness they conclude that breadth and depth of personal relationship increases the output quality while similarity of knowledge regarding shared interpretations, language, and codes increases the output quantity.

Singh (2005) provides empirical evidence for the positive effect of personal networks on intraregional and intrafirm knowledge flows. His results also show that

knowledge flows are stronger between geographically closer located actors confirming findings by Jaffe et al. (1993). A connection between geographic proximity and being embedded within a network is shown by Broekel et al. (2015), who find that companies located within clusters are better integrated in subsidized R&D collaboration networks.

Grossman and Helpman (2001) subdivide lobbying costs in three classes; exogenous, endogenous, and access costs, respectively. While exogenous costs refer to fixed costs an interest group has to take as given for its lobbying activities, endogenous costs depend on how a signal is send to the policymaker and can be chosen by the interest group. Access costs are defined by the policymaker to grant a meeting to the interest group. The prevailing knowledge states that the lobbying costs of interest groups are by far higher than their contributions to political campaigns (Grossman and Helpman, 2001; Bennedsen and Feldmann, 2002; De Figueiredo and Cameron, 2009). Tovar (2011) provides empirical evidence for the importance of endogenous lobbying costs for the determination of trade policy[10].

Interest groups transfer their signal to policymakers, among other channels, through meetings at the policymakers´ offices or at informal meetings via chosen representatives or by engaging lawyers or policy experts, submitting mailings and providing research results or technical information (Tovar, 2011). De Figueiredo and Kim (2004) show that firms use rather own staff to lobby if the topics are highly firm specific and sensitive while external agents are preferred in case of topics general to the industry. The timing of the signal transfer can be before, while, or after a decision was made by the authority, depending on the nature and the process of the decision and its effects (Crombez, 2002; Grossmann and Pyle, 2013; You, 2017). European Commission (EC) is involved in interaction with interest groups since it has to rely often on interest representatives or other experts to collect the information needed to make policy decisions as EC itself does not have a sufficient number of qualified staff to deal with all the questions that need to be clarified (Van Schendelen, 1996, p. 26).

[10] See Coen (2007) for an overview of empirical and theoretical studies about lobbying the EU.

1.2.3 Subsidy literature and likelihood of receiving subsidies

Public authorities provide subsidies to companies for innovative activities in order to overcome a situation where market failures can lead to a lower level of innovative activities than the socially optimal level (Arrow, 1962; Stiglitz, 1986). First, companies performing R&D may not be able to appropriate full returns from their innovation activities as competitors may benefit partly from the newly created knowledge through spillovers and imitating the innovation without facing costs of the creation of the innovation by themselves. Second, financial markets may provide a lower level of financing for innovative activities to companies due to the risky nature of R&D, since it is uncertain whether R&D activity will lead successfully to innovation (Griliches, 1986; Hall, 2002). For an extensive overview about empirical studies on the topic of R&D subsidies and their effects on private R&D investment we refer to Zúñiga-Vicente et al. (2014).

A variety of empirical examinations at the firm level addressing the effect of innovation subsidies on the firm's innovative performance are available that use companies´ observables as covariates in modelling the subsidy receipt likelihood. Non-parametric matching approaches are often relied upon in order to classify highly similar companies by means of observables in a treatment group that received the subsidy and in a control group that did not receive the subsidy. After defining the groups it is verified whether they show a statistically significant difference on average in terms of their innovative performance (Czarnitzki and Lopes-Bento, 2013, 2014; Bérubé and Mohnen, 2009).

Broekel et al. (2015) point to the lack of R&D subsidy allocation literature taking into account geographic aspects. They empirically show that companies located in clusters, i.e. creating high geographic proximity to other companies in their or adjacent activity fields which is conducive for knowledge exchange and creation of new knowledge (Audretsch and Feldman, 1996; Baptista and Swann, 1998), are better embedded in networks of subsidized innovation activities and more successful in receiving innovation subsidies from both EU and national authorities.

Literature in the subsidy field did not take into account the potential effect of geographic proximity to the subsidy granting authority yet. We argue that being closer

to the subsidy granting authority can provide companies with the advantages identified in the political economy literature and other fields that paid already attention to the impact of geographic proximity. Representatives of companies located closer to the authority could be able to conduct their lobbying/networking activities at a lower transaction costs level, since it will be easier for them to be involved in formal and informal relationships with representatives of the authority. Tacit knowledge exchange taking place in such relationships may trigger the subsidy granting authority to define the eligibility and goals for the subsidy programs in favor of interest groups who efficiently interact with the subsidy granting authorities' personnel. Furthermore, lobbying/networking may lead to less information asymmetry for companies interested in subsidies. Thus, such companies might be able to adapt their proposals for their subsidy applications at a superior level than their less successful or none lobbying/networking competitors.

We address the gap in the literature by studying (research question 1) "whether the geographic proximity between firms and the European Commission (EC) as a subsidy granting authority plays a role in the likelihood for firms in being granted with an innovation subsidy from the EU". Moreover, we examine (research question 2) "whether group members located closer to the EC exert a positive effect on the likelihood of being granted". The latter question is relevant since companies can place an office close to the EU authorities as described by Van Schendelen (2013, p. 233). Such an office could potentially gather and transfer knowledge to group members or transfer information to the authorities on behalf of the group members which are located further away from the funding authority.

1.2.4 EU funding for innovative activities

In general, the EU provides funding for activities which further its policies. The funding can take place in different forms; grants, loans, guarantees, equity, subsidies, prizes, and public procurement contracts respectively[11]. One of the main policy goals of the EU is to support innovative activities in Europe. Currently, the largest funding

[11] https://ec.europa.eu/info/funding-tenders/how-eu-funding-works/types-funding_en (accessed last on 29.07.2019)

opportunity provided by the EU specifically for research and innovation is the funding programme Horizon 2020. It comprises the period 2014 to 2020 and has a planned budget of 80 billion Euro available for funding[12]. Its predecessor was the Framework Programme 7 (FP7) which covered the time period 2007 to 2013 and provided a planned budget of 53.2 billion Euro for funding[13]. These two programmes fall within the time horizon of the study at hand. Further programmes for stimulating research and innovation are the European Structural and Investment Funds (ESIF), Research Fund for Coal and Steel, Structural Reform Support Programme (SRSP), Environment and Climate Action (LIFE), and EU Health Programme[14].

In order to receive funding from the EU, an application process must be followed according to the calls published by the European Commission (EC). The calls are outlined by EC's personnel in collaboration with Advisory Groups[15] which include experts from both academia and industry. The calls define among others the eligibility criteria for potential applicants and the goals of the projects. One eligibility criterion can be collaboration of the applicant with other applicants from other European or associated countries[16] since the EC follows the goal to stimulate international cooperation in research and innovation. In case a collaboration is required, applicants can apply jointly or apply individually and use services provided by the EU, national authorities, and other organizations to find a collaboration partner[17].

The project proposals handed in by the applicants are scrutinized by specialists (not members of the Advisory Group) which are either independent specialists or members of the EC staff with the necessary knowledge referring to the call contents and requirements before a decision is made whether an applicants' proposal is successful

[12] http://ec.europa.eu/programmes/horizon2020/en/what-horizon-2020 (accessed last on 29.07.2019)
[13] http://ec.europa.eu/research/fp7/pdf/fp7-brochure_en.pdf (accessed last on 29.07.2019)
[14] https://ec.europa.eu/info/research-and-innovation/funding/funding-opportunities/funding-programmes-and-open-calls_en (accessed last on 29.07.2019)
[15] The EU is transparent about members of Advisory Groups. See for Advisory Groups for FP7 on https://ec.europa.eu/research/fp7/index_en.cfm?pg=eag (accessed last on 29.07.2019)
[16] https://ec.europa.eu/info/research-and-innovation/funding/how-apply/application-process_en (accessed last on 29.07.2019)
[17] https://ec.europa.eu/info/funding-tenders/funding-opportunities/find-project-partner_en (accessed last on 29.07.2019)

or not[18]. External experts and specialists involved in drafting the calls and deciding about applications are reimbursed for their travel and subsistence costs[19] only and have some power, limited through monitoring by other participating experts and specialists as well as EC personnel, to place their interests[20].

For Flanders, in the period 2006-2012, two out of three innovation subsidies stemming from the EU are related to the EU Framework Programmes. To allocate direct R&D grants, the European Commission selects (not self-selection) individuals from a wide pool of evaluators registered for evaluation, call-by-call based on their expertise and experience. Furthermore, geography, gender and rotation are considered when inviting evaluators. Experts agree to terms and conditions of an appointment letter and typically review 6 to 8 proposals remotely, and then spend a couple of days in Brussels to come to an agreement (based on a harmonized procedure supervised by an administrator from the European Commission) with other experts or to participate in hearings with the potential beneficiary. Agreement is made on consensus marks and attention is paid to a predefined set of criteria. Evaluation summary reports are sent to applicants and final ranked lists are drawn up. Experts sign a confidentiality and conflict of interest declaration and names of experts are published after the evaluations (European Commission, 2007).

Researchers recognized the important role of expert panels who decide about success of public support applications but also in review processes other than for public support such as peer review of scientific work. Banal-Estañol et al. (2019) investigate the research grant decisions in UK's Engineering and Physical Sciences Research Council and find evidence for expert panel bias against proposals with structurally more diverse teams, i.e. those teams are less likely to be granted, although such teams are more successful with their projects than less diverse teams. Li (2017) points on the expert panels informational advantage resulting in superior ability to separate between good and bad projects. She also draws attention on personal preferences of the evaluators within expert panels may have, which in turn could bias

[18] https://ec.europa.eu/info/funding-tenders/how-eu-funding-works/how-get-funding/selection-process_en (accessed last on 29.07.2019)
[19] See for example in Mandate Reports for Advisory Groups for FP7 on https://ec.europa.eu/research/fp7/index_en.cfm?pg=eag (accessed last on 29.07.2019)
[20] Van Schendelen (2013, p. 96) mentions misuse cases through experts at DG ENVI and DG SANCO.

the selection systematically. Examining the peer review at the US National Institutes of Health for grants she concludes that preferences of evaluators matter for the funding decisions leading to a systematic bias.

Murray et al. (2016) investigate the research grant proposal success rate and funding level for basic scientific research in Canada. Their findings suggest that there is a systematic bias resulting in lower success rates as well as lower funding level for applications from smaller institutions. After checking for other potential reasons the authors believe that the bias is most likely arising within the process of application evaluation. Further research reveals that a variety of different factors such as network connection of or relatedness between reviewer and applicant, being part of an elite group, gender of the applicant or reviewer, and race of the applicant can be associated with a bias regarding the decisions of expert panels (Teplitskiy et al., 2018; Viner et al., 2004; Jappelli et al., 2017; Ginther et al., 2011).

1.3 Data and econometric methods

1.3.1 Data

The data used to conduct the empirical analyses stem from the Belgian part of the Community Innovation Survey (CIS) for Flanders which is implemented by the Centre for Research & Development Monitoring (ECOOM) in Leuven. The CIS is harmonized at EU level and is developed based on the guidelines of the Oslo manual (OECD/Eurostat, 2005). The surveyed companies are asked whether they received funding from the EU for innovative activities whereat the question allows to differentiate between two categories, funding received from FP7 or its successor Horizon 2020 and other EU funding programmes respectively. The information whether EU funding was received or not is utilized as the outcome variable for the study at hand.

In the cross sectional sample / panel sample used for the empirical analyses 30.8% / 30.2% of the firms reported having received funding only stemming from FP7 or Horizon 2020, 36.2% / 34.5% reported to have received funding only stemming from other EU funding programmes, while the remaining funding receivers reported to

have received funding from both FP7 or Horizon 2020 and other EU funding programmes. That in turn means that although FP7 and Horizon 2020 are the major funding sources for innovative activities stemming from the EU, other EU funding programmes also play an important role.

The CIS covers information about a representative sample of all companies[21] in Flanders in manufacturing and business-related services whereat the waves of the years 2008, 2010, 2012, and 2014 are used for the empirical analyses. Since Flanders surrounds the small Brussels Capital Region (where funding EC authorities are located) and is sufficiently large to observe different levels of geographic proximity, it is particularly convenient to study our research questions by utilizing data about this region.

The geographic distance (direct distance in km) of the companies to the EU district in Brussels were generated by using the Geographic Information System (QGIS)[22] and the companies' address information. To calculate the distance QGIS geocodes the address information of the companies in the sample by using OpenStreetMap or Google Maps services. After geocoding, the location of an address is available on the map with its longitude and latitude coordinates. QGIS uses this information to calculate the distance between two geocoded addresses which are for the examination at hand EC in Brussels and the companies (and their group members) in the sample stemming from the CIS for Flanders.

Group member information stemming from Bureau van Dijk`s databank "Belfirst" is used to take into account potential lobbying/networking activities of group members located closer to the European district than the surveyed focal company, respectively. As group member information immediate shareholder, controlling shareholder, subsidiary, and domestic ultimate owner variables from Belfirst are utilized. Further variables for regional information stem from Belfirst and Statistics Belgium.

[21] The initial sample is drawn from the population of companies with at least 10 employees at the beginning of the period under consideration.

[22] QGIS is a free and open source Geographic Information System available at https://www.qgis.org/en/site

The initial sample consists of 14,782 firm-year observations (8,698 firms) in total. After dropping observations with missing values in variables of interest and restricting the sample to companies which show at least once some innovative activity[23] 7,511 firm-year observations (4,118 firms) remain for pooled cross-sectional estimations. Whether a company is seen as innovative or not is deviated according to the directives defined in the Oslo Manual (OECD/Eurostat, 2005).

In order to conduct meaningful panel regressions that allow controlling for unobserved heterogeneity among firms, we introduce an additional restriction, i.e. the same company must at least be present in two periods in the sample allowing us to observe changes for the same observation over time. Applying the additional restriction, 5.484 firm-year observations (2.091 firms) remain for panel estimations. Descriptive statistics separated by sample and separated by sample and subsidy status are available in Table 1. 1 and Table 1. 2. Figure 1. 1 and Figure 1. 2 illustrate the geographic positions of subsidy recipients and non-subsidy recipients distinguished by sample. The figures show that there are also few observations present within Brussels Capital Region since the Flemish research center (ECOOM) that conducts the CIS for Flanders also contacts those companies which are active in Flanders but have their administrative headquarters located in Belgium but outside of Flanders[24].

1.3.2 Variables

The dependent variable for all estimations[25] is a dummy variable ($EUSUBS$) which takes the value 1 if the surveyed company obtained a direct R&D grant from the EU for innovative activities. Thus the dependent variable does not comprehend information about all subsidies the EU has granted to the firms within the time period analyzed, but only for subsidies particularly for innovative activities. To answer the

[23] Innovative activity here refers to (a) having at least once introduced a new or significant improved product to the market (product innovation), or (b) having at least once introduced a new process of production or distribution (process innovation), or (c) having ongoing innovation projects, or (d) having abandoned innovation projects. Companies that never showed any affinity to innovation are excluded as applying for innovation subsides with the EU institutions appears not to be relevant for them.

[24] An example of such a case is the Vlaamse Maatschappij Voor Watervoorziening which is the largest drinking water company exclusively active in Flanders but having its headquarter in Brussels.

[25] For robustness checks with Federal and Regional Governments' subsidies the dependent variable is adapted with receipt of subsidies from those sources (Table 1. 11 and Table 1. 12).

first research question whether higher geographic proximity increases access to public funding, the variable of main interest is the direct distance ($DIST$) of the company to the European district in Brussels in units of kilometers. To address the second research question, whether group members located closer to the EC positively affect the likelihood of being granted with a subsidy, $DIST$ is substituted by the distance measured at an alternative measurement level which provides the distance of a companies' group member that is closest to the EU district ($DISTgp$)[26]. By doing so, we account for the possibility of a "subsidiary strategy", i.e. that a group member might carry out lobbying/networking activities and transfer the gained knowledge to the surveyed company as described by Van Schendelen (2013, p. 233).

As we are interested in the effect of geographic distance between the company's location and the EU district in Brussels, it is also essential to control for a number of regional factors that determine the local economic circumstances of the firm, as these in turn may influence the occurrence of innovation subsidies. To take into account regional factors, the number of companies nearby ($lnCOMPnr$), the unemployment rate of the region ($lnUNEMP$) and population size ($lnPOPUL$) each transformed to logarithm are used as covariates. $lnCOMPnr$ is calculated by considering companies within the same zip code and same sector at the NACE 2 digit level[27] in order to account for the possible effect of regional competition. $lnUNEMP$ and $lnPOPUL$ are measured at the broader level of Provinces and can be important factors, as companies in economically less developed regions might apply for subsidies more often or the subsidy granting authority may choose companies in economical less developed/rural regions (Cohesion Policy) more often.

The equation to be estimated also includes a number of other control variables at the firm level which might play a role in the likelihood of receiving subsidies. The logarithm of employment ($lnEMP$) and its square ($lnEMP^2$) are used to control for the size of the companies as size is empirically found to be an important determinant for innovativeness of a company (Veugelers and Cassiman, 1999) and is commonly used in estimating the subsidy receipt likelihood (Czarnitzki and Fier, 2002; Duguet 2003;

[26] Group members with an ownership tie of at least 50% are taken into account.

[27] The Statistical Classification of Economic Activities in the European Community (NACE).

Aerts and Schmidt, 2008). Employment numbers are lagged by two years[28] to avoid simultaneity with the dependent variable and are transformed to natural logarithms likewise some of the other covariates to account for the skewed distribution of the variable.

The logarithm of companies´ age ($lnAGE$) is taken into account to control for possible organizational inertia (Hannan and Freeman, 1977) that may develop in maturing firms. $GROUP$ (=1 if company belongs to a conglomerate) and foreign parent company dummies ($FOREIGN$) (=1 if parent company outside of Belgium) are used to account for the group structure (Almus and Czarnitzki 2003; Aerts and Schmidt, 2008). Being a group member may enable a company to introduce and spread innovation sooner than a stand-alone company and may therefore be preferable to the subsidy granting authority. In contrast, a firm with a foreign parent company may be less successful with its subsidy applications, as its main decision makers may suffer under higher information asymmetry resulting out of more distant location from the subsidy granting authority. A dummy variable indicating whether the company got a regional subsidy ($SUBSreg$) (=1 if yes) in the previous period from a regional authority controls for prior subsidy receipt (Duguet 2003; González and Pazó, 2008; Aschhoff, 2009) in order to account for a potentially conducive effect for the company to seek a direct R&D grant from the EU successfully.

A dummy for permanent R&D activity at firm level ($PERMRD$) (=1 if company performs R&D on a permanent basis and not only occasionally or not at all) accounts for the experience of the company in performing R&D activities[29] (Almus and Czarnitzki, 2003; Czarnitzki et al.; 2007 ; Aschhoff, 2009). Further covariates are the logarithm of labor productivity ($lnPROD$) (sales divided by employment) and an

[28] For CIS 2008 the employment number of 2006 is used. The same lag applies for the following waves of CIS.

[29] The information whether a company is a permanent R&D performer or not is only available in the last two of the four surveys used for the analyses. Thus the value for the variable *PERMRD* for the first two periods was imputed. If a company was a permanent R&D performer within the last two periods it was assumed to having been a permanent R&D performer in the first two periods as well. That means the value of 1 was imputed for the first two periods if the value was 1 within the last two periods. To check whether the imputation has a strong influence on the coefficient for the variable *PERMRD* in the main results Pooled Probit, Random Effects Probit, and Pooled OLS regressions are employed (not reported) by using data only from the last two periods. The coefficient remains significant at 1% level and has a similar extent confirming that the imputation does not lead to distortion of the main results.

exporter dummy ($EXPORT$) (=1 if company exports products outside of Belgium). $lnPROD$ controls for a possible picking-the-winner strategy of the subsidy granting authority as higher productivity may be an important indicator used by the subsidy granting authority. $EXPORT$ accounts for the exporting companies' possibly higher innovative capacity that may increase their likelihood to apply for subsidies for innovative activities (Czarnitzki and Lopes-Bento, 2013).

All models are estimated with industry (IND) and time period ($YEAR$) dummies. Descriptive statistics by sample as well as by sample and subsidy status are available in Table 1. 1 and Table 1. 2. Number of observations in each of the ten industry sectors for each sample are available in Table 1. 3 while correlation matrix tables with all variables used for the main empirical analyses distinguished by cross sectional and panel sample are presented in Table 1. 4.

1.3.3 Econometric Methods

"Pooled Probit" (1), "Random Effects Probit" (2), "Chamberlain's Correlated Random Effects Probit" (3) and as robustness checks also "Pooled Ordinary Least Squares (Pooled OLS)" (4) are applied to investigate the relationship between geographic distance to the EC in Brussels and the likelihood to receive direct R&D grants from the European Union.

$$\mathrm{y}_{\mathrm{it}}^{*} = P(y_{it} = 1 \mid x_{it}) = x_{it}'\,\beta \; + \; \varepsilon_{it} \tag{1}$$

$$\mathrm{y}_{\mathrm{it}}^{*} = P(y_{it} = 1 \mid x_{it}, c_i) = x_{it}'\,\beta \; + c_i \; + \; \varepsilon_{it} = x_{it}'\,\beta \; + v_{it} \tag{2}$$

$$\mathrm{y}_{\mathrm{it}}^{*} = P(y_{it} = 1 \mid x_{it}, c_i) = x_{it}'\,\beta + \psi + \bar{x}_i\delta + \alpha_i + \varepsilon_{it} = x_{it}'\,\beta + \psi + \bar{x}_i\delta + v_{it} \tag{3}$$

$$\mathrm{y}_{\mathrm{it}}^{*} = x_{it}'\,\beta \; + \; \varepsilon_{it} \tag{4}$$

$\mathrm{y}_{\mathrm{it}}^{*}$ is a vector of the latent unobserved variable (likelihood of being subsidized) whereat $i = 1,2,\ldots,N$ gives the number of the observation and $t = 1,2,\ldots,T$ refers to the time period. y_{it} is a vector containing the observed status (subsidized=1 or not subsidized=0) of the dependent variable for observation i in time period t. x_{it} is a vector containing the values of the explanatory variables for i in t and β is a vector

containing the coefficient estimations for each of the explanatory variables. $\bar{x}_i$ is a vector of variables which are generated by the average values for i over time for all time variant covariates30[31] in the model while δ is a vector containing the coefficient estimations for the average covariates[32]. c_i is an unobserved, time invariant effect of i. In (3) c_i was replaced by $c_i = \psi + \bar{x}_i\delta + \alpha_i$ as described in Wooldridge (2010, p. 615-616). ε_{it} and v_{it} are error terms for i in t whereat v_{it} contains $(c_i + \varepsilon_{it})$ in (2) and $(\alpha_i + \varepsilon_{it})$ in (3).

The model with all explanatory variables in case of Pooled Probit (1) is as follows:

$$\begin{aligned} P(EUSUBS_{it} = 1 \mid x_{it}) = {} & \beta_0 + \beta_1 DIST_{it} + \beta_2 lnEMP_{it-1} + \beta_3 lnEMP_{it-1}^2 \\ & + \beta_4 lnAGE_{it} + \beta_5 SUBSreg_{it} + \beta_6 GROUP_{it} \\ & + \beta_7 FOREIGN_{it} + \beta_8 EXPORT_{it} + \beta_9 PERMRD_{it} \\ & + \beta_{10} lnPROD_{it} + \beta_{11} lnCOMPnr_{it} + \beta_{12} lnUNEMP_{it} \\ & + \beta_{13} lnPOPUL_{it} + \sum_{k=14}^{22} \beta_k IND_{kit} \\ & + \sum_{k=23}^{25} \beta_k YEAR_{kit} + \varepsilon_{it} \end{aligned} \quad (4)$$

Model (1) treats the data as an independent cross section of size N times T. In order to take into account the unobserved heterogeneity (c_i) Random Effects Probit (2) is applied which treats the data as a panel and takes the dependency of values for each observation along the time dimension into account. However, this method requires that explanatory variables are uncorrelated with the unobserved heterogeneity, which may not be fulfilled. In order to overcome this shortcoming and to allow for correlation between the unobserved heterogeneity and the observed covariates Chamberlain's Correlated Random Effects Probit (3) is applied. This method comes very close to the traditional Fixed Effects Method which cannot be applied for

[31] Those variables are generated by calculating the sum of all values of a variable for each company for all time periods and dividing the obtained sum by the number of the time periods. For instance, the average variable for productivity would be the average productivity of the company considering all periods where the company was observed.

[32] As stated in Wooldridge (2010, p. 616) the time dummies are not considered for generating average covariates since they do not vary across i.

our analyses due to time invariance of the distance variable (*DIST*) as companies in our sample do not relocate within the considered short time period except a few cases. (1), (2), and (3) restrict the estimated latent variable to be within the range from 0 to 1. The Pooled OLS (4) method treats the data as an independent cross section of size N times T whereat the fitted values of the dependent variable are not restricted and therefore can also take values below 0 or above 1.

1.4 Results

1.4.1 Geographic distance and EU innovation subsidies

Table 1. 5 presents the results of the above described econometrics models (except the OLS model which is applied as a robustness check). The results show a significant negative relationship between the distance of the company and the likelihood of obtaining direct R&D grants from the EU. This relationship holds for all sets of main estimations we employ, also by using the alternative distance variable taking into account the distance of group members of the surveyed companies (Table 1. 6) which are located closer to the EU district in Brussels[33]. Main results yield coefficients to the geographic distance ($DIST$) variable which implicate a decrease of 4 to 5 percentage points[34] (Table 1. 7) in the likelihood of being granted with a subsidy from the EU if a company is located 100 km further away from the EU district in Brussels.

The delta in the likelihood might not appear as substantial at first glance. But taking into account that the likelihood on average for being subsidized for a company in our cross sectional sample amounts to 5.7 percentage (Table 1. 1), the relative chance of being subsidized changes by a distance modification of 100 km by 70 to 88 percentage points[35], revealing the importance of geographic proximity. We consider these results

[33] The possibility of a non-linear relationship between the variable distance and the dependent variable was tested delivering no evidence for such a relationship.

[34] All following interpretations likewise 4 to 5 percentage are based on average marginal effects (AME) (see Table 1. 7 and Table 1. 8).

[35] Calculated by taking the value of the average marginal effect for variable *DIST* for models applied with full set of covariates (Table 1. 7 ; (0.0004 or 0.0005) * 100km ➔ 4% or 5%) divided by the average likelihood of being subsidized (Table 1. 1 ; 5.7%). Marginal effects estimated change under application of marginal effects at the mean (MEM) or the estimation of the marginal effects

as a confirmation that the lobbying/networking activities of the companies can be conducted at a lower transaction cost level by lower physical distance which in turn leads to lower level of information asymmetry and higher success rate in subsidy applications. Comparison of the results in Table 1. 6 and Table 1. 5 leads us to the conclusion that group members located closer to the authority do not transfer in higher success rate with subsidy applications as we do not observe a higher significance or extent of the coefficients for the distance variable when the location of group members is taken into account.

The likelihood of getting an EU subsidy increases disproportionately with an increase of the size of a company in terms of employees which is in line with the findings by Czarnitzki & Lopes-Bento (2013, 2014). This confirms that larger companies may apply more often for innovation subsidies or are from the perspective of the subsidy granting authority more eligible for a subsidy grant than their smaller competitors. An increase of the age of the companies shows a negative effect only for the cross sectional estimation statistically significant at 10 % level, providing weak evidence for a possible inertia of incumbents. Companies which were subsidized by the regional authorities before show a 3.4 to 9.5 percentage points higher likelihood at 1% significance level (Table 1. 7) to be granted except in case of Chamberlain's Random effects probit (CRE) model.

Regional sourced subsidy receipt in case of CRE model shows a negative effect of around 1.2 percentage points which is significant at 10% level whereat the positive effect is picked up by the highly correlated (0.74) average version of the variable[36] which is significant at 1% level showing 18 percentage points higher likelihood to be granted. That previous subsidy receipt is conducive for the success rate of future applications is in line with findings by Duguet (2003), González and Pazó (2008), and Aschhoff (2009). Being a member of a company conglomerate is not associated with the dependent variable but there is a significant, negative relation for companies with a foreign parent company. Such companies are around 1.6 to 1.9 percentage points

measuring the distance in alternative units such as in natural logarithm. The extent reported here is to be seen as a maximum while in other specifications (not reported) the expected change in the subsidy receipt likelihood can drop up to 27.5% by a change of distance by 93km.

[36] For the sake of lucidity results tables show only the joint significance of all average variables applied within Chamberlain's Random Effects Probit Models.

less likely to be granted with a subsidy from the EU which is presumably due to the lower geographic proximity of central decision makers to the funding authority, leading to higher information asymmetry.

Companies which export their products outside of Belgium are not significantly different in the likelihood of being subsidized by the EU. Likewise in Czarnitzki & Fier (2002) and Aschhoff (2009) permanent R&D performers are 3.4 to 5.1 percentage points more likely to obtain subsidies from the EU. This result provides evidence for the potential preference of innovation subsidy granting EU authorities towards R&D experienced companies, besides the fact that such companies will apply more often for subsidies. Labor productivity is not significantly associated with the likelihood of getting EU subsidies.

There is evidence for a negative effect of regional competition (measured as the number of companies within the same zip code area and industry sector). Presumably more companies in a region within the same sector lead to a higher number of applications for the same subsidies from the same region. This results in higher competition for the same subsidies which in turn could lead to a lower likelihood of being subsidized for each of the companies within the same region and sector. Unemployment rate yields a positive and significant coefficient at 10 % at 5% levels only in random effects and Chamberlain's Correlated random effects estimations providing evidence for a possible support for economically poor performing regions by the EU. The estimations with the panel sample show a negative significant effect of higher population numbers on the likelihood of being subsidized in some settings, delivering evidence for a possible support for rural regions by the EU (Cohesion Policy) or a higher application aptitude of companies located in rural regions.

1.4.2 Robustness checks

A variety of econometric estimations are employed to check the robustness of the main results. In Table 1. 9 a possible effect of the distribution of the variable $DIST$ on the main results is verified by running the econometric estimations with the distance variable transformed to natural logarithm ($lnDIST$). The findings confirm the prior results reported in Table 1. 5.

In order to check whether the distance variable measures solely the power of attraction of the large city of Brussels with its well established infrastructure and social activity possibilities rather than the effect of being close to EU innovation funding administrators three robustness checks are performed. The first one is conducted by taking the distance of the companies in our sample to Antwerp, by far the largest city in Flanders, whereat the dependent variable remains unmodified. If the distance variable in the main results would capture the attractiveness of the large city of Brussels the same would be expected with another large city as well. The results in Table 1. 10 show that the distance variable becomes insignificant by taking the companies´ distance to Antwerp which hints in the direction that the coefficient for the distance variable in the main results is not capturing the attractiveness of the city of Brussels.

The second robustness check is conducted by taking the distance of companies to the Belgian Federal Government in Brussels by also adapting the dependent variable ($FedGovSubs$) which takes the value 1 if the company received a subsidy granted by the Federal Government. As the Federal Government support for innovative activities in our sample are mainly non-competitive tax incentives[37], i.e. every company fulfilling the requirements will be granted with tax deduction without a competitive selection procedure, lobbying or networking activities seem less relevant[38]. Thus one would expect the distance to the Federal Government to be at least less important to get subsidy grants compared with the distance to the EU Authorities. The results in Table 1. 11 show that, compared to EU subsidies, the distance variable is significant in the simple models at a lower level and becomes insignificant if controlling for further covariates in the full models.

The third robustness check takes the distance of companies to the Flemish innovation subsidy authority, Agency for Innovation by Science and Technology (IWT)[39], located in Brussels. The dependent variable ($RegGovSubs$) takes the value of

[37] Belgian Federal Government provides indirect subsidies for innovative activities via tax reliefs (in Flemish): https://www.vlaio.be/nl/subsidies-financiering/subsidiedatabank/zoek?thema=28&steunverlenende_overheid%5B%5D=50 (last accessed on 29.07.2019)

[38] Lobbying and networking activities could still play a role in defining the requirements for the eligibility for and magnitude of tax incentives.

[39] IWT was active until 2015 and was replaced by Flanders Innovation & Entrepreneurship (VLAIO).

1 if the focal company received an innovation subsidy sourced by the regional government and allocated by IWT. While IWT's subsidy allocation activities can be well monitored by a single authority (Flemish Government) the supranational EU authorities are more difficult to monitor. Due to stricter monitoring, potential lobbying or networking activities would be expected to be less successful and thus geographic proximity is expected to play a minor role compared to the case of EU authorities. Also this robustness check gives statistical insignificant coefficients regarding the distance variable (Table 1. 12) and delivers a confirmation that the distance variable is not measuring the power of attractiveness of the large city of Brussels.

Another robustness check (Table 1. 13) addresses concerns that the subsidy receiver and none subsidy receiver groups might be very different from each other, i.e. unobserved differences between these groups could lead to omitted variable bias. We restrict the sample on regional subsidy receivers to obtain a subsample that ensures the presence of very similar companies in both groups only and run the estimations on that subsample. Results of this robustness check also confirm the findings obtained with the estimations with the full sample, i.e. the distance variable is statistically significant with negative coefficients and provides certainty that the main results are not driven by systematically deviating treated and control groups of companies.

Table 1. 14 (i) and Table 1. 15 (ii) present results with two different approaches to check for the potential effect of group members. Instead of the modified distance variable *DISTgp*, (i) a dummy variable (*GPMEM*) indicating the presence of a group member closer to the authority and (ii) an additional distance variable (*GPDIST*) containing the distance of the group members, in both (i) and (ii) in addition to unmodified *DIST* variable are considered in the models. Also those settings shows that having a group member located closer to the EU administration does not matter for getting a grant whereat again all the other coefficients remain largely the same as in the main results (Table 1. 5 and Table 1. 6). Using Pooled Ordinary Least Squares (Pooled OLS) method with clustered standard errors, Table 1. 16 and Table 1. 17 provide results which show that the variables of the main interest, *DIST* and *DISTgp*,

are likewise in the main results negative and significant at 1% level confirming the direction and significance of the main results in Table 1. 5 and Table 1. 6.

1.5 Conclusion

Over the past decades increasing attention has been paid to the role of geographic proximity and knowledge exchange for innovation (Boschma, 2005). However, the role of geographic proximity in getting access to public funding for innovation has been far less studied (Broekel et al. 2015). As Boschma (2005) states, geographic proximity solely is not sufficient to have any impact. In the context of innovation subsidies networking and lobbying efforts may be the underlying mechanisms whereat higher geographic proximity would be associated with lower transaction costs for these activities. Consequently, we added to the literature by studying the role of geographic proximity to the European Commission (EC) administration in Brussels and the probability of successful access to public innovation support by the European Union (EU). To examine our research subject, access to EU public funding for innovation by firms within the period 2006-2014 in Flanders, the region adjacent to and surrounding the Brussels Capital Region (host of the EC innovation granting authorities), is utilized. Furthermore, we investigated whether closer proximity of a group member of the focal firm to the EC has a positive influence on access of the focal firm to EU public funding for innovation.

The conducted analyses provide empirical evidence that higher geographic proximity to the EC administration in Brussels matters for Flemish companies in terms of being more successful in getting granted with innovation subsidies from the EU. Besides methodological variations verifying our results, logical consequences of absence or ineffectiveness of potential lobbying and networking activities are confirmed by placebo tests that check with two alternative authorities (Belgian Federal Government and Flemish Subsidy Authority) both located in Brussels and granting innovation subsidies. These tests deliver, in line with theoretical expectancy, no statistical significant effect of geographic proximity, since those authorities are expected to be less prone to a possible influence by lobbying or networking.

Additionally, another placebo test taking the distance to the largest city of Belgium (Antwerp) gives us confidence that we are not capturing merely the effect of the attractiveness of a large city (Brussels). Results hold also by restricting the sample on regional subsidy receivers to ensure that treated and control groups are not systematically different from each other and thus the analyses do not suffer under omitted variable bias.

Similar studies deliver evidence for negative effects of geographic proximity for collaboration in innovation (e.g. Morescalchi et al., 2015), while our study reveals that further distances to the funding source for innovation can reduce the probability of being granted with subsidies. This seems to indicate that, as it is the case in innovation activities (Howells, 2002), also the information included in applications for innovation subsidies is – at least partly - tacit in nature and affected by lower endogenous (signaling) and lower access costs (Grossman and Helpman, 2001) created by high geographic proximity. The findings support the idea of geographic proximity as enabler for building stronger relations between representatives of the companies and representatives of the EU authorities. Based on earlier work by Tovar (2011) in the field of lobbying for trade policy, we can relate our findings to larger opportunities for meetings at the policymakers' offices, contacts at informal meetings via chosen representatives, and opportunities for providing more detailed information regarding technical and other information with regard to the innovation projects. Our findings for access to public subsidies for innovation complement the positive findings of endogenous lobbying costs for the determination of trade policy as reported by Tovar (2011) and the findings about how networks can shape expert panel decisions by Teplitskiy et al. (2018).

Our research also demonstrates that group members which are located closer to the subsidy granting authority do not entail a higher probability for the focal firm of being subsidized, suggesting that the actual location of the company itself is the important determinant having an effect on the success rate of companies' subsidy applications. This finding largely is in line with the previous arguments regarding the importance of the exchange of tacit knowledge, even between firms belonging to the same group. These results need to be seen in a context of relatively small distances (up to 130 km) to the funding source.

In conclusion, our research revealed the importance to take into account the role of geographic proximity, which serves as proxy for opportunities for networking and lobbying, in influencing the chances for successful access to public funding for innovation. This factor has been largely overlooked in the empirical and theoretical literature on subsidy allocation (Broekel et al., 2015). For future research, collecting and utilizing data on networking and lobbying efforts for the purpose of accessing grants is recommended in order to overcome the weaknesses arising through approximating networking and lobbying efforts by geographic distance. In this respect, it would be interesting to provide direct evidence for the potential effects of networking and lobbying and disentangle the effects of these activities; e.g. are these due to representatives of companies being better informed about the requirements to be successful with applications for subsidies, because of larger possibilities to influence the design of policy programs in the first place, or because of larger influence in the decision making process.

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Tables and Figures

Table 1. 1 Descriptive statistics distinguished by sample

	Cross Sectional Sample (N=7,511)				Panel Sample (N=5,484)			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
EUSUBS	0.057	0.232	0	1	0.064	0.244	0	1
DIST	53.614	26.576	0.054	129.828	53.846	26.742	0.054	129.828
DISTgp	50.032	27.480	0.054	129.828	49.856	27.824	0.054	129.828
lnEMP	3.834	1.369	0	9.036	4.081	1.342	0	8.503
lnAGE	3.174	0.687	0.693	5.572	3.222	0.667	0.693	5.572
SUBSreg	0.079	0.270	0	1	0.103	0.304	0	1
GROUP	0.603	0.489	0	1	0.644	0.479	0	1
FOREIGN	0.293	0.455	0	1	0.323	0.468	0	1
EXPORT	0.653	0.476	0	1	0.675	0.468	0	1
PERMRD	0.321	0.467	0	1	0.378	0.485	0	1
lnPROD	5.447	0.944	0	11.188	5.471	0.927	0	10.836
lnCOMPnr	2.988	1.429	0.693	7.711	2.920	1.419	0.693	7.711
lnUNEMP	0.039	0.013	0.021	0.163	0.039	0.013	0.021	0.163
lnPOPUL	14.079	0.251	13.625	14.405	14.076	0.251	13.625	14.405

Table 1. 2 Descriptive statistics by sample and subsidy receipt

Cross Sectional Sample:

	EUSUBS =1, N=428				*EUSUBS* =0, N=7,083			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
EUSUBS	1	0	1	1	0	0	0	0
DIST	44.846	25.873	0.489	129.828	54.143	26.527	0.054	129.828
DISTgp	40.378	27.089	0.489	129.828	50.615	27.397	0.054	129.828
lnEMP	4.627	1.784	0.000	9.007	3.786	1.325	0.000	9.036
lnAGE	3.122	0.780	0.693	4.920	3.177	0.681	0.693	5.572
SUBSreg	0.353	0.478	0	1	0.063	0.242	0	1
GROUP	0.738	0.440	0	1	0.595	0.491	0	1
FOREIGN	0.341	0.475	0	1	0.290	0.454	0	1
EXPORT	0.722	0.449	0	1	0.649	0.477	0	1
PERMRD	0.757	0.429	0	1	0.294	0.456	0	1
lnPROD	5.411	1.189	0	9.061	5.449	0.927	0	11.188
lnCOMPnr	2.733	1.419	0.693	6.829	3.003	1.428	0.693	7.711
lnUNEMP	0.046	0.027	0.021	0.163	0.039	0.012	0.021	0.163
lnPOPUL	14.075	0.225	13.625	14.405	14.079	0.253	13.625	14.405

Panel Sample:

	EUSUBS =1, N=350				*EUSUBS* =0, N=5,134			
EUSUBS	1	0	1	1	0	0	0	0
DIST	44.239	26.031	0.489	129.828	54.501	26.667	0.054	129.828
DISTgp	39.257	27.270	0.489	129.828	50.579	27.717	0.054	129.828
lnEMP	4.855	1.761	0.000	8.445	4.028	1.292	0.000	8.503
lnAGE	3.179	0.802	0.693	4.920	3.225	0.657	0.693	5.572
SUBSreg	0.409	0.492	0	1	0.082	0.275	0	1
GROUP	0.789	0.409	0	1	0.634	0.482	0	1
FOREIGN	0.369	0.483	0	1	0.320	0.467	0	1
EXPORT	0.729	0.445	0	1	0.672	0.470	0	1
PERMRD	0.811	0.392	0	1	0.348	0.476	0	1
lnPROD	5.439	1.218	0	8.599	5.473	0.904	0	10.836
lnCOMPnr	2.670	1.374	0.693	6.781	2.937	1.421	0.693	7.711
lnUNEMP	0.046	0.028	0.021	0.163	0.039	0.011	0.021	0.163
lnPOPUL	14.067	0.224	13.625	14.405	14.077	0.253	13.625	14.405

Table 1. 3 Industry classification

Variable	Industry	2 Digit NACE-Codes (2008)	# of Observations Cross Sectional Sample	# of Observations Panel Sample
Sector 1	Textile, Paper, Wood	13-18	517	351
Sector 2	Chemicals, Plastics	19-22	817	688
Sector 3	Metal	24-25	555	400
Sector 4	Food, Beverages	10-12	604	473
Sector 5	Machinery, Vehicles	28-30, 33	735	594
Sector 6	Electronics	26-27	338	282
Sector 7	Other Industries	1, 8, 23, 31-32, 35-36, 38-39, 41-43, 58, 74	725	524
Sector 8	Trade	45-47	964	585
Sector 9	Transport, Other Services	37, 49-53, 59-61, 64-66, 68-70, 73, 77-91, 93-99	869	553
Sector 10	Information Services	62-63, 71-72	1387	1034

Table 1. 4 Correlation matrices

Cross Sectional Sample

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	*EUSUBS*	1.00												
2	*DIST*	-0.08***	1.00											
3	*DISTgp*	-0.09***	0.89***	1.00										
4	*lnEMP*	0.14***	-0.08***	-0.15***	1.00									
5	*lnAGE*	-0.02	-0.01	-0.03***	0.37***	1.00								
6	*SUBSreg*	0.25***	-0.00	-0.02	0.18***	0.02*	1.00							
7	*GROUP*	0.07***	-0.11***	-0.19***	0.42***	0.06***	0.09***	1.00						
8	*FOREIGN*	0.03**	-0.19***	-0.18***	0.35***	0.05***	0.03***	0.52***	1.00					
9	*EXPORT*	0.04***	0.06***	0.04***	0.09***	0.06***	0.09***	0.07***	0.06***	1.00				
10	*PERMRD*	0.23***	0.01	-0.02*	0.24***	-0.00	0.29***	0.15***	0.06***	0.17***	1.00			
11	*lnPROD*	-0.01	-0.04***	-0.07***	0.16***	0.14***	0.02*	0.20***	0.17***	0.15***	0.05***	1.00		
12	*lnCOMPnr*	-0.04***	-0.11***	-0.10***	-0.11***	-0.07***	-0.09***	-0.01	0.02	-0.11***	-0.07***	0.06***	1.00	
13	*lnUNEMP*	0.12***	-0.36***	-0.33***	0.16***	0.03*	0.08***	0.10***	0.13***	0.00	0.07***	0.07***	0.07***	1.00
14	*lnPOPUL*	-0.00	-0.32***	-0.30***	0.03**	0.05***	-0.02*	0.02**	0.05***	-0.00	-0.02	0.05***	0.11***	0.20***

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

Panel Sample

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	*EUSUBS*	1.00												
2	*DIST*	-0.09***	1.00											
3	*DISTgp*	-0.10***	0.89***	1.00										
4	*lnEMP*	0.15***	-0.09***	-0.16***	1.00									
5	*lnAGE*	-0.02	-0.02	-0.04***	0.33***	1.00								
6	*SUBSreg*	0.26***	-0.01	-0.02	0.17***	0.00	1.00							
7	*GROUP*	0.08***	-0.12***	-0.19***	0.42***	0.04***	0.08***	1.00						
8	*FOREIGN*	0.03	-0.19***	-0.18***	0.35***	0.04***	0.02*	0.51***	1.00					
9	*EXPORT*	0.03**	0.05***	0.03**	0.09***	0.05***	0.09***	0.07***	0.08***	1.00				
10	*PERMRD*	0.23***	0.00	-0.02	0.22***	-0.03**	0.28***	0.15***	0.06***	0.16***	1.00			
11	*lnPROD*	-0.01	-0.04***	-0.07***	0.16***	0.12***	0.02*	0.19***	0.16***	0.15***	0.06***	1.00		
12	*lnCOMPnr*	-0.04***	-0.11***	-0.09***	-0.09***	-0.06***	-0.09***	0.00	0.01	-0.13***	-0.06***	0.04***	1.00	
13	*lnUNEMP*	0.13***	-0.37***	-0.33***	0.18***	0.05***	0.10***	0.11***	0.14***	-0.00	0.05***	0.07***	0.04***	1.00
14	*lnPOPUL*	-0.01	-0.32***	-0.30***	0.04***	0.06***	-0.02*	0.02	0.06***	0.00	-0.01	0.05***	0.10***	0.20***

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

Table 1. 5 Geographic distance and EU subsidies

Results with distance of surveyed companies.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST	-0.006***	-0.007***	-0.013***	-0.005***	-0.006***	-0.009***	-0.009***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
lnEMP				-0.197**	-0.281***	-0.461***	-0.179
				(0.082)	(0.103)	(0.160)	(0.282)
$lnEMP^2$				0.041***	0.049***	0.084***	0.035
				(0.009)	(0.011)	(0.019)	(0.047)
lnAGE				-0.089*	-0.038	-0.081	0.052
				(0.051)	(0.061)	(0.098)	(0.264)
SUBSreg				0.664***	0.709***	0.522***	-0.237
				(0.080)	(0.087)	(0.137)	(0.150)
GROUP				0.025	0.109	0.047	-0.117
				(0.076)	(0.092)	(0.147)	(0.214)
FOREIGN				-0.192**	-0.204**	-0.336**	-0.334
				(0.084)	(0.096)	(0.149)	(0.242)
EXPORT				0.053	0.032	0.107	0.175
				(0.066)	(0.079)	(0.126)	(0.164)
PERMRD				0.485***	0.495***	0.906***	0.641**
				(0.120)	(0.148)	(0.251)	(0.262)
lnPROD				-0.027	-0.026	-0.038	-0.031
				(0.039)	(0.049)	(0.077)	(0.141)
lnCOMPnr				-0.058**	-0.058*	-0.106**	-0.066
				(0.027)	(0.033)	(0.054)	(0.113)
lnUNEMP				2.685	2.859	7.113*	12.580**
				(2.198)	(2.681)	(4.094)	(5.342)
lnPOPUL				-0.179	-0.279*	-0.527**	0.298
				(0.131)	(0.157)	(0.262)	(2.106)
Constant	-1.148***	-1.078***	-2.253***	1.335	2.677	5.423	4.149
	(0.134)	(0.162)	(0.347)	(1.890)	(2.280)	(3.831)	(4.042)
lnsig2u			1.215***			0.703***	0.652***
			(0.177)			(0.196)	(0.194)
[1] chi2(11)							79.30
Prob>chi2							0.0000
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01 ; Standard errors allowing for intragroup correlation (cluster) in brackets.
Coefficients reported. Variable *DIST* in km.

[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST* and *PERMRD* which are time invariant.

Table 1. 6 Geographic distance and EU subsidies - controlling for group members

Results taking into account the group members´ distance, if a group member located closer to the EU district in Brussels present. If yes, the distance of the surveyed company is substituted with group members´ distance.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DISTgp	-0.006***	-0.007***	-0.012***	-0.004***	-0.005***	-0.007**	-0.007**
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
lnEMP				-0.190**	-0.270***	-0.449***	-0.186
				(0.082)	(0.103)	(0.159)	(0.282)
$lnEMP^2$				0.040***	0.047***	0.082***	0.038
				(0.009)	(0.011)	(0.019)	(0.047)
lnAGE				-0.089*	-0.038	-0.084	0.038
				(0.051)	(0.060)	(0.098)	(0.265)
SUBSreg				0.667***	0.715***	0.528***	-0.233
				(0.080)	(0.087)	(0.137)	(0.150)
GROUP				0.007	0.088	0.019	-0.130
				(0.076)	(0.092)	(0.147)	(0.214)
FOREIGN				-0.167**	-0.174*	-0.289**	-0.302
				(0.083)	(0.094)	(0.147)	(0.242)
EXPORT				0.051	0.028	0.103	0.173
				(0.066)	(0.079)	(0.126)	(0.164)
PERMRD				0.482***	0.491***	0.896***	0.631**
				(0.120)	(0.148)	(0.250)	(0.260)
lnPROD				-0.030	-0.030	-0.044	-0.032
				(0.040)	(0.049)	(0.078)	(0.141)
lnCOMPnr				-0.058**	-0.058*	-0.105**	-0.068
				(0.027)	(0.033)	(0.053)	(0.112)
lnUNEMP				3.481	3.799	8.614**	13.633***
				(2.133)	(2.590)	(3.966)	(5.166)
lnPOPUL				-0.163	-0.266*	-0.492*	0.398
				(0.130)	(0.156)	(0.258)	(2.127)
Constant	-1.157***	-1.092***	-2.342***	1.040	2.403	4.789	3.550
	(0.129)	(0.154)	(0.332)	(1.866)	(2.251)	(3.751)	(3.942)
lnsig2u			1.190***			0.696***	0.642***
			(0.175)			(0.195)	(0.193)
[1] chi2(11)							79.38
Prob>chi2							0.0000
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01. Standard errors allowing for intragroup correlation (cluster) in brackets.
Coefficients reported. Variable *DISTgp* in km.
[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DISTgp* and *PERMRD* which are time invariant.

Table 1. 7 Geographic distance and EU subsidies (marginal effects)

Results with distance of surveyed companies.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST	-0.0007***	-0.0008***	-0.0007***	-0.0004***	-0.0005***	-0.0005***	-0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
lnEMP				0.0147***	0.0162***	0.0177***	0.0076
				(0.0026)	(0.0033)	(0.0033)	(0.0117)
lnAGE				-0.0080*	-0.0036	-0.0046	0.0028
				(0.0046)	(0.0058)	(0.0056)	(0.0142)
SUBSreg				0.0847***	0.0940***	0.0342***	-0.0120*
				(0.0141)	(0.0158)	(0.0110)	(0.0072)
GROUP				0.0022	0.0102	0.0026	-0.0064
				(0.0068)	(0.0085)	(0.0083)	(0.0118)
FOREIGN				-0.0166**	-0.0189**	-0.0185**	-0.0173
				(0.0070)	(0.0086)	(0.0079)	(0.0123)
EXPORT				0.0048	0.0030	0.0060	0.0092
				(0.0059)	(0.0074)	(0.0069)	(0.0085)
PERMRD				0.0459***	0.0473***	0.0516***	0.0344**
				(0.0123)	(0.0146)	(0.0145)	(0.0142)
lnPROD				-0.0024	-0.0025	-0.0022	-0.0016
				(0.0036)	(0.0047)	(0.0044)	(0.0076)
lnCOMPnr				-0.0052**	-0.0056*	-0.0061**	-0.0035
				(0.0025)	(0.0032)	(0.0030)	(0.0060)
lnUNEMP				0.2428	0.2744	0.4058*	0.6738**
				(0.1985)	(0.2569)	(0.2324)	(0.2875)
lnPOPUL				-0.0161	-0.0268*	-0.0301**	0.0160
				(0.0118)	(0.0151)	(0.0149)	(0.1128)
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01. Average Marginal effects (AME) reported. Variable *DIST* in km. The average variables used in Chamberlain's Correlated Random Effects Probit Model (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST* and *PERMRD* which are time invariant.

Table 1. 8 Geographic distance and EU subsidies - controlling for group members (marginal effects)

Results taking into account the group members´ distance, if a group member located closer to the EU district in Brussels present. If yes, the distance of the surveyed company is substituted with group members´ distance.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DISTgp	-0.0007***	-0.0009***	-0.0006***	-0.0004***	-0.0004***	-0.0004**	-0.0004***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
lnEMP				0.0143***	0.0156***	0.0172***	0.0085
				(0.0026)	(0.0033)	(0.0033)	(0.0118)
lnAGE				-0.0081*	-0.0037	-0.0048	0.0020
				(0.0046)	(0.0058)	(0.0056)	(0.0142)
SUBSreg				0.0855***	0.0952***	0.0348***	-0.0118*
				(0.0142)	(0.0159)	(0.0110)	(0.0072)
GROUP				0.0007	0.0083	0.0011	-0.0071
				(0.0069)	(0.0086)	(0.0083)	(0.0119)
FOREIGN				-0.0145**	-0.0163*	-0.0160**	-0.0158
				(0.0070)	(0.0086)	(0.0079)	(0.0124)
EXPORT				0.0046	0.0027	0.0058	0.0091
				(0.0059)	(0.0075)	(0.0070)	(0.0085)
PERMRD				0.0456***	0.0470***	0.0512***	0.0340**
				(0.0123)	(0.0146)	(0.0145)	(0.0141)
lnPROD				-0.0027	-0.0029	-0.0025	-0.0016
				(0.0036)	(0.0047)	(0.0044)	(0.0076)
lnCOMPnr				-0.0053**	-0.0056*	-0.0060**	-0.0036
				(0.0025)	(0.0032)	(0.0030)	(0.0060)
lnUNEMP				0.3152	0.3652	0.4928**	0.7327***
				(0.1928)	(0.2484)	(0.2250)	(0.2787)
lnPOPUL				-0.0148	-0.0255*	-0.0282*	0.0214
				(0.0118)	(0.0150)	(0.0147)	(0.1143)
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01. Average Marginal effects (AME) reported. Variable *DISTgp* in km. The average variables used in Chamberlain's Correlated Random Effects Probit Model (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DISTgp* and *PERMRD* which are time invariant.

Table 1. 9 Results with log distance variable

Results with distance of surveyed companies transformed to natural logarithm.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
lnDIST	-0.240***	-0.272***	-0.510***	-0.156***	-0.183***	-0.308***	-0.319***
	(0.050)	(0.058)	(0.110)	(0.053)	(0.063)	(0.109)	(0.114)
lnEMP				-0.197**	-0.279***	-0.460***	-0.182
				(0.082)	(0.103)	(0.159)	(0.282)
$lnEMP^2$				0.041***	0.049***	0.084***	0.035
				(0.009)	(0.011)	(0.019)	(0.047)
lnAGE				-0.089*	-0.039	-0.083	0.061
				(0.051)	(0.061)	(0.098)	(0.265)
SUBSreg				0.666***	0.712***	0.523***	-0.240
				(0.080)	(0.087)	(0.137)	(0.150)
GROUP				0.030	0.118	0.056	-0.120
				(0.077)	(0.093)	(0.148)	(0.213)
FOREIGN				-0.188**	-0.201**	-0.331**	-0.330
				(0.084)	(0.095)	(0.149)	(0.243)
EXPORT				0.054	0.032	0.109	0.172
				(0.066)	(0.079)	(0.126)	(0.164)
PERMRD				0.479***	0.484***	0.889***	0.620**
				(0.120)	(0.148)	(0.251)	(0.262)
lnPROD				-0.028	-0.028	-0.040	-0.031
				(0.040)	(0.049)	(0.078)	(0.142)
lnCOMPnr				-0.058**	-0.059*	-0.107**	-0.067
				(0.027)	(0.033)	(0.054)	(0.113)
lnUNEMP				1.811	1.718	5.065	10.294*
				(2.349)	(2.872)	(4.308)	(5.577)
lnPOPUL				-0.065	-0.150	-0.313	0.575
				(0.129)	(0.156)	(0.255)	(2.116)
Constant	-0.551**	-0.399	-0.947*	0.124	1.311	3.232	2.041
	(0.226)	(0.266)	(0.499)	(1.830)	(2.225)	(3.704)	(3.950)
lnsig2u			1.202***			0.704***	0.655***
			(0.175)			(0.195)	(0.193)
[1] chi2(11)							79.57
Prob>chi2							0.0000
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01 ; Standard errors allowing for intragroup correlation (cluster) in brackets.
Coefficients reported. Variable ln*DIST* in km transformed to natural logarithm.
[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except ln*DIST* and *PERMRD* which are time invariant.

Table 1. 10 Results taking distance to Antwerp

Results with distance of surveyed companies to Antwerp.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST_Antw	-0.001	-0.001	-0.002	-0.001	-0.002	-0.002	-0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
lnEMP				-0.189**	-0.270***	-0.453***	-0.179
				(0.082)	(0.103)	(0.160)	(0.284)
$lnEMP^2$				0.041***	0.048***	0.084***	0.035
				(0.009)	(0.011)	(0.019)	(0.047)
lnAGE				-0.088*	-0.037	-0.084	0.038
				(0.050)	(0.060)	(0.098)	(0.268)
SUBSreg				0.669***	0.719***	0.526***	-0.236
				(0.081)	(0.087)	(0.138)	(0.150)
GROUP				0.032	0.122	0.058	-0.116
				(0.076)	(0.093)	(0.148)	(0.214)
FOREIGN				-0.168**	-0.180*	-0.290*	-0.314
				(0.084)	(0.095)	(0.149)	(0.244)
EXPORT				0.047	0.025	0.100	0.173
				(0.066)	(0.078)	(0.126)	(0.164)
PERMRD				0.485***	0.499***	0.914***	0.659**
				(0.120)	(0.147)	(0.250)	(0.262)
lnPROD				-0.251**	-0.285*	-0.472*	-0.367
				(0.123)	(0.154)	(0.261)	(0.270)
lnCOMPnr				-0.029	-0.029	-0.042	-0.028
				(0.040)	(0.050)	(0.079)	(0.142)
lnUNEMP				-0.059**	-0.059*	-0.109**	-0.073
				(0.027)	(0.033)	(0.054)	(0.113)
lnPOPUL				4.899**	5.366**	10.957***	15.074***
				(2.162)	(2.643)	(4.143)	(5.529)
Constant				-0.157	-0.290	-0.502	0.268
				(0.177)	(0.209)	(0.352)	(2.182)
lnsig2u	-1.456***	-1.423***	-2.897***	0.692	2.471	4.503	5.859
	(0.122)	(0.147)	(0.343)	(2.590)	(3.075)	(5.202)	(5.400)
[1] chi2(11)							79.52
Prob>chi2							0.0000
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01 ; Standard errors allowing for intragroup correlation (cluster) in brackets.
Coefficients reported. Variable *DIST_Antw* in km.

[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST_Antw* and *PERMRD* which are time invariant.

Table 1. 11 Results taking distance to Federal Government

Results with distance of surveyed companies to Federal Government.

	Dependent variable: Federal Government subsidy receipt dummy *FedGovSubs*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST_FedGov	-0.002*	-0.002**	-0.003**	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
lnEMP				-0.116*	-0.086	-0.093	-0.165
				(0.070)	(0.090)	(0.106)	(0.209)
$lnEMP^2$				0.030***	0.028***	0.034***	0.074**
				(0.008)	(0.010)	(0.012)	(0.036)
lnAGE				-0.047	-0.028	-0.022	0.264
				(0.038)	(0.045)	(0.054)	(0.169)
SUBSreg				0.370***	0.402***	0.362***	-0.102
				(0.072)	(0.077)	(0.087)	(0.108)
GROUP				0.088	0.133*	0.124	0.068
				(0.057)	(0.070)	(0.083)	(0.149)
FOREIGN				-0.114**	-0.099	-0.113	-0.202
				(0.058)	(0.065)	(0.078)	(0.190)
EXPORT				0.266***	0.297***	0.341***	0.298***
				(0.055)	(0.066)	(0.078)	(0.106)
PERMRD				0.581***	0.650***	0.760***	0.689***
				(0.076)	(0.093)	(0.113)	(0.115)
lnPROD				-0.337***	-0.301***	-0.389***	-0.366***
				(0.077)	(0.097)	(0.115)	(0.116)
lnCOMPnr				-0.044	-0.027	-0.043	-0.105
				(0.031)	(0.038)	(0.045)	(0.093)
lnUNEMP				-0.000	0.008	0.005	-0.031
				(0.018)	(0.022)	(0.026)	(0.062)
lnPOPUL				0.666	0.755	1.542	6.977*
				(2.007)	(2.430)	(2.782)	(4.139)
Constant				-0.047	-0.017	-0.032	-0.367
				(0.099)	(0.118)	(0.137)	(0.983)
lnsig2u	-0.653***	-0.598***	-0.878***	-0.348	-1.275	-1.307	-2.191
	(0.098)	(0.117)	(0.168)	(1.437)	(1.727)	(2.014)	(2.061)
[1] chi2(11)							55.50
Prob>chi2							0.0000
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01 ; Standard errors allowing for intragroup correlation (cluster) in brackets. Coefficients reported. Variable *DIST_FedGov* in km.

[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST_FedGov* and *PERMRD* which are time invariant.

Table 1. 12 Results taking distance to Flemish Subsidy Authority

Results with distance of surveyed companies to subsidy authority of Flanders located in Brussels.

	Dependent variable: Regional authority subsidy receipt dummy *RegGovSubs*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST_RegAut	-0.001	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
lnEMP				-0.242***	-0.326***	-0.393***	-0.058
				(0.064)	(0.083)	(0.118)	(0.212)
$lnEMP^2$				0.045***	0.057***	0.074***	0.008
				(0.008)	(0.010)	(0.014)	(0.035)
lnAGE				-0.106***	-0.114**	-0.187***	-0.027
				(0.035)	(0.044)	(0.065)	(0.159)
GROUP				0.098*	0.154**	0.196**	0.216
				(0.053)	(0.067)	(0.096)	(0.146)
FOREIGN				-0.289***	-0.325***	-0.435***	-0.206
				(0.060)	(0.072)	(0.102)	(0.204)
EXPORT				0.213***	0.247***	0.294***	0.238**
				(0.048)	(0.060)	(0.081)	(0.102)
PERMRD				0.553***	0.643***	0.948***	0.954***
				(0.072)	(0.090)	(0.141)	(0.141)
lnPROD				-0.007	0.006	-0.014	-0.035
				(0.027)	(0.036)	(0.050)	(0.097)
lnCOMPnr				-0.032*	-0.044*	-0.057*	0.065
				(0.018)	(0.023)	(0.034)	(0.070)
lnUNEMP				1.657	0.119	1.747	3.013
				(1.980)	(2.582)	(3.153)	(3.919)
lnPOPUL				-0.136	-0.272**	-0.392**	0.142
				(0.094)	(0.118)	(0.172)	(0.885)
Constant	-0.629***	-0.657***	-1.233***	1.443	3.282*	4.771*	5.292**
	(0.100)	(0.125)	(0.218)	(1.345)	(1.699)	(2.481)	(2.569)
lnsig2u			0.846***			0.241*	0.261**
			(0.112)			(0.125)	(0.125)
[1] chi2(10)							13.64
Prob>chi2							0.1901
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	7511	5484	5484	7511	5484	5484	5484

* p<0.10, **p<0.05, *** p<0.01 ; Standard errors allowing for intragroup correlation (cluster) in brackets. Coefficients reported. Variable *DIST_RegAut* in km. Variable SUBSreg is excluded in order to avoid auto correlation with the dependent variable.

[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 10 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST_RegAut* and *PERMRD* which are time invariant. Subsidy authority of Flanders, Agency for Innovation by Science and Technology (IWT), located in Brussels was active until 2015. From 2015 onwards IWT was replaced by Flanders Innovation & Entrepreneurship (VLAIO) which is located in Brussels as well.

Table 1. 13 Results with subsample of regional subsidy receivers

Results with log of distance of surveyed companies to EU Authorities in Brussels.

	Dependent variable: EU subsidy receipt dummy $EUSUBS$						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST	-0.010***	-0.010***	-0.019***	-0.009***	-0.009***	-0.016***	-0.015***
	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
lnEMP				-0.319**	-0.253	-0.471*	-0.401
				(0.152)	(0.156)	(0.243)	(0.333)
$lnEMP^2$				0.054***	0.048***	0.082***	0.044
				(0.016)	(0.016)	(0.027)	(0.050)
lnAGE				-0.048	-0.054	-0.103	-0.094
				(0.086)	(0.088)	(0.143)	(0.297)
GROUP				0.127	0.135	0.009	-0.146
				(0.145)	(0.151)	(0.231)	(0.308)
FOREIGN				-0.201	-0.186	-0.331	-0.327
				(0.137)	(0.139)	(0.213)	(0.295)
EXPORT				0.096	0.062	0.192	0.316
				(0.124)	(0.126)	(0.199)	(0.253)
PERMRD				0.483*	0.472*	0.818*	0.797*
				(0.249)	(0.251)	(0.439)	(0.434)
lnPROD				-0.108*	-0.109*	-0.124	0.148
				(0.056)	(0.057)	(0.092)	(0.155)
lnCOMPnr				0.013	0.021	0.006	-0.025
				(0.048)	(0.049)	(0.083)	(0.161)
lnUNEMP				0.008	0.209	2.440	5.682
				(3.547)	(3.616)	(5.445)	(5.037)
lnPOPUL				-0.292	-0.325	-0.433	4.940*
				(0.249)	(0.253)	(0.449)	(2.784)
Constant	-0.209	-0.283	-0.429	4.093	4.280	5.750	6.676
	(0.257)	(0.269)	(0.496)	(3.570)	(3.625)	(6.486)	(6.591)
lnsig2u			0.970***			0.757***	0.805***
			(0.249)			(0.249)	(0.250)
[1] chi2(10)							9.96
Prob>chi2							0.4440
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	1197	1167	1167	1197	1167	1167	1167

* p<0.10, **p<0.05, *** p<0.01. Coefficients reported. Standard errors allowing for intragroup correlation (clustered) in brackets. Variable $DIST$ in km.

[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 10 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST* and *PERMRD* which are time invariant.

Table 1. 14 Results with group member dummy

Results with distance of surveyed companies and group member dummy ($GPMEM$ = 1 if a group member located closer to the EU district in Brussels present).

	Dependent variable: EU subsidy receipt dummy $EUSUBS$						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST	-0.007***	-0.007***	-0.013***	-0.005***	-0.006***	-0.009***	-0.009***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
GPMEM	0.251***	0.274**	0.244	0.018	0.025	-0.007	-0.051
	(0.097)	(0.108)	(0.173)	(0.096)	(0.105)	(0.158)	(0.162)
lnEMP				-0.197**	-0.280***	-0.461***	-0.178
				(0.082)	(0.103)	(0.160)	(0.282)
$lnEMP^2$				0.041***	0.049***	0.084***	0.035
				(0.009)	(0.011)	(0.019)	(0.047)
lnAGE				-0.089*	-0.038	-0.081	0.058
				(0.051)	(0.061)	(0.098)	(0.264)
$SUBSreg$				0.664***	0.710***	0.522***	-0.239
				(0.080)	(0.087)	(0.137)	(0.150)
GROUP				0.020	0.102	0.048	-0.107
				(0.080)	(0.097)	(0.152)	(0.217)
FOREIGN				-0.188**	-0.199**	-0.338**	-0.342
				(0.084)	(0.095)	(0.148)	(0.242)
EXPORT				0.053	0.032	0.107	0.175
				(0.066)	(0.079)	(0.126)	(0.164)
PERMRD				0.485***	0.493***	0.907***	0.644**
				(0.120)	(0.147)	(0.250)	(0.261)
lnPROD				-0.027	-0.027	-0.038	-0.031
				(0.039)	(0.049)	(0.077)	(0.141)
lnCOMPnr				-0.058**	-0.058*	-0.106**	-0.066
				(0.027)	(0.033)	(0.054)	(0.113)
lnUNEMP				2.698	2.877	7.108*	12.504**
				(2.197)	(2.681)	(4.098)	(5.407)
lnPOPUL				-0.179	-0.280*	-0.527**	0.291
				(0.131)	(0.157)	(0.262)	(2.106)
Constant	-1.164***	-1.099***	-2.267***	1.346	2.691	5.418	4.097
	(0.136)	(0.165)	(0.348)	(1.892)	(2.283)	(3.832)	(4.041)
lnsig2u			1.204***			0.703***	0.653***
			(0.175)			(0.196)	(0.193)
[1] chi2(11)							79.67
Prob>chi2							0.0000
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	1197	1167	1167	1197	1167	1167	1167

* p<0.10, **p<0.05, *** p<0.01. Coefficients reported. Standard errors allowing for intragroup correlation (clustered) in brackets. Variable $DIST$ in km.

[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST*, *GPMEM*,and *PERMRD* which are time invariant.

Table 1. 15 Results with distance and group members´ distance

Results with distance of surveyed companies and group members´ distance (*GPDIST*), if a group member located closer to the EU district in Brussels present.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*						
	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Pooled Probit (cross sectional sample)	Pooled Probit (panel sample)	Random Effects Probit (panel sample)	Chamberlain's Random Effects Probit (panel sample)
DIST	-0.007***	-0.007***	-0.012***	-0.005***	-0.005***	-0.008***	-0.008**
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
GPDIST	0.002	0.003	-0.001	-0.002	-0.002	-0.005	-0.005
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)
lnEMP				-0.195**	-0.278***	-0.456***	-0.172
				(0.082)	(0.104)	(0.161)	(0.283)
$lnEMP^2$				0.041***	0.049***	0.084***	0.033
				(0.009)	(0.012)	(0.019)	(0.047)
lnAGE				-0.089*	-0.037	-0.078	0.058
				(0.051)	(0.061)	(0.098)	(0.264)
SUBSreg				0.663***	0.709***	0.521***	-0.238
				(0.080)	(0.087)	(0.137)	(0.150)
GROUP				0.034	0.117	0.068	-0.106
				(0.077)	(0.093)	(0.148)	(0.213)
FOREIGN				-0.202**	-0.214**	-0.363**	-0.346
				(0.083)	(0.095)	(0.149)	(0.243)
EXPORT				0.053	0.031	0.106	0.175
				(0.066)	(0.079)	(0.126)	(0.165)
PERMRD				0.488***	0.498***	0.920***	0.656**
				(0.119)	(0.147)	(0.251)	(0.262)
lnPROD				-0.026	-0.025	-0.035	-0.030
				(0.039)	(0.049)	(0.078)	(0.142)
lnCOMPnr				-0.057**	-0.058*	-0.104*	-0.065
				(0.027)	(0.033)	(0.054)	(0.113)
lnUNEMP				2.682	2.872	7.191*	12.793**
				(2.199)	(2.683)	(4.109)	(5.390)
lnPOPUL				-0.183	-0.285*	-0.544**	0.257
				(0.131)	(0.157)	(0.263)	(2.096)
Constant	-1.146***	-1.076***	-2.257***	1.383	2.735	5.580	4.247
	(0.135)	(0.162)	(0.346)	(1.889)	(2.276)	(3.837)	(4.049)
lnsig2u			1.218***			0.709***	0.658***
			(0.176)			(0.196)	(0.194)
[1] chi2(11)							79.53
Prob>chi2							0.0000
year dummies	yes	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes	yes
N	1197	1167	1167	1197	1167	1167	1167

* p<0.10, **p<0.05, *** p<0.01. Coefficients reported. Standard errors allowing for intragroup correlation (clustered) in brackets. Variable *DIST* and *GPDIST* in km.

[1] Joint significance test for all average variables used in Chamberlain's Correlated Random Effects Probit Model. The average variables (in total 11 variables) are not reported in the table and consist of the averaged versions of all variables listed in the Table above except *DIST*, *GPDIST*,and *PERMRD* which are time invariant.

Table 1. 16 Pooled OLS results

Results with distance of surveyed companies.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*			
	Pooled OLS (cross sectional sample)	Pooled OLS (panel sample)	Pooled OLS (cross sectional sample)	Pooled OLS (panel sample)
DIST	-0.001***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
lnEMP			-0.050***	-0.068***
			(0.014)	(0.020)
$lnEMP^2$			0.008***	0.010***
			(0.002)	(0.003)
lnAGE			-0.005	-0.002
			(0.005)	(0.007)
SUBSreg			0.149***	0.148***
			(0.020)	(0.021)
GROUP			0.002	0.011
			(0.007)	(0.009)
FOREIGN			-0.022**	-0.027**
			(0.010)	(0.012)
EXPORT			0.006	0.005
			(0.006)	(0.008)
PERMRD			0.060***	0.060***
			(0.010)	(0.012)
lnPROD			-0.003	-0.004
			(0.004)	(0.006)
lnCOMPnr			-0.005*	-0.005
			(0.003)	(0.003)
lnUNEMP			1.038*	1.275*
			(0.562)	(0.721)
lnPOPUL			-0.023	-0.037**
			(0.014)	(0.018)
Constant	0.105***	0.118***	0.436**	0.642**
	(0.016)	(0.021)	(0.199)	(0.255)
R-squared	0.026	0.028	0.125	0.142
year dummies	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes
N	7511	5484	7511	5484

* p<0.10, **p<0.05, *** p<0.01. Standard errors allowing for intragroup correlation (cluster) in brackets.
Variable *DIST* in km.

Table 1. 17 Pooled OLS results (incl. group members)

Results taking into account the group members´ distance, if a group member located closer to the EU district in Brussels present. If yes, the distance of the surveyed company is substituted with group members´ distance.

	Dependent variable: EU subsidy receipt dummy *EUSUBS*			
	Pooled OLS (cross sectional sample)	Pooled OLS (panel sample)	Pooled OLS (cross sectional sample)	Pooled OLS (panel sample)
DISTgp	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
lnEMP			-0.050***	-0.067***
			(0.014)	(0.019)
$lnEMP^2$			0.008***	0.010***
			(0.002)	(0.002)
lnAGE			-0.005	-0.002
			(0.005)	(0.007)
SUBSreg			0.149***	0.149***
			(0.020)	(0.021)
GROUP			-0.000	0.008
			(0.007)	(0.009)
FOREIGN			-0.020**	-0.025**
			(0.010)	(0.012)
EXPORT			0.006	0.005
			(0.006)	(0.008)
PERMRD			0.060***	0.060***
			(0.010)	(0.012)
lnPROD			-0.003	-0.005
			(0.004)	(0.006)
lnCOMPnr			-0.005*	-0.005
			(0.003)	(0.003)
lnUNEMP			1.114**	1.372*
			(0.557)	(0.714)
lnPOPUL			-0.021	-0.034*
			(0.014)	(0.018)
Constant	0.104***	0.116***	0.400**	0.603**
	(0.015)	(0.020)	(0.194)	(0.249)
R-squared	0.027	0.029	0.125	0.142
year dummies	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes
N	7511	5484	7511	5484

* p<0.10, **p<0.05, *** p<0.01. Standard errors allowing for intragroup correlation (cluster) in brackets.
Variable *DISTgp* in km.

Figure 1. 1 Map Cross sectional sample (all observations)

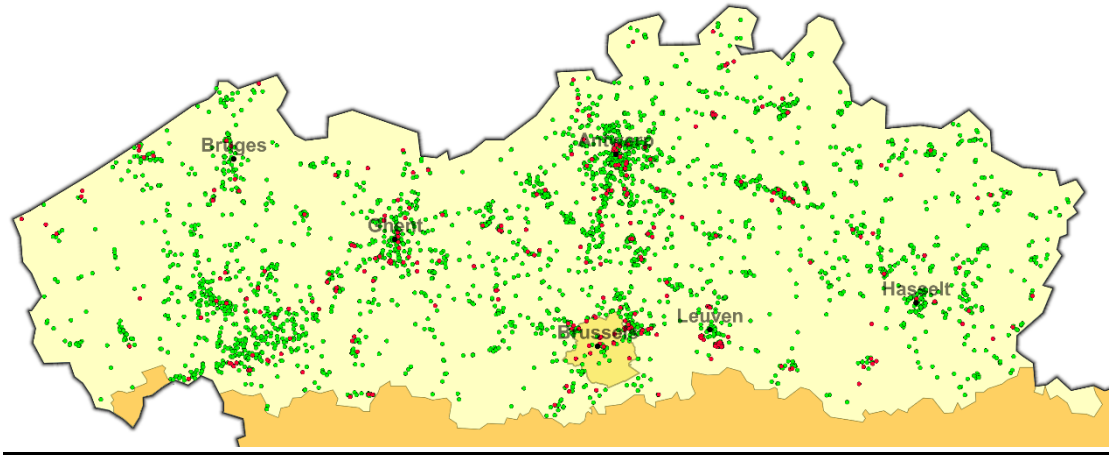
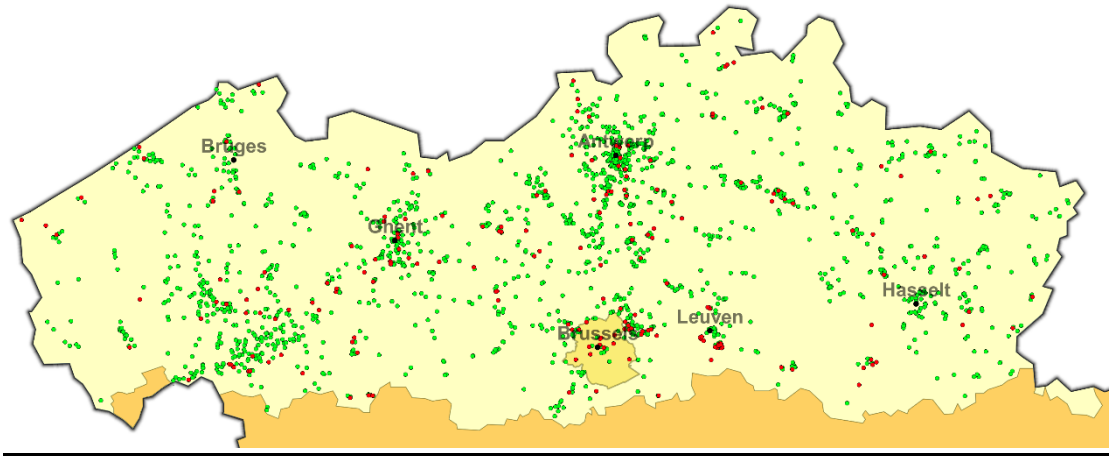


Figure 1. 2 Map Panel sample (all observations)



A Red dot represents the position of a subsidy recipient while a green dot represents the position of a non-subsidy recipient. A black dot represents the position of a city.
Source: Own creation by using QGIS.

Chapter 2 The role of subsidy source and regional context in innovation subsidies' input additionality[40]

2.1 Introduction

In the economic literature subsidy impact evaluation is a frequently addressed research subject since it is particularly vital for policy makers but also for other interested groups such as scientists and tax payers to know about the impact of realized subsidy programmes out of several reasons. First, policy makers need a scientific proof about whether public support granted causally and successfully leads to the desired effect in order to legitimate the redistribution of public financial means via public support programmes. Second, it is necessary to understand how efficient a public funding programme is or to what extent it actually supports the goals aimed to be achieved through the supported activities. The effectiveness of subsidies' impact once quantified can be utilized to determine the optimal form of a grant in order to suffice for the delivery of the desired results and to avoid effectless public redistribution. Third, there is a necessity to develop an understanding about determinants such as subsidy mode[41] or source that can exert influence on the subsidy programmes' impact significantly besides the subsidy size and type[42]. Empirical evidence about potential effects of these factors can be taken into account in order to design the optimum setting for future subsidy programmes.

The scientific world has recognized the importance of subsidy impact evaluation and addressed research subjects related to this topic in a variety of empirical scientific examinations. The focus in this paper is on firm level input additionality of public subsidies for innovation. The paper's novelty resides in its focus on the effects of different sources of funding, the mix of funding sources, and of (interaction with) the regional context. Input additionality is measured both in a narrow way by focusing on additionality in terms of (whether or not combined with external) R&D expenditure

[40] This study is coauthored by Prof. Dr. Peter Teirlinck.
[41] Direct vs. indirect subsidies (e.g. tax benefits).
[42] Different types of direct and indirect subsidies such as cash grants, interest free loans, tax breaks, or accelerated depreciation.

intensity, and by taking a broader perspective by focusing on additionality in terms of innovation expenditure intensity.

Examining the impact of public funding granted for innovative activities, researchers have investigated among others the input additionality, i.e. whether the subsidized firms invest additional financial means in R&D and other innovative activities compared to their non-subsidized peers. Despite the number of examinations available in the literature (see e.g. Zúñiga-Vicente et al. (2014) for an overview of empirical papers that investigate the impact of public R&D subsidies on private R&D investment for the five decades before 2014), there are still research questions not addressed at a satisfying depth yet.

Czarnitzki and Lopes-Bento (2014) emphasize the lack of empirical evidence for innovation subsidy impact evaluations which take into account the different sources of subsidies. Guerzoni and Raiteri (2015) and Dumont (2017) draw the attention towards the not sufficiently investigated but highly relevant effects of interactions of public funding policies (policy mix). Following these authors we take into account both different sources of public funding for innovation and the mix between these sources. Another overlooked topic in the additionality literature is highlighted by Montmartin et al. (2018) who point on the potential effects of spatial dimension on subsidy outcomes at regional level. This topic has been neglected within the empirical subsidy impact literature so far. Compared to Montmartin et al. (2018) who focus on macro-economic effects of the French policy mix at the level of 94 departments in France, our study to our knowledge is the first to explicitly take into account the regional context for measuring firm level additionality.

The authors call for similar examinations by using different data sources and focusing on different countries to enrich the literature. Following their call, this paper examines the impact of innovation subsidies on input additionality in terms of R&D and innovation expenditure intensity for a representative sample of the private enterprise sector in Belgium. The analyses distinguish between different subsidy sources, regional authorities, Federal Government, and European authorities respectively. In addition, the potential effect of the presence of policy mix as well as the effect of a particular regional context, i.e. being located in one of the three Belgian (NUTS 1) regions Brussels-Capital, Flanders, and Wallonia is assessed. Belgium is a

particularly interesting case as it has besides the Belgian Federal Government also the regional authorities which independently shape the policy in their territories and grant public funding. Subsidies sourced by different authorities may have significantly different influence on the outcome of the subsidized activities. For each of the subsidy granting authority there can be differences regarding the application processes, mode of the public funds, monitoring processes as well as other procedures that take place during the supported activities, and requirements regarding the expected outcomes on the subsidized activities.

In section 2 of the paper an overview about the subsidy impact evaluation literature is provided. In the same section the role of subsidy sources, policy mix, and regional context are discussed to motivate the research questions. Section 3 describes the data used for the empirical analyses, the method applied, and the variables considered. Section 4 provides the results of the empirical analyses before the paper finalizes with a policy conclusion in section 5.

2.2 Literature

2.2.1 Subsidy impact evaluation literature

Public authorities support entities within their territory to trigger development in the direction of desired political, economic, and social goals. Subsidies for innovative activities aim to further economic goals mainly and are legitimated in the scientific literature with the reasoning that in absence of the subsidies market failures will arise. That in turn leads to a level of innovative activities below the socially optimal level, leading to a lower economic wealth status (Arrow, 1962; Stiglitz, 1988). There are three main arguments for these market failures to occur in this context. First, the outcome of innovative activities, in particular research & development (R&D), bear uncertainty as ex ante it is unclear whether the innovative activity will be completed successfully. In case the activity is successfully completed there can be still uncertainty about whether the innovative outcome will match with the demand in the market. Second, private capital providers anticipating the high risk of uncertainty for

innovative activities may offer a suboptimal level of capital in order to avoid lost costs in case of failed projects. Third, the return generated by the outcomes of innovative projects may not be fully appropriated by the parties involved in the innovative activities as there will be spillovers to competitors which will gain as free riders by imitating the innovative outcome without facing the costs for the innovative activity (Griliches, 1986; Hall, 2002). Consequently, the incentive for potential innovators to undertake the innovative activity may be below the optimal level due to uncertainty, free riders, or lack of financial means.

These arguments justify public funding for innovative activities in the business enterprise sector. However, another question arises at the side of the supporting public authority: did the subsidy recipient invest the financial means granted in the innovative activities actually or used it for other activities instead (moral hazard)? The behavior of the subsidy recipient is not directly observable as it is possible that the subsidy recipient may have potentially undertaken the innovative activity also in absence of the public funding but used the subsidy received to substitute own financial means. One way to find out whether moral hazardous behavior is present is to test empirically for input additionality.

Doing that is possible by comparing the innovation expenditures of the subsidized party with its non-subsidized peers. As non-subsidized peers will suffer under a higher level of capital restriction, by trend they are expected to have less expenditures for innovative activities then a subsidy recipient. If the subsidy recipient spends at least parts of the subsidy received additional to own financing means in innovative activities the difference will be observable by employing an empirical comparison. Thus in the literature most of the related examinations test empirically for the presence of input additionality (Aerts & Schmidt, 2008; Özçelik & Taymaz, 2008; Aschhoff, 2009; Bérubé and Mohnen, 2009; Czarnitzki et al., 2010; Czarnitzki & Lopes-Bento, 2010, 2013, 2014; Czarnitzki & Hussinger, 2018) whereat the majority of empirical evidence supports that innovation subsidies lead to input additionality.

2.2.2 Role of subsidy source

The potential role of subsidy source for subsidized innovative activities has been addressed by few studies which provide empirical evidence that the subsidy source indeed matters. Blanes and Busom (2004) point on potential effects on the effectiveness of public funding by failing to reach the targeted company population through the public funding granting authorities and/or applying inaccurate selection rules by the authorities. Based on an empirical analysis using data on Spanish companies, they observe that different subsidy granting authorities reach in practice differing populations of firms and conclude that public funding allocation through different authorities is expected to have diverse additionality effects partly because of the allocation heterogeneity.

Czarnitzki and Lopes-Bento (2014) examine whether public support sourced by national and EU authorities lead to significantly different outcomes by using German data. Results of their analyses reveal that national public funding recipients are more likely to apply for patents in period t+1, although between national and EU sourced funded companies' projects there is no statistical significant difference in means of productivity. Busom et al. (2015) provide empirical evidence that the pool of companies for different public support modes can be divers. They find that companies with higher productivity levels tend to receive rather direct subsidies (such as direct R&D grants) than indirect subsidies (such as tax benefits), while for market leading or market share extending companies it is the other way around. Dumont (2017) points on potentially biased regression results by evaluating subsidy impact if the (non-random) selection of supported firms by the subsidy granting authorities is not accounted for.

There is need for further examinations addressing the role of subsidy source to enrich the literature by using different data sources or superior methodological approaches. In order to address potential differing effects of subsidy sources, the first research question of the examination at hand is:

"Are different innovation subsidy sources associated with different input additionality in terms of R&D and innovation expenditures?"

To do that, data about Belgium is utilized which hosts five different independent public subsidy granting authorities, the European Union, Belgian Federal Government, and regional authorities of Brussels-Capital, Flanders, and Wallonia that operate at three different hierarchical levels, being transnational, national, and regional levels respectively. In addition there are differences in the mode of subsidies granted by those authorities. The Belgian Federal Government mainly grants tax benefits while EU authorities and Belgian regional authorities mainly provide direct R&D grants.

Tax benefits are non-competitive indirect subsidies, i.e. there is neither a fixed budget of the amount that can be funded nor a competition for the funding (no selection through the authority and no uncertainty of subsidy status by eligibility). If a company pays taxes and fulfills the requirements to be eligible for tax benefits, mostly fulfilled by having R&D activities, it has the certainty of being funded. In contrast, direct subsidies are granted competitively, i.e. a selection of the subsidized companies through the authorities takes place which involves besides companies' eligibility characteristics also efforts for the application process without having a certainty to be subsidized.

In a majority of the cases funding seeking parties have to apply for public funding in a competitive selection process and fulfill the eligibility criteria defined by each of the funding authorities. As the authorities may have different goals, different weights for the same goals, or different views on how these goals should be achieved, in the first stage the criteria they would like to see by the applicants may differ from each other. In the second stage the authorities may have different capabilities to check whether the criteria required are actually met by the applicants. Accordingly, there can be systematic differences in characteristics of the granted applicants between different funding authorities induced by different selection criteria and selection capability.

In addition, most of the funded projects are monitored by the funding authorities while the funded projects are implemented. The manner, strictness, and accuracy of the monitoring processes most likely differ between the authorities and possibly exert influence on the funded projects' success rates and success levels. As an example, it is thinkable that a stricter and more frequent monitoring conducted by experts on behalf

of the funding authorities could lead to higher success rates of the supported projects as well as superior appropriation of the outcomes. Furthermore, authorities may apply different rules on the funded projects' outcomes. Such rules can require among others the registration of intellectual property rights (disclosure of information), commercialization within a certain time period, or to share the outcome with other parties to realize spillover effects.

2.2.3 Role of policy mix

Another important facet when evaluating the potential effect arising out of different subsidy sources is whether combinations of those subsidy sources, i.e. the receipt of public funding from more than a single source simultaneously, lead to a superior, neutral, or negative effect on the subsidies' impact. Receiving subsidies from different sources or subsidy programmes at the same time is referred to as policy mix. The potential variation of subsidy impact in case of the presence of policy mix was recognized and investigated by some researchers using different approaches.

Guellec and Van Pottelsberghe De La Potterie (2003) analyze data stemming from 17 OECD member countries and point on possible interaction of direct subsidies and tax benefits. They conclude that direct subsidies and tax incentives are substitutes and that increasing the intensity of one of those public support modes lowers the effectiveness of the other one. Hægeland and Møen (2007) find that direct subsidies and tax incentives are complements at the firm level while they are substitutes at the aggregated level (innovation system level).

Czarnitzki and Lopes-Bento (2014) find that national and EU sourced innovation subsidies in Germany are complements since companies receiving funds from both sources simultaneously invest more in R&D and innovation activities than their counterfactuals. Guerzoni and Raiteri (2015) point on the under investigated but high relevance of potential interactions of public funding policies. Analyzing data stemming from 27 EU members, Norway, and Switzerland, they conclude that the measured impact of one mode of public funding changes when other modes of funding are considered as well. Dumont (2017) investigates the effectiveness of national public funding (without considering EU funding) in Belgium when firms are granted

simultaneously with funding from different sources and concludes that the effectiveness decreases when direct subsidies are combined with several tax benefit types.

Guerzoni and Raiteri (2015) emphasize the presence of potential hidden treatments in case confounding determinants in place are not taken into account. Such a confounding variable can be the presence of another treatment, e.g. a second public fund receipt, which is not considered when measuring the impact of a certain subsidy. Therefore, it is recommended to allow for the presence of a policy mix within the empirical setting of a subsidy impact evaluation whenever the data enables the researcher to do so. Since our data enables to test for potential effects of policy mix, the second research question is:

"Does receiving subsidies from different combinations of public funding sources lead to changes in subsidy impact?"

2.2.4 Role of regional context

Jaffe et al. (1993) show in an empirical, seminal work that knowledge spillovers can be geographically bounded, even if the knowledge is publicly available in patent documents. Other examinations focus on networks of innovators and find empirical evidence for a positive effect of geographic proximity on the likelihood of being involved in collaboration for R&D activities (Ponds et al., 2007; Hoekman et al., 2009, 2010, 2013; Morescalchi et al., 2015). This can be closely related to the existence and specificities of regional innovation systems (Cook, 2002; Asheim and Isaksen, 2002; Asheim and Coenen, 2005).

Montmartin et al. (2018) emphasize that the heterogeneity in means of spatial dimension has been largely ignored within the empirical subsidy impact literature. They point on that space is expected to have a non-neutral effect on firms' innovative activities due to different regional agglomeration effects which can be divers since they are based on the local nature of knowledge spillovers or express locally different flows of knowledge spillovers. That in turn could create a different competitive situation in attracting R&D investments specific to local determinants.

In addition, spatial dependencies between regions, e.g. presence of competition between regions, may lead to different behavior of companies regarding their innovative activity strategies. Accordingly, Montmartin et al. (2018) see the possibility that companies in different regions may respond to the same or similar public support schemes in deviating ways. Applying a macroeconomic impact analysis on the policy mix in place in France they conclude that local economic structure (local sectoral specialization and local access to financing) and design (size and targeting) of policies are extremely important for the efficiency of public funding. They find crowding-in effects on R&D investments only by public support through national subsidies.

Besides economic reasons mentioned above also institutional differences and cultural differences between regions may lead to diverse effects on public support impact. Therefore, not only different sources of subsidies in Belgium but also regional location of companies is taken into account in the empirical setting applied for the analysis in this paper. Implicitly, the third research question addressed is:

"Does being located in a specific region in combination with receiving subsidies from a certain source or a mix of sources make a difference in terms of input additionality of subsidies?

In the next section we will highlight the specificities of the three regions considered in this paper.

2.3 Context, data and econometric methods

2.3.1 Different funding sources and regions in Belgium

Public funding for innovative activities in Belgium is mainly granted by the EU, the Belgian Federal Government, and three autonomous regional governments (Brussels-Capital, Flanders, and Wallonia). The regional authorities run public support programmes for innovative activities in their territory, both independently as well as in coordination with each other and the Federal Government. In the following a short

overview about the public support sources/authorities for research and innovation in the private sector in Belgium is provided.

2.3.1.1 Funding sourced by the European Union

The European Union subsidizes research and innovation in firms by means of two major programmes. First, the Framework Programme (FP)[43] with its current version Horizon 2020 is the largest subsidy programme of the EU which aims to support research and other innovative activities only. Last fully completed FP (FP7) granted more than 50 bn Euro over 7 years (2007-2013) while the current programme Horizon 2020 has a planned volume of more than 80 bn Euro for the time period from 2014 to 2020. Second, the European Structural and Investment Funds (ESIF) programme is the largest EU funding programme. It allocates more than half of the EU budget and targets both innovative as well as non-innovative activities. The predecessor of ESIF (Cohesion Policy) had a planned volume of around 344 bn Euro for the time period from 2007 to 2013 while the current ESIF programme running from 2014 to 2020 has a planned volume of around 454 bn Euro.

EU subsidy programmes usually provide financing (such as direct R&D grants) only for parts of the granted projects implicating that the recipients have to finance parts of the subsidized activities by themselves. While applications for some programmes, like it is the case for the FP, are managed exclusively by the European Commission (EC), a majority of the applications (80% of the allocated funds) are managed by national authorities in collaboration with the EC[44]. Interested organizations or individuals in the majority of the funding programmes have to apply either directly by the EC or by the national authorities in response to calls proposed by these authorities. The grants are allocated competitively to the applicants with the best application proposals that fulfill the requirements listed within the calls.

[43] For an overview of EU funding programmes see https://ec.europa.eu/info/funding-tenders/funding-opportunities/funding-programmes/overview-funding-programmes_en (last accessed on 14.10.2019)

[44] See on https://ec.europa.eu/info/funding-tenders/how-eu-funding-works/management-eu-funding_en (last accessed on 14.10.2019)

2.3.1.2 Funding sourced by the Belgian Federal Government

The Federal Governments' main tool to support business enterprises' R&D activities within Belgium is a set of different tax measures managed by the Federal Public Service of Finance. Among others tax deductions on intellectual property, on innovation income, on R&D investments, as well as tax exemptions on payroll costs of researchers (payroll withholding tax)[45] belong to the set of the tax measures. According to the OECD Database[46] the support Federal Government provided as tax incentives increased from 80 Mio. Euro in 2006 to 1.1 bn Euro in 2014. OECD (2018) reports that Belgium's total government support (including regional authorities) to business R&D as percentage of GDP is ranked third among OECD and partner economies. Bloom et al. (2019) review the literature on policy tools that aim to increase innovation and conclude that R&D tax credits lead to benefits in a shorter time frame and result in higher net benefits compared with direct R&D subsidies.

2.3.1.3 Funding sourced by the Belgian Regional Authorities

While the Belgian Federal Government supports business enterprises' R&D activities mainly by tax benefits the regional authorities of Brussels-Capital, Flanders, and Wallonia offer primarily direct R&D grants. In the following a short overview about each of the regional authorities' activities to fund innovative activities within their territory is provided.

Brussels-Capital region in Belgium was created in 1989 and started to support innovative activities on its territory only from the beginning of 2000's under own administration after these activities have been undertaken by the Belgian federal authorities in the name of Brussels-Capital authorities before (BELSPO, 2010). Innoviris[47] is the authority managing the financial support for innovative activities for companies as well as for research organizations in the name of Brussels-Capital

[45] See on https://assets.kpmg.com/content/dam/kpmg/be/pdf/Markets/rd-incentives-21-2-2017.pdf (last accessed on 14.10.2019)
[46] https://stats.oecd.org/
[47] Successor of ISRIB (Institute for the Encouragement of Scientific Research and Innovation of Brussels)

Government. The R&D subsidy budget[48] of Innoviris is modest, but increased from 24 Mio Euro in 2006 to 32.9 Mio Euro in 2014. There are different financial support programmes with each different eligibility requirements that all aim to improve the innovative performance of the region and offered to organizations which are geographically located within the region.

The Science, Technology and Innovation (STI) policy of the Flemish government is designed by its Department of Economy, Science and Innovation (EWI). EWI administers the Special Research fund (BOF) and Industrial Research Fund (IOF) which provide financial aid to stimulate the academic research in universities and to support the diffusion of scientific knowledge for social or industrial utilization. Besides EWI Vlaio[49] (Flanders Innovation & Entrepreneurship agency) provides support for industrial R&D and innovation projects conducted by companies and offers advisory services for funding seekers during their application as well as project implementation stages. Furthermore it supports networking and cooperation activities between all agents involved in innovative projects within Flanders. PMV (Flanders Holding Company) is another agency in Flanders that supports innovation activities by providing aid to projects which are important for the region's future development. The agency either provides funding as an investor or organizes and supports partnerships between financing partners and innovative companies including start-ups that face liquidity problems.

Two regional government departments in the Walloon region are responsible for the Science, Technology and Innovation (STI) policy design and implementation. The Directorate General for Economy, Employment and Research (DGO6) focuses on the industry side of the Walloon STI policy while the Directorate General for Non-Obligatory Education and Scientific Research (DGENORS) takes over the policy parts oriented towards the academic world (BELSPO 2010). DGO6 created through the merger of two predecessor institutions[50] is active since August 2008 and provides support for preparatory (feasibility, technical, sectoral) studies and intellectual

[48] Source: Annual Innoviris Reports (only in Dutch and French; last accessed on 14.10.2019) https://innoviris.brussels/nl/activiteitenverslagen
[49] Successor of IWT (Institute for Innovation by Science and Technology)
[50] Ministry of Walloon Region (MRW) and Ministry of Equipment and Transport (MET)

property registration besides selecting, funding, and monitoring innovation projects in industrial research.

2.3.1.4 Heterogeneous context of the three Belgian regions

Despite the small size of the Belgian territory, the three regions in Belgium present some interesting differences. While the economic prosperity is developed well in the regions Brussels-Capital and Flanders, Wallonia's economic development is lacking behind. In order to get an idea one can compare the GDP levels and unemployment rates in each of the regions. GDP per capita[51] in the last year (2014) of the time period considered for the analyses at hand is highest in Brussels-Capital with 61,700 Euro followed by Flanders with 36,500 Euro, and 26,000 Euro in Wallonia. The regional unemployment rates for the same year were 18.3% in Brussels-Capital, 5.1% in Flanders, and 11.9% in Wallonia. The numbers reveal there are significant differences between the regions.

The Brussels-Capital Region can be classified as a capital region strongly specialized in knowledge intensive business services. It is pronounced by a highly international constellation of its citizens mainly due to large multinational organizations located in this region such as the European Union and the North Atlantic Treaty Organization (NATO) as well as the administrative centers of a number of multinational companies. The language used here is a mix out of French, Flemish, and English. In contrast Flemish is the main language in Flanders and French the main language in Wallonia. Besides the language, citizens living in these two regions have different cultural traditions. In addition to the differences mentioned above, companies located in different regions face also a different set of authorities and legislation which could lead to differences in their performance (Capron and Meeusen, 2000). All those differences together suggest to take into account the regional location of the companies in an empirical exercise such as the examination at hand.

[51] Data source: https://ec.europa.eu/eurostat/data/database

2.3.2 Data

For the examination at hand the main data source considered is the Community Innovation Survey (CIS) for Belgium. The Belgian version of the CIS is carried out every second year and provides information about a representative sample of the universe of the firms sized ten and more employees[52] which are located in Belgium. The survey offers data about firm characteristics, firms' innovation subsidy receipt status, and firms' innovative activities. The waves of the years 2008, 2010, 2012, and 2014 containing data for the time period from 2006 to 2014 are considered for the empirical analyses. Regional variables are generated by using data from Bureau van Dijk's databank "Belfirst" and Statistics Belgium.

The initial sample consists of 20,821 firm-year observations (12,160 firms) in total. After dropping observations with missing values in variables of interest and restricting the sample to companies which show at least once innovative activity[53] 4,630 firm-year observations (3,330 firms) remain for the estimation of the propensity scores prior to the implementation of the non-parametric matching procedure. Within the sample of innovative firms 1,663 firm year observations (1,237 firms) received subsidies for innovative activities. The decision whether a firm is innovative or not is made following the Oslo Manual directives (OECD/Eurostat, 2019).

The Oslo Manual provides a definition about the activities related to technological product and process innovation. According to this definition all scientific, technological, organizational, financial, and commercial actions aiming towards the implementation of technologically new or improved processes and products are innovative activities. Consequently, all firms showing activities following this definition are considered to be innovative whereat organizational and marketing innovation activities are excluded as these activities are usually not granted with innovation subsidies. As it will be described in the next section, a matching procedure

[52] The sampling for the surveys is implemented based on the universe of Flemish companies with a minimum of 10 employees. Number of employees of a surveyed company can change within the survey period, i.e. can be below 10 employees.

[53] Innovative activity means here: (i) having introduced a new or significantly improved product (product innovation), or (ii) having introduced a new process (process innovation), or (iii) having ongoing/abandoned innovative projects. Companies without any of these activities are excluded from the sample as it seems not to be logical to compare those with innovative companies in order to address the research question.

is performed which leaves us with 1,638 firm year observations (1,228 firms) in the matched sample due to lack of proper matches within the control group for some of the subsidized companies. This sample consists of 1234 observations in Flanders (Table 2. 11) with a relative large number compared to other regions since the authority in Flanders applies voluntarily a larger sample for its part of the CIS. 281 and 123 observations from Wallonia and Brussels-Capital regions enter the sample besides companies from Flanders.

2.3.3 Econometric methods

For the examination at hand a non-parametric matching procedure, nearest neighbor matching following Cochran and Rubin (1973), is considered to create a control group which consists of companies which are not treated (non-subsidized) but are very similar to the treated companies in all of their for the analysis utilized observable characteristics (see Table 2. 3 for a step by step description of the matching procedure). In a first step a Probit estimation (Table 2. 4) is applied in order to obtain the propensity scores for each of the observation in the sample to be used to identify pairs of treated and untreated companies within the matching procedure. The same table also shows the results for Probit regressions by using subsidy receipt information distinguished by each of the subsidy sources in order to test whether taking all subsidy receipt information from all sources jointly in a single dependent variable would lead to strongly deviating propensity scores.

If the results of the distinct and joint dependent variables would lead to significantly deviant coefficients, using subsidy receipt information stemming from all subsidy sources in a single Probit estimation could be seen as problematic. As shown in Table 2. 4, the results for each of the Probit estimations deliver similar coefficients indicating that the approach of taking all subsidy receipt information in a single dependent variable to calculate the propensity scores is not an improper approach. Table 2. 5 provides the correlation matrix of the variables used for the propensity score estimation and

Figure 2. 1 illustrates the propensity scores before and after matching for both the treatment and control groups. Table 2. 7 shows the Probit regression with the matched sample delivering insignificant coefficients and thus confirming that the matching procedure was successfully applied, i.e. there are on average no differences between the treatment and the control group.

In the second step the matching procedure is performed. The common support requirement, that ensures the matched treated and non-treated observations are similar at a sufficient level (within a certain propensity score band), is not fulfilled for all subsidized companies, i.e. for some subsidized observations there is no eligible observation in the control group. Therefore, the number of subsidized firms drops after the matching procedure to 1,638 firm year observations (1,228 firms).

Applying a non-parametric matching procedure comes with the advantage that there are no assumptions involved neither for the functional form nor for the distribution of the error term while the disadvantage arises out of the fact that it relies on observable characteristics only. As the data used (CIS) is not constructed as a panel, the difference in difference method is not applicable. The difficulty to find a valid instrument prohibits an instrumental variable estimation and the matching method remains as the best choice. The evaluation of the treatment effect on the treated can be expressed as (Czarnitzki and Lopes-Bento, 2013):

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

Y^{T} is the outcome variable whereat S indicates the treatment status of the group of companies with $\mathrm{S}=1$ being the treatment and $\mathrm{S}=0$ being the control group. Y^{C} gives the potential value of the treated observation if it would not have received the treatment. While $\mathrm{E}(\mathrm{Y}^{\mathrm{T}}|\mathrm{S}=1)$ is directly observed in the data, $\mathrm{E}\left(\mathrm{Y}^{\mathrm{C}}\middle|\mathrm{S}=1\right)$ is not observable and thus has to be estimated. Since subsidy receipt is not random (self-selection of the companies to the funding condition as well as selection through the subsidy granting authorities), not all of the observations from the population of non-subsidized companies are eligible to be used in the control group.

To overcome this selection bias issue, Rubin (1977) introduced the so called conditional independence assumption (CIA) which states that for companies with the same set of exogenous characteristics (X) the likelihood of being treated and the treatment effect are statistically independent from each other. As the matching procedure ensures that the treatment group and control group are in their observable (exogenous) characteristics statistically indifferent from each other, the CIA is fulfilled. A potential difference of the outcome variable between the two groups is consequently assigned to the treatment. Under the assumption of CIA the expected value of the outcome variable is the same for treated and untreated:

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

The treatment effect can be expressed as:

$$\mathrm{E}(\alpha_{\mathrm{TT}})=\mathrm{E}(\mathrm{Y^T}|\mathrm{S}=1,\mathrm{X}=\mathrm{x})-\mathrm{E}\left(\mathrm{Y^C}\middle|\mathrm{S}=1,\mathrm{X}=\mathrm{x}\right)$$

After a comparison of the variable means for the matched sample between the treated and untreated groups in order to obtain the overall effect of being treated (Table 2. 6), as a third step Ordinary Least Squares (OLS) estimations in different model settings are performed (Table 2. 8 – Table 2. 10) by regressing the overall treatment effect on subsidy sources by taking into account possible effects of the company's regional location. OLS estimations are applied by using the matched sample whereat the differences of the outcome variables between the treated and control groups (treatment effects) are utilized as dependent variables, i.e. the treatment effect is regressed on different subsidy sources as well as companies' region of location. That way, it is assessed whether the allover treatment effect can be associated with the treatment group's source of subsidy or regional location. OLS estimations reveal the potential effects of receiving a subsidy from a certain source including policy mix, regional location, as well as the combinations of regional location and receiving a subsidy from a certain source or mix of sources.

The OLS model (IV) with all explanatory variables including interaction terms that refer to the combinations of subsidy sources can be expressed as follows:

$$y_{(i-j)} = \beta_0 + \beta_1 Brussels_i + \beta_2 Wallonia_i + \beta_3 Regional_i + \beta_4 FGovernment_i + \beta_5 (RegFGovEU_i) + \beta_6 (RegFGov_i) + \beta_7 (RegEU_i) + \beta_8 (FGovEU_i) + \varepsilon_{(i-j)}$$

$y_{(i-j)}$ is the difference of the outcome variable (= treatment effect) between the treated observation i (with $i = 1,2,\ldots,N$ and N=1,638) and untreated matched observation j (with $j = 1,2,\ldots,N$ and N=1,638) whereat $\varepsilon_{(i-j)}$ is the error term. Further control variables used to estimate the propensity scores are not included in the OLS estimations as it is through the matching procedure ensured that none of these variables between the control group and the treatment group are on average significantly different from each other[54] (see Table 2. 6 and Table 2. 7).

2.3.4 Variables

To perform the propensity score estimation a dummy variable (*All subs.*) serves as the dependent variable taking the value of 1 if a company was subsidized with an innovation subsidy from any subsidy granting authority European Union (EU), Belgian Federal Government, and Belgian regional governments of Brussels-Capital, Flanders, and Wallonia. That means, for the empirical analyses only subsidies granted for innovative activities are taken into account since the data used, Community Innovation Survey (CIS), provides the subsidy receipt status only for innovation subsidies.

Besides industry (IND) and time period ($YEAR$) dummies a set of control variables providing information at the firm and regional levels are utilized to perform the propensity score estimation (Table 2. 4). The natural logarithm of the employment number ($lnEMP$) controls for a possible effect of the size of the companies whereat the second lag (employment number from 2 years before) is applied to avoid possible

[54] In robustness checks (available as online appendix) a possible effect of including those variables are tested and deliver no significant change of the results.

simultaneity with the dependent variable, i.e. the employment number may increase within the same period of the subsidy receipt due to subsidy receipt itself. Transforming the employment number to its natural logarithm avoids that the skewed distribution of the variable affects the estimation results.

The squared term of the second lag of the employment number ($lnEMP^2$) enters the model to control for a possible nonlinear effect of the company size on the dependent variable[55]. Both variables are identified as important determinants for the subsidy receipt likelihood and used commonly in the literature (Veugelers and Cassiman, 1999; Czarnitzki and Fier, 2002; Duguet 2003; Aerts and Schmidt, 2008). Next variable at the firm level entering the model is the natural logarithm of the age of the company ($lnAGE$) which controls for the potential effect of maturing companies' possible organizational inertia due to rigidities that may develop in the working routines (Hannan and Freeman, 1977).

Since whether a company is a permanent R&D performer or not is an important determinant for being similar in means of experience in performing R&D activities (Almus and Czarnitzki, 2003; Czarnitzki et al. 2007; Aschhoff, 2009) between the control and treatment groups the dummy variable $PERMRD$ enters the model identifying a permanent R&D performer[56] by taking the value of 1. Another dummy variable ($GROUP$) accounts for the group structure of a firm indicating with the value of 1 the affiliation to a consortium. Being affiliated to a consortium may be an important determinant for a subsidy granting authority taken into account in the selection of granted companies. It signals that a company may be able to realize synergy effects through access to a larger pool of knowledge and financial means in order to conduct innovative activities.

In addition a consortium member can possibly create positive externalities faster by spreading innovation generated by the subsidized innovative activity faster to the economy through other consortium members. Besides the variable $GROUP$, the

[55] Not present in Table 2. 4 since marginal effects are reported.

[56] Belgian part of CIS provides the information of being a permanent R&D performer only for the survey waves 2012 and 2014 within the analyzed time period. Therefore the value for the variable *PERMRD* for the waves 2008 and 2010 was imputed. If a company was a permanent R&D performer within the waves 2012 to 2014 it was assumed to having been a permanent R&D performer in the 2008 to 2010 waves as well.

variables $FMOTHeu$ (=1 if mother company located outside of Belgium but inside Europe) and $FMOTHnoneu$ (=1 if mother company located outside of Europe) capture more in detail the group structure situation of a firm (Almus and Czarnitzki 2003; Aerts and Schmidt, 2008). Having a mother company outside of Belgium or Europe may have an influence through subsidy granting authorities' potential preference to subsidize rather ultimately national or European owned firms.

In order to control for a possible superior range of products hinting on a higher innovative capacity (Czarnitzki and Lopes-Bento, 2013) of a company enabling it to export products to the markets outside of Belgium, the dummy variable $EXPORT$ enters the model indicating with the value of 1 that a company is an exporter. Another covariate at the firm level is the labor productivity ($lnPROD$) of a company calculated by dividing the sales by employment number and transforming the result to natural logarithm. Labor productivity controls for a possible preference of the granting authority, which may apply the picking-the-winner-strategy, by preferring firms with higher productivity.

$lnCOMPnr$ is the first covariate providing information at the regional level. It controls for the regional competition level a company faces which is approximated by the natural logarithm of the number of companies within the same zip code and sector (2 digit NACE code). The unemployment rate ($lnUNEMP$) for the age range from 25 to 54 and the size of the population ($lnPOPUL$) each transferred to their natural logarithm are measured at the province levels of Belgium. They control for possible preferences of the granting authorities as their policy could suggest to grant rather companies in rural areas or areas with high unemployment rates to support the economic development in such regions.

In Table 2. 6 results of the matching procedure are available. The difference of the three outcome variables on average between the matched pairs of treated and control groups are provided as allover treatment effects of being subsidized. The first variable $RDINTinternal$ is the internal R&D intensity calculated by dividing internal R&D expenditures by sales. Analog $RDINTtotal$ gives the total R&D intensity calculated by dividing the total R&D expenditures by sales. $INNOINT$ provides the total innovation intensity of a company obtained by dividing total innovation expenditures by sales. Total innovation expenditures include, besides expenditures related to R&D activities,

expenditures for engineering, design and other creative work activities, marketing and brand equity activities, IP-related activities, employee training activities, software development and database activities, and activities related to the acquisition or lease of tangible assets (OECD, 2019, p. 95).

Table 2. 8 to Table 2. 10 show the results of Ordinary Least Squares (OLS) estimations which are performed in order to examine the possible differences of the subsidy effects in (i) being located in different Belgian regions, (ii) receiving subsidies from different sources including possible policy mix effects, as well as possible effects of (iii) simultaneously receiving a subsidy from a certain authority and being located in a certain Belgian region. The dependent variable for the results in Table 2. 8 is the difference of the variable $RDINTinternal$ between the treated and control group which is basically the treatment effect measured as $RDINTinternal$.

Analog, the results in Table 2. 9 refer to the variable $RDINTtotal$ and in Table 2. 10 to the variable $INNOINT$. The covariates belong only to the subsidized observations in the matched sample as the purpose is to find out whether these are statistical significantly related with the treatment effect. The covariates $Brussels$ and $Wallonia$ are dummy variables indicating with the value of 1 that a company is located in Brussels-Capital and Wallonia whereat the reference category is Flanders ($Flanders$). Covariates $Regional$ and $FGovernment$ are dummy variables indicating with the value of 1 the receipt of an innovation subsidy stemming from a regional authority, respectively Belgian Federal Government. Innovation subsidy receipt sourced by the EU (EU) serves as reference category.

The remaining covariates taken into account for the OLS estimations are interaction terms generated by using the above described covariates. $RegFGovEU$ is an interaction term generated by the covariates $Regional$, $FGovernment$, and EU. For the other interaction terms ($RegFGov$, $RegEU$, $FGovEU$, $RegBru$, $RegWal$, $FGovBru$, $FGovWal$) the same applies by using the covariates indicated by the name of the interaction terms. Number of observations for each of the covariates and the corresponding reference categories are available in Table 2. 11.

Descriptive statistics by subsidy status are available in Table 2. 1, while Table 2. 2 provides t-test results on the mean differences for the subsidized and non-subsidized subsamples at the stage before the non-parametric matching procedure is applied. In

Table 2. 14 the number of observations in each of the 10 industry sectors are available for the states before and after matching[57].

2.4 Results

The comparison of the means of the outcome variables between treated and control groups after matching delivers (Table 2. 6) that subsidized companies (regardless of subsidy source and location of the companies) have an internal R&D intensity that is on average 3.4 percentage points higher and total R&D intensity that is on average 4.2 percentage points higher than unsubsidized companies. The total intensity for innovation expenditure is on average 4.7 percentage points higher than the untreated groups' total innovation intensity. These differences are significant at 1 percent level.

The OLS results (Table 2. 8 – Table 2. 10) in the first model setting (I) controlling only for the regional context of the companies show that being located in Brussels-Capital compared to the situation of being located in Flanders is positively related to the treatment effect (dependent variable). The coefficients reveal that being located in Brussels-Capital is associated with 4 percentage points higher treatment effect regarding internal R&D intensity, 4.5 percentage points higher treatment effect regarding total R&D intensity, and 6.5 percentage points higher treatment effect regarding total innovation intensity. Furthermore, there is statistical significant evidence that subsidized companies located in Wallonia exhibit 1.8 to 2.4 percentage points less in R&D and innovation intensities compared to companies located in Flanders.

The second setting of the OLS models (II) taking into account the different subsidy sources for each of the outcome variables deliver evidence for a higher effect of subsidies stemming from regional authorities and Belgian Federal Government compared to the situation of being subsidized with direct R&D grants from the EU authorities. According to the results, the treatment effect on total R&D intensity is 5.2 percentage points higher for regional subsidies and 4.4 percentage points higher for

[57] Table 2. 3 provides a description of the matching procedure.

Federal Government subsidies (Table 2. 9) compared to the reference category of being subsidized with EU grants. Similarly the treatment effect on internal R&D intensity is 4.6 percentage points higher in case of regional subsidies and 3.9% higher for federal subsidies (Table 2. 8). The treatment effect on total innovation intensity is 5.5 and 4.3 percentage points higher in case of regional and federal funding (Table 2. 10).

Model III for different performance variables takes simultaneously into account the source of the subsidies and the regional location of the companies. It delivers similar empirical evidence as in models I and II. The treatment effect on internal R&D intensity (Table 2. 8) is 3.7 percentage points higher in case of being in Brussels-Capital and 1.9 percentage points lower in case of being in Wallonia compared to being located in Flanders. Being subsidized by regional authorities is associated with 4.6 percentage points higher treatment effect regarding internal R&D intensity and 3.8 percentage points higher in case of being subsidized by the federal authority compared to the status of being subsidized by the EU authorities.

Analog, the treatment effect on total R&D intensity (Table 2. 9) is in case of being located in Brussels-Capital 4.1 percentage points higher and being located in Wallonia with 2.1 percentage points lower compared with the reference category of being located in Flanders. Being subsidized from regional authorities and Federal Government leads to a 5.2 and 4.2 percentage points higher treatment effect on total R&D intensity compared to the situation of receiving EU subsidies. For the total innovation intensity (Table 2. 10) the treatment effect is 6.1, 5.4, and 4.2 percentage points higher in case of being located in Brussels-Capital, being subsidized with regional grants, and being subsidized with federal grants. It is 2.5 percentage points lower for being located in Wallonia.

In addition to model III, model IV takes the interaction between subsidy receipt sources into account and shows whether the combination of subsidies from certain sources exerts a superior treatment effect. Thus model IV is the most accurate setting to obtain insights on the first and second research questions which are about the potential effect of different subsidy sources and presence of policy mix. In this setting the coefficient for being located in Brussels-Capital remains positive for all three outcome variables but is only statistically significant for total innovation intensity and

suggests that companies in Brussels-Capital have a 4.9 percentage points higher treatment effect regarding total innovation intensity compared to the reference category of being located in Flanders.

Being located in Wallonia is statistically significantly associated with -2.2 to -2.8 percentage points deviation of the treatment effect on intensities compared with the reference category. The treatment effect on internal R&D intensity is by 4.0 and 4.2 percentage points higher in case of being subsidized only by regional or only by Federal Government subsidies compared to the status of the reference category of being subsidized only with subsidies from EU authorities. The same coefficients for other outcome variables are positive but not statistically significant.

Another variable (*RegEU*) indicating the status of being subsidized simultaneously by a regional authority and by EU authorities delivers statistically significant coefficients suggesting that those companies exhibit 8.1, 9.4, and 6.6 percentage points higher treatment effects regarding internal R&D, external R&D, and total innovation intensities compared with the situation of being subsidized by EU authorities only. The remaining states of being subsidized by all three different sources simultaneously (*RegFGovEU*), by regional authorities and Federal Government simultaneously (*RegFGov*), and by Federal Government and EU authorities simultaneously (*FGovEU*) are not associated statistically significantly with the dependent variables.

In model V the covariates from model III are supplemented with interactions of subsidy sources and companies region of location in order to test for potential effects of being subsidized from a certain source and being located in a certain region at the same time. Thus model V allows for obtaining insights on the third research question. The interactions between subsidy sources are excluded since including them would lead to a situation with a high number of interactions terms with a small number of observations for most of the categories.

In this setting the variables indicating only the regional location become statistically insignificant for all of the three outcome variables. The regional subsidy receipt dummy is statistically significant and shows that the treatment effect regarding internal R&D intensity is higher by 4.2, and both for total R&D and total innovation intensities are higher by 4.9 percentage points than the reference category of being

subsidized by the EU authorities only. Federal subsidy receipt is associated with higher treatment effects (respectively 3.1, 3.6, and 3.4 percentage points) regarding internal R&D, total R&D and total innovation intensities compared with the reference category.

The interaction terms reveal that there is a significant positive effect of receiving a subsidy from the Federal Government and being located in Brussels-Capital simultaneously (*FGovBru*). This effect amounts to 10.8, 10.0, and 11.5 higher percentage points for the internal R&D, total R&D, and total innovation intensities compared with the reference category of being subsidized with Federal Government subsidies and being located in Flanders (*FGovFla*) simultaneously. Compared to the same reference category being located in Wallonia and receiving a Federal Government subsidy (*FGovWal*) at the same time is not significantly different. Two further interactions terms, being located in Brussels-Capital and receiving regional subsidies at the same time (*RegBru*), and being located in Wallonia and receiving regional subsidies at the same time (*RegWal*) respectively, are not significantly different than the reference category (*RegFla*) status of being located in Flanders and receiving a subsidy from the regional authorities at the same time.

2.5 Robustness Checks

In an alternative matching approach (Table 2. 12) as a robustness check the matching of the matched pairs are restricted to stem from the same region. It might be the case that the situation of the companies from different regions are comparable at a lower level as only companies within the same region apply for subsidies from the same regional authority and share the same institutional, economic, and legislative environment. Restricting the pool of the control group leaves us with fewer observations as a higher number of treated observation are left without a proper match within the same region. Thus for the analyses, 1,426 firm year observations (1,097 firms) remain.

The results are very similar to the approach with matching across regions. Therefore, we have the certainty that allowing matched pairs to stem from different

regions does not lead to a bias of the results. Table 2. 13 shows the results of the probit regression with the matched sample to demonstrate that between the treated and control groups there are statistically no differences on average. Table 2. 14 provides the number of observations per industry sector and propensity scores are illustrated in Figure 2. 2 for the states before and after matching. The results of the alternative matching within regions are used for further robustness checks below to assess whether the OLS estimation results would strongly deviate under this approach.

Further robustness checks (Table 2. 16 – Table 2. 36) are performed in order to test whether the main results of the OLS estimations in the paper (Table 2. 8 – Table 2. 10) hold under different circumstances. These checks are applied by considering the covariates utilized in the propensity score estimation in OLS estimations, applying the alternative matching approach described above, and excluding the peaks (smallest and largest values) of the treatment effects regarding total innovation intensity variables' distribution in OLS estimations (see Table 2. 15 for an overview of robustness checks). Comparing the results from the paper (Table 2. 8 to Table 2. 10) with the results of the robustness checks the stability of the findings to a number of modifications in the empirical settings is assessed in the following.

The first robustness check is employed by including the covariates utilized in the probit regressions in OLS models. Since the nearest neighbor matching procedure is not an exact matching approach, which would leave us with a very small matched sample, and the treatment and control groups are statistically indifferent from each other only on average, taking into account the covariates from the propensity score matching could still have an effect on the results obtained by the OLS estimations. Table 2. 16 to Table 2. 18 show OLS estimations which incorporate additional covariates.

While being in Brussels (*Brussels*), which was statistically significant in some of the models before, becomes insignificant for all outcome variables, coefficients for being in Wallonia (*Wallonia*) become pronounced stronger and statistically significant at higher significance levels for all outcome variables. For the treatment effect of total R&D intensity the coefficient for the variable *FGovBru*, that was statistically significant at 10% level, becomes insignificant while the extent of the coefficient remains similar. All other coefficients remain similar in their extent and also at similar significance

levels compared to the results before. It can be concluded that adding the additional covariates does not lead to strongly deviating results.

The second robustness check (Table 2. 19 – Table 2. 21) tests for an effect of a modification of the matching procedure on OLS estimations such that the matched pairs are restricted to stem from the same region. OLS estimation with the alternative matched sample confirm the results from default matched sample whereat almost all coefficients are even pronounced stronger and in many cases the significance levels are higher. The third robustness check (Table 2. 22 – Table 2. 24) also uses the modified matched sample and considers all covariates from the Probit regressions in the OLS estimations. Also this setting delivers similar results as the results from unmodified matched sample.

The largest changes worth to be mentioned are differences of the significance levels of the region dummies. While being in Brussels is significant at higher levels for both of the R&D intensities, it becomes insignificant for the total innovation intensity. Being in Wallonia in turn becomes insignificant for both of the R&D intensities. It can be concluded that matching within regions only does not leave us with results strongly deviating from the default matched sample but leaves us with less observations. In order to keep a larger sample size it turns out to be proper to use the matching approach with matching across regions as done in the paper.

The fourth robustness check (Table 2. 25 – Table 2. 27) uses the default matched sample that allows matching across regions and tests whether the OLS results are driven by smallest and largest values across the treatment effect distribution by dropping the first and last percentiles of the treatment effect regarding the total innovation intensity variable. The results show again similar coefficients and significance levels almost for all of the covariates. In this setting being in Wallonia becomes insignificant in almost all models for all outcome variables. In turn being subsidized with a Federal Government subsidy and being located in Wallonia at the same time (*FGovWal*) for both of the R&D intensity treatment effect variables statistically significant and has a negative sign.

The fifth robustness check (Table 2. 28 – Table 2. 30) uses additional covariates in addition to the setting from the fourth robustness check. Being in Brussels becomes insignificant for all models and outcome variables. For the treatment effect of total

R&D intensity *FGovBRU* becomes statistically insignificant. *FGovWal* becomes statistically significant and has a negative sign for both internal and total R&D intensity treatment effects. *RegEU* becomes statistically insignificant in case of the treatment effect for total innovation intensity but in turn *RegFGovEU* becomes statistically significant. Dropping the first and last percentiles with and without additional covariates in majority confirm the findings from the default analyses.

The sixth robustness check (Table 2. 31 – Table 2. 33) go further with checking the potential effects of the small and large values of the treatment effect regarding to total innovation intensity and drop the parts of the distribution below 5th and above 95th percentiles. The results of the OLS estimations remain very similar compared to the default setting. Main observed differences are that being in Wallonia becomes insignificant for all outcome variables, being in Brussels and receiving regional subsidies (*RegBru*) at the same time becomes statistically significant for internal R&D and total innovation intensities. In general the extent of the coefficients decrease which is not surprising since the larger values in both directions are dropped from the sample. The seventh robustness check (Table 2. 34 – Table 2. 36) applies additional covariates to the setting from the sixth robustness check. Results remain similar to the results from the sixth robustness check whereat the variable *FGovBru* is statistically significant only for total innovation intensity treatment effect.

In a summary, there is no evidence for strongly deviating results by applying alternative approaches regarding the matching procedure, considering additional covariates in OLS estimations, or by cutting the largest and smallest values of the distributions of the treatment effects utilized as dependent variables in OLS estimations.

2.6 Conclusion

This paper follows up on the underdeveloped scientific evidence for potential effects of public funding source heterogeneity, policy mix, and regional context on public funding impact by utilizing Community Innovation Survey data for the period 2006-2014 that provides a representative sample of companies active within the

Belgian economy. The focus was on input additionality both in terms of internal and total R&D intensity and in terms of total innovation expenditure intensity. A non-parametric matching approach has been relied upon, and a distinction is made between the following innovation subsidy sources: European authorities, federal government, and regional governments.

Four main findings were identified. First there is a significant overall, positive effect of innovation subsidies for total and internal R&D intensities as well as total innovation intensity respectively. No evidence is found for a full crowding-out effect of public funding. The overall statistically significant positive treatment effect on input additionality is in line with the literature (Czarnitzki & Lopes-Bento, 2010, 2013; Czarnitzki & Hussinger, 2018) and is strongest for the internal R&D intensity. The treatment effect on total R&D intensity, that includes outsourced R&D expenses besides internal R&D expenses, is higher than for internal R&D intensity suggesting that the public support also triggers a higher level of external R&D intensity. Furthermore, allover treatment effect for total innovation expenditure intensity is higher than for total R&D intensity which in turn means that subsidized companies spend also more on other innovative means such as engineering, design and other creative work activities, machines, software, licenses, training, and marketing for their innovative activities (OECD, 2019, p. 95).

Second, relating the overall treatment effects with different subsidy sources and the policy mix of these sources revealed that EU subsidies and regional subsidies are complements. This confirms earlier findings by Czarnitzki & Lopes-Bento (2014). The combination of both funding sources is associated with higher treatment effects for all input additionality measures applied. Inclusion of policy mix is found to substantially influence significance levels, confirming hidden treatments as described by Guerzoni and Raiteri (2015). No evidence was found for any of the considered subsidy sources to be a substitute to the receipt of public funding from another subsidy source. Receiving only regional or only federal subsidies is significantly related with higher treatment effects for internal R&D intensity only. No significant effect is found for combined federal and regional subsidies.

Third, the treatment effect is demonstrated to significantly differ when the regional localization of the companies is taken into account. The treatment effect for being

located in the less economically developed region of Wallonia for all intensity measures is associated with lower treatment effects compared with the reference category of being located in the more prosperous region of Flanders. Companies located in the highly international and high income per capita region of Brussels-Capital region experience higher treatment effects of subsidies for innovation intensity. This confirms the importance of the regional context for effects of public funding for innovation, as put forward by Montmartin et al. (2018) based on an analysis for 94 regions in France.

Fourth, testing for the receipt of a subsidy from a certain source and being located in a certain region at the same time revealed that companies located in the Brussels-Capital region and receiving Federal Government subsidies are associated with a significant higher treatment effect for all intensity measures. This finding confirms that the regional context of a company can make a difference even for the same subsidy source, a finding confirming the views by Montmartin et al. (2018). This finding is the more remarkable since the Belgian Federal Governments' subsidies in our sample are mainly indirect subsidies (tax benefits), i.e. no competitive selection process is in order to receive these subsidies, and thus the treatment chance for all companies in all Belgian regions is the same while the treatment size is non-limited. The evidence shows that - after controlling for a broad range of firm characteristics - companies in Brussels-Capital particularly react with strong input additionality on tax benefits sourced by the Belgian Government which is not the case for companies located in other regions. Being located in another region and receiving a subsidy from a certain source simultaneously is not related with a difference in means of the treatment effect.

From a policy making perspective, these findings suggest that subsidy source, mix of subsidy sources, as well as regional context matter for input additionality of public funding for research and innovation. The findings for the small open economy of Belgium also demonstrate that, in view of input additionality of innovation subsidies, there's room for further optimization of the allocation of federal subsidies across the regions. Regional authorities in Flanders and Wallonia could possibly increase the input additionality of the subsidized companies within their territories by providing assistance in how to benefit more effectively from tax benefits. The regional

authorities of the same regions could also encourage companies which receive regional subsidies to apply for subsidies sourced by the EU to take advantage out of the complementarities revealed in our results.

The lack of complementarity between regional and federal subsidies (in contrast to positive effects of combined regional and EU subsidies) invites for an examination of why this is the case and possibly achieve improvement of the situation by coordinating better between direct measures at regional level and indirect support at the federal level. Regional authority in Wallonia could possibly enhance the subsidy impact in its territory by analyzing differences: regarding the institutions, administrative rules, subsidy programme/allocation frameworks, as well as the population of the subsidized companies compared to other Belgian regions.

Finally, there seems to be a regional context effect in the sense that subsidies to firms in economically stronger regions result in larger input additionality of innovation subsidies. These findings for the small open Belgian economy have interesting implications for policy making in other countries and e.g. also at the level of the EU's Framework and Structural and Investment Funds programmes, as they demonstrate that there's room for optimizing additionality effects of public funding for R&D and innovation by better taking into account a combination of the (mix of) different sources of public funding for innovation, and the location of the beneficiary.

Our findings are robust to modifications of the matching strategy (matching within vs. across regions), modifications of the OLS settings (utilization of covariates from the first stage vs. excluding them), and exclusion of the smallest and largest companies in means of the distribution of innovation intensity measure (exclusion of the smallest and largest 1 percentile and 5 percentiles). However, the binary variables of receipt of innovation subsidies from a certain government rather than absolute amounts of funding pose a limitation on the study. Also, it is recommended to test the combined policy mix, different forms of subsidies, and regional context in a larger or different set of regions to account for diversity in regional context. Another area for further research is to examine whether the subsidy recipients are performing superior compared to their non-subsidized peers among others in means of higher innovative sales, number of innovative products, or number of patent applications. These forms

of output additionality can give additional insights in the effectiveness of the different public funding sources.

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Tables and Figures

Table 2. 1 Descriptive statistics by subsidy status (before matching)

	Subsidized (N=1,663)				Non Subsidized (N=2,967)			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
RDINTinternal	7.108	14.169	0	97.979	2.172	8.152	0	100
RDINTtotal	8.153	15.761	0	97.979	2.434	8.522	0	100
INNOINT	9.959	17.155	0	99.945	3.795	9.947	0	100
lnEMP	4.253	1.516	0	9.323	3.742	1.261	0	9.373
lnAGE	3.187	0.706	0.693	7.605	3.161	0.700	0.693	5.342
PERMRD	0.773	0.419	0	1	0.403	0.491	0	1
GROUP	0.667	0.471	0	1	0.616	0.486	0	1
FMOTHeu	0.188	0.391	0	1	0.211	0.408	0	1
FMOTHnoneu	0.114	0.317	0	1	0.108	0.310	0	1
EXPORT	0.838	0.369	0	1	0.704	0.456	0	1
lnPROD	5.521	0.845	0.324	11.068	5.500	0.904	0.127	11.558
lnCOMPnr	2.595	1.560	0	7.179	3.086	1.679	0	7.711
lnUNEMP	-2.965	0.536	-3.848	-1.732	-2.997	0.546	-3.848	-1.732
lnPOPUL	13.985	0.346	12.484	14.405	14.024	0.310	12.484	14.405

Table 2. 2 T-tests on mean differences (before matching)

	Subsidized (N=1,663)		Non Subsidized (N=2,967)		Difference		
Variable	Mean	SD	Mean	SD	Mean	SE	T-test Results
RDINTinternal	7.108	14.169	2.172	8.152	4.940	0.378	***
RDINTtotal	8.153	15.761	2.434	8.522	5.719	0.417	***
INNOINT	9.959	17.155	3.795	9.947	6.165	0.459	***
lnEMP	4.253	1.516	3.742	1.261	0.511	0.044	***
lnAGE	3.187	0.706	3.161	0.700	0.026	0.022	
PERMRD	0.773	0.419	0.403	0.491	0.369	0.014	***
GROUP	0.667	0.471	0.616	0.486	0.051	0.015	***
FMOTHeu	0.188	0.391	0.211	0.408	-0.023	0.012	*
FMOTHnoneu	0.114	0.317	0.108	0.310	0.006	0.010	
EXPORT	0.838	0.369	0.704	0.456	0.133	0.012	***
lnPROD	5.521	0.845	5.500	0.904	0.022	0.027	
lnCOMPnr	2.595	1.560	3.086	1.679	-0.491	0.049	***
lnUNEMP	-2.965	0.536	-2.997	0.546	0.032	0.017	*
lnPOPUL	13.985	0.346	14.024	0.310	-0.039	0.010	***

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

Table 2. 3 Matching procedure by steps

Step 1	Estimate a Probit model under considering relevant observable characteristics of the companies to obtain the propensity score $\widehat{\mathrm{P}}(\mathrm{X})$ for each of the observation in the sample.
Step 2	In order to comply with the common support criterion remove observations from the treatment group if there is no proper match in the control group, i.e. drop observations from the sample which have propensity scores below or above the propensity score band determined by the control groups' propensity scores. Common support criterion is applied also regarding variables which may be considered as matching arguments besides propensity score.
Step 3	Pick a treated observation and drop it from the sample of treatment group.
Step 4	Deviation in means of Mahalanobis distance between non-treated observations and the chosen treated observation in step 3 serves to identify the closest observation from the control group. $\mathrm{MD}_{\mathrm{ij}} = \left(\mathrm{Z}_{\mathrm{j}} - \mathrm{Z}_{\mathrm{i}}\right)' \Omega^{-1} \left(\mathrm{Z}_{\mathrm{j}} - \mathrm{Z}_{\mathrm{i}}\right)$ where Ω is the covariance matrix of the covariates utilized as matching arguments calculated based on the control group only. Caliper matching (Cochran and Rubin, 1973) is applied by including a maximum of $\mathrm{MD}_{\mathrm{ij}}$ to avoid matches where $\mathrm{Z}_{\mathrm{j}}$is more distant from Z_{i} then a level, $\left\|\mathrm{Z}_{\mathrm{j}} - \mathrm{Z}_{\mathrm{i}}\right\| < \varepsilon$, that ensures a proper match.
Step 5	Assign the control group member with the lowest $\mathrm{MD}_{\mathrm{ij}}$ as match to the in step 3 chosen observation but keep the control group member in the sample in order to allow it to serve as a match for the remaining treated observations. If the caliper threshold ε is lower than the $\mathrm{MD}_{\mathrm{ij}}$ of each observation from the control group, drop the treated observation from the sample since there is no proper match available.
Step 6	Steps 3 to 5 are repeated for all treated observations.
Step 7	Average effect of being subsidized is calculated as the average difference of treated and matched control group observations: $\widehat{\alpha}_{\mathrm{TT}} = 1 \,/\, \mathrm{n}^{\mathrm{T}} \left(\sum_{\mathrm{j}} \mathrm{Y}_{\mathrm{i}}^{\mathrm{T}} - \sum_{\mathrm{i}} \widehat{\mathrm{Y}}_{\mathrm{i}}^{\mathrm{C}} \right)$. $\widehat{\mathrm{Y}}_{\mathrm{i}}^{\mathrm{C}}$ is the counterfactual for i and n^{T} the sample size of subsidized observations.
Step 8	Since the same observation from the control group can serve as a match for more than one treated observation the t-statistics on mean differences can be biased and are adapted by following the approach by Lechner (2001), which corrects the standard errors accordingly.

Table 2. 4 Probit regression to estimate propensity scores (All subs.) and Probit regressions with each of subsidy type for comparison (marginal effects)

Dep. variable:	*All subs.*	*Reg. subs.*	*EU subs.*	*FGov. subs.*
lnEMP	0.035***	0.020***	0.010***	0.026***
	(0.007)	(0.006)	(0.002)	(0.005)
lnAGE	-0.012	-0.006	-0.001	-0.012
	(0.011)	(0.010)	(0.004)	(0.008)
PERMRD	0.230***	0.158***	0.054***	0.125***
	(0.019)	(0.017)	(0.009)	(0.015)
GROUP	-0.009	-0.004	0.001	-0.000
	(0.018)	(0.015)	(0.006)	(0.012)
FMOTHeu	-0.066***	-0.073***	-0.017***	-0.008
	(0.020)	(0.016)	(0.005)	(0.013)
FMOTHnoneu	-0.083***	-0.086***	-0.018***	-0.029**
	(0.023)	(0.017)	(0.006)	(0.015)
EXPORT	0.087***	0.065***	0.011**	0.047***
	(0.017)	(0.014)	(0.005)	(0.011)
lnPROD	0.004	-0.000	0.003	0.000
	(0.009)	(0.008)	(0.003)	(0.006)
lnCOMPnr	-0.015***	-0.014***	-0.007***	-0.005
	(0.005)	(0.004)	(0.002)	(0.004)
lnUNEMP	0.054***	0.067***	0.022***	-0.006
	(0.014)	(0.012)	(0.005)	(0.010)
lnPOPUL	-0.085***	-0.081***	-0.010	0.017
	(0.023)	(0.019)	(0.007)	(0.016)
Year dummies	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
N	4,630	4,630	4,630	4,630

* p<0.10, **p<0.05, *** p<0.01 ; Marginal effects at the means (MEM) reported. Standard errors in brackets. First model with All subs. as dependent variable is considered for propensity scores and utilized for the matching procedure. Results in the second column refer to subsidy receipt from regional authorities (Reg. subs.), while third and fourth columns refer to subsidy receipt from EU (EU subs.) and Belgian Federal Government (FGov. subs.).

Table 2. 5 Correlation matrix (before matching, sample and variables used for propensity score estimation)

	1	2	3	4	5	6	7	8	9	10	11
1 *All subs.*	1.00										
2 *lnEMP*	0.18***	1.00									
3 *lnAGE*	0.02	0.35***	1.00								
4 *PERMRD*	0.36***	0.26***	0.01	1.00							
5 *GROUP*	0.05***	0.40***	0.07***	0.14***	1.00						
6 *FMOTHeu*	-0.03*	0.21***	0.02	-0.02	0.38***	1.00					
7 *FMOTHnoneu*	0.01	0.21***	0.02	0.07***	0.27***	-0.18***	1.00				
8 *EXPORT*	0.15***	0.08***	0.05***	0.18***	0.08***	0.01	0.06***	1.00			
9 *lnPROD*	0.01	0.13***	0.09***	0.06***	0.22***	0.13***	0.14***	0.08***	1.00		
10 *lnCOMPnr*	-0.14***	-0.13***	-0.09***	-0.13***	0.00	0.04***	-0.01	-0.12***	0.05***	1.00	
11 *lnUNEMP*	0.03*	0.09***	0.03**	-0.02*	0.06***	0.10***	0.03***	0.00	0.01	0.16***	1.00
12 *lnPOPUL*	-0.06***	0.02*	0.06***	-0.02	0.02	0.03***	0.01	-0.03***	0.05***	0.06***	-0.17***

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

Table 2. 6 Matching results (across regions)

	Subsidized (N=1,638)		Non Subsidized (N=1,638)		Difference		T-tests on mean difference
Variable	Mean	SD	Mean	SD	Mean	SE*	p-value*
RDINTinternal	**7.118**	**14.249**	**3.679**	**10.837**	**3.439**	**0.563**	**0.000**
RDINTtotal	**8.151**	**15.828**	**3.969**	**11.118**	**4.183**	**0.596**	**0.000**
INNOINT	**9.971**	**17.234**	**5.320**	**12.221**	**4.652**	**0.653**	**0.000**
lnEMP	4.215	1.466	4.172	1.403	0.043	0.067	0.519
lnAGE	3.181	0.687	3.180	0.680	0.001	0.032	0.969
PERMRD	0.770	0.421	0.763	0.426	0.007	0.020	0.716
GROUP	0.664	0.472	0.632	0.482	0.032	0.023	0.155
FMOTHeu	0.189	0.392	0.170	0.376	0.020	0.018	0.279
FMOTHnoneu	0.114	0.317	0.107	0.310	0.006	0.015	0.680
EXPORT	0.837	0.369	0.831	0.375	0.006	0.018	0.730
lnPROD	5.522	0.845	5.496	0.795	0.026	0.038	0.493
lnCOMPnr	2.614	1.557	2.557	1.635	0.057	0.077	0.456
lnUNEMP	-2.972	0.532	-2.950	0.552	-0.022	0.026	0.399
lnPOPUL	13.986	0.343	13.968	0.356	0.018	0.017	0.282

* Lechners Approximation

Figure 2. 1 Propensity score graphs (across regions)

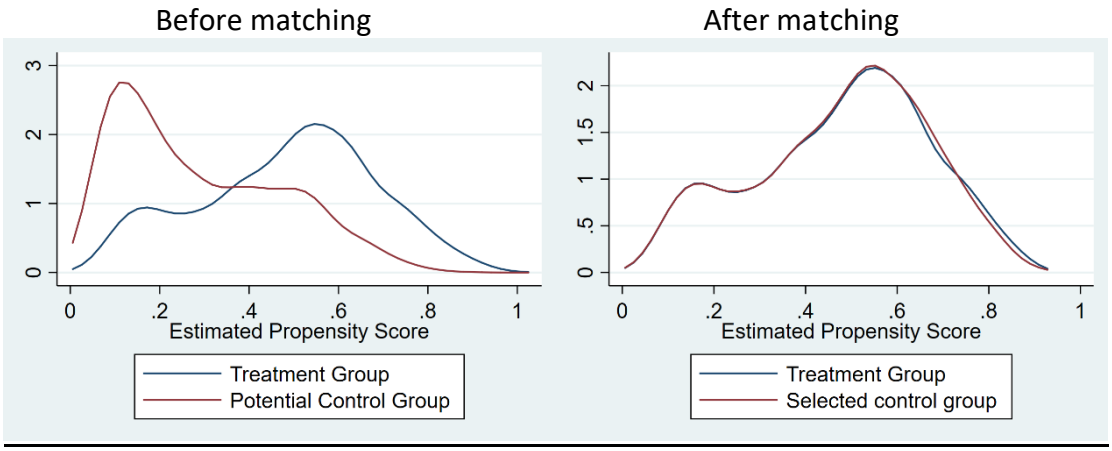


Table 2. 7 Probit regression with matched sample

Dependent variable: Subsidy receipt dummy (*All subs.*)

Variable	Coefficient	Standard Error
$lnEMP$	-0.107	(0.074)
$lnEMP^2$	0.012	(0.008)
$lnAGE$	0.010	(0.036)
$PERMRD$	-0.069	(0.074)
$GROUP$	0.064	(0.056)
FMOTHeu	0.048	(0.066)
FMOTHnoneu	0.002	(0.079)
$EXPORT$	0.020	(0.061)
$lnPROD$	0.012	(0.030)
$lnCOMPnr$	0.019	(0.016)
$lnUNEMP$	-0.044	(0.043)
$lnPOPUL$	0.059	(0.065)
Constant	-0.963	(0.924)
year dummies	yes	
Joint sign. test	chi2(3)=0.87	
sector dummies	yes	
Joint sign. test	chi2(9)=3.60	
Sign. test entire model	chi2(25)=18.66 Prob>chi2=0.8131	
N	3,276	

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

Sector and Year dummies' coefficients are all insignificant.

Table 2. 8 Treatment effect (internal R&D intensity) on subsidy sources and regions

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group (matching across regions; no additional covariates)

Variable	I	II	III	IV	V
Brussels	3.993*		3.693*	2.450	-5.161
	(2.088)		(2.053)	(1.988)	(4.840)
Wallonia	-1.860*		-1.865*	-2.236**	-0.044
	(1.023)		(1.036)	(1.032)	(2.506)
Regional		4.609***	4.559***	4.023*	4.166***
		(1.041)	(1.015)	(2.349)	(1.131)
FGovernment		3.939***	3.802***	4.238*	3.063***
		(1.033)	(1.034)	(2.376)	(1.141)
RegFGovEU				0.772	
				(4.500)	
RegFGov				-2.831	
				(2.589)	
RegEU				8.093***	
				(2.234)	
FGovEU				1.007	
				(3.211)	
RegBru					5.298
					(4.957)
RegWal					-1.636
					(2.292)
FGovBru					10.806**
					(5.010)
FGovWal					-1.586
					(2.522)
_cons	3.458***	-1.793	-1.649	-2.037	-0.992
	(0.461)	(1.133)	(1.177)	(2.310)	(1.284)
R-squared	0.005	0.013	0.018	0.048	0.022
N	1,638	1,638	1,638	1,638	1,638

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 9 Treatment effect (total R&D intensity) on subsidy sources and regions

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group (matching across regions; no additional covariates)

Variable	I	II	III	IV	V
Brussels	4.473**		4.122*	2.713	-3.786
	(2.249)		(2.214)	(2.157)	(5.117)
Wallonia	-2.039*		-2.062*	-2.480**	0.453
	(1.099)		(1.111)	(1.107)	(2.645)
Regional		5.233***	5.176***	3.471	4.928***
		(1.130)	(1.109)	(2.522)	(1.255)
FGovernment		4.386***	4.235***	3.498	3.642***
		(1.132)	(1.130)	(2.544)	(1.276)
RegFGovEU				-0.627	
				(4.916)	
RegFGov				-1.698	
				(2.789)	
RegEU				9.377***	
				(2.381)	
FGovEU				2.251	
				(3.523)	
RegBru					4.545
					(5.221)
RegWal					-2.271
					(2.412)
FGovBru					10.031*
					(5.286)
FGovWal					-2.040
					(2.653)
_cons	4.197***	-1.716	-1.558	-0.990	-1.077
	(0.502)	(1.229)	(1.265)	(2.480)	(1.409)
R-squared	0.006	0.014	0.019	0.053	0.022
N	1,638	1,638	1,638	1,638	1,638

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 10 Treatment effect (innovation intensity) on subsidy sources and regions

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group (matching across regions; no additional covariates)

Variable	I	II	III	IV	V
Brussels	6.493***		6.097***	4.920**	-3.556
	(2.356)		(2.321)	(2.293)	(5.582)
Wallonia	-2.393*		-2.465*	-2.790**	-0.521
	(1.382)		(1.395)	(1.398)	(3.345)
Regional		5.505***	5.383***	4.382	4.947***
		(1.221)	(1.199)	(2.726)	(1.334)
FGovernment		4.339***	4.162***	3.976	3.406**
		(1.225)	(1.226)	(2.750)	(1.352)
RegFGovEU				2.447	
				(5.086)	
RegFGov				-2.053	
				(3.044)	
RegEU				6.604***	
				(2.549)	
FGovEU				0.107	
				(3.554)	
RegBru					5.920
					(5.684)
RegWal					-1.666
					(3.136)
FGovBru					11.491**
					(5.129)
FGovWal					-1.878
					(3.492)
_cons	4.574***	-1.422	-1.283	-1.049	-0.589
	(0.543)	(1.338)	(1.379)	(2.665)	(1.510)
R-squared	0.009	0.012	0.020	0.035	0.023
N	1,638	1,638	1,638	1,638	1,638

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 11 Number of observation in each of the subsidy receipt category in OLS estimations

	Nr. of observation	
Variable	Matching across regions	Matching within regions
Brussels	123	97
Wallonia	281	195
*Flanders**	1,234	1,134
Regional	1,186	1,012
FGovernment	788	684
*EU**	332	265
RegFGovEU	133	101
RegFGov	384	312
RegEU	247	189
FGovEU	170	135
*EU** only	48	42
RegBru	105	82
RegWal	240	166
*RegFla**	841	764
FGovBru	49	35
FGovWal	90	62
*FGovFla**	649	587

* Reference category

Table 2. 12 Matching results (within regions)

	Subsidized (N=1,426)		Non Subsidized (N=1,426)		Difference		T-tests on mean difference
Variable	Mean	SD	Mean	SD	Mean	SE*	p-value*
RDINTinternal	**6.750**	**13.957**	**3.241**	**9.006**	**3.510**	**0.514**	**0.000**
RDINTtotal	**7.693**	**15.488**	**3.528**	**9.567**	**4.164**	**0.559**	**0.000**
INNOINT	**9.537**	**16.924**	**4.946**	**10.967**	**4.591**	**0.625**	**0.000**
lnEMP	4.110	1.340	4.048	1.292	0.062	0.062	0.319
lnAGE	3.192	0.631	3.193	0.612	-0.001	0.030	0.979
PERMRD	0.750	0.433	0.735	0.442	0.015	0.021	0.462
GROUP	0.651	0.477	0.627	0.484	0.025	0.023	0.286
FMOTHeu	0.176	0.381	0.165	0.371	0.011	0.018	0.530
FMOTHnoneu	0.112	0.316	0.115	0.319	-0.003	0.015	0.853
EXPORT	0.825	0.380	0.845	0.362	-0.020	0.018	0.247
lnPROD	5.503	0.811	5.478	0.820	0.025	0.039	0.516
lnCOMPnr	2.621	1.516	2.627	1.491	-0.006	0.072	0.933
lnUNEMP	-3.017	0.512	-3.030	0.504	0.014	0.024	0.568
lnPOPUL	14.014	0.299	14.015	0.297	-0.001	0.014	0.929

* Lechners Approximation

Figure 2. 2 Propensity score graphs (within regions)

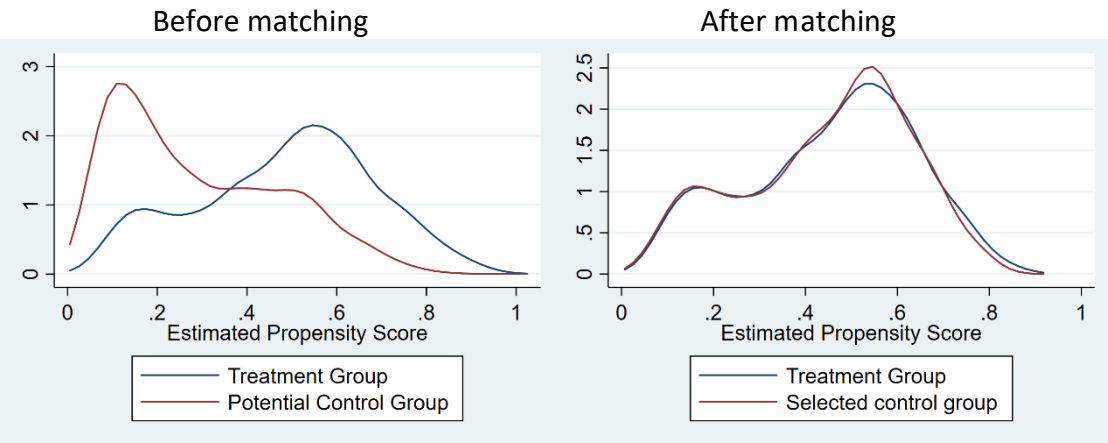


Table 2. 13 Probit regression with matched sample (within regions)

Dependent variable: Subsidy receipt dummy (*All Subs.*)

Variable	Coefficient	Standard Error
lnEMP	-0.046	(0.096)
lnEMP²	0.007	(0.011)
lnAGE	-0.006	(0.042)
PERMRD	-0.029	(0.077)
GROUP	0.053	(0.060)
FMOTHeu	-0.015	(0.072)
FMOTHnoneu	-0.077	(0.085)
EXPORT	-0.088	(0.066)
lnPROD	0.028	(0.032)
lnCOMPnr	-0.001	(0.018)
lnUNEMP	0.028	(0.049)
lnPOPUL	-0.000	(0.083)
Constant	-0.008	(1.169)
year dummies	yes	
Joint sign. test	chi2(3)=0.62	
sector dummies	yes	
Joint sign. test	chi2(9)=6.06	
Sign. test entire model	chi2(25)=16.99 Prob>chi2=0.8821	
N	2,852	

* p<0.10, **p<0.05, *** p<0.01
Sector and Year dummies' coefficients are all insignificant.

Table 2. 14 Industry classification

				Matching across regions	Matching within regions
Variable	Industry	2 Digit NACE-Codes (2008)	# of observations before matching	# of observations after matching*	# of observations after matching*
Sector 1	Textile, Paper, Wood	13-18	337	281	249
Sector 2	Chemicals, Plastics	19-22	481	460	367
Sector 3	Metal	24-25	318	211	187
Sector 4	Food, Beverages	10-12	326	197	215
Sector 5	Machinery, Vehicles	28-30, 33	417	345	299
Sector 6	Electronics	26-27	239	260	213
Sector 7	Other Industries	1, 8, 23, 31-32, 35-36, 38-39, 41-43, 58, 74	509	379	311
Sector 8	Trade	45-47	637	242	225
Sector 9	Transport, Other Services	37, 49-53, 59-61, 64-66, 68-70, 73, 77-91, 93-99	495	225	203
Sector 10	Information Services	62-63, 71-72	871	676	583
	All Industries		4,630	3,276	2,852

Table 2. 15 Overview robustness check tables

	A	B	C	D
Tables 2.16-18		*		
Tables 2.19-21	*			
Tables 2.22-24	*	*		
Tables 2.25-27			*	
Tables 2.28-30		*	*	
Tables 2.31-33				*
Tables 2.34-36		*		*

A. Matching within regions (default is matching across regions)
B. With additional covariates (default is no additional covariates)
C. First and last percentile of the treatment effect regarding total innovation intensity variable dropped
D. Below 5^{th} and above 95^{th} percentile of the treatment effect regarding total innovation intensity variable dropped

Table 2. 16 Treatment effect (internal R&D intensity) on subsidy sources and regions (matching across regions; additional covariates)

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	2.817		2.258	1.328	-4.599
	(2.716)		(2.704)	(2.649)	(5.235)
Wallonia	-3.876**		-4.103**	-4.603***	-1.756
	(1.731)		(1.753)	(1.739)	(3.031)
Regional		3.896***	3.866***	2.721	3.721***
		(1.033)	(1.022)	(2.428)	(1.128)
FGovernment		3.200***	3.072***	2.880	2.557**
		(1.043)	(1.027)	(2.484)	(1.119)
RegFGovEU				1.081	
				(4.209)	
RegFGov				-1.433	
				(2.692)	
RegEU				7.161***	
				(2.120)	
FGovEU				0.103	
				(3.058)	
RegBru					3.915
					(4.930)
RegWal					-2.359
					(2.451)
FGovBru					8.531*
					(4.868)
FGovWal					-1.420
					(2.553)
_cons	43.778**	15.015	41.885**	43.843**	42.308**
	(19.842)	(18.099)	(19.959)	(19.403)	(19.839)
R-squared	0.089	0.091	0.097	0.118	0.100
N	1,638	1,638	1,638	1,638	1,638

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 17 Treatment effect (total R&D intensity) on subsidy sources and regions (matching across regions; additional covariates)

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	3.018		2.392	1.435	-2.859
	(2.932)		(2.925)	(2.866)	(5.550)
Wallonia	-4.219**		-4.479**	-4.969***	-1.357
	(1.887)		(1.907)	(1.884)	(3.253)
Regional		4.358***	4.327***	1.982	4.380***
		(1.110)	(1.102)	(2.580)	(1.238)
FGovernment		3.492***	3.353***	1.914	3.040**
		(1.125)	(1.111)	(2.633)	(1.240)
RegFGovEU				0.414	
				(4.576)	
RegFGov				-0.140	
				(2.872)	
RegEU				7.810***	
				(2.232)	
FGovEU				0.898	
				(3.267)	
RegBru					2.712
					(5.185)
RegWal					-3.104
					(2.628)
FGovBru					7.059
					(5.166)
FGovWal					-1.838
					(2.700)
_cons	48.114**	16.557	45.896**	48.563**	46.081**
	(21.684)	(19.225)	(21.729)	(21.087)	(21.579)
R-squared	0.107	0.108	0.115	0.136	0.116
N	1,638	1,638	1,638	1,638	1,638

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 18 Treatment effect (innovation intensity) on subsidy sources and regions (matching across regions; additional covariates)

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	1.853		1.166	0.452	-6.005
	(3.263)		(3.286)	(3.247)	(6.031)
Wallonia	-6.103***		-6.397***	-6.683***	-3.431
	(2.282)		(2.318)	(2.311)	(3.952)
Regional		4.759***	4.753***	1.889	4.673***
		(1.208)	(1.202)	(2.828)	(1.337)
FGovernment		3.709***	3.556***	1.358	2.960**
		(1.217)	(1.206)	(2.868)	(1.319)
RegFGovEU				2.897	
				(4.778)	
RegFGov				1.005	
				(3.153)	
RegEU				5.247**	
				(2.401)	
FGovEU				-0.968	
				(3.314)	
RegBru					3.502
					(5.523)
RegWal					-3.077
					(3.310)
FGovBru					10.018**
					(5.102)
FGovWal					-1.651
					(3.513)
_cons	49.035*	4.260	46.448*	49.630*	47.129*
	(26.217)	(23.480)	(26.267)	(25.900)	(26.021)
R-squared	0.101	0.101	0.109	0.117	0.111
N	1,638	1,638	1,638	1,638	1,638

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 19 Treatment effect (internal R&D intensity) on subsidy sources and regions (matching within regions; no additional covariates)

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	5.807***		5.510***	4.031**	-4.920
	(1.970)		(1.926)	(1.786)	(5.143)
Wallonia	-2.668**		-2.830**	-3.356***	-0.934
	(1.193)		(1.215)	(1.196)	(3.196)
Regional		5.315***	5.282***	2.456	4.912***
		(1.073)	(1.048)	(1.690)	(1.118)
FGovernment		3.973***	3.884***	1.715	3.051***
		(1.084)	(1.092)	(1.721)	(1.143)
RegFGovEU				1.766	
				(4.979)	
RegFGov				-1.319	
				(2.028)	
RegEU				9.768***	
				(2.654)	
FGovEU				3.822	
				(3.390)	
RegBru					6.806
					(5.184)
RegWal					-1.978
					(3.145)
FGovBru					12.774**
					(5.103)
FGovWal					-0.987
					(3.676)
_cons	3.479***	-2.168*	-2.090*	-0.365	-1.409
	(0.460)	(1.132)	(1.177)	(1.621)	(1.218)
R-squared	0.012	0.017	0.028	0.093	0.034
N	1,426	1,426	1,426	1,426	1,426

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 20 Treatment effect (total R&D intensity) on subsidy sources and regions (matching within regions; no additional covariates)

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	6.154***		5.789***	4.213**	-4.064
	(2.214)		(2.169)	(2.046)	(5.531)
Wallonia	-3.226**		-3.444***	-4.006***	-0.979
	(1.282)		(1.307)	(1.286)	(3.465)
Regional		6.031***	6.024***	1.843	5.741***
		(1.185)	(1.164)	(1.940)	(1.259)
FGovernment		4.385***	4.263***	0.677	3.498***
		(1.202)	(1.208)	(1.964)	(1.290)
RegFGovEU				-0.307	
				(5.472)	
RegFGov				0.128	
				(2.311)	
RegEU				11.128***	
				(2.853)	
FGovEU				5.636	
				(3.755)	
RegBru					6.364
					(5.501)
RegWal					-2.579
					(3.413)
FGovBru					12.197**
					(5.310)
FGovWal					-1.174
					(3.985)
_cons	4.187***	-2.219*	-2.079	0.778	-1.492
	(0.505)	(1.252)	(1.293)	(1.869)	(1.365)
R-squared	0.012	0.018	0.030	0.095	0.033
N	1,426	1,426	1,426	1,426	1,426

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 21 Treatment effect (innovation intensity) on subsidy sources and regions (matching within regions; no additional covariates)

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	8.224***		7.812***	6.315***	-0.690
	(2.481)		(2.453)	(2.360)	(6.212)
Wallonia	-3.390**		-3.672**	-4.204***	-3.869
	(1.413)		(1.435)	(1.428)	(3.913)
Regional		5.990***	5.923***	2.000	5.483***
		(1.295)	(1.275)	(1.983)	(1.374)
FGovernment		3.961***	3.856***	0.672	2.580*
		(1.301)	(1.308)	(2.017)	(1.397)
RegFGovEU				3.397	
				(5.706)	
RegFGov				-0.052	
				(2.474)	
RegEU				9.643***	
				(2.778)	
FGovEU				2.118	
				(3.983)	
RegBru					4.960
					(6.160)
RegWal					-1.102
					(3.859)
FGovBru					11.597**
					(5.747)
FGovWal					3.016
					(4.353)
_cons	4.495***	-1.559	-1.491	1.287	-0.534
	(0.559)	(1.366)	(1.408)	(1.872)	(1.484)
R-squared	0.015	0.014	0.028	0.070	0.031
N	1,426	1,426	1,426	1,426	1,426

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 22 Treatment effect (internal R&D intensity) on subsidy sources and regions (matching within regions; additional covariates)

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	7.045**		6.295**	5.408*	-1.571
	(2.882)		(2.912)	(2.930)	(5.338)
Wallonia	-1.224		-1.642	-2.214	1.037
	(1.970)		(2.019)	(2.051)	(3.662)
Regional		4.752***	4.679***	1.190	4.610***
		(1.070)	(1.063)	(1.786)	(1.131)
FGovernment		3.304***	3.173***	0.338	2.587**
		(1.056)	(1.046)	(1.819)	(1.094)
RegFGovEU				2.464	
				(4.608)	
RegFGov				0.352	
				(2.070)	
RegEU				8.168***	
				(2.412)	
FGovEU				2.246	
				(3.219)	
RegBru					4.485
					(4.848)
RegWal					-3.253
					(3.115)
FGovBru					10.216**
					(4.728)
FGovWal					-0.912
					(3.531)
_cons	-2.814	-11.311	-5.956	-1.537	-3.851
	(26.572)	(27.437)	(26.721)	(26.183)	(26.753)
R-squared	0.126	0.130	0.138	0.181	0.141
N	1,426	1,426	1,426	1,426	1,426

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 23 Treatment effect (total R&D intensity) on subsidy sources and regions (matching within regions; additional covariates)

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	7.029**		6.171*	5.344	-0.721
	(3.325)		(3.363)	(3.350)	(5.765)
Wallonia	-1.888		-2.375	-2.906	1.108
	(2.258)		(2.308)	(2.308)	(4.042)
Regional		5.422***	5.356***	0.497	5.414***
		(1.166)	(1.162)	(1.979)	(1.257)
FGovernment		3.646***	3.506***	-0.788	3.041**
		(1.149)	(1.142)	(2.001)	(1.219)
RegFGovEU				0.918	
				(4.939)	
RegFGov				1.976	
				(2.295)	
RegEU				8.946***	
				(2.556)	
FGovEU				3.604	
				(3.399)	
RegBru					3.805
					(5.083)
RegWal					-4.055
					(3.407)
FGovBru					9.144*
					(4.865)
FGovWal					-1.243
					(3.828)
_cons	-1.083	-14.311	-4.826	-0.007	-2.800
	(29.540)	(29.684)	(29.613)	(28.851)	(29.637)
R-squared	0.144	0.149	0.157	0.198	0.159
N	1,426	1,426	1,426	1,426	1,426

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 24 Treatment effect (innovation intensity) on subsidy sources and regions (matching within regions; additional covariates)

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	3.231		2.338	1.671	-3.707
	(3.759)		(3.793)	(3.737)	(6.534)
Wallonia	-5.318**		-5.838**	-6.218**	-4.961
	(2.461)		(2.502)	(2.474)	(4.607)
Regional		5.569***	5.584***	0.537	5.461***
		(1.300)	(1.296)	(1.995)	(1.395)
FGovernment		3.579***	3.453***	-0.923	2.402*
		(1.264)	(1.258)	(2.020)	(1.334)
RegFGovEU				4.170	
				(5.244)	
RegFGov				2.379	
				(2.435)	
RegEU				7.552***	
				(2.480)	
FGovEU				0.242	
				(3.699)	
RegBru					2.216
					(5.734)
RegWal					-2.716
					(3.874)
FGovBru					9.917*
					(5.469)
FGovWal					2.748
					(4.209)
_cons	-3.732	-38.826	-7.869	-3.000	-3.634
	(31.529)	(31.323)	(31.403)	(30.857)	(31.388)
R-squared	0.125	0.129	0.136	0.161	0.138
N	1,426	1,426	1,426	1,426	1,426

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 25 Treatment effect (internal R&D intensity) on subsidy sources and regions (matching across regions; no additional covariates; first and last percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	4.343***		4.145**	3.031*	-3.796
	(1.666)		(1.644)	(1.621)	(4.220)
Wallonia	-0.877		-0.895	-1.219	1.694
	(0.776)		(0.788)	(0.798)	(2.100)
Regional		3.680***	3.566***	1.685	3.298***
		(0.895)	(0.884)	(1.305)	(0.995)
FGovernment		2.848***	2.814***	1.729	2.712***
		(0.873)	(0.869)	(1.383)	(0.987)
RegFGovEU				4.840	
				(3.581)	
RegFGov				-1.011	
				(1.665)	
RegEU				5.736***	
				(1.991)	
FGovEU				-1.588	
				(2.173)	
RegBru					5.527
					(4.399)
RegWal					-1.475
					(1.957)
FGovBru					8.432**
					(4.069)
FGovWal					-4.057**
					(1.956)
_cons	3.294***	-0.573	-0.627	0.549	-0.390
	(0.393)	(0.932)	(0.955)	(1.257)	(1.059)
R-squared	0.007	0.011	0.017	0.049	0.024
N	1,606	1,606	1,606	1,606	1,606

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 26 Treatment effect (total R&D intensity) on subsidy sources and regions (matching across regions; no additional covariates; first and last percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	5.039***		4.817***	3.525*	-2.597
	(1.844)		(1.817)	(1.803)	(4.495)
Wallonia	-1.051		-1.058	-1.434*	2.158
	(0.815)		(0.828)	(0.837)	(2.237)
Regional		4.292***	4.161***	1.007	4.000***
		(0.991)	(0.984)	(1.576)	(1.129)
FGovernment		3.392***	3.351***	0.963	3.359***
		(0.972)	(0.965)	(1.642)	(1.123)
RegFGovEU				3.775	
				(4.067)	
RegFGov				0.190	
				(1.935)	
RegEU				6.848***	
				(2.078)	
FGovEU				-0.328	
				(2.639)	
RegBru					5.136
					(4.648)
RegWal					-2.054
					(2.096)
FGovBru					7.926*
					(4.294)
FGovWal					-4.459**
					(2.082)
_cons	3.964***	-0.586	-0.646	1.609	-0.541
	(0.430)	(1.033)	(1.049)	(1.532)	(1.196)
R-squared	0.008	0.013	0.021	0.056	0.025
N	1,606	1,606	1,606	1,606	1,606

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 27 Treatment effect (innovation intensity) on subsidy sources and regions (matching across regions; no additional covariates; first and last percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	6.379***		6.092***	5.032***	-3.055
	(1.839)		(1.810)	(1.818)	(4.914)
Wallonia	-0.662		-0.731	-0.992	0.891
	(1.041)		(1.062)	(1.071)	(2.810)
Regional		4.813***	4.610***	1.637	4.142***
		(1.054)	(1.049)	(1.684)	(1.182)
FGovernment		3.418***	3.416***	1.002	3.083**
		(1.043)	(1.042)	(1.747)	(1.196)
RegFGovEU				6.735	
				(4.132)	
RegFGov				0.562	
				(2.089)	
RegEU				3.931*	
				(2.233)	
FGovEU				-2.457	
				(2.493)	
RegBru					5.968
					(5.092)
RegWal					-0.474
					(2.716)
FGovBru					10.569***
					(3.823)
FGovWal					-3.738
					(2.823)
_cons	4.266***	-0.509	-0.685	1.745	-0.189
	(0.469)	(1.111)	(1.133)	(1.616)	(1.273)
R-squared	0.010	0.013	0.021	0.037	0.027
N	1,606	1,606	1,606	1,606	1,606

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 28 Treatment effect (internal R&D intensity) on subsidy sources and regions (matching across regions; additional covariates; first and last percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	3.521		3.078	2.330	-3.017
	(2.434)		(2.418)	(2.381)	(4.548)
Wallonia	-2.522*		-2.730*	-3.076**	0.651
	(1.529)		(1.544)	(1.530)	(2.665)
Regional		3.206***	3.164***	1.006	3.154***
		(0.891)	(0.881)	(1.390)	(0.983)
FGovernment		2.367***	2.266***	0.932	2.364**
		(0.873)	(0.858)	(1.464)	(0.971)
RegFGovEU				5.190	
				(3.439)	
RegFGov				-0.138	
				(1.759)	
RegEU				5.031***	
				(1.883)	
FGovEU				-2.618	
				(2.192)	
RegBru					4.237
					(4.350)
RegWal					-2.372
					(2.141)
FGovBru					6.509*
					(3.906)
FGovWal					-4.007**
					(2.033)
_cons	48.352***	29.694**	46.768***	49.927***	45.329***
	(16.227)	(12.535)	(16.304)	(15.750)	(16.254)
R-squared	0.094	0.094	0.101	0.124	0.105
N	1,606	1,606	1,606	1,606	1,606

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 29 Treatment effect (total R&D intensity) on subsidy sources and regions (matching across regions; additional covariates; first and last percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	3.933		3.423	2.639	-1.607
	(2.667)		(2.657)	(2.618)	(4.857)
Wallonia	-2.744		-2.978*	-3.318**	1.106
	(1.688)		(1.702)	(1.681)	(2.885)
Regional		3.680***	3.633***	0.260	3.774***
		(0.977)	(0.970)	(1.614)	(1.106)
FGovernment		2.793***	2.681***	0.054	2.942***
		(0.955)	(0.943)	(1.681)	(1.095)
RegFGovEU				4.768	
				(3.923)	
RegFGov				1.108	
				(1.990)	
RegEU				5.529***	
				(1.950)	
FGovEU				-1.689	
				(2.593)	
RegBru					3.504
					(4.611)
RegWal					-3.027
					(2.330)
FGovBru					5.390
					(4.131)
FGovWal					-4.421**
					(2.170)
_cons	49.432***	29.099**	47.711***	51.668***	46.031**
	(17.963)	(13.321)	(17.979)	(17.334)	(17.921)
R-squared	0.109	0.110	0.118	0.141	0.120
N	1,606	1,606	1,606	1,606	1,606

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 30 Treatment effect (innovation intensity) on subsidy sources and regions (matching across regions; additional covariates; first and last percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	2.679		2.073	1.562	-4.952
	(2.956)		(2.975)	(2.947)	(5.322)
Wallonia	-3.771*		-4.058**	-4.141**	-1.113
	(2.033)		(2.065)	(2.060)	(3.450)
Regional		4.342***	4.321***	0.110	4.216***
		(1.048)	(1.046)	(1.744)	(1.182)
FGovernment		3.145***	3.038***	-0.717	2.891**
		(1.020)	(1.012)	(1.795)	(1.162)
RegFGovEU				7.419*	
				(4.065)	
RegFGov				2.709	
				(2.142)	
RegEU				2.686	
				(2.102)	
FGovEU				-3.689	
				(2.553)	
RegBru					3.921
					(4.979)
RegWal					-2.042
					(2.867)
FGovBru					9.312**
					(3.687)
FGovWal					-3.827
					(2.856)
_cons	55.474***	27.346	53.243**	57.973***	52.330**
	(21.494)	(16.724)	(21.534)	(21.161)	(21.425)
R-squared	0.101	0.104	0.111	0.120	0.115
N	1,606	1,606	1,606	1,606	1,606

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 31 Treatment effect (internal R&D intensity) on subsidy sources and regions (matching across regions; no additional covariates; below fifth and above ninety-fifth percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	2.250*		2.088*	1.356	-4.109
	(1.275)		(1.263)	(1.247)	(2.668)
Wallonia	-0.463		-0.544	-0.760	0.164
	(0.536)		(0.541)	(0.552)	(1.715)
Regional		2.442***	2.396***	1.306	2.046***
		(0.651)	(0.636)	(1.205)	(0.697)
FGovernment		1.596***	1.588**	0.845	1.372**
		(0.616)	(0.622)	(1.259)	(0.664)
RegFGovEU				0.853	
				(2.765)	
RegFGov				-0.543	
				(1.391)	
RegEU				4.199***	
				(1.527)	
FGovEU				1.276	
				(1.657)	
RegBru					4.655*
					(2.791)
RegWal					-0.071
					(1.599)
FGovBru					6.296*
					(3.580)
FGovWal					-1.986
					(1.404)
_cons	2.942***	0.505	0.489	1.101	0.839
	(0.269)	(0.679)	(0.708)	(1.188)	(0.747)
R-squared	0.003	0.010	0.013	0.046	0.020
N	1,476	1,476	1,476	1,476	1,476

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 32 Treatment effect (total R&D intensity) on subsidy sources and regions (matching across regions; no additional covariates; below fifth and above ninety-fifth percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	2.366*		2.174*	1.375	-4.072
	(1.301)		(1.290)	(1.273)	(2.787)
Wallonia	-0.507		-0.619	-0.860	0.047
	(0.552)		(0.559)	(0.569)	(1.796)
Regional		2.556***	2.512***	0.556	2.160***
		(0.696)	(0.683)	(1.485)	(0.762)
FGovernment		1.547**	1.534**	-0.014	1.190
		(0.653)	(0.658)	(1.534)	(0.726)
RegFGovEU				0.038	
				(3.004)	
RegFGov				0.432	
				(1.660)	
RegEU				5.127***	
				(1.573)	
FGovEU				1.454	
				(1.980)	
RegBru					4.397
					(2.912)
RegWal					-0.220
					(1.673)
FGovBru					6.994**
					(3.550)
FGovWal					-1.541
					(1.439)
_cons	3.400***	0.906	0.897	2.219	1.316
	(0.288)	(0.735)	(0.764)	(1.473)	(0.830)
R-squared	0.003	0.010	0.013	0.050	0.019
N	1,476	1,476	1,476	1,476	1,476

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 33 Treatment effect (innovation intensity) on subsidy sources and regions (matching across regions; no additional covariates; below fifth and above ninety-fifth percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	4.050***		3.861***	3.220***	-5.407**
	(1.237)		(1.209)	(1.209)	(2.627)
Wallonia	0.893		0.790	0.610	0.113
	(0.647)		(0.653)	(0.655)	(1.872)
Regional		2.816***	2.617***	0.761	1.893**
		(0.688)	(0.679)	(1.567)	(0.764)
FGovernment		1.528**	1.661**	0.310	1.041
		(0.659)	(0.658)	(1.605)	(0.739)
RegFGovEU				2.862	
				(2.324)	
RegFGov				0.563	
				(1.749)	
RegEU				3.774***	
				(1.324)	
FGovEU				-1.621	
				(1.064)	
RegBru					6.749**
					(2.698)
RegWal					1.305
					(1.789)
FGovBru					9.886***
					(2.727)
FGovWal					-1.359
					(1.700)
_cons	3.453***	1.141	0.812	2.181	1.627*
	(0.280)	(0.733)	(0.752)	(1.550)	(0.835)
R-squared	0.011	0.011	0.021	0.041	0.035
N	1,476	1,476	1,476	1,476	1,476

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. *Regional*: regional subsidy dummy ; *FGovernment*: Federal Government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidy dummies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 34 Treatment effect (internal R&D intensity) on subsidy sources and regions (matching across regions; additional covariates; below fifth and above ninety-fifth percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of internal R&D intensity (internal R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	2.174		1.855	1.368	-2.005
	(1.558)		(1.536)	(1.565)	(2.870)
Wallonia	-1.097		-1.264	-1.538*	0.106
	(0.893)		(0.898)	(0.910)	(2.011)
Regional		2.236***	2.207***	0.632	2.093***
		(0.637)	(0.626)	(1.211)	(0.668)
FGovernment		1.379**	1.342**	0.125	1.377**
		(0.634)	(0.625)	(1.271)	(0.650)
RegFGovEU				0.794	
				(2.533)	
RegFGov				0.396	
				(1.403)	
RegEU				3.876***	
				(1.469)	
FGovEU				0.745	
				(1.487)	
RegBru					2.829
					(2.711)
RegWal					-0.643
					(1.765)
FGovBru					4.274
					(3.474)
FGovWal					-2.347
					(1.429)
_cons	28.745***	19.271**	27.189***	30.346***	26.328***
	(9.747)	(7.920)	(9.937)	(9.873)	(9.811)
R-squared	0.121	0.124	0.128	0.153	0.132
N	1,476	1,476	1,476	1,476	1,476

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 35 Treatment effect (Total R&D intensity) on subsidy sources and regions (matching across regions; additional covariates; below fifth and above ninety-fifth percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of total R&D intensity (total R&D expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	2.432		2.099	1.639	-1.640
	(1.598)		(1.580)	(1.608)	(2.920)
Wallonia	-0.940		-1.121	-1.378	0.114
	(0.931)		(0.937)	(0.953)	(2.134)
Regional		2.278***	2.244***	-0.215	2.135***
		(0.676)	(0.667)	(1.427)	(0.724)
FGovernment		1.279*	1.240*	-0.822	1.162*
		(0.661)	(0.653)	(1.486)	(0.702)
RegFGovEU				0.135	
				(2.749)	
RegFGov				1.442	
				(1.614)	
RegEU				4.590***	
				(1.488)	
FGovEU				0.874	
				(1.806)	
RegBru					2.419
					(2.756)
RegWal					-0.749
					(1.875)
FGovBru					4.722
					(3.442)
FGovWal					-1.840
					(1.460)
_cons	26.927***	18.296**	25.236**	28.853***	24.787**
	(10.273)	(8.257)	(10.464)	(10.404)	(10.378)
R-squared	0.138	0.141	0.144	0.172	0.147
N	1,476	1,476	1,476	1,476	1,476

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Table 2. 36 Treatment effect (innovation intensity) on subsidy sources and regions (matching across regions; additional covariates; below fifth and above ninety-fifth percentile of the treatment effect regarding total innovation intensity variable dropped)

OLS estimation with dependent variable: The difference of innovation intensity (innovation expenditures share on sales) between treatment and control group.

Variable	I	II	III	IV	V
Brussels	3.803**		3.461**	3.210**	-3.212
	(1.571)		(1.574)	(1.575)	(2.811)
Wallonia	-0.027		-0.201	-0.274	-0.004
	(1.060)		(1.080)	(1.076)	(2.177)
Regional		2.490***	2.428***	-0.637	1.993***
		(0.671)	(0.667)	(1.488)	(0.753)
FGovernment		1.624**	1.584**	-1.041	1.201*
		(0.645)	(0.640)	(1.529)	(0.720)
RegFGovEU				2.737	
				(2.215)	
RegFGov				2.410	
				(1.659)	
RegEU				3.366***	
				(1.270)	
FGovEU				-2.059**	
				(1.049)	
RegBru					4.359*
					(2.539)
RegWal					0.434
					(1.915)
FGovBru					8.288***
					(2.584)
FGovWal					-1.751
					(1.695)
_cons	34.185***	31.887***	32.567***	36.230***	32.355***
	(12.073)	(9.897)	(12.247)	(12.220)	(12.166)
R-squared	0.135	0.139	0.143	0.159	0.153
N	1,476	1,476	1,476	1,476	1,476

* p<0.10, **p<0.05, *** p<0.01 ; Robust standard errors in brackets. Year and sector dummies as well as all covariates used in Probit regressions above are included but not reported for the sake of lucidity.
Regional: regional subsidy dummy ; *FGovernment*: Federal government subsidy dummy; *RegFGovEU*: interaction of regional, Federal Government, and EU subsidies (*RegFGov, RegEU, and FGovEU analog*); *RegBru*: interaction of regional subsidy and region dummy Brussels (*RegWal, FGovBru, and FGovWal analog*)

Chapter 3 The impact of EU's ESIF programme on the regional economic development

3.1 Introduction

In article 174 of the Treaty on the Functioning of the European Union (TFEU) the task to strengthen the economic, social and territorial cohesion of the Union is determined. To do that, the European Union (EU) takes measures to reduce disparities of the economic wealth status among European regions. The European Structural and Investment Funds (ESIF) is the instrument created subsequently to follow up on this duty. ESIF comprehends various public support programmes with different eligibility criteria to serve different goals which all aim at achieving the objectives set by article 174. The composition of ESIF support programmes were adapted over time according to the prevailing challenges identified by the European Commission (EC). Currently the active programmes are the European Regional Development Fund (ERDF), Cohesion Fund (CF), European Social Fund (ESF), European Agricultural Fund for Rural Development (EAFRD), and European Maritime and Fisheries Fund (EMFF)[58].

In order to trigger economic development according to the diverse regional economic situations, three priorities (labeled objectives) were set up to define the eligibility of regions for different levels of public support. Probably, the most important priority defined is the Objective 1[59] classification. A region exhibiting a level of Gross Domestic Product (GDP) per capita below the 75% threshold of EU average is classified as an Objective 1 region which is associated with the eligibility for highest level of regional public support. At the beginning of each ESIF public support programme period (7 years), the EC identifies regions which are appointed as Objective 1 Regions. The classification into the group of Objective 1 Regions remains valid for the duration of the ESIF programme period. The lion's share (e.g. more than

[58] https://ec.europa.eu/info/funding-tenders/funding-opportunities/funding-programmes/overview-funding-programmes/european-structural-and-investment-funds_en#thefunds (last access 11.08.2020)
[59] Also labeled as Convergence region.

2/3 of the ERDF, ESF, and CF in the period 2007-2013[60]) of ESIF financial means are granted to Objective 1 regions. EU regions featuring a better economic state then defined for the Objective 1 group are classified into two other groups, Objective 2 and Objective 3 regions respectively. The former comprehends regions that exhibit a GDP per capita level within the band of 75% to 90% of the EU average and the latter above 90%.

More than half of the EU budget is channeled as public support through ESIF programmes[61]. Policy makers, academic scholars, and the public are interested whether the redistribution of public funds through ESIF in order to facilitate the catching-up of economically weak EU regions actually leads to the desired economic development.

There are a number of academic, empirical studies available which provide insights on the impact of the ESIF measures. The literature available considers, however, mostly only parts of ESIF or only specific regions/countries. Besides not taking into account all ESIF programmes and the entire EU territory, empirical studies are often performed with data containing inaccurate information. Subsidy information utilized often refer to planned projects or project commitments rather than to actually realized projects. In some cases the subsidy amounts used are approximations and do not correspond to actually granted amounts. The reason of this deficiency is that until recently accurate data of actual money transfers was not collected systematically by a central authority.

Gathering the actual subsidy payment data is not an easy task as the allocation of the ESIF grants is administered by multiple authorities in different countries. The funds are partly administered by the EC and partly by different national authorities within the subsidy recipients' countries. Therefore, it is difficult to trace the exact funding at the individual project level accurately. For a reliable scientific impact analysis of ESIF, it would be necessary to monitor and document which projects were planned, which planned projects have been partly or fully realized or cancelled, whether new projects

[60] https://ec.europa.eu/regional_policy/archive/objective1/index_en.htm (last access 11.08.2020)
[61] https://ec.europa.eu/info/funding-tenders/funding-opportunities/funding-programmes/overview-funding-programmes/european-structural-and-investment-funds_en (last access 11.08.2020)

in addition to the planned projects have been supported, and when the corresponding expenditures exactly took place.

The EC recognized the need for accurate data and made efforts to create a new database to enable researchers to generate more reliable empirical evidence on the impact of ESIF. The first version of the data was published mid-2018 and this chapter is the first or one of the first ESIF impact evaluations utilizing the new data.

The new data provides information on subsidy payments as actually transferred by the EC rather than merely planned payments or project commitments. The exact expenditures as paid out by the national authorities are still not available. Some projects are conducted partly or fully before the funding by the EC is transferred, while for other projects the opposite can be the case, i.e. the funding flows first but the subsidized activity takes place at a later point. In an attempt to improve the data in means of reflecting the actual expenditures at the project level, the EC has assigned a research group at the University of Bergen to create a dataset that aims to adapt the EC's payment data by taking account for the timing of the expenditures at the project level. Therefore, the new dataset published by the EC contains besides the EC's payment transfers also "modelled" payment transfer data created by BERGEN (2017). The modelled data is generated by simulating the real expenditures per project. The simulation process is based on assumptions which are defined by Bergen (2017) and were elaborated after an evaluation of some subsidized projects, i.e. the modelled data do not reflect the real state either.

This paper aims to empirically examine the ESIF programmes´ impact[62] on the economic development of the recipients at the regional level by applying state of art econometric methods and utilizing the new data made available by the EC. In the analyses conducted both payment information (transfers as applied by the EC and modelled transfers as generated by Bergen (2017)) are utilized and results compared. Furthermore, the analysis accounts for the Objective 1 status of regions; including the subsidy amounts received by those regions.

The next section provides an overview of the existing literature on the impact of ESIF. In the third section, data, variables, and econometric methods used for the

[62] Direct EU grants both R&D and non-R&D grants.

empirical analysis are described. The fourth and fifth sections present the empirical findings and the paper concludes in the sixth section.

3.2 Literature

Literature examining the ESIF impact utilizes a variety of different empirical methods starting from cross section analyses and reaching out to panel methods (see e.g. Table 1 in Mohl and Hagen (2010) for an overview of Structural Funds[63] evaluations) which take into account the potential endogeneity of the public support and utilized covariates. The public supports´ impact is measured mostly in means of GDP growth whereat empirical evidence delivered is divers and provides evidence for a positive impact in majority of the examinations while also neutral and negative impacts are reported.

Common to all of the examinations performed is that the empirical evaluation of the ESIF impact takes place without having actual payment data but planned funding, commitment of funding, or approximations of funding data since actual ESIF payment data were not available until mid-2018. Some empirical approaches take the classification of Objective 1 region[64] as the treatment without considering any subsidy amounts. In addition, the literature considers often only parts of ESIF leading to results potentially suffering under hidden treatment (Guerzoni and Raiteri, 2015; Dumont, 2017). Furthermore, available literature utilizes often none or very few information on regional economic factors due to lack of data. All important information should be ideally covered within an econometric model as covariates in order to avoid potentially misleading results due to omitted variable bias.

[63] Structural Funds (SF) represents a part of ESIF and comprehends the European Regional Development Fund (ERDF) and the European Social Fund (ESF). The term SF is used sometimes non-uniformly in the literature. While SF is used comprehending only ERDF, it incorporates sometimes multiple funds (ERDF, ESF, EAGGF (European Agricultural Guidance and Guarantee Fund) and FIFG (Financial Instrument for Fisheries Guidance) together as in Esposti and Bussoletti (2008)). In the text of the paper at hand, utilized terms referring to specific papers follow the original use of the terms as done in those papers, i.e. if in the referred paper the term SF is used here in the paper also the term SF is used when it is reported about that specific paper.

[64] EU authorities replaced the term Objective 1 Region by the term Convergence Objective recently whereat there is no difference in the definition of what those terms mean. The paper at hand sticks to the term Objective 1 Region to avoid confusion since the referring scientific literature in majority uses this term.

Becker et al. (2010, 2012, 2018) subsequently elaborate on the ESIF impact utilizing different econometric methods and EU-wide data delivering interesting insights. Their paper from 2010 based on data on Structural Funds (compiled by the authors from EC documents for the time period 1989 to 2006) reports an impact on Objective 1 regions of about 1.6% higher GDP growth. The article published in 2012 tests for Structural and Cohesion Funds' impact for the time period 1994 to 2006 by using funding data gathered from different sources for different time periods. Their findings hint on positive but with an increase of the funding volume declining impact on the economic development. They point on suboptimal low levels of funding for some regions while other regions are subsidized with suboptimal high levels of funding. The examination published in 2018 evaluates the impact of Structural and Cohesion Funds for the time period 1989 to 2013 and provides empirical evidence that Objective 1 regions exhibit 1.2% to 1.9% higher GDP growth rates. But their findings suggest also that the economic gains are more or less undone when Objective 1 status is lifted.

Aiello and Pupo (2012) examine the impact of Structural Funds (SF) for the time period 1996-2007 in Italy with funding data they have gathered from national authorities. They emphasize that the results provided by the existing empirical SF impact literature might be biased due to lack of accurate funding data since the data used usually is planned or commitment data rather than actual payment data. The authors distinguish between north and south of Italy and find statistically significant positive impact of SF on GDP level in general, about 0.9%, whereat the impact is slightly higher in the economically less developed southern regions of about additional 0.06%.

Mohl and Hagen (2010) investigate based on self-compiled EU-wide SF data which is gathered partly from reports of the EC and partly directly received from the EC on payments and commitments for the time period 1994 to 2006. They conclude that a 1% increase of subsidies to an Objective 1 region approximately leads to a 0.05% higher GDP per capita.

Esposti and Bussoletti (2008) focus on the SF`s impact for the time period 1989 to 2000 based on EU-wide data collected by the authors from EC's Annual Reports (planned/commitment data) whereat parts of the data used as covariates are approximated values due to lack of data. The authors conclude that the impact on

Objective 1 regions is divers and quite limited in its extent. While positive impact is evident over EU on average, the impact is negative for some regions.

Dall'Erba and Le Gallo (2008) evaluate the convergence process between 1989 and 1999 by analyzing EU-wide SF data gathered from Annual Reports of the EC and conclude empirically that the public support impact through SF is without statistical significant effects, i.e. does not lead to the desired acceleration of the economic development in the subsidized regions and thus the regional economic disparities remain as a result.

3.3 Data and econometric methods

3.3.1 Data

European Commission (EC) started mid-2018 to provide new data[65] on actual payments as transferred by the EC through the European Structural and Investment Funds (ESIF). The data features subsidy transfers by year and region (NUTS1 and NUTS2 categorizations) whereat the time span available starts retrospectively from 1989 onwards. Payments to non-European Union (EU) regions are also covered for example for countries which are in process of joining the EU and receiving subsidies from the EU already.

The new data contains almost all actual payments of ESIF programmes; Structural Funds (SF), Cohesion Funds (CF), European Social Funds (ESF), and European agricultural fund for rural development (EAFRD) respectively[66]. Although payments actually undertaken by the EC are reflecting the real flow of financial means, they do not necessarily reflect the correct timing of the activities/expenditures on the ground. In some cases parts of projects are already realized before the subsidy payment by the EC takes place and in other cases the opposite occurs and the projects on the ground are realized after some time following to the payments by the EC.

[65] Available on: https://cohesiondata.ec.europa.eu/browse?limitTo=datasets (last access 11.08.2020)
[66] According to Bergen (2017) these four funds account for around 95% of the financial means distributed through ESIF.

EC has commissioned a researcher group at the University of Bergen (BERGEN, 2017) with the task to improve the non-synchronous timing of the EC transfers and the project realizations/expenditures on the ground. The researchers generate data on the payments which aim to reflect the real volume as well as the real timing of the expenditures on the ground more accurately. To do that, they examine the processes and timing of ESIF fund transfers to recipient countries closer, formulate rules based on their analyses about how the EC transfers could be generally distributed accordingly over time for all projects. This means that each transfer applied by the EC is distributed over several years according to assumptions/rules elaborated by the researchers. They apply Monte Carlo simulations to generate the "modelled" payment data which according to BERGEN (2017) come closer to representing the real expenditures on the ground. For the empirical investigation at hand both actual payment data by the EC and modelled data by BERGEN (2017) are considered.

In addition to the ESIF payment data (real transfers and modelled transfers) published by the EC which serve as treatment variables, two further sources, EUROSTAT[67] and Urban Data Platform[68], are considered as sources of data to gather information for control variables. Urban Data Platform is a joint initiative of EC's Directorate General Joint Research Centre (DG JRC) and the Directorate General for Regional and Urban Policy (DG REGIO). Most of the data from those sources are available from 2000 onwards. Therefore, the empirical analyses performed in this paper are restricted on the time period of 16 years starting from 2000 until 2015.

Partly data for the same information is available in both sources Eurostat and Urban Data Platform. In such cases more comprehensive/complete information is considered for the analyses. In some cases data from one source was supplemented with data from the second source to create a variable that is more comprehensive (see Table 3. 1).

The unit of the empirical analyses is the NUTS 2 region as defined by the EU. NUTS 2 code definitions changed within the analyzed time period several times. The data

[67] https://ec.europa.eu/eurostat/data/database (last access 11.08.2020)

[68] Urban data Platform includes data formerly available by "Cambridge Econometrics' European regional database" and is now available free of charge on https://urban.jrc.ec.europa.eu/#/en/my-place?context=Default&territorialscope=EU28&level=NUTS2 (last access 11.08.2020)

gathered from different sources are not always uniform, i.e. in the same NUTS 2 code version. In the majority of the cases data provided is coded in NUTS 2013 version whereat there are also other code versions present such as codes belonging to NUTS 2010 version. In some cases information for the same variable was adapted by using NUTS classification conversion tables[69] provided by EUROSTAT. Finally one of the variables, voting power of the EU members in the Council of the European Union, used as a covariate was defined according to the EU treaties valid in different time periods[70].

The data source and description of variables used in the econometric estimations are available in Table 3. 1 while Table 3. 2 and Table 3. 3 provide descriptive statistics for the entire sample and for the subsamples of Objective 1 and non-Objective 1 regions. Descriptive statistics of the subsidy amounts modelled by Bergen (2017) and as transferred by the EC are quite similar. Bergen (2017) redistribute the payments as transferred by the EC over time (see Table 3. 4 for an example) whereat the sum of payments over all periods remain almost unchanged[71].

Figure 3. 1 and Figure 3. 2 show the distribution of the payment information by Objective 1 status and modelled vs. non-modelled versions. The figures show that the distribution of the payment information as transferred by the EC and as modelled by BERGEN (2017) differ only slightly. As a consequence of redistributing the EC subsidy transfers over time by Bergen (2017) the minimum subsidy received by a region is around 50 Euro per capita-year-region whereat this number is 0 in case of the data as transferred by the EC.

Table 3. 3 presents differences between Objective 1 regions and non-Objective 1 regions. While subsidy transfers to Objective 1 regions is around 405 Mio. Euro on average per year-region, other regions receive on average about five times less public support with around 78 Mio. Euro. Non-Objective 1 regions exhibit higher levels of GDP per capita, employment rate, population density, tertiary education level, and

[69] See for different versions of NUTS categorizations and conversions tables from version to version on https://ec.europa.eu/eurostat/web/nuts/history (last access 11.08.2020)
[70] See on https://en.wikipedia.org/wiki/Voting_in_the_Council_of_the_European_Union (last access 11.08.2020)
[71] It is not clear where the difference comes from. Possibly a small fraction of the payments were redistributed to before or after the period available in the data.

gross fixed capital. Interestingly, industry employment rate is higher in Objective 1 regions. Table 3. 5 provides the number of NUTS 2 regions in the sample per year and the correlation matrix of the variables can be found in Table 3. 6.

3.3.2 Variables

Gross Domestic Product (GDP) per capita in purchasing power standard transformed to its natural logarithm (*lnGDPpps*) serves as the dependent variable. The first lag of the dependent variable (*L.lnGDPpps*) enters the model on the right side of the equation to check for the initial level of the GDP making the model applied dynamic. ESIF subsidy payments by the European Commission (EC) in two different versions, (i) actual payments by the EU (*lnSubsTot*) and (ii) modelled payments (*lnSubsTotMod*) as developed by BERGEN (2017) enter models applied in distinct estimations as treatment variables. Each payment information are in per capita units and transferred to their natural logarithms.

Another variable (*Obj1*) indicating with a value of 1 a regions classification within the group of Objective 1 regions by the EC also serves as a treatment variable in some of the econometric estimations applied. Objective 1 regions are economically underdeveloped regions (GDP level under the threshold of 75% of the EU average) which qualify for a larger share of the funds to trigger economic catch up. The same variable is also considered to create an interaction variable in combination with the subsidy payment variables *lnSubsTot* and *lnSubsTotMod* in order to estimate the subsidy response elasticities instead of the fixed effect of being an Objective 1 Region merely.

Further variables are utilized as covariates within the models. *Votpower*[72] controls for the potential effect of the voting power[73] (Becker et al. 2010, 2012) of the subsidy recipient country at the Council of the European Union which decides about the utilization of EU's financial means as EU's budgetary authority. Voting power within

[72] Voting power is calculated by dividing the votes of the member states according to the EU-treaty in power by the sum of all votes. See for an overview of voting power of all member states at different time periods under https://de.wikipedia.org/wiki/Rat_der_Europ%C3%A4ischen_Union

[73] Alternative measures Shapley-Shubik Index and Nucleolus as provided in Zaporozhets et al. (2016) were also considered (not reported) delivering similar results in the estimations applied.

the EU changes over time when new members join the EU and the treaties in place are replaced by new treaties. *Emprate* takes the potential effect of the regional employment rate on the GDP into account (Becker et al. 2012; Gagliardi & Percoco, 2016) whereat the variable incorporates individuals within the age range from 20 to 64. Economically less developed regions for instance may exhibit chronic low employment rates.

Another control variable (*Ind.emp*) considers the structure of the regional industry (Becker et al. 2012) by considering information on the share of the industrial employment. High industrial employment rate may have a positive effect on the GDP level of a region. The variable *lnpopulden* controls for a possible effect of the population density of the region (Becker et al. 2010, 2012) transformed to its natural logarithm. High population density and low population density may be connected to different economic structures within the regions.

The education level of the regional population is taken into account with the variable *lnterteduc* (Esposti & Bussoletti 2008; Gagliardi & Percoco, 2016). This variable considers the potential effect of higher education on the GDP by utilizing the information natural logarithm of the population share for the age range 25 to 64 with tertiary level degree education. A region with higher share on tertiary level educated population may be more productive than others.

Another variable with a potential effect on the dependent variable is the natural logarithm of gross fixed capital (*lngfcap*) (Esposti & Bussoletti 2008) within the region. A higher level of capital stock may have a positive effect on the productivity in the region. Its first lag is applied since the capital stock already available is expected to play a role for the GDP rather than the capital stock which is build up within an economic year itself. Finally, the size of the regions' surface in natural logarithm of squared kilometers is considered with the variable *lntotalarea* to test for a possible effect of the largeness of a region. The size of the region might play a role for instance through different infrastructure (larger regions may have different infrastructure such as more highways or railways) and land use (larger regions may have more agriculture or more space for large production facilities).

3.3.3 Econometric methods

The empirical examination of the determinants for the regional Gross Domestic Products´ (GDP) development through an econometric estimation model is not a straight forward exercise. The reason for that is the fact that many of the determinants to be considered tend to change nearly simultaneously with the GDP itself, i.e. the dependent variable and covariates are highly correlated with each other. As an example the employment rate is expected to have an influence on the GDP but evolves most likely almost simultaneously with the GDP. The lagged value of the GDP is a strong predictor for GDP´s future levels and thus it is desirable to account for this factor in the econometric model. But considering such variables in an econometric model would clearly create endogeneity issues due to simultaneity of the dependent variable with the regressors of the model and thus, could lead to biased estimates.

Therefore, the econometric method applied must be able to handle endogeneity which can be mastered by instrumental variable (IV) estimation approaches. Such an estimation method is the dynamic panel estimation method called Generalized Method of Moments (GMM)[74] introduced by Arellano and Bond (1991) based on the IV estimator of Anderson and Hsiao (1981). Two different versions of this method (Difference and System GMM) are considered for the empirical evaluation of the potential impact of ESIF on the economic development of the EU at the regional level of NUTS 2 classification.

Two-step Difference GMM (Arellano and Bond, 1991) method, applied for the analyses at hand transforms all variables to their first differences generating a first differenced error term which is uncorrelated with the lagged level variables and thus enables their utilization as instrumental variables. Two-step Difference GMM is compared to the one-step estimator also efficient in presence of heteroscedasticity and does not assume independency between the unobserved (regional) individual effects and the covariates (i.e. the assumption that the instrumenting variables would be uncorrelated with the regional fixed effects as it must be assumed in the case of the Two-step System GMM estimator).

[74] Estimations were performed by using Stata and applying the command xtabond2 developed by Roodman (2009).

Two step System GMM as outlined by Arellano and Bover (1995) and developed by Blundell and Bond (1998) adds on top of the procedure applied in Two-step Difference GMM in order to utilize more information that can be considered as instrumental variables. It uses in addition to the first differences sample also the level information of the variables by extending the first differences sample with the original level sample. This happens basically by appending the differences sample with the level sample so that the same sample contains the first differences information as well as the level information in distinct observation units.

For observations that contain the level information in the sample, the (lagged) first differences are used as instrumental variables while, as in case of Difference GMM, for observations that contain the first difference information in the sample (lagged) level information are used as instrumental variables. Running the econometric estimation with this sample implicitly assumes that the same linear relationship with the same coefficients apply to both the transformed (first differences) and untransformed (original level) variables.

Two-step Difference GMM in its simple form with the lagged dependent variable and one control variable transforms the following dynamic panel model

$$y_{it} = \gamma\, y_{i,t-1} + \beta_1\, x_{it} + \varepsilon_{it} \quad \text{with} \quad \varepsilon_{it} = \mu_i + \nu_{it}$$

through applying the first differences into following model

$$y_{it} - y_{i,t-1} = \gamma(y_{i,t-1} - y_{i,t-2}) + \beta_1(x_{it} - x_{i,t-1}) + (\varepsilon_{it} - \varepsilon_{i,t-1})$$

y_{it} is the dependent variable, i.e. the observed outcome value for the observation i (with $i = 1,2,\ldots,N$) in period t (with $t = 1,\ldots,T$). For the Difference GMM the difference of the observed value in t and $t-1$ is calculated and serves as the dependent variable. For a dynamic panel estimation the first lag of the dependent variable, $(y_{i,t-1} - y_{i,t-2})$ enters the model on the right side of the equation and γ serves as the coefficient delivering the potential effect of the lagged dependent variable.

$(x_{it} - x_{i,t-1})$ is a control variable also expressed in its first difference between time period t and $t-1$. The coefficient β_1 reveals the potential effect of this control variable. Finally, the error term $(\varepsilon_{it} - \varepsilon_{i,t-1})$, which includes the individual fixed effects (μ_i) and the idiosyncratic shocks (ν_{it}), enters the model also expressed in first difference. Applying the first difference on μ_i excludes the individual fixed effects out of the model since the difference amounts to zero.

The Difference GMM model applied (with all variables except squared and interaction terms) for the empirical examination can be expressed as follows:

$$
\begin{aligned}
lnGDPpps_{\mathrm{it}} - lnGDPpps_{\mathrm{i,t-1}} = {} & \gamma\left(lnGDPpps_{\mathrm{i,t-1}} - lnGDPpps_{\mathrm{i,t-2}}\right) \\
& + \beta_1\left(lnSubsTot_{\mathrm{it}} - lnSubsTot_{\mathrm{i,t-1}}\right) + \beta_2\left(Obj1_{\mathrm{it}} - Obj1_{\mathrm{i,t-1}}\right) \\
& + \beta_3\left(Votpower_{\mathrm{it}} - Votpower_{\mathrm{i,t-1}}\right) + \beta_4\left(Emprate_{\mathrm{it}} - Emprate_{\mathrm{i,t-1}}\right) \\
& + \beta_5\left(lnd.emp_{\mathrm{it}} - lnd.emp_{\mathrm{i,t-1}}\right) + \beta_6\left(lnpopulden_{\mathrm{it}} - lnpopulden_{\mathrm{i,t-1}}\right) \\
& + \beta_7\left(lnterteduc_{\mathrm{it}} - lnterteduc_{\mathrm{i,t-1}}\right) + \beta_8\left(lngfcap_{\mathrm{it-1}} - lngfcap_{\mathrm{i,t-2}}\right) \\
& + \beta_9\left(lntotalarea_{\mathrm{it}} - lntotalarea_{\mathrm{i,t-1}}\right) + \left(\varepsilon_{it} - \varepsilon_{i,t-1}\right)
\end{aligned}
$$

Difference GMM estimates in first differences transformed model from above by utilizing the level values of the same regressors as instrumental variables whereat for endogenous and predetermined regressors only lagged level values qualify as valid instrumental variables. Thus, before applying the GMM estimator, it is necessary to think about the regressors' relation with the error term and to classify the regressors in one of the three categories, (i) strictly exogenous, (ii) predetermined, or (iii) endogenous.

The classification of each of the regressors has to be chosen by the researcher within the software package (here Stata) by applying a certain type of instrumenting style (gmm- vs. iv-style). For variables in the category (i) the iv-style instrumenting is the correct choice. This type of instrumenting allows the utilization of past (all lags) and contemporaneous values as instruments since none of those are correlated with the error term.

Variables in the categories (ii) and (iii) belong to the gmm-style type of instrumenting whereat category (ii) variables can be considered from first lag onwards

(second lag, third lag and so on) and (iii) category variables can be considered from second lag onwards as instruments to perform an estimation with valid instruments. The difference in applicable levels of lags as instruments for (ii) and (iii) relates to their correlation with the error term. While for (ii) first lag level and onwards do not correlate with the error term, the same is true for (iii) from second lag onwards.

In case of the estimations applied for the examination at hand the lagged dependent variable (first lag of *lnGDPpps*), *lnSubsTot* or *lnSubsTotMod*, *Obj1*, *Emprate*, *Ind.emp*, *lnterteduc*, and *lngfcap* are assumed to be endogenous variables (category (iii)). It is obvious that the lagged values of GDP will be highly correlated with the current level. The subsidy payment volumes and Objective 1 status are directly related to the GDP level of a region since regions with lower GDP levels qualify for more public support from ESIF and economically only most poorly performing regions in means of GDP are eligible for the Objective 1 region classification.

Employment rate, industry share of the employment, education level within the region, as well as the gross fixed capital available from the last period are expected to be linked with the current GDP level/development of the region. Thus, these variables are indicated as endogenous for the estimations performed. The remaining regressors voting power (*Votpower*), population density (*lnpopulden*), and the surface of the region (*lntotalarea*) are assumed to be strictly exogenous (category (i)) since it is not expected that these variables will have a direct link with the GDP of the region.

In addition to the classification of the regressors, lags used as instruments must be chosen within certain lag level bands by the researcher. Not determining the starting period and last period of lags to be used as instrumental variables would lead to utilization of contemporaneous values and all available lags as instruments. If the starting period for the lags used is inappropriate, correlation between the error term and regressors will be present in case of endogenous and predetermined regressors. If the last period of the lags is not defined all lags available will be used as instrumental variables which in turn could lead to an inappropriate high number of instruments weakening the instruments' validity. Thus, the lag levels used for the estimations applied have been limited on the second to fourth lags to work with valid instruments.

Whether the model specifications lead to valid instruments to obtain consistent estimates are tested with the test on overidentifying restrictions (Hansen, 1982; J-

Test), test on lack of second order autocorrelation (Arellano and Bond, 1991), and test on exogeneity of subset of instruments (C-test; Difference-in-Hansen-test). The results of these tests are reported along with the estimation results for all GMM estimations. Main results of the GMM estimations are available in Table 3. 7 to Table 3. 10. Robustness checks in Table 3. 11 and Table 3. 12 report results for Least-square-dummy-variable (LSDV) estimations and Table 3. 13 to Table 3. 16 report GMM estimations considering first lags of the subsidy variables as treatment variables instead of the contemporaneous values.

3.4 Results

For each of the different econometric method applied and subsidy payment information (direct EU grants) considered, there are six different models estimated. All models applied take into account the entire set of the available control variables. The changes applied lie in the variations of the considered treatment variables. The first three models (I, II, III) do not take into account the possible non-linear effect of the subsidy payment into account while the remaining models (IV, V, VI) also account for a potential non-linear treatment effect by including the squared term of the subsidy payment variable in the model specification. Models II and V estimate the fixed treatment effect of being an Objective 1 region in addition to the subsidy payment variable while models III and VI also take into account the received amount of subsidies within an Objective 1 region. Following subsections report the results and discuss briefly how the results differ between methods applied and payment information used.

3.4.1 Difference GMM

Table 3. 7 provides the Difference GMM estimation results which are obtained by utilizing the total subsidy payment as transferred by the EC to the recipient NUTS 2 regions. The coefficient for the lagged dependent variable obtained is around 0.7 and significant at 1% level for all models. The sign and significance levels are as expected, since the GDP level/development (i.e. GDP per capita in means of purchasing power

standard) from the previous year is usually a strong predictor for the current GDP level/development. The first and fourth models control for the treatment effect of total subsidy payment whereat the latter also tests for a possible non-linear relationship. The coefficients can be interpreted as elasticities as on both sides of the equation log values are considered. While no evidence for a non-linear relationship is present, the coefficients indicate at a significance level of 1% that a 10% increase of the total subsidy payment (*lnSubsTot*) the GDP growth (*lnGDPpps*) will respond with an increase of 0.09% to 0.13%[75].

In the second and fifth models subsidy payment as well as being an Objective 1 region (*Obj1*) are simultaneously assessed on potential treatment effects. There is again no evidence for a non-linear relationship of subsidy payments' impact. At 1% level significant, coefficients show that the GDP growth increases by 0.08% to 0.13% if the subsidy payment increases by 10% while the fixed effect of being in an Objective 1 region (without consideration of subsidy amounts received) leads to additional 1.31%[76] to 1.41% higher GDP growth.

The third and sixth models control for total subsidy payment by considering also payments received by the Objective 1 regions. To do that, the interaction of the variables *lnSubsTot* and *Obj1* is applied. The coefficient of the interaction term provides the elasticity of the subsidy payments' impact within Objective 1 regions rather than merely the fixed effect of being an Objective 1 region. Coefficients of the total payment variable and the interaction variable are both positive and statistically significant at 1% level. If the total subsidy payment increases by 10% the GDP growth increases by 0.08% to 0.14% while the GDP growth within an Objective 1 region increases by additional 0.02% to 0.03%. This finding indicates that the subsidy payment in Objective 1 regions trigger a higher acceleration of the GDP growth which can be interpreted as economic catch up of the Objective 1 regions with wealthier EU regions.

[75] This value was calculated based on the coefficient estimate of 0.014 in Table 3. 7 Model IV in case of a 10% increase of the treatment (both dependent and treatment variables in log) as follows: ((1.1^0.014)-1)100=0.1335≈0.13% The same calculation was employed for other coefficients of continuous variables in log.

[76] This value was calculated for the coefficient of the variable *Obj1* (0.013) in Table 3. 7 model II as follows: (*e*^0.013)/100=1.308≈1.31 The same calculation was employed for other *Obj1* (dummy) coefficients.

Other covariates showing statistical significant results are positive for employment rate (*Emprate*) and negative for the population density (lnpopulden) as well as the regions surface (*lntotalarea*). For the remaining covariates there is no statistically significant effects evident.

Further remarks to Table 3. 7 relate to the tests applied. Test on lack of second order autocorrelation (m2-Test; AR(2)) does not reject the null hypothesis of the absence of autocorrelation in none of the models. The Hansen test (J-Test) on overidentifying instruments is never significant and thus, does not reject the null hypothesis of the validity of the instruments. The Difference in Hansen Test (C-Test; test on exogeneity of subset of instruments) does not reject the null hypothesis of exogeneity for none of the instruments in all models applied.

3.4.2 Difference GMM with modelled payment data

Table 3. 8 reports the results of the Difference GMM estimations with the modelled payment information (*lnSubsTotMod*). These payment information represent different timing of payments, which are created by BERGEN (2017), compared with the actual transfers by the EC. The lagged dependent variable's coefficient is around 0.7 and significant at 1% level in all models applied.

First model considering the total subsidy payment variable reveals that the GDP growth increases by 0.1% in case of a 10% increase of the subsidy amount whereat this finding is statistically significant at 1% level. Fourth model takes the squared term of the subsidy variable into account and shows a positive significant coefficient at 10% level hinting weakly on an increasing effect of subsidy payments. This relation remains also for the other models which include the squared subsidy payment as a covariate whereat in all three models with the squared variable the total subsidy payment variable itself becomes statistically insignificant.

Model II with the total payment variable and Objective 1 region dummy suggests 0.1% increase of the GDP growth in case of a 10% increase of the total subsidy amount. In addition, 1.31% increase of the GDP growth for being an Objective 1 region is evident. Both results are statistically significant at 1% level. Model V shows an impact

of being an Objective 1 region with 1.01% GDP growth statistically significant at 5% level.

Model III takes the interaction between the Objective 1 dummy and total subsidy payment variable into account whereat the impact of the subsidy variable remains the same as in the first and second models. The interaction terms' coefficient hints on an additional 0.02% increase of the GDP growth within an Objective 1 region statistically significant at 1% level in case of a 10% increase of the subsidy amount. The same result is valid for the interaction term applied in Model VI but only statistically significant at 5% level. The coefficients and their significance levels for the other covariates are very similar to the results obtained with Difference GMM with non-modelled payment data in Table 3. 7. Tests applied do not reject the null hypothesis of the absence of second order autocorrelation, exogeneity or validity of the instruments.

3.4.3 System GMM

Table 3. 9 provides the System GMM estimation results which are obtained by utilizing the total subsidy payment as transferred by the EC to the recipients. The coefficient of the lagged dependent variable is around 0.95 and statistically significant at 1% level for all models applied.

Within the first three models which do not account for a potential non-linear effect, the estimates for the total subsidy payment variable hint on a 0.03% to 0.04% increase of the GDP level if the subsidy amount increases by 10%. The statistical significance levels vary between 1% to 10%. The estimated impact increases to 0.13% to 0.14% statistically significant at 1% level within the models accounting for a possible non-linear relationship. The non-linear effects estimated are statistically significant at 1% level and hint on a decreasing impact of the subsidies with a coefficient of -0.002.

Models considering the Objective 1 dummy as well as the interaction of this dummy with the subsidy payment amount do not show a statistically significant effect of these variables. Voting power (*Votpower*) is negatively associated with the dependent variable while employment rate (*Emprate*) and industry employment rate (*Ind_emp*) are positively associated, all statistically significant at 1% level. All other covariates'

coefficients are not statistically significantly associated with the dependent variable except for tertiary education level (*Interteduc*) which is positively associated at 10% significance level only in models I and II. Tests applied do not reject the null hypothesis of the absence of second order autocorrelation, exogeneity or validity of the instruments.

3.4.4 System GMM with modelled payment data

Table 3. 10 reports the results when System GMM with the modelled payment information (*lnSubsTotMod*) is considered. The coefficient of the lagged dependent variable is around 0.95 and statistically significant at 1% level for all models applied.

Within the first three models which do not account for a potential non-linear effect, the estimates for the total subsidy payment variable reveal a 0.04% increase of the GDP level if the subsidy amount increases by 10%. The statistical significance level changes between 1% and 5% levels. The estimated impact increases to 0.08% to 0.09% within the models accounting for a possible non-linear relationship statistically significant at 1% level. A non-linear effect at 10% significance level is evident only in the fifth model and hints on a decreasing impact of the subsidies with a coefficient of -0.001.

Models considering the Objective 1 dummy as well as the interaction of this dummy with the subsidy payment amount do not exhibit a statistically significant effect. Voting power (*Votpower*) is negatively associated with the dependent variable while employment rate (*Emprate*) and industry employment rate (*Ind_emp*) are positively associated all statistically significant at 1% level. Tertiary education level (*lnterteduc*) is also positively associated with the GDP level in all estimations applied but only at 10% significance level. Gross fixed capital (*lngfcap*) is positively associated with the dependent variable at 10% significance level only in model I. All other covariates' coefficients are not significantly associated with the dependent variable. Tests applied do not reject the null hypothesis of the absence of second order autocorrelation and validity of the instruments. Exogeneity of the instruments are not rejected except for one variable (*Votpower*) in model III.

3.4.5 Differences in results

Looking at the treatment variables, the most important difference between Difference and System GMM estimates is that the variables which include Objective 1 information (Objective 1 dummy and the interaction of Objective 1 dummy with the subsidy payment variables) become statistically insignificant when System GMM method is applied. This is surprising as Objective 1 regions receive higher subsidy amounts compared to other regions. Thus, one would expect variables containing the Objective 1 information to be statistically significantly related to GDP also in case of System Difference estimations.

A weak point of the System GMM method is that it can perform poorly in case of dummy variables that predominantly exhibit the values 0 or 1 (Roodman, 2009). In the data set utilized, relatively wealthy regions exhibit always the value 0 for the dummy variable Objective 1 which is the case for 157 regions out of 261 regions in the sample. Out of the remaining 104 regions, which are at least once classified as an Objective 1 region, 17 cases do not exhibit any switch in the dummy variable Objective 1 (i.e. keep a value of 1 always), 47 cases exhibit a switch from 0 to 1, 35 cases exhibit a switch from 1 to 0, while only 5 cases exhibit a switch twice (from 0 to 1 to 0). Objective 1 variable possibly does not feature enough variation in its values for a consistent estimate in case of System GMM. This could be the explanation why the coefficients for Objective 1 dummy and the interaction term become insignificant in case of System GMM.

Estimates obtained for the lagged dependent variable are higher in case of System GMM estimations being around 0.7 for Difference and 0.95 for System GMM. Total subsidy payment variable exhibits similar coefficients (0.008 to 0.015 in Difference and 0.003 to 0.015 in System GMM) and significance levels both in Difference and System GMM. But in case of Difference GMM where modelled payment information is applied, the variable for subsidy payment becomes insignificant while a positive and significant non-linear effect is evident. In this case the positive effect of the subsidies is picked up by the squared subsidy payment variable. In all other cases the squared subsidy payment coefficient exhibits a negative sign.

System GMM shows a statistically significant negative effect for the variable voting power (*Votpower*) while the estimates for the same variable are positive but statistically insignificant in Difference GMM. A similar difference is evident for the variable industry employment rate (*Ind_emp*) where the estimate for this variable is statistically significant and positive in System GMM while negative but statistically insignificant in Difference GMM. Population density (*lnpopulden*) estimate is negative and statistically significant in Difference GMM while System GMM estimate is statistically insignificant. Tertiary education level (*lnterteduc*) estimate shows a weak positive effect only in case of System GMM in combination with modelled payment information. The size of regions' surface (*lntotalarea*) is statistically significantly and negatively related with the dependent variable in Difference GMM while no statistically significant effect in System GMM is evident.

3.5 Robustness checks

As a robustness check on whether the results, in particular sign and statistically significance levels, for the treatment variable estimates obtained by GMM estimations are similar when applying an alternative econometric method, the Least-squares dummy-variable (LSDV) method, (see Table 3. 11 and Table 3. 12) is considered. LSDV estimator accounts for small sample size (N) but assumes strict exogeneity of the regressors. The latter is in case at hand not a realistic assumption since some of the regressors are clearly prone to endogeneity and the number of observations (N) available for the analyses is not that small either.

The estimates for the lagged dependent variable in LSDV model are around 0.81 in all models both for modelled and non-modelled subsidy payment variables at a significance level of 1%. Total subsidy payment variable's impact estimates suggest 0.02% to 0.07% increase in GDP level if the subsidy payment increases by 10%. These results are statistically significant at different levels whereat in models II and III with non-modelled payment information the coefficients for total subsidy payment variable are insignificant. In the same models Objective 1 dummy and the interaction terms applied confirm a statistically significant positive impact. A decrease of the

positive subsidy impact with increasing subsidy volume is evident in models V and VI in case of non-modelled payment information.

All models with Objective 1 dummy indicate an increase of the GDP level. The estimated values vary between 0.06% to 0.09% at statistical significance levels of 1% to 5%. All models applying the interaction of Objective 1 dummy with payment information show an increase of GDP level between 0.01% and 0.02% in case the subsidy amount increases by 10%. These results are statistically significant at different levels (1% to 10%). Covariates exhibiting a statistically significant positive effect are voting power (*Votpower*), employment rate (*Emprate*) and gross fixed capital (*lngfcap*) while population density (*lnpopulden*) indicates a negative effect on GDP level.

Further estimates as robustness checks are run to test whether it makes a difference to apply the first lag of the total subsidy payment variable in GMM estimations (see Table 3. 13 to Table 3. 16) instead of the contemporaneous values. The results obtained show only minor changes in general whereat the Objective 1 dummy and its interaction with subsidy payment are estimated with slightly higher coefficients in case of Difference GMM.

3.6 Conclusion

This paper provides an empirical impact evaluation of the European Structural and Investment Funds (ESIF) which is created to follow up on the task of the European Union (EU) as determined by the Article 174 of the Treaty on the Functioning of the European Union (TFEU). The main contribution of the examination at hand is the utilization of new data published by the European Commission (EC) consisting of the actual amounts of financial means (direct EU grants) transferred to EU's NUTS 2 regions through ESIF. A comprehensive set of covariates, longer time period, and larger geographic area are considered for the analyses than usually done in the literature.

The existing literature is based on data utilizing inaccurate (planned transfers/commitments) data and thus gives reason for further checks for falsification/verification of the available empirical evidence. The analyzed time period

spans the years from 2000 to 2015 whereat the limitation on this period is owed to data availability reasons.

The econometric approaches applied for the main analyses are dynamic panel estimation methods (Difference and System GMM) accounting for the endogeneity of the economic factors which are utilized for the models estimated. The impact of ESIF is measured at three different levels, (i) the impact of total subsidy amounts only, (ii) the effect of total subsidy amounts and the fixed effect of being an Objective 1 region, and (iii) the effect of total subsidy amounts and the amounts received by the Objective 1 regions. In addition, the possible effect of the timing of the expenditures on the ground as estimated by BERGEN (2017) are considered for comparison. While System GMM estimations do not identify an effect on Objective 1 regions, Least Squares Dummy Variable (LSDV) method as a robustness check confirms the positive impact of the ESIF grants in general and the additional economic development within Objective 1 regions. Presumably, the System GMM results suffer under the utilization of the Objective 1 dummy variable which does not vary much and hence, leads possibly to inconsistent estimates.

Empirical evidence obtained suggests that the ESIF programmes are successfully triggering economic development in means of accelerated GDP growth as measured in Purchasing Power Standard (PPS) whereat the aim to create additional economic acceleration in Objective 1 regions is achieved. Thus, it is recommended that the public support for Objective 1 regions should be continued to help these regions to catch up with wealthier EU regions.

GDP growth acceleration identified (general effect) lies between 0.08% and 0.14% in case of an increase of the subsidy amount by 10%. In addition to that general effect, Objective 1 regions exhibit 0.02% to 0.03% additional acceleration in case of an increase of the subsidy amount by 10%. The fixed effect of being an Objective 1 region is measured as 1.31% to 1.41% additional growth on top of the general effect. The fixed effect of being an Objective 1 region may appear as quite large in first glance but is in line with some of the empirical work in the literature. It is estimated with 1.6% in Becker et al. (2010), 1.5% in Becker et al. (2012), and 1.2% to 1.9% in Becker et al. (2018). The utilization of the alternative (modelled) payment information as

suggested by BERGEN (2017) instead of the payment amounts as transferred by the EC does not lead to a large difference in the subsidy impact estimates.

In future research, it would be desirable to work with even more accurate subsidy payment data which represents the real timing of the expenditures on the ground. Furthermore, it would be useful to collect data and provide empirical evidence for Objective 1 regions' potentially differing subsidy responses. Data useful and to be collected for this purpose could be differences in regional (national) public support programmes (policy mix, hidden treatment), administrative differences within the regions, other regional differences such as land use, systematic differences in type of projects supported within the regions or other economically relevant factors which could lead to differences in public supports' impact. Insights on whether the factors listed above play a role in subsidies' impact may enable the EC to redistribute the public means more effectively to stimulate even higher levels of economic growth.

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Tables and Figures

Table 3. 1 Variables: description and source

Variable	Description	Data Source
lnGDPpps	Natural logarithm of GDP per capita in purchasing power standard	Urban Data Platform
lnSubsTot	Natural logarithm of ESIF subsidy payments in total per capita	European Commission
lnSubsTotMod	Natural logarithm of ESIF subsidy payments in total per capita as modelled by BERGEN (2017)	European Commission
Votpower	Voting power of the country in the Council of the European Union	Calculated according to EU treaties
Emprate	Employment rate (age range 20-64)	Urban Data Platform
Ind.emp	Industry employment share	Urban Data Platform supplemented with Eurostat data
lnpopulden	Natural logarithm of population density	Eurostat
lnterteduc	Natural logarithm of population share with tertiary education level (age range 25-64)	Urban Data Platform
lngfcap	Natural logarithm of gross fixed capital	Urban Data Platform
lntotalarea	Natural logarithm of total area of the region	Eurostat
Obj1	Objective 1 region dummy	Council Regulation (EC) No 1260/1999; No 1083/2006; No 2014/99/EU

Table 3. 2 Descriptive statistics

	All Regions (261 Regions; 4011 Year-Region obs.)			
Variable	Mean	SD	Min	Max
Subsidy[1]	157.97	242.26	0	2406.01
Subsidy_pc[2]	110.53	158.21	0	1299.53
SubsidyMod[1]	158.55	234.74	0.00005	2072.60
SubsidyMod_pc[2]	110.62	152.57	0.00004	1250
lnGDPpps	9.994	0.404	8.183	11.240
lnSubsTot[3,4]	3.885	1.375	0	7.171
lnSubsTotMod[3,4]	3.895	1.398	-10.047	7.131
Obj1	0.246	0.431	0	1
Votpower	0.064	0.032	0	0.115
Emprate	69.068	7.550	40.300	88.400
Ind.emp	0.179	0.073	0.021	0.402
lnpopulden	5.018	1.123	1.194	8.782
lnterteduc	3.093	0.409	1.281	4.020
lngfcap	22.475	1.009	18.975	25.548
lntotalarea	9.145	1.204	2.565	12.333

[1] In Mio. Euro.

[2] Per capita in Euro.

[3] Per capita in Euro transferred to natural logarithm.

[4] When transferring *lnSubsTot* to natural logarithm ln(1+*x*) was applied in order to keep the zero values which would turn to missing values otherwise. The same was not applied to *lnSubsTotMod* since this variable does not exhibit any zero values whereat applying (1+*x*) leads to minor changes in the estimates.

Table 3. 3 Descriptive statistics by Objective 1 status

	Objective 1 Year-Region obs. (N=986)				Non Objective 1 Year-Region obs. (N=3,025)			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
Subsidy[1]	404.94	340.35	2.64	2406.01	77.47	117.16	0	2105.62
Subsidy_pc[2]	296.12	204.20	4.87	1299.53	50.04	68.70	0	813.02
SubsidyMod[1]	403.74	326.47	4.58	2072.60	78.63	111.19	0.00005	1755.53
SubsidyMod_pc[2]	296.67	192.49	10.35	1250.25	49.98	61.93	0.00004	735.31
lnGDPpps	9.749	0.216	9.003	10.392	10.074	0.419	8.183	11.240
lnSubsTot[3]	5.472	0.709	1.769	7.171	3.368	1.121	0	6.702
lnSubsTotMod[3]	5.497	0.654	2.337	7.131	3.372	1.158	-10.047	6.600
Votpower	0.058	0.027	0.009	0.115	0.065	0.033	0	0.115
Emprate	63.718	7.841	42.100	80.000	70.812	6.572	40.300	88.400
Ind.emp	0.188	0.086	0.021	0.402	0.176	0.068	0.026	0.385
lnpopulden	4.605	1.089	1.194	8.740	5.152	1.101	1.194	8.782
lnterteduc	2.909	0.389	1.281	3.671	3.152	0.397	1.872	4.020
lngfcap	21.981	1.007	19.119	24.579	22.637	0.956	18.975	25.548
lntotalarea	9.382	1.469	2.565	12.332	9.068	1.093	2.565	12.333

[1] Mio. Euro.

[2] Per capita in Euro.

[3] Per capita in Euro transferred to natural logarithm.

[4] When transferring *lnSubsTot* to natural logarithm ln(1+*x*) was applied in order to keep the zero values which would turn to missing values otherwise. The same was not applied to *lnSubsTotMod* since this variable does not exhibit any zero values whereat applying (1+*x*) leads to minor changes in the estimates.

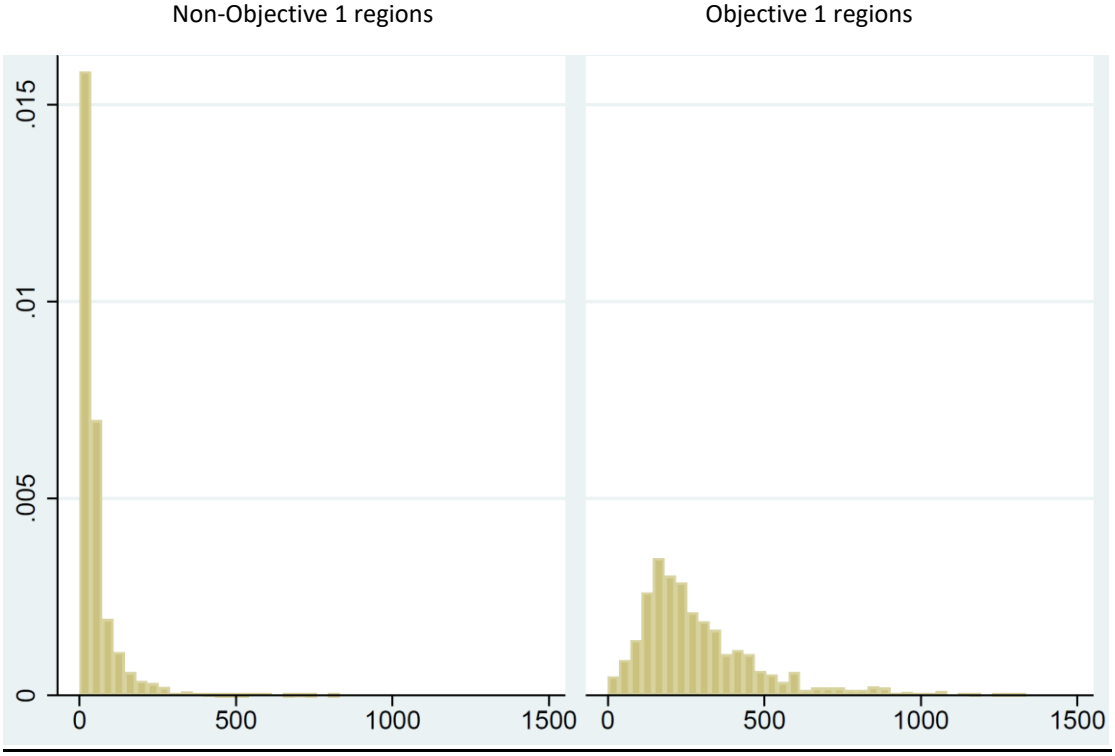
Table 3. 4 An example of EU payments and Modelled payments by Bergen (2017)

NUTS2 Code	Year	EU payment	Modelled payment	Obj1 status
PL12	2002	17.729.416	37.045.827	0
PL12	2003	26.044.250	118.686.153	0
PL12	2004	139.241.232	165.280.746	0
PL12	2005	104.954.986	252.689.246	0
PL12	2006	232.688.538	417.029.869	0
PL12	2007	711.742.077	887.197.592	1
PL12	2008	937.912.099	1.065.573.020	1
PL12	2009	1.149.519.918	1.265.208.924	1
PL12	2010	1.484.753.178	1.244.424.180	1
PL12	2011	1.433.125.783	1.525.621.332	1
PL12	2012	1.774.579.364	1.829.823.685	1
PL12	2013	1.898.672.206	1.953.893.859	1
PL12	2014	2.105.620.041	1.755.532.828	0
PL12	2015	1.416.946.714	910.087.441	0
Total		13.433.529.802	13.428.094.702	

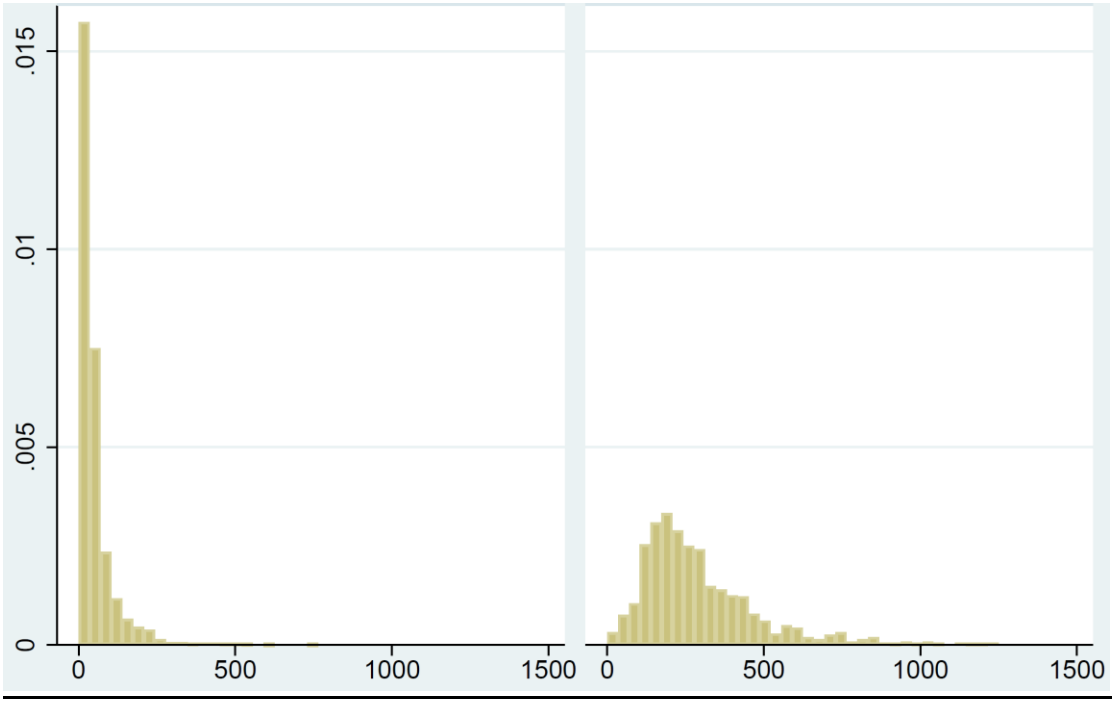
Payment information in Euro per year.

Figure 3. 1 Density of EU per capita payments and modelled payments by Bergen (2017)

Annual payment information as transferred by the EC



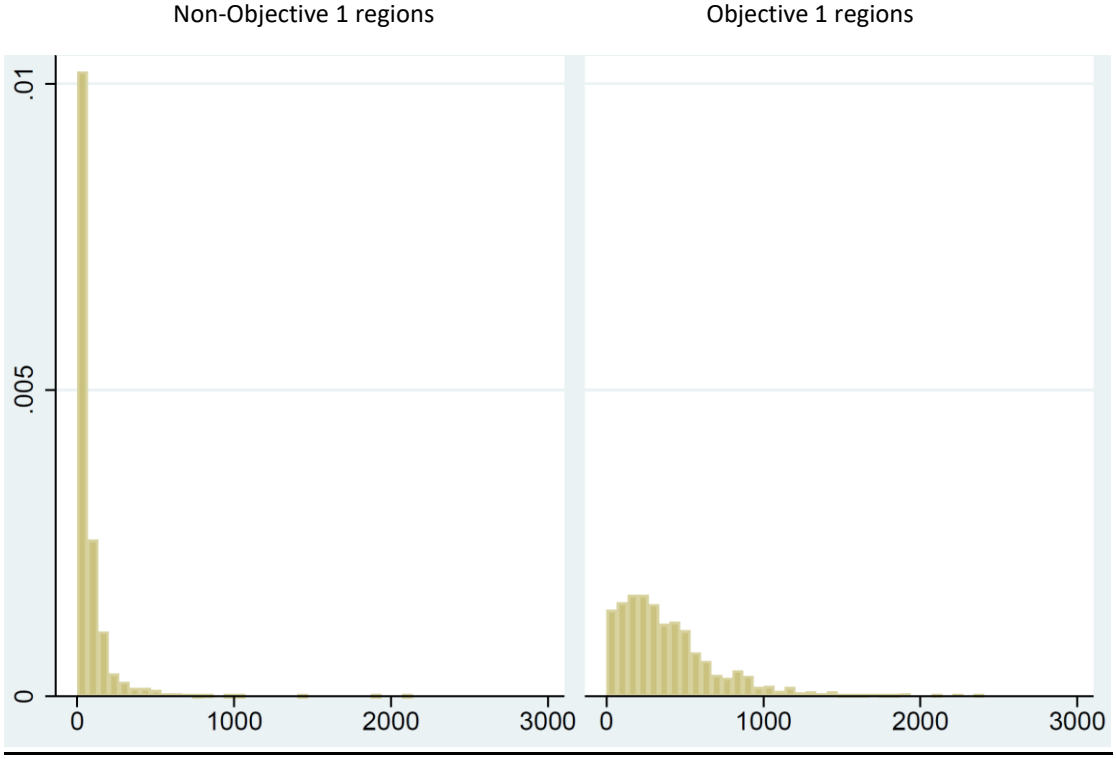
Annual payment information as modelled by BERGEN (2017)



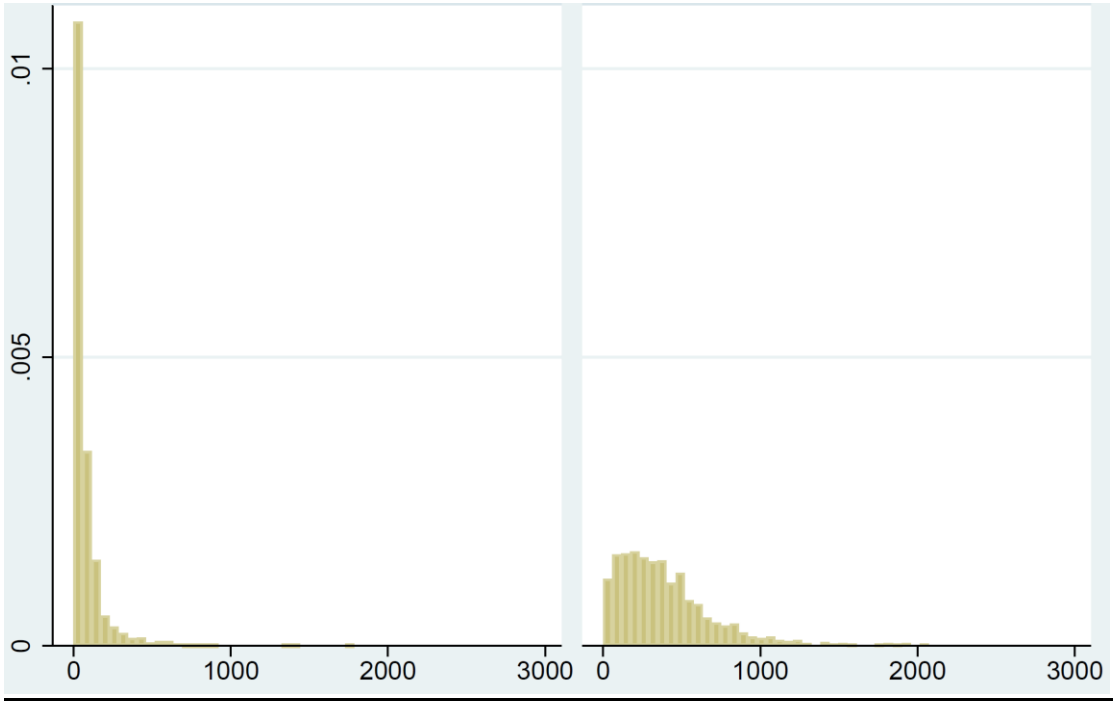
In Euro per year/capita.

Figure 3. 2 Density of EU payments and modelled payments by Bergen (2017)

Annual payment information as transferred by the EC



Annual payment information as modelled by BERGEN (2017)



In Mio. Euro per year.

Table 3. 5 Number of NUTS 2 Objective 1 regions by year

Year	Objective 1 Regions	Non Objective 1 Regions	Total
2000	50	170	220
2001	50	173	223
2002	50	191	241
2003	50	196	246
2004	50	196	246
2005	52	199	251
2006	52	199	251
2007	72	186	258
2008	72	187	259
2009	72	186	258
2010	72	186	258
2011	72	188	260
2012	72	188	260
2013	72	188	260
2014	64	196	260
2015	64	196	260
Total	986	3025	4011

Nuts 2 Regions SI03 and SI04 were dropped from the sample since in the ESIF payment data these are only present in 2015 and thus cannot be utilized for panel analyses. Some other regions available in the ESIF payment data (BE10, FR91, FR92, FR93, FR94, HR03, HR04, UKI1, UKI2) were dropped from the sample due to missing covariate data. Data comprehend NUTS 2 regions for some countries receiving subsidies from the EU before obtaining the membership of the EU.

Table 3. 6 Correlation matrix

	1	2	3	4	5	6	7	8	9	10
1 ln*GDPpps*	1.00									
2 *lnSubsTot*	-0.12***	1.00								
3 *lnSubsTotMod*	-0.18***	0.95***	1.00							
4 *Obj1*	-0.35***	0.66***	0.65***	1.00						
5 *Votpower*	0.27***	-0.01	-0.03**	-0.09***	1.00					
6 *Emprate*	0.56***	-0.33***	-0.36***	-0.40***	0.04***	1.00				
7 *Ind.emp*	-0.32***	-0.06***	-0.04**	0.07***	-0.14***	-0.04	1.00			
8 *lnpopulden*	0.35***	-0.30***	-0.30***	-0.21***	0.21***	0.10***	-0.16***	1.00		
9 *lnterteduc*	0.54***	-0.10***	-0.15***	-0.26***	0.14***	0.45***	-0.35***	0.23***	1.00	
10 *lngfcap*	0.59***	-0.29***	-0.32***	-0.28***	0.41***	0.34***	-0.05***	0.33***	0.38***	1.00
11 *lntotalarea*	-0.31***	0.08***	0.08***	0.11***	-0.05***	-0.08***	0.28***	-0.76***	-0.14***	0.21***

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

Table 3. 7 Difference GMM

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.699***	0.709***	0.708***	0.703***	0.715***	0.713***
	(0.029)	(0.028)	(0.028)	(0.029)	(0.027)	(0.028)
lnSubsTot	0.009***	0.008***	0.008***	0.014***	0.014***	0.015***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
lnSubsTot^2				-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)
Obj1		0.013***			0.014***	
		(0.004)			(0.004)	
*lnSubsT*Obj1*			0.002***			0.003***
			(0.001)			(0.001)
Votpower	0.052	0.071	0.078	0.014	0.030	0.033
	(0.098)	(0.097)	(0.095)	(0.092)	(0.091)	(0.093)
Emprate	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ind.emp	-0.146	-0.164	-0.147	-0.162	-0.184	-0.177
	(0.222)	(0.201)	(0.203)	(0.225)	(0.200)	(0.203)
lnpopulden	-0.457***	-0.375***	-0.369***	-0.468***	-0.381***	-0.382***
	(0.063)	(0.063)	(0.063)	(0.065)	(0.061)	(0.061)
lnterteduc	-0.029	-0.024	-0.024	-0.025	-0.018	-0.017
	(0.019)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)
lngfcap	0.030*	0.025	0.024	0.032*	0.026	0.026
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
lntotalarea	-0.847**	-0.724**	-0.745**	-0.843**	-0.713**	-0.725**
	(0.396)	(0.348)	(0.352)	(0.394)	(0.336)	(0.335)
N	3486	3486	3486	3486	3486	3486
# Instruments	251	269	269	251	269	269
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.992	0.969	0.978	0.939	0.893	0.921
Sargan Test [1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test [1,3]	0.168	0.308	0.346	0.153	0.329	0.315
Difference in Sargan/Hansen Test (C statistic)						
L.lnGDPpps [1]	1.000	1.000	1.000	1.000	1.000	1.000
lnSubsTot [1]	1.000	1.000	1.000	1.000	1.000	1.000
Obj1 [1]	-	1.000	1.000	-	1.000	1.000
Emprate [1]	0.997	1.000	1.000	0.997	1.000	1.000
Ind.emp [1]	0.999	1.000	1.000	0.997	1.000	1.000
lnterteduc [1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap [1]	1.000	1.000	1.000	0.999	1.000	1.000
Votpower [1]	0.964	0.693	1.000	0.995	1.000	1.000
lnpopulden [1]	0.767	0.803	1.000	0.778	0.401	1.000
lntotalarea [1]	0.905	0.444	1.000	0.992	1.000	1.000
Year dummies [1]	0.996	0.997	1.000	0.998	1.000	1.000

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 8 Difference GMM (modelled subsidy amounts)

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.696***	0.704***	0.702***	0.691***	0.696***	0.696***
	(0.029)	(0.028)	(0.028)	(0.029)	(0.028)	(0.028)
lnSubsTotMod	0.011***	0.011***	0.011***	0.005	0.005	0.006
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
lnSubsTotMod^2				0.001*	0.001**	0.001*
				(0.001)	(0.001)	(0.001)
Obj1		0.013***			0.010**	
		(0.004)			(0.004)	
*lnSubsT*Obj1*			0.002***			0.002**
			(0.001)			(0.001)
Votpower	0.081	0.094	0.101	0.093	0.105	0.111
	(0.095)	(0.090)	(0.091)	(0.095)	(0.093)	(0.092)
Emprate	0.003***	0.003***	0.004***	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ind.emp	-0.117	-0.098	-0.087	-0.077	-0.063	-0.065
	(0.223)	(0.205)	(0.207)	(0.223)	(0.210)	(0.207)
lnpopulden	-0.421***	-0.323***	-0.322***	-0.397***	-0.315***	-0.313***
	(0.063)	(0.064)	(0.065)	(0.066)	(0.064)	(0.065)
lnterteduc	-0.024	-0.018	-0.019	-0.032*	-0.027	-0.025
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
lngfcap	0.029	0.020	0.020	0.024	0.017	0.017
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
lntotalarea	-0.673*	-0.578*	-0.567*	-0.674*	-0.580*	-0.574*
	(0.359)	(0.320)	(0.319)	(0.360)	(0.327)	(0.326)
N	3486	3486	3486	3486	3486	3486
# Instruments	251	269	269	251	269	269
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.935	0.910	0.913	0.906	0.890	0.895
Sargan Test [1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test [1,3]	0.126	0.309	0.301	0.117	0.293	0.300
Difference in Hansen Test (C statistic)						
L.lnGDPpps [1]	1.000	1.000	1.000	1.000	1.000	1.000
lnSubsTotMod [1]	1.000	1.000	1.000	1.000	1.000	1.000
Obj1 [1]	-	1.000	1.000	-	1.000	1.000
Emprate [1]	1.000	1.000	1.000	0.999	1.000	1.000
Ind.emp [1]	1.000	1.000	1.000	1.000	1.000	1.000
lnterteduc [1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap [1]	1.000	1.000	1.000	1.000	1.000	1.000
Votpower [1]	0.686	1.000	1.000	0.500	0.374	0.428
lnpopulden [1]	0.619	1.000	0.327	0.818	0.469	1.000
lntotalarea [1]	0.990	1.000	0.426	0.911	1.000	1.000
Year dummies [1]	0.978	1.000	1.000	0.980	1.000	1.000

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 9 System GMM

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.948***	0.952***	0.950***	0.946***	0.950***	0.950***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
lnSubsTot	0.004***	0.003*	0.004**	0.015***	0.014***	0.015***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
lnSubsTot^2				-0.002***	-0.002***	-0.002***
				(0.001)	(0.001)	(0.001)
Obj1		0.002			0.005	
		(0.005)			(0.005)	
*lnSubsT*Obj1*			-0.000			0.001
			(0.001)			(0.001)
Votpower	-0.103***	-0.095***	-0.099***	-0.131***	-0.126***	-0.126***
	(0.036)	(0.037)	(0.037)	(0.038)	(0.038)	(0.038)
Emprate	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind.emp	0.154***	0.146***	0.147***	0.154***	0.146***	0.145***
	(0.027)	(0.025)	(0.025)	(0.028)	(0.025)	(0.025)
lnpopulden	-0.001	0.001	0.001	-0.000	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lnterteduc	0.009*	0.008*	0.008	0.008	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lngfcap	0.008	0.005	0.006	0.008	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lntotalarea	-0.007	-0.004	-0.005	-0.007	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.264***	0.255***	0.261***	0.278***	0.270***	0.272***
	(0.059)	(0.059)	(0.060)	(0.064)	(0.062)	(0.062)
N	3748	3748	3748	3748	3748	3748
# Instruments	336	356	356	336	356	356
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.842	0.822	0.833	0.736	0.700	0.712
Sargan Test [1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test [1,3]	0.987	0.999	0.999	0.986	0.998	0.998
Difference in Sargan/Hansen Test (C statistic)						
Level instrum. [1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lnGDPpps [1]	1.000	1.000	1.000	1.000	1.000	1.000
lnSubsTot [1]	1.000	1.000	1.000	1.000	1.000	1.000
Obj1 [1]	-	1.000	1.000	-	1.000	1.000
Emprate [1]	1.000	1.000	1.000	1.000	1.000	1.000
Ind.emp [1]	1.000	1.000	1.000	1.000	1.000	1.000
lnterteduc [1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap [1]	1.000	1.000	1.000	1.000	1.000	1.000
Votpower [1]	0.330	1.000	1.000	1.000	0.191	0.439
lnpopulden [1]	0.570	1.000	1.000	1.000	0.150	1.000
lntotalarea [1]	0.289	1.000	1.000	0.377	0.118	0.109
Year dummies [1]	0.999	1.000	1.000	1.000	1.000	1.000

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 10 System GMM (modelled subsidy amounts)

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.946***	0.949***	0.948***	0.946***	0.950***	0.949***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)
lnSubsTotMod	0.004***	0.004**	0.004***	0.009***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
lnSubsTotMod^2				-0.001	-0.001*	-0.001
				(0.000)	(0.000)	(0.000)
Obj1		0.001			0.003	
		(0.004)			(0.004)	
*lnSubsT*Obj1*			-0.000			0.000
			(0.001)			(0.001)
Votpower	-0.099***	-0.094***	-0.095***	-0.107***	-0.105***	-0.104***
	(0.035)	(0.036)	(0.035)	(0.036)	(0.036)	(0.036)
Emprate	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind.emp	0.152***	0.141***	0.141***	0.151***	0.139***	0.138***
	(0.030)	(0.028)	(0.028)	(0.030)	(0.028)	(0.028)
lnpopulden	-0.001	0.001	0.001	-0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lnterteduc	0.010*	0.009*	0.009*	0.009*	0.008*	0.008*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lngfcap	0.009*	0.007	0.007	0.009	0.006	0.006
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
lntotalarea	-0.007	-0.005	-0.005	-0.007	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Constant	0.269***	0.262***	0.266***	0.278***	0.264***	0.266***
	(0.066)	(0.065)	(0.068)	(0.070)	(0.066)	(0.066)
N	3748	3748	3748	3748	3748	3748
# Instruments	336	356	356	336	356	356
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.795	0.784	0.788	0.792	0.776	0.778
Sargan Test [1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test [1,3]	0.986	0.998	0.998	0.985	0.998	0.998
Difference in Sargan/Hansen Test (C statistic)						
Level instrum.[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lnGDPpps[1]	1.000	1.000	1.000	1.000	1.000	1.000
lnSubsTot[1]	1.000	1.000	1.000	1.000	1.000	1.000
Obj1[1]	-	1.000	1.000	-	1.000	1.000
Emprate[1]	1.000	1.000	1.000	1.000	1.000	1.000
Ind.emp[1]	1.000	1.000	1.000	1.000	1.000	1.000
lnterteduc[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap[1]	1.000	1.000	1.000	1.000	1.000	1.000
Votpower[1]	0.482	0.107	0.057	0.693	0.357	0.208
lnpopulden[1]	0.406	0.839	1.000	1.000	0.386	0.620
lntotalarea[1]	0.529	0.547	1.000	1.000	0.623	1.000
Year dummies[1]	1.000	1.000	0.999	1.000	1.000	1.000

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 11 Least-squares dummy-variable (LSDV) estimation

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.816***	0.816***	0.817***	0.817***	0.817***	0.818***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
lnSubsTot	0.002**	0.001	0.001	0.006**	0.007**	0.007***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
lnSubsTot^2				-0.000	-0.001**	-0.001**
				(0.000)	(0.000)	(0.000)
Obj1		0.007***			0.009***	
		(0.003)			(0.003)	
*lnSubsT*Obj1*			0.001**			0.002***
			(0.001)			(0.001)
Votpower	0.334***	0.318***	0.327***	0.315***	0.285***	0.289***
	(0.075)	(0.077)	(0.076)	(0.069)	(0.072)	(0.071)
Emprate	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind.emp	-0.061	-0.069	-0.068	-0.056	-0.062	-0.061
	(0.058)	(0.058)	(0.058)	(0.057)	(0.057)	(0.057)
lnpopulden	-0.107***	-0.105***	-0.104***	-0.111***	-0.111***	-0.111***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
lnterteduc	0.011*	0.009	0.009	0.012**	0.010*	0.010*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
lngfcap	0.019***	0.018***	0.018***	0.019***	0.018***	0.018***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
lntotalarea	-0.049	-0.079	-0.075	-0.046	-0.080	-0.080
	(0.111)	(0.113)	(0.112)	(0.110)	(0.109)	(0.108)
Constant	2.131**	2.430**	2.389**	2.102**	2.446**	2.445**
	(1.024)	(1.038)	(1.034)	(1.012)	(1.002)	(0.993)
R-squared	0.996	0.996	0.996	0.996	0.996	0.996
N	3748	3748	3748	3748	3748	3748

* p<0.10, **p<0.05, *** p<0.01 ; Command areg (Stata) used which assumes that N is fixed and T ➔ ∞ (alternative approach applied but not reported is assuming T is fixed and N ➔ ∞ by using xtreg command which leads to slightly smaller standard errors in some cases and to higher significance levels for a few coefficients). Standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 12 Least-squares dummy-variable (LSDV) estimation (modelled subsidy amounts)

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.811***	0.812***	0.812***	0.811***	0.812***	0.812***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
lnSubsTotMod	0.004***	0.003***	0.003***	0.004*	0.005**	0.006**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
lnSubsTotMod^2				-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)
Obj1		0.006**			0.007**	
		(0.003)			(0.003)	
*lnSubsT*Obj1*			0.001*			0.001**
			(0.001)			(0.001)
Votpower	0.311***	0.293***	0.298***	0.311***	0.290***	0.293***
	(0.067)	(0.071)	(0.071)	(0.067)	(0.069)	(0.068)
Emprate	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind.emp	-0.063	-0.070	-0.070	-0.063	-0.068	-0.068
	(0.058)	(0.059)	(0.059)	(0.058)	(0.058)	(0.058)
lnpopulden	-0.100***	-0.098***	-0.098***	-0.100***	-0.101***	-0.101***
	(0.027)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)
lnterteduc	0.010*	0.008	0.009	0.011*	0.009	0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
lngfcap	0.018***	0.017***	0.017***	0.018***	0.018***	0.017***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
lntotalarea	-0.017	-0.045	-0.044	-0.016	-0.044	-0.045
	(0.112)	(0.114)	(0.114)	(0.112)	(0.111)	(0.110)
Constant	1.860*	2.132**	2.120**	1.852*	2.131**	2.137**
	(1.033)	(1.049)	(1.047)	(1.031)	(1.026)	(1.017)
R-squared	0.996	0.996	0.996	0.996	0.996	0.996
N	3748	3748	3748	3748	3748	3748

* p<0.10, **p<0.05, *** p<0.01 ; Command areg (Stata) used which assumes that N is fixed and T ➔ ∞ (alternative approach applied but not reported is assuming T is fixed and N ➔ ∞ by using xtreg command which leads to slightly smaller standard errors in some cases and to higher significance levels for a few coefficients). Standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 13 Difference GMM first lag subsidy

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.682***	0.701***	0.694***	0.683***	0.695***	0.692***
	(0.028)	(0.028)	(0.027)	(0.027)	(0.026)	(0.026)
L.lnSubsTot	0.012***	0.010***	0.010***	0.013**	0.007	0.009**
	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)
L.lnSubsTot^2				-0.000	0.000	0.000
				(0.001)	(0.001)	(0.001)
Obj1		0.016***			0.016***	
		(0.004)			(0.004)	
*L.lnSubsT*Obj1*			0.003***			0.003***
			(0.001)			(0.001)
Votpower	0.079	0.084	0.112	0.068	0.122	0.121
	(0.118)	(0.113)	(0.113)	(0.108)	(0.100)	(0.100)
Emprate	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ind.emp	-0.091	-0.095	-0.121	-0.089	-0.124	-0.127
	(0.220)	(0.204)	(0.199)	(0.214)	(0.199)	(0.197)
lnpopulden	-0.423***	-0.334***	-0.333***	-0.424***	-0.334***	-0.334***
	(0.066)	(0.061)	(0.062)	(0.067)	(0.063)	(0.064)
lnterteduc	-0.046**	-0.041**	-0.042**	-0.045**	-0.043**	-0.042**
	(0.020)	(0.019)	(0.019)	(0.021)	(0.020)	(0.020)
lngfcap	0.028	0.019	0.020	0.028	0.020	0.021
	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
lntotalarea	-0.773**	-0.697*	-0.719**	-0.771**	-0.704**	-0.709**
	(0.377)	(0.357)	(0.363)	(0.375)	(0.353)	(0.351)
N	3486	3486	3486	3486	3486	3486
# Instruments	248	266	266	248	266	266
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.702	0.603	0.594	0.712	0.581	0.593
Sargan Test[1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test[1,3]	0.097	0.242	0.229	0.091	0.235	0.236
Difference in Sargan/Hansen Test (C statistic)						
L.lnGDPpps[1]	0.994	1.000	0.999	0.995	1.000	1.000
L.lnSubsTot[1]	0.998	1.000	1.000	0.998	1.000	1.000
Obj1[1]	-	1.000	1.000	-	1.000	1.000
Emprate[1]	0.989	0.999	0.999	0.988	1.000	1.000
Ind.emp[1]	1.000	1.000	1.000	1.000	1.000	1.000
lnterteduc[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap[1]	1.000	1.000	1.000	1.000	1.000	1.000
Votpower[1]	0.236	1.000	0.515	0.252	0.290	0.311
lnpopulden[1]	0.963	1.000	1.000	0.987	1.000	1.000
lntotalarea[1]	0.876	1.000	0.566	0.870	0.797	0.836
Year dummies[1]	0.966	0.999	0.997	0.968	0.998	0.998

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 14 Difference GMM first lag subsidy (modelled subsidy amounts)

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.671***	0.683***	0.677***	0.662***	0.671***	0.668***
	(0.029)	(0.028)	(0.028)	(0.028)	(0.027)	(0.027)
L.lnSubsTotMod	0.013***	0.011***	0.011***	0.010***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
L.lnSubsTotMod^2				0.001	0.001	0.001
				(0.001)	(0.000)	(0.001)
Obj1		0.015***			0.014***	
		(0.004)			(0.004)	
*L.lnSubsT*Obj1*			0.003***			0.003***
			(0.001)			(0.001)
Votpower	0.025	0.036	0.054	0.045	0.061	0.074
	(0.099)	(0.096)	(0.095)	(0.096)	(0.091)	(0.091)
Emprate	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ind.emp	-0.175	-0.187	-0.193	-0.180	-0.198	-0.203
	(0.228)	(0.212)	(0.212)	(0.227)	(0.213)	(0.213)
lnpopulden	-0.427***	-0.349***	-0.345***	-0.408***	-0.337***	-0.336***
	(0.064)	(0.063)	(0.063)	(0.069)	(0.066)	(0.066)
lnterteduc	-0.039**	-0.034*	-0.034*	-0.044**	-0.039*	-0.038*
	(0.019)	(0.018)	(0.019)	(0.021)	(0.020)	(0.020)
lngfcap	0.032*	0.025	0.025	0.032*	0.025	0.026
	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)
lntotalarea	-0.751*	-0.660*	-0.670*	-0.768*	-0.671*	-0.681*
	(0.385)	(0.340)	(0.344)	(0.393)	(0.346)	(0.349)
N	3486	3486	3486	3486	3486	3486
# Instruments	248	266	266	248	266	266
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.702	0.674	0.663	0.683	0.646	0.645
Sargan Test[1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test[1,3]	0.097	0.255	0.260	0.101	0.253	0.258
Difference in Sargan/Hansen Test (C statistic)						
L.lnGDPpps[1]	1.000	1.000	1.000	0.998	1.000	1.000
L.lnSubsTotMod[1]	0.999	1.000	1.000	0.998	1.000	1.000
Obj1[1]	-	1.000	1.000	-	1.000	1.000
Emprate[1]	0.999	1.000	1.000	0.998	1.000	1.000
Ind.emp[1]	1.000	1.000	1.000	1.000	1.000	1.000
lnterteduc[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap[1]	1.000	1.000	1.000	1.000	1.000	1.000
Votpower[1]	0.174	0.229	0.209	0.141	0.149	0.155
lnpopulden[1]	0.786	1.000	1.000	0.742	1.000	1.000
lntotalarea[1]	0.610	1.000	0.884	0.605	1.000	0.945
Year dummies[1]	0.990	1.000	1.000	0.991	1.000	1.000

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 15 System GMM first lag subsidy

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.945***	0.947***	0.945***	0.942***	0.945***	0.943***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)
L.lnSubsTot	0.003***	0.003	0.003*	0.015***	0.012***	0.013***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
L.lnSubsTot^2				-0.001***	-0.001***	-0.001***
				(0.000)	(0.000)	(0.000)
Obj1		0.003			0.004	
		(0.004)			(0.004)	
*L.lnSubsT*Obj1*			-0.000			0.000
			(0.001)			(0.001)
Votpower	-0.104***	-0.095**	-0.100***	-0.142***	-0.127***	-0.132***
	(0.037)	(0.038)	(0.038)	(0.041)	(0.041)	(0.041)
Emprate	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind.emp	0.147***	0.136***	0.141***	0.147***	0.137***	0.139***
	(0.027)	(0.026)	(0.026)	(0.027)	(0.025)	(0.026)
lnpopulden	-0.000	0.001	0.000	0.000	0.001	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lnterteduc	0.007	0.007	0.007	0.006	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lngfcap	0.008	0.006	0.007	0.008	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lntotalarea	-0.007	-0.005	-0.006	-0.007	-0.006	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.295***	0.288***	0.280***	0.316***	0.313***	0.322***
	(0.063)	(0.063)	(0.065)	(0.066)	(0.067)	(0.067)
N	3748	3748	3748	3748	3748	3748
# Instruments	332	352	352	332	352	352
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.758	0.758	0.760	0.870	0.862	0.860
Sargan Test[1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test[1,3]	0.982	0.998	0.998	0.983	0.998	0.997
Difference in Sargan/Hansen Test (C statistic)						
Level instrum.[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lnGDPpps[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lnSubsTot[1]	1.000	1.000	1.000	1.000	1.000	1.000
Obj1[1]	-	1.000	1.000	-	1.000	1.000
Emprate[1]	1.000	1.000	1.000	1.000	1.000	1.000
Ind.emp[1]	1.000	1.000	1.000	1.000	1.000	1.000
lnterteduc[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap[1]	1.000	1.000	1.000	1.000	1.000	1.000
Votpower[1]	1.000	1.000	0.245	0.536	1.000	1.000
lnpopulden[1]	0.388	0.037	0.485	1.000	1.000	0.129
lntotalarea[1]	0.140	0.211	1.000	0.211	1.000	0.642
Year dummies[1]	1.000	0.037	1.000	1.000	1.000	1.000

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

Table 3. 16 System GMM first lag subsidy (modelled subsidy amounts)

Variable	I	II	III	IV	V	VI
L.lnGDPpps	0.945***	0.946***	0.945***	0.942***	0.946***	0.945***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
L.lnSubsTotMod	0.003***	0.003**	0.004**	0.010***	0.009***	0.009***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)
L.lnSubsTotMod^2				-0.001**	-0.001**	-0.001**
				(0.000)	(0.000)	(0.000)
Obj1		0.000			0.004	
		(0.004)			(0.004)	
*L.lnSubsT*Obj1*			-0.000			0.000
			(0.001)			(0.001)
Votpower	-0.104***	-0.102***	-0.106***	-0.133***	-0.127***	-0.128***
	(0.037)	(0.036)	(0.037)	(0.037)	(0.038)	(0.038)
Emprate	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind.emp	0.145***	0.133***	0.134***	0.139***	0.129***	0.131***
	(0.029)	(0.026)	(0.026)	(0.028)	(0.025)	(0.025)
lnpopulden	-0.000	0.000	0.001	-0.001	0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lnterteduc	0.009*	0.009*	0.008*	0.008	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lngfcap	0.008	0.007	0.007	0.009	0.006	0.007
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
lntotalarea	-0.006	-0.005	-0.005	-0.007	-0.005	-0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Constant	0.289***	0.294***	0.300***	0.322***	0.288***	0.313***
	(0.067)	(0.065)	(0.066)	(0.070)	(0.067)	(0.067)
N	3748	3748	3748	3748	3748	3748
# Instruments	332	352	352	332	352	352
AR(1) [1,2]	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) [1,2]	0.759	0.757	0.754	0.763	0.770	0.763
Sargan Test[1,3]	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test[1,3]	0.981	0.998	0.998	0.983	0.998	0.998
Difference in Sargan/Hansen Test (C statistic)						
Level instrum.[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lnGDPpps[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lnSubsTot[1]	1.000	1.000	1.000	1.000	1.000	1.000
Obj1[1]	-	1.000	1.000	-	1.000	1.000
Emprate[1]	1.000	1.000	1.000	1.000	1.000	1.000
Ind.emp[1]	1.000	1.000	1.000	1.000	1.000	1.000
lnterteduc[1]	1.000	1.000	1.000	1.000	1.000	1.000
L.lngfcap[1]	1.000	1.000	1.000	1.000	1.000	1.000
Votpower[1]	0.268	0.331	0.143	1.000	0.246	1.000
lnpopulden[1]	0.810	0.255	0.125	1.000	0.598	0.076
lntotalarea[1]	1.000	1.000	0.379	1.000	1.000	1.000
Year dummies[1]	1.000	1.000	1.000	1.000	1.000	1.000

* p<0.10, **p<0.05, *** p<0.01 ; [1] p-values reported; [2] Arellano-Bond test autocorrelation first order (1) and second order (2); [3] Test of overidentifying restrictions; Windmeijer (2005) finite sample correction applied for standard errors reported in brackets. Year dummies are included in all models (not reported).

General Conclusions

The goal of this dissertation was to extent the existing literature on R&D subsidies by taking into account factors and new information not yet considered. This has been done by performing three empirical examinations. In the first chapter the role of geographic proximity as a proxy variable for lobbying/networking potential was evaluated in the context of the R&D subsidy granting process. In the second chapter the role of different subsidy sources and regional heterogeneity in the subsidies' impact have been examined. In the third chapter, the European Unions' public support programme ESIF was evaluated regarding its impact on regional economic development utilizing newly available data that had not been considered in the existing literature. In the following the evidence found, conclusions that have been made, and limitations of the three studies are elaborated briefly.

Chapter 1 Geographic proximity to the European Commission and the likelihood to be granted with a subsidy from the EU

In the first chapter, the potential effect of the geographic proximity between innovation subsidy seeking companies and innovation subsidy granting authorities is examined. By using a representative sample of Flemish companies, the relation between their physical distance to the subsidy granting authority and their likelihood to receive an innovation subsidy is investigated. The results show that in case of EU authorities located in Brussels there is a statistically significant effect related to the distance, i.e. the closer a company is located to the EU authorities in Brussels the higher is its likelihood to be granted an innovation subsidy from the EU.

Considering other subsidy granting authorities (the Belgian Federal Government and the Regional Government of Flanders) located in Brussels, there is no statistically significant relation between companies' distance to the programme-managing authority and the likelihood of being granted an innovation subsidy. The occurrence of these results were in line with the hypotheses considered in the conceptual part of the study. Geographic proximity is expected to play a role only in presence of lobbying and networking activities of the companies. As Boschma (2005) states, the presence of high geographic proximity solely is not sufficient to have an effect. It is well known

that the EU authorities are subject to intense lobbying efforts by economic and political agents (Van Schendelen, 1996, 2013)[77].

For that reason a Lobby-Register (Transparency Register[78]) was established and furthermore the EU-politicians are expected to disclose their meetings with lobbying agents. The debate whether these measures are sufficient to avoid mis-allocation of public funding due to lobbying is still ongoing. First, the registration of such meetings takes place on a voluntary basis only. Second, it is not possible to trace effectively informal lobbying activities. While EU authorities are subject to intense lobbying, the Belgian Federal Government and Regional Flemish Government seem less prone of being in strong focus of lobbying parties. It therefore appears plausible that the empirical estimations applied in this chapter suggest a role for the geographic proximity in case of strongly lobbied EU authorities but not in case of other less-lobbied authorities.

A second hypothesis tested is whether company conglomerates may utilize their groups' subsidiaries which are more closely located to subsidy granting authorities than the headquarter. However, no statistical significant evidence has been identified. That in turn suggests, the companies' own location is decisive when taking the geographic proximities' effect into account. A limitation here is that the dataset used does not contain the possible presence of external agents which could be commissioned to conduct lobbying activities in the name of a company. Also the distances observed in our data are limited as we only consider the region of Flanders in Belgium. It is well possible that group members play a role when further distances are taken into account.

Another possible limitation of the analyses conducted is the utilization of geographic proximity as a proxy for lobbying and networking activities. Comprehensive data on lobbying and networking activities are not available currently and therefore it would be desirable to conduct research on this subject in the future with more precisely measured and more detailed lobbying/networking activity data.

[77] See also: Corporate Europe Observatory (CEO), a non-profit organization watching lobbying activities on the European policy making. https://corporateeurope.org/

[78] https://ec.europa.eu/transparencyregister/public/homePage.do?redir=false&locale=en

Chapter 2 The role of subsidy source and regional context in innovation subsidies' input additionality

In the second chapter, the possible heterogeneity of innovation subsidies' impact is assessed for situations in which subsidy recipients are granted public support from different sources (Guellec and Van Pottelsberghe De La Potterie 2003, Blanes and Busom, 2004). First, it is possible that different companies are granted with subsidies from different sources leading to heterogeneous treatment effects. Second, the same company could be granted simultaneously innovation subsidies from different sources and such multiple treatments could also be a reason for heterogeneity in treatment effects. Third, the two possibilities described above could occur in the same sample of companies in parallel. The goal of this chapter has been to disentangle such heterogeneity in treatments and their possible heterogeneous effects.

Furthermore, the regional context could also play a role in moderating the impact of received subsidies (Montmartin et al., 2018). As an example, the same subsidy programme could have different effects for two groups of companies where the first group is located in a well-developed region with prospering economic status and the second group is located in a less-developed region with poorer economic status. Not taking such regional heterogeneity into account could lead to biased results in the estimations of treatment effects. Such examples of possible omitted variable bias have been addressed recently by several researchers (Hægeland and Møen, 2007; Czarnitzki and Lopes-Bento, 2014; Montmartin et al., 2018).

Following up on this strand of literature, the potential effect of different subsidy sources and regional context have been researched utilizing a representative sample of companies active in Belgium. Different subsidy sources considered are EU authorities, the Belgian Federal Government, and Belgian Regional Governments. While the Belgian Federal Government mostly grants indirect subsidies in form of withholding taxes for R&D employees, the other authorities grant direct subsidies only. The Brussels-Capital region, Flanders, and Wallonia are the different regions where the companies in the sample are located. Nearest neighbour matching procedures are applied in a first step to create a matched control group of companies.

Comparisons of matched treatment and control groups show empirical evidence for a general, positive effect of subsidies on innovation inputs of the companies.

In a second step Ordinary least squares (OLS) estimations are applied by regressing the estimated treatment effects from the first step on subsidized firms' characteristics, in particular their regional location, as well as the sources of subsidies. The second step delivers several insights. Subsidies granted by regional authorities and the EU seem to be complements, i.e. companies that received subsidies simultaneously from these sources invest more in R&D and innovation compared to other combinations of subsidy sources (policy mix). This result shows that subsidy sources should be considered and that the effects can be heterogeneous.

Companies located in Wallonia respond with lower treatment effects on subsidy receipts compared to companies in other regions. In contrast, firms located in Brussels show the highest treatment effects when subsidized. These results confirm that the firms' regional context can lead to heterogeneity in subsidies' impact.

Finally, a somewhat unexpected insights hints on the regional heterogeneity of subsidy impacts even for non-competitive subsidies such as tax benefits. Companies located in Brussels respond with a stronger treatment effect when they are subsidized with tax benefits. Since these subsidies are granted without a selection process on R&D project quality by the managing authority, the result may be assigned to the subsidy type.

Chapter 3 The Impact of EU's ESIF programme on the regional economic development

The European Union (EU) provides public support through different programmes which aim for economic development and sustainability as well as the reduction of regional economic disparities within its territory. A large part of the EU budget is distributed through the European Structural and Investment Funds (ESIF) which comprehend different public support programmes to target different goals. Regional development of economically poor regions is one of the major priorities and thus certain regions within the EU are classified as less developed regions, called Objective 1 or Convergence regions, which qualify for a higher level of public support. Other

regions not falling in this regional category also receive subsidies but more rarely and at a lower level in terms of volume.

Economic literature mostly focused on the Objective 1 regions' development and the EU's public support to these regions. Until mid-2018 the data available to assess the impacts of EU support had a limited reliability as real money transfers of public support were not available. Instead scholars had to rely on so called planned/committed subsidy payment data which did not necessarily correspond to actual money transfers; especially the timing of the actual payments may have deviated non-negligibly from initial planning. The European Commission (EC) improved the situation with more reliable data recently. The third chapter's subject is thus to provide new evidence on EU's public support through ESIF; also not only focusing on Objective 1 regions but all subsidized regions. General Method of Moments (GMM) panel estimations are applied by taking into account relevant regional economic factors as well as their endogeneity with the dependent variable (Gross Domestic Product (GDP)). The analyses reveal statistically significant and positive effects on recipient regions' GDP growth and that Objective 1 regions exhibit additional economic growth. Thus, the results confirm that the ESIF programme leads to positive economic developments. Furthermore, the classification of Objective 1 regions works as aimed and generates higher economic growth.

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