Faculty of Economics and Business

KU Leuven – University of Leuven

Learning how to behave
An analysis of the behavioural changes induced by public support for R&D

Dissertation presented

to obtain the degree of

Doctor in Business Economics

by

Daniel NEICU

Doctoral Committee

Supervisor
Prof. Dr. Stijn Kelchtermans

Co-supervisors
Prof. Dr. Reinhilde Veugelers
Prof. Dr. Peter Teirlinck

External Members
Prof. Dr. Albert Banal-Estañol
Prof. Dr. Pierre Mohnen

I would like to thank my family, friends, supervisors, committee members, colleagues and everyone else who has supported me in writing this thesis.

Contents

List of Figures

List of Tables

Introduction

"If we expect evaluations to be able to confirm 'what works' in an area of high complexity such as innovation policy, then we are surely expecting too much."[1]

This research aims to contribute to the increasing demand for evidence-based policy making by analysing the spread and impact of policy support measures aimed at achieving a socially optimal level of R&D and innovation. Moreover, I analyse how public funds affect the behaviour of supported firms, but also individual researchers. I emphasise the word 'contribute' here as I do not pretend to provide an all-encompassing view of what works and what does not, but merely add a brick in the growing wall of evidence of how R&D support affects beneficiaries and ultimately society.

The motivation for public intervention in private R&D stems from the link between research and development, innovation and economic growth (Mansfield, 1972). Underinvestment in R&D – as a component of innovation systems – hinders growth, which paves the way for growth-seeking governments to support firms' efforts in R&D in order to achieve a 'socially optimal' R&D activity that will produce the innovations needed for advancing the overall societal wealth. In other words, when innovation suffers, society suffers.

Underinvestment in R&D is typically based on two main market failure arguments (Arrow, 1962). First, because knowledge is a non-rival and non-exclusive good, firms cannot fully appropriate the returns on their R&D investments; this stems from knowledge having high fixed costs of production and low marginal costs of utilisation. Second, uncertainty is a defining characteristic of innovative activity. When firms engage in R&D, they cannot fully predict the output by the inputs they employ. If economic actors are risk averse, they will discriminate against risky projects (Arrow & Lind, 1970).

More recently though, RDI policy has been observed from a slightly different perspective that complements the focus on the individual firm with a more systemic rationale for intervention (Laranja, Uyarra, & Flanagan, 2008; Dodgson et al., 2011; Edquist, 2011).[2] The 'systemists',

---

[1] Flanagan and Uyarra (2016, p. 184).

[2] The term 'systemic' here should be read with a dose of circumspection; it does not imply a systematic approach to categorising rationales for policy intervention, but merely defines problems within a framework of innovation systems, rather than the linear, neo-classical approach to innovation.

if I may, argue that having a market fail implies departure from an ideal innovation system, which would be near-impossible to define (Edquist, 2011, p. 1726). They prefer regarding innovation as a system – or, to be precise, a multitude of systems – which R&D, financing and institutions are parts of.[3] For them, policy intervention is required by systemic problems rather than market failures. Systemic problems are direct results of the evolutionary nature of innovation systems, where path dependency can accommodate trajectories that lead to devolution rather than evolution. For example, in the late '70s JVC's VHS became the standard consumer analogue video recording system despite the existence of technically superior alternatives, such as the Betamax. In evolutionary theory, a system needs to produce more offspring than can survive in order to ensure that competition leads the fittest to pass on their genes. Similarly, an innovation system needs to support alternative paths that might lead to better results. Bluntly put, institutions have the role of ensuring enough variation in R&D as to create the premises for evolution – or survival of the fittest innovator. With the risk of spoiling the narrative with specificity, I note here that 'cherry-picking' the most promising research is not a role of institutions, but of the system itself. In this framework, policy should not be subsidising top R&D performers, but rather ensure that a wide variety of firms and / or projects compete with each other.

The 'choice' of rationale for policy intervention – at least in scholarly environments – has so far had less to do with the economic context and more with the prevailing school of thought in economic theory at a given point in time. The persistence of market failure arguments for policy intervention is tied to the prevalence of neo-classical welfare economics (Laranja et al., 2008, p. 824). As evolutionary economic theories appeared, the linear approach to innovation has been gradually complemented by the systemic view (Magro & Wilson, 2013).

My thesis tries to bridge the gap between the market failure and systemic strands of theory, in response to recent calls from scientists and policy makers alike for a more integrated view of research, development and innovation (Laranja, Uyarra, & Flanagan, 2008; Dodgson et al., 2011; Edquist, 2011). I understood these calls from three perspectives: a) the need to analyse R&D support both vertically – that is, at the intersection between supra-national, national and

[3] I refer to R&D and institutions as 'parts' of the system, rather than 'components'. A more exact wording – in systemic jargon – would be 'activities' of the system of innovation (SI).

sub-national policy (Martin, 2016)[4] – and horizontally – i.e. the variation between different policy implementations, such as direct and indirect measures; b) a need to focus on possible interactions that happen not only at policy level, but also between users of policies; c) and finally, the necessity for a 'high-resolution' analysis of knowledge creation through research by focusing not only on firms, but also zooming-in on the behaviour of individual researchers as part of a knowledge-creation system. This ABC that I develop throughout my thesis acknowledges the fact that research and innovation systems are dynamic and evolve through time and across borders and actors, but also that creation through R&D has multiple loci and sources (Lundvall, 2007; Dodgson et al., 2011). Failure to address issues on any of these dimensions may result in what can be defined as 'system failure'. For example, unsolved systemic problems in academic research will result in a reduced pool of scientific knowledge that entrepreneurs can draw upon to create innovations for society through R&D activity. Similarly, failure to address problems at the entrepreneurship level will results in less innovation and, consequently, a reduced public appetite to fund science at the bottom of this food chain.

The political answers to the issues with R&D and innovation described so far come in various shapes and colours. In Belgium alone, there are more than 20 different support measures for R&D. For example, there are six R&D-related tax exemptions granted by the federal government, and they apply – in theory – uniformly across the national territory. On the other hand, regional authorities have devolved powers which allow them to set separate subsidy schemes. While this may allow communities to tackle local issues through R&D support, it results in over 15 subsidy schemes spread over the three regions – Brussels, Flanders and Wallonia. The birth of such 'multi-headed monster' policies came from common-held views that policy makers were under-utilising the portfolio of instruments that were available to them (Flanagan, Uyarra, & Laranja, 2011), and the subsequent systemic shift from national to multi-level intervention (Martin, 2016, p. 166). Recent audits of the Belgian R&D support landscape have found it to resemble a maze which firms find difficult to navigate, resulting in many eligible firms not using support they are entitled to (Soete, 2012; Dumont, 2013).[5]

---

[4] The supra-national level – although an important part of a systemic approach to the analysis of R&D and innovation policy – is out of scope of this thesis. I do, however, admit this shortcoming and strongly advocate future research should integrate, to the extent possible, this extra policy dimension.

[5] The 'Soete Reports' analyse R&D support in Flanders, the largest of the three administrative regions in Belgium. Even in this relatively small – on an international scale – 6.4 million-inhabitant region, there is a high degree of fragmentation in the R&D support landscape. Considering that the Walloon and Brussels-Capital regions follow

Chapter I

Building on this observation, in the first chapter I analyse to what extent there is a lack of information about support measures for R&D and what are the behavioural processes that firms rely on to overcome this deficit. My research complements the literature on peer effects on firms' decision-making (Gort & Konakayama, 1982; Kennedy, 2002; Lu, 2002; Debruyne & Reibstein, 2005; Leary & Roberts, 2014) by studying the adoption of R&D support. The theoretical basis for this analysis is that peer effects may play a role if the R&D support landscape is complex, and firms rely on their peers' decisions as an input in their own adoption decisions.

Specifically, using a complex empirical identification strategy, I show that firms' decisions to use R&D tax credits are influenced by the choices of their peers, defined at the intersection of geographical and economic proximity. The setting has similarities with regional systems of innovation literature where tacit knowledge – in my case information about cost-reducing R&D tax credits – is geographically bound as it is spread through interpersonal contacts between employees and managers of different firms (Maskell & Malmberg, 1999). This social dimension is a key issue in studying adoption decisions, that is, its comprehensive assessment necessitates rising above the level of the individual firm to include social feedback effects (Hall, 2004).

The fact that information travels in peer groups that follow industry and distance-based default lines suggests possible policy interventions for reducing inefficiencies in the take-up of R&D support. Adoption by eligible firms could be expedited by communicating the measure to sufficiently fine-grained sectors, and in a geographically-distributed way. As opposed to broad policy communications, 'narrowcasting' would help to reach many localized firm clusters, or peer groups, allowing for rapid peer-to-peer influence once initial adoption has taken place.

Chapters II and III

The build-up of the number of firms receiving R&D support – whether affected by their peers or other factors – has been constant over time, and in 2011 there were almost 2,000 Belgian companies receiving either payroll tax exemptions or subsidies (or both) for R&D. The government's budgetary effort surpassed 500 million Euros for these financing lines alone. This

similar patterns, the overall national policy is intricate and requires skilled managers to make proper use of public support and lower firms' R&D cost.

non-negligible amount has led me to examine those companies that manage to navigate their way through the multitude of support schemes. More precisely, in the second and third chapters, I analyse the effects of R&D payroll tax credits and subsidies on firms' R&D behaviour, both from an integral perspective, but also by focusing on the split between (basic and applied) research and development. Moreover, I shed light on the interaction between two policy measures, in a bid to help policy makers construct a more coherent support environment.

There is a chronic lack of empirical evidence of the interaction between direct and indirect – and, more generally between different levels of – support for R&D, which has been signalled multiple times in recent years (Flanagan et al., 2011; Aranguren et al., 2014). A study for the European Commission concludes: "*the limited empirical evidence indicates that interactions between different policy measures probably exist*" (Straathof et al., 2015). Furthermore, the interaction between (inter-)national and regional policy is even more opaque, in the context of distribution of authority from national level 'downstream' – to regional level – but also 'upstream' – to international structures (Flanagan et al., 2011; Lanahan & Feldman, 2015; Martin, 2016). Federal systems of governance provide an ideal context to study interactions between policies at different levels of administration (Lanahan & Feldman, 2015, p. 1387). Although incomparable in size to the US, Belgium does offer fertile ground for study by having numerous R&D policies spread across federal and regional governmental agencies. My analysis provides evidence that federal fiscal exemptions and regional subsidies do seem to interact in ways that increase firms' response to receiving them – but that also depend on how responses are defined.

Although empirical evidence is not yet abundant, the theoretical consensus seems to be that different policies will interact with one another, sometimes in unpredictable ways. Martin (2016, p. 167) provides a useful analogy with healthcare, where drugs used to treat different ailments may interact in complex manners. Even though each drug may be the best treatment for its target illness, other drugs may counteract its effect and vice-versa; as physicians need to take all these interactions into account, policy makers should also design R&D instruments without neglecting how they may affect each other.

The interaction of public policies has rarely been defined or analysed. With a few exceptions, such as the Small Business Innovation Research (SBIR) state programmes in the US that were introduced with the specific aim to reinforce federal SBIR funding of innovative SMEs

(Lanahan & Feldman, 2015), the reasons and ways in which different policies may interact or not are rather cloudy.[6]

First, the simultaneous use of tax credits and subsidies might simply create a volume effect. That is, users of the policy mix may take advantage of the fact that the amount of support received is increased by combining two measures. For example, the average subsidy received by Belgian firms in my sample in 2011 was 259 thousand Euros, while the average amount of tax credits was 198 thousand Euros. On the other hand, the average value of support for those combining the two was a whopping 788 thousand Euros. Although skewed, this number seems to point to the possibility that combining support measures in a mix provides larger amounts for funding R&D, which may induce a more-than-proportional response from companies. This scale effect is especially plausible if both support measures would have the same scope.

Second, just as different medical treatments are prescribed for different health problems, R&D policies might be used to tackle different issues with innovation activity. For example, as regional subsidies in Belgium come in a large variety of forms, one may assume that some support measures tackle specific problems, such as lack of access to finance for SMEs, lacklustre innovation results in some industries, high unemployment of qualified researchers in some regions and so on. Wage-based fiscal exemptions, although also coming in a (smaller) variety of deductions, apply more evenly to firms across geographical regions. In this case, their main objective is to provide incentives for companies to increase private investment in research and development. Recently, Busom et al. (2014) analysed how Spanish firms' different characteristics are correlated with the use of either direct or indirect support. They find that subsidies and tax credits do not address the same barriers to innovation, and as such they cannot be substituted with one another. Subsidies seem to be more sought after than tax credits by firms that find it hard to access external financing for their R&D, while tax credits are more utilised by firms with less appropriability concerns. However, the latter result may be instrument-specific, as Spanish tax credits are deductions on firms' corporate tax liability, and thus apply to profit-making enterprises. Companies in poorer financial health will find it difficult to finance their R&D projects from external sources, but, if their projects have innovative potential, they can be granted subsidies. In this case, the amount of tax credits they might receive is more uncertain than grants, as it depends on the firms' ex post tax positions

[6] I refer to interaction in a rather loose manner – it generally refers to the effect of using a policy mix rather than a single policy.

(Busom et al., 2014, p. 577). I argue that the Belgian wage withholding tax exemption that I analyse throughout this thesis behaves differently from its Spanish counterpart in the sense that companies are almost sure of the amount exempted ex ante, as this is based on the wages of their researchers and the administrative burden of applying is low.[7]

Third, policies may have varying impact on different types of R&D activities. For example, tax credits might increase spending on closer-to-market (development) projects (David et al., 2000; Czarnitzki et al., 2011), while subsidies could be used for more basic research (Clausen, 2009; Dumont, 2015). If this were the case, then the fact that each policy changes the balance between research and development could go unseen in a traditional input additionality analysis.

Finally, another possible reason for interaction effects between subsidies and tax credits could be the following: while R&D subsidies are generally targeted towards long-term research projects, there may be spillovers with respect to the way tax credits are used by the firm. For example, I show in the second chapter that subsidies do not affect by themselves the amount of (basic and applied) research performed by firms; but when used alongside tax credits, they increase spending on these activities. The reasons for this kind of interaction may be well beyond the power of the Community Innovation Survey (CIS) data, in the sense that R&D spending – even split into different activities – can only capture one facet of firms' behaviour. Although highly informative, analyses based on CIS do not reach the detailed behavioural aspects captured by the focused survey at the basis of the data used in the third chapter. Results such as increasing the speed of R&D activities or scaling-up R&D projects when firms use subsidies and tax credits together cannot be shown when only looking at R&D spending. But they become evident when behavioural aspects are zoomed-in on in the specific way that the Belspo survey on the use of tax exemptions does. This data allows me to delve deeper into the changes in R&D behaviour in the third chapter and reveal that those firms that add subsidies to tax credits use are able to increase the speed at which they produce research results and increase the scale and number of R&D projects. Furthermore, I am also able to show a reorientation of the resources freed up by tax exemptions towards research and away from development.

In order to justify the existence of these effects, one needs to analyse how the subsidy (i.e. R&D project) changes the R&D environment such that the firm uses the tax credit differently. I argue that it may be a very real possibility that subsidized firms direct the financial resources freed

[7] Note that, as I mention in the second chapter, Belgium also provides an R&D investment tax credit similar to the Spanish and other national systems, which due to data constraints is out of scope of my research.

up by the tax exemption towards the subsidized project(s), and as such provide direction for the use of the R&D tax credit. In other words, those financial resources may find a 'productive home' within the context of the subsidized project. More specifically, the subsidized R&D projects may serve as a roadmap, pointing to a more productive way for allocating additional R&D resources. For example, the tax credit may create room for additional experimentation in the subsidized R&D activities that the firm would not have undertaken otherwise.

Chapter IV

In the fourth chapter I change the scope of the analysis and shift focus from companies to individual researchers. In doing so, I analyse what individual and institutional factors – funding being among them – encourage academics to change their behaviour and venture into new scientific fields.

As most previous studies have focused on scientific productivity and collaborations (Bozeman & Gaughan, 2007; Goldfarb, 2008; Defazio, Lockett, & Wright, 2009; Auranen & Nieminen, 2010; Jacob & Lefgren, 2011; Grimpe, 2012; Hottenrott & Lawson, 2013; Kelchtermans & Veugelers, 2011, 2013; Whalley & Hicks, 2014), I set to provide empirical evidence regarding what drives exploratory behaviour in science. My results on the impact of funding show that academics at the University of Leuven are less inclined to venture into new research fields if they have obtained funding from the faculty's research council. This mechanism favours more senior researchers with a better track record and higher rank. I also find that scholars with a better track record are more likely to enter new fields, and the positive effect from productivity on new field entry is even more pronounced when I correct for (instrumented) funding. Moreover, only when correcting for the effect of funding, researchers that have progressed through the promotion ladder are more likely to venture into new fields.

The results suggest that grants lead academics to stay within their existing research areas, rather than diversifying their portfolios by entering new fields. Recent calls from prominent scientists show that there is a pressing need to improve the design of funding mechanisms, which has underscored that we still do not fully understand the amalgam of incentives given by funding (Lane, 2009). My research fits in this context and contributes to the scarce empirical productions that explain scientific behaviour other than productivity. I argue that policy design is of utmost importance at all stages of innovation systems, including the production of academic research. It is thus important that policy makers have robust evidence of how funding affects science, and my results show that at least one type of grants lead towards specialisation rather than diversification. This does not in itself imply that policy has failed science. For example, it may be the case that this specific line of finance has been directed towards specialisation as a response to ‘too much’ experimentation through entering new fields and a consequent drop in scientific productivity. My research should be read as an analysis of a multitude of drivers of experimentation, as it stops short – thus far – of addressing the policy motivations that may stand behind the intervention.

I. Peer effects in the take-up of R&D tax Credits

Abstract

This paper starts from the observation that the majority of firms in Belgium that were eligible for a newly-introduced R&D tax credit does not use it, or is slow to adopt, despite significant potential cost savings. We hypothesize that the R&D support landscape is too complex for firms to navigate and that they may cope by relying on their peers' behaviour to inform their own decision. We identify endogenous peer effects in industry and location-based peer groups by exploiting the intransitivity in firms' networks as well the variation in peer group size. The results show that firms' decision to use R&D tax credits are indeed influenced by the choices of their peers, primarily in the time window immediately following their introduction. Our analysis complements existing literature on peer effects on firms' decision-making and suggests improvements for the communication of new public support for business R&D.

Keywords R&D tax credits, peer effects, information diffusion, social interactions.

JEL Codes D01 – D22 – D80 – D85 – O30.

Acknowledgements Financial support from KU Leuven – HU Brussels (ZKC7171) and the National Bank of Belgium is gratefully acknowledged. The authors would also like to thank the Belgian Federal Public Service Finance for providing data used in this paper.

1 Introduction

Social, or ‘peer-to-peer’, interactions have been considered in the literature as a way to transfer knowledge (Noorderhaven & Harzing, 2009; Corredoira & Rosenkopf, 2010). In particular, economic agents may draw lessons and create expectations from the observation of actions and outcomes experienced by others (Manski, 2000). Through this lens, peer effects have been studied extensively for explaining social behaviour, such as job-searching (Nanda & Sørensen, 2010; Cappellari & Tatsiramos, 2011) or the initiation of sexual activity (Card & Giuliano, 2011). The social connectedness of firm decision-making has been investigated less, arguably due to the difficulty in directly observing inter-company interaction, which we address in section 2. Nevertheless, this social dimension is a key issue in studying adoption decisions, that is, its comprehensive assessment necessitates rising above the level of the individual firm to include social feedback effects (Hall, 2004). Despite the empirical challenges in observing peer groups, a number of studies have looked into the role of ‘social influence’ in the corporate world by considering, in various settings, whether a larger number of adopters of a certain decision increases the probability of it spreading further. Evidence of such imitation behaviour has been provided in studies of market entry (Gort & Konakayama, 1982; Kennedy, 2002; Lu, 2002; Debruyne & Reibstein, 2005), investment banking (Haunschild & Miner, 1997) and corporate financial policy (Leary & Roberts, 2014).

Our paper complements the literature on peer effects on firms’ decision-making by studying the adoption of R&D support. The theoretical basis for our analysis is that peer effects may play a role if the R&D support landscape is complex and firms may rely on their peers’ decisions as an input in their own adoption decisions. In Belgium, the setting we study, one would at first sight expect rapid and widespread adoption, with little role for peer effects. Reasons include the fact that the administrative cost of applying for the tax credit is essentially zero and that the tax credit is effectively implemented as a *wage subsidy for R&D workers*, so a firm needn’t report positive profits to benefit from the measure. In other words, not using the R&D tax credit while being eligible comes down to leaving money on the table. However, audits of the portfolio of R&D support mechanisms have found it to resemble a thicket that firms find difficult to navigate, up to the point where many eligible firms do not use support they are entitled to (Soete, 2012).[8] Dumont (2013), reporting descriptive evidence on the uptake of the fiscal incentives for R&D introduced in Belgium in 2005, concludes that most R&D active companies do not use the measure four years after its introduction. Our sample of Belgian firms shows that even by 2011, hardly 40% of the firms eligible for the tax credit use it. Similar evidence has been reported for other countries. For example, Falk et al. (2009) find that companies in Austria lack awareness of the structure of tax incentives and point towards insufficient information as a reason for non-adoption. A study by Bozio et al. (2014) reveals that in France, after the shift from an incremental to a more generous volume-based tax credit scheme in 2008, the share of eligible firms that does not apply still surpasses one in three companies.

The situation in which initially only a relatively small share of eligible firms adopts the tax credit in a complex support environment creates the opportunity for peer effects to occur. More specifically, if information about support is complex – i.e. the abundance of support schemes – and uncertain – in terms of eligibility – firms may resort to heuristics in their decision-making. One such approach is to imitate decisions of peers who have adopted the measure earlier. Prior work has found evidence of peer effects in firm decision-making in diverse areas, including financial decisions (Leary & Roberts, 2014), market entry strategy (Debruyne & Reibstein, 2005) and compensation of top management (Albuquerque, 2009).

Using the peer effects rationale, we investigate to what extent firms' adoption of the R&D tax credit can be attributed to decisions of their peers, rather than own firm characteristics or unobserved shocks pushing whole groups of companies towards adoption of the tax credit.

Analysing a sample of 1,981 R&D active companies in Belgium, and relying on an innovative – in this setting – IV approach for identifying the endogenous peer effects, we find that a firm's decision to take up R&D tax credits is influenced by the choices of its peers. We start from the empirical observation that a majority of possible users of R&D tax credits seem reluctant to use them, despite the significant wage cost reduction involved. Attributing low adoption rates to lack of information, this paper is the first to demonstrate how peer effects shape firms' response to R&D public support schemes with limited information regarding peer networks.

[8] The so-called 'Soete reports' considered R&D support in the Flemish region, which is the largest of the three regions in Belgium. However, the R&D support landscape in the Walloon and Brussels Capital Region is also characterized by a proliferation of support measures.

Our findings show that imitation is one of the strategies employed by firms in order to cope with the multitude of public support measures they face.

Our paper makes the following contributions. First, we complement the literature on support for innovation by showing how peer effects influence firms' usage of public support schemes. This is important, as an accurate understanding of the dynamics of firm choices is essential for reducing inefficiencies, i.e. the belated absorption of public support for R&D. Our results suggest that firms develop strategies to cope with the complexity of the R&D support landscape by imitating firms who adopt earlier. The finding that imitation occurs in peer groups that follow industry and distance-based default lines suggests possible policy interventions for reducing inefficiencies in usage of R&D support. More specifically, adoption by eligible firms could be expedited by communicating the measure to sufficiently fine-grained sectors and in a geographically-distributed way. As opposed to broad policy communications, 'narrowcasting' would help to reach many localised firm clusters, or peer groups, allowing for rapid peer-to-peer influence, once initial adoption has taken place. Second, the establishment of peer effects as a significant factor driving firms' selection into support schemes informs the methodological literature on selection bias in program evaluation (Imbens & Wooldridge, 2009).[9] Namely, the existence of peer effects calls for looking beyond the individual firm to explain selection into support programs. More generally, by using recent advances in identification strategy for peer effects (Bramoullé et al., 2009; De Giorgi et al., 2010), this paper contributes to the broader literature on peer effects between firms. More specifically, by relying on a nearest-neighbour peer group definition, peer groups vary at the individual firm level. This variation implies the presence of excluded peers – i.e. firms that are not part of firm *i*'s peer group, but who are peers of *i*'s peers. The exogenous characteristics of these excluded peers act as instruments for the endogenous peer effect because they are correlated with the adoption decision of firm *i*'s peers by means of social interactions, but they are uncorrelated with shocks affecting firm *i* and its peer group. Given the high degree of clustering in many 'small world' firm networks (e.g. Fleming & Marx, 2006), this approach of exploiting intransitivity in firms' networks is more generally applicable to identify peer effects in other settings. One example would be the

[9] Imbens and Wooldridge (2009, p. 14) signal that only recently have social interactions been regarded as an 'object of interest', rather than nuisance, in studies of program evaluation. Our paper adds evidence to this very recent trend and does so in a new setting – that of tax credits for R&D.

analysis of knowledge spillovers in networks of inventive activity, as measured by co-patenting between firms.

The rest of the paper is organized as follows. Section 2 presents the definition of peer groups, which ties into our identification strategy and empirical model, both of which are discussed in section 3. Section 4 discusses the results of the analysis of peer effects in R&D tax credit adoption and reports the robustness checks. Section 5 concludes.

2 Peer group definition

Any identification of peer effects on decision-making needs to start from the definition of peer groups. This constitutes a key challenge since the circles of peers in which information is transferred may be informal and therefore hard to trace empirically. While some settings in social interaction literature provide an institutional dimension that offers a handle on peer groups, e.g. class allocations of students, it is not straightforward which firms jointly constitute a peer group. In order to deal with the lack of precise information on peers, we draw on literature that has studied firm interactions to identify the defining characteristics of firms' peers. In particular, we consider industry and geographical location to determine a company's network, following the long-standing observation in economic geography literature that economic activity tends to be clustered in relatively small geographic areas (e.g. Marshall, 1920; Krugman, 1991). The intersection of industry and geography therefore provides an intuitive perspective on peer groups. Further, Porter (1990) argued that innovation dynamics in clusters are stimulated by local competition and peer pressure among firms. These efforts and the associated influence of peers needn't be restricted to innovation in a narrow sense, but may well extend to all innovation-enabling activities, such as accessing public R&D support. A more general motivation to include the industry dimension in the construction of peer groups is homophyly, which is considered an important determinant for social network formation, with actors more likely to connect to, or be influenced by, others who resemble themselves in one or more dimensions (Boschma & Frenken, 2010). Empirical work has found industry to be a defining feature of the context where different types of inter-firm influences take place. For example, the revision of a company's previous financial statements has been found to induce share price declines not only for the focal firm, but also among non-restating firms in the same industry (Gleason et al., 2008). Graham & Harvey (2001) showed that the financing decisions of peer firms in the same industry, in particular competitors, influence the focal firm's own decisions. Measuring firms' industry membership at 3-digit SIC level, Leary and Roberts (2014) show how within-industry peers are a more important determinant of firms' financial policies, such as their leverage ratio, than changes in firm-specific characteristics.

Besides industry, geographical proximity is also prominent in social interaction literature, since short distances favour contacts and facilitate knowledge exchange (e.g. Bell & Song, 2007; Nam, Manchanda, & Chintagunta, 2007). Several empirical studies have shown the geographically bounded nature of (technological) knowledge spillovers (e.g. Jaffe et al., 1993; Almeida & Kogut, 1999; Audretsch & Feldman, 1996; Fritsch & Franke, 2004). Further, geographical proximity correlates positively with other dimensions of proximity, such as social and cognitive proximity (Boschma, 2005), and therefore partially captures other linkages with peers, such as social relations between employees or being embedded in the same knowledge community.

Based on these insights from previous work on firm interactions and knowledge spillovers, we define peer groups using a nearest-neighbour logic. More specifically, we take as a firm's peers the K closest firms (KNN) within the same 3-digit NACE sector.[10] This definition allows for intransitivity in the network – i.e. peers of a firm's peers are not necessarily peers of the firm itself. We exploit this feature in order to identify peer effects, as explained in section 3.

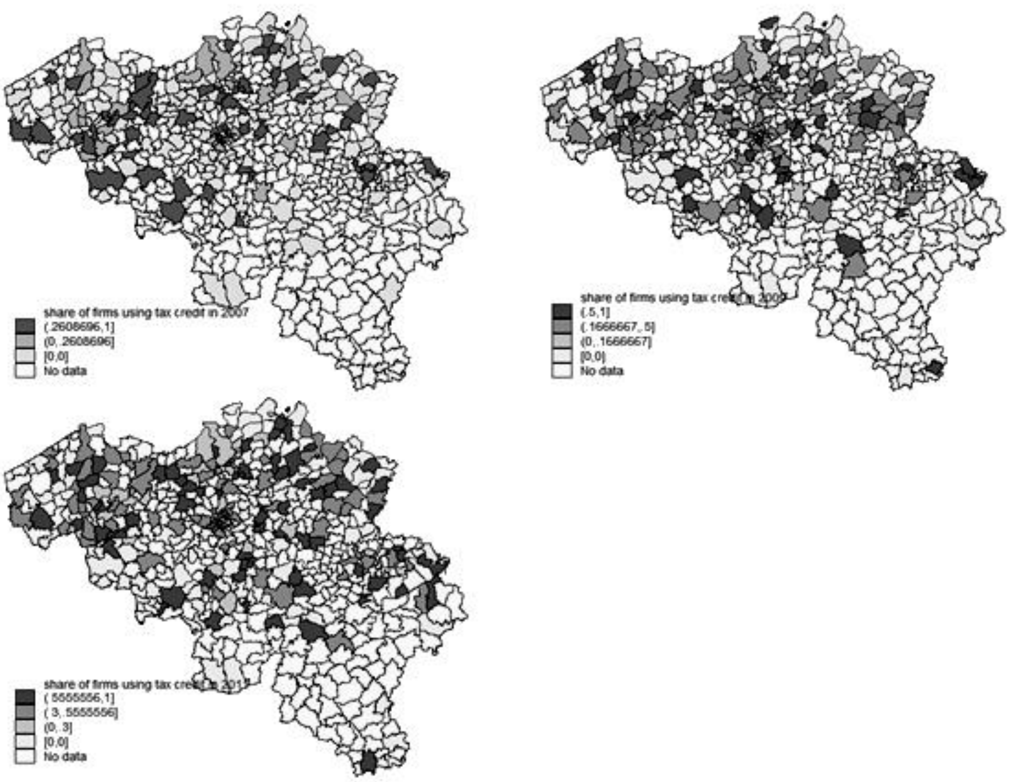
As a first check on the potential role of distance in peer influence, Figure I.1 relates firms' use of R&D tax credits to location in 2007, the earliest year in which any peer effect emanating from early adopters (in 2006) was possible, and in the subsequent years we analyse – 2009 and 2011. It shows the share of tax credit users by municipality, the finest level of detail at which we observe firms' locations.[11] It indicates that use of R&D tax credits is not uniformly spread, but rather that locations with higher shares of users tend to be clustered. Note that firms may be considered randomly allocated to a location with respect to their usage of R&D tax credits. In other words, it is unlikely that firms would co-locate for reasons that drive their decision to

[10] The peer groups we consider are geographically confined to Belgium, which we deem reasonable since R&D tax credits are granted by the Belgian federal authority, and firms within Belgium therefore constitute the relevant firm network.

[11] Technically, we observe a firm's location by an NIS-code, which denotes a statistical unit corresponding to municipalities. The median size of a municipality is 40.1 km², with a standard deviation of 37.7 km². The average number of firms per municipality is 3.18, with a standard deviation of 4.23.

use R&D tax credits. The analysis will control for other R&D-related factors that may explain co-location of firms, such as R&D intensity.

Figure I.1 Tax credit use by municipality in 2007, 2009 and 2011



Finally, we note that it is common for empirical work using social network data to observe only a sample of all the nodes in a network. Our work is no exception: the data we use for the peer group definition and the estimation is a sample of R&D tax credit users, namely those firms for which characteristics from the business R&D survey are available.[12] Using a sample of the population would imply measurement error if there are firms in the population that are not part of the sample but that are in the (true) peer groups of sampled firms. It is important for our approach that firms were not selected into the sample based on location, making it a reasonable assumption that missing links in peer groups are random.[13] However, even in the

[12] Note that firms are not selected into the sample based on the dependent variable, as we observe both users and non-users of the R&D tax credit.

[13] Since the importance of R&D tends to be strongly related to the type of industry, which is the other dimension in our peer group definition, firms in a given industry are likely to be treated similarly with respect to inclusion in the business R&D survey, and thus our sample.

case of fully random sampling, networks can still be misspecified (Chandrasekhar & Lewis, 2011). While the definition of peer groups draws on prior evidence and is informed by the patterns shown in the descriptive statistics, the lack of direct observation of peer groups and the sampling still allow for measurement error and thus a misspecified network structure. Two remarks are in order here. First, virtually all studies of peer effects suffer from potential measurement error in the definition of peer groups, since it is not typically known what is the precise mechanism that underlies the interaction, the type and degree of interaction being specific to the empirical context (De Giorgi et al., 2010). In our analysis of the adoption of public support for R&D, peer effects may arise due to imitation of other firms' decisions, without the need for close interaction. This alleviates concerns about not observing explicit collaborations between firms, and even makes such information unnecessary. More generally, empirical work shows a broad range of peer group definitions, ranging from very comprehensive, e.g. the effect on consumption by peers of the same race in the same state of residence in the U.S. (Charles, Hurst, & Roussanov, 2009) to highly restrictive, e.g. the effect on student performance by roommates in the same college dorm (Sacerdote, 2001). Our definition is rather comprehensive, which is consistent with the setting under consideration, where any influence by peers on the focal firm's decision to adopt the R&D tax credit merely requiring observation of peers' behaviour, rather than explicit interaction.

Second, we adopt a conservative approach regarding the specification of peer groups and conduct a series of robustness checks in section 4.6 to ascertain that any identified peer influence is not conditional on a given measurement of peer groups. First, we apply a network randomization test, in which we scramble the peer groups by reshuffling the sampled firms across locations and industries, and then re-estimate the model to verify that the results on peer effects are not obtained when considering any random peer network. Second, we check the sensitivity of results for different choices of peer group size (K). Third, we define peer groups at different industry aggregation levels and include additional industry and regional controls in the model.

3 Identification strategy and model

The identification of peer effects is notoriously challenging, as originally explained by Manski (1993). In this section, we explain the two key identification problems and how we exploit intransitivity in the firm network, i.e. partially overlapping peer groups, to address them (Bramoullé et al., 2009; De Giorgi et al., 2010). The first problem, referred to as *reflection*, essentially means that it is hard to disentangle whether a firm's decision to use the R&D tax credit system causes its peers to do the same, or whether it does so as a consequence of its peers' actions. In other words, the setting of peer effects suffers from a simultaneity problem. The second problem in identifying peer effects consists of endogeneity due to endogenous peer group formation and unobserved correlated shocks. Both of these factors may cause the decisions of an individual firm and its peer group to be correlated, confounding any true peer effects. Common unobserved shocks refer to factors that cause both the focal firm and its peer group to adopt the R&D tax credit, without any peer influence taking place. In our setting this would occur if, for example, the focal firm and its peers rely on the same external accountant, alerting all its clients of the introduction of the R&D tax credit system.

Following De Giorgi, Pellizzari, & Redaelli (2010), we now provide a more detailed discussion of the identification challenges and the approach we take to address them. Consider the following linear-in-means spatial[14] model, omitting time subscripts for simplicity:

$$y_i = \alpha + \beta E(y|G_i) + \gamma E(x|G_i) + \delta x_i + u_i \qquad (1)$$

The dependent variable y_i indicates whether firm i has adopted the R&D tax credit,[15] x_i are firm characteristics, $E(y|G_i)$ is the average choice of firms in i's peer group, which is denoted by G_i. $E(x|G_i)$ are the average characteristics of firm i's peers. Practically, a firm's peers are indicated through the use of a spatial weighting matrix W, which implements the peer group definition such that $Wy = E(y|G_i)$ and $Wx = E(x|G_i)$. Parameter β captures the *endogenous effect* i.e. 'true' peer effect, and γ the *exogenous effect*, sometimes also referred to as the *contextual effect* (Manski, 1993).

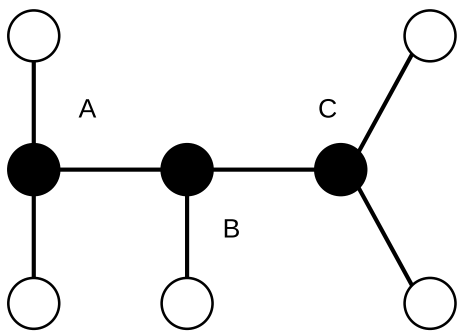
We focus first on the reflection problem and assume for now the absence of any endogeneity concerns i.e. $E(u_i|G_i, x_i) = 0$. As mentioned before, our identification approach hinges on the fact that peer groups are only partially overlapping. To understand this, first consider the case

[14] The label 'spatial' is due to the fact that the modelled interactions are determined by firms' locations.

[15] Note that although our dependent variable (adoption of the R&D tax credit) is binary, we stick to the approach taken by De Giorgi, Pellizzari, & Redaelli (2010), who study the binary choice of major in higher education. They also opt for a linear model, which allows for a clearer exposition of the identification strategy. Some work has been done on identifying peer effects in binary choice models, exploiting non-linearity to separate endogenous from exogenous effects (Brock & Durlauf, 2007). However, current implementations in statistical software ignore the existence of correlated effects – i.e. spatially correlated errors – due to strict multivariate distributional assumptions needed to identify the model. We consider that accounting for unobserved peer group characteristics that may drive firms' adoption decision to be paramount to properly identifying the endogenous peer effect, and we thus choose to estimate a (spatial) linear probability model.

where peer groups overlap perfectly such that, if firm i and firm j are in the same peer group, their peer groups coincide i.e. $G_i = G_j$. As Manski (1993) already argued, in this case the endogenous effect β cannot be identified separately from exogenous effect γ.[16] A less ambitious approach is therefore to simply estimate a single parameter for the combination of endogenous and exogenous effects without separating them.[17] However, in our empirical framework, the KNN-based peer groups are not fixed across firms, hence $E(y|G_i)$ varies within peer groups. Consider the following simple example to illustrate how this feature achieves identification in the face of the reflection problem. Say firms A, B and C are part of the same industry, which also contains other firms. Firms A and B are nearest neighbours (with $K = 3$) and thus part of the same peer group, based on industry and distance. Firm B and C are also nearest neighbours, but, given the geographical distribution of firms in the industry, firms A and C are not (see Figure I.2). This layout results in 'excluded peers' – i.e. firms who are not in the focal firm's peer group but who are part of the groups of its peers. Firm A is excluded from the peer group of firm C, and vice versa, while B's peer group includes both A and C.

Figure I.2 Example layout of peer groups



More formally, rewrite equation (1) by taking averages over peer groups, allowing them to vary by firm i:

$$E(y_i|G_i) = \alpha + \beta E\big[E\big(y|G_j\big)|G_i\big] + \gamma E\big[E\big(x|G_j\big)|G_i\big] + \delta E(x_i|G_i) \quad (2)$$

[16] Taking the average of equation (1) over group G_i shows that $E(y|G_i)$ is a linear combination of the other regressors: $(y|G_i) = [\alpha/(1-\beta)] + [\gamma + \delta/(1-\beta)]E(x|G_i)$.

[17] Typically, the absence of either endogenous peer effects (e.g. Brooks-Gunn et al., 1993) or contextual peer effects (e.g. Klier & McMillen, 2008) is assumed.

with j a member of i's peer group, and G_j never identical to G_i.[18] With respect to the preceding example we can write, omitting firms other than A, B or C: $G^A = \{B\}$, $G^B = \{A, C\}$, $G^C = \{B\}$. Equation (1) can then be written for the three firms as follows:

$$y_A = \alpha + \beta y_B + \gamma x_B + \delta x_A + u_A^A$$

$$y_B = \alpha + \beta\left(\frac{y_A + y_C}{2}\right) + \gamma\left(\frac{x_A + x_C}{2}\right) + \delta x_B + u_B^B$$

$$y_C = \alpha + \beta y_B + \gamma x_B + \delta x_C + u_C^C$$

To see how we achieve identification, consider the reduced form equations:

$$y_A = \left(\alpha + \frac{\alpha\beta(1+\beta)}{1-\beta^2}\right) + \left(\frac{\beta(\gamma+\delta)}{1-\beta^2} + \gamma\right)x_B + \left(\frac{\beta(\gamma+\delta\beta)}{1-\beta^2}\right)\left(\frac{x_A + x_C}{2}\right) + \delta x_A + \sigma_A^A$$

$$y_B = \left(\frac{\alpha(1+\beta)}{1-\beta^2}\right) + \left(\frac{\gamma+\delta}{1-\beta^2}\right)x_B + \left(\frac{\gamma+\delta\beta}{1-\beta^2}\right)\left(\frac{x_A + x_C}{2}\right) + \sigma_B^B$$

$$y_C = \left(\alpha + \frac{\alpha\beta(1+\beta)}{1-\beta^2}\right) + \left(\frac{\beta(\gamma+\delta)}{1-\beta^2} + \gamma\right)x_B + \left(\frac{\beta(\gamma+\delta\beta)}{1-\beta^2}\right)\left(\frac{x_A + x_C}{2}\right) + \delta x_C + \sigma_C^C$$

where the reduced form error terms σ_A^A, σ_B^B and σ_C^C are linear combinations of the structural error terms u_A^A, u_B^B and u_C^C. The four structural parameters are identified from the four reduced form parameters.[19] Note that our identification approach relies on the assumption that – referring to the example – excluded peer firm C does not influence firm A directly. As argued in the section on peer group definition, it seems reasonable to assume that distant firms, in terms of both geographical distance and type of industry, only exert an indirect influence.

The second main identification problem concerns endogeneity due to self-selection of firms into peer groups or the presence of unobserved group-level shocks. Formally, the error term may be written as:

---

[18] As we explain below, our choice of the number of nearest neighbours allows for partially overlapping peer groups.

[19] In this example, the third equation is redundant, which reflects the fact that only observations with distinct groups of peers contribute to identification.

$$u_i^g = \mu_i + \theta^g + \epsilon_i$$

with g denoting the peer group (A, B or C in the preceding example), μ_i an individual fixed effect, and θ^g a group fixed effect (e.g. the aforementioned 'common accountant' effect[20]) and ϵ_i is independently identically distributed random error.

In our setting, firms' peer group membership is determined by their location and industry. It is unlikely that firms sort into these peer groups in a way that correlates with their subsequent R&D tax credit usage, making μ_i negligible or zero.[21] The more serious concern leading to endogeneity, is the existence of unobserved correlated effects at the group level, θ^g. It turns out the mechanism of excluded peers serves a double purpose. While it deals with the reflection problem in the absence of endogeneity – as discussed above – it also supplies valid instruments for endogenous peer effects. Consider firm i's excluded peers i.e. the firms who are excluded from i's peer group but who are included in the group of one or more of i's peers. Their characteristics x are by design uncorrelated with the group fixed effect of focal firm i, but are correlated with the mean adoption decision of i's group through peer interactions. In terms of the earlier example, x_C is a valid instrument for y_B in group A because x_C – which is uncorrelated with θ^A since C is not a peer of A – affects y_C and the latter affects y_B through endogenous effects since C is a peer of B. In our sample, the excluded peers for a firm i include all firms not among the K nearest neighbours in the industry as the focal firm. Table I.1 shows the characteristics of peer groups in our sample for different years and values of K, in particular the share of firms that have at least K nearest neighbors in their industry. These are the firms for which the aforementioned identification strategy based on excluded peers is empirically feasible in our sample. For $K = 10$, we still have a majority of firms for which peer groups do not encompass all firms at the 3-digit NACE industry code level, and therefore serves as the empirical upper bound for K. For firms with less than K nearest neighbors in their industry, the intransitivity principle cannot be used to identify endogenous peer effects because there are no excluded peers to instrument peer choice and characteristics. However, Lee (2007) and Bramoullé, Djebbari, & Fortin (2009) have shown that peer effects are identified if at least two

---

[20] Another example would be the case of several biotech spin-off companies co-locating in the science park of their university and where the involved scientists learn about R&D tax credits through the TTO or a scientific entrepreneurship program run by the university.

[21] In other studies of peer effects this tends to be a more severe issue, e.g. when analysing students' choice of major one needs to worry about (unobserved) factors like ability causing selection.

peer groups have different sizes. In this case, the effect of a firm's characteristics x_i on its own decision y_i can be split into the direct effect and an indirect one, through feedback effects – x_A affects y_B, which in turn affects y_A, assuming A and B are peers. This indirect effect decreases with group size, which is a term of the denominator of the reduced-form coefficient of x_i (Bramoullé et al., 2009). Jointly, intransitivity and variation in group sizes are two network properties that ensure identification. Thus, we set $K = 10$, which effectively acts as an upper bound on the number of peers, and instrument the endogenous peer effect Wy by Wx and, using information of excluded peers, WX^2. For firms with less than 10 peers, identification comes from variation in peer group sizes. For the remainder of the paper, we use the 3-digit NACE industry level and ten nearest neighbours as the main peer group definition.

Table I.1Percentage of firms with at least K peers in 3-digit NACE industries

K	2007	2009	2011
2	89%	94%	92%
3	80%	87%	87%
4	75%	83%	80%
5	65%	78%	75%
6	63%	69%	69%
7	60%	65%	67%
8	57%	64%	65%
9	56%	60%	62%
10	54%	55%	58%

To estimate the model in equation (1), we use Kelejian & Prucha's (2010) spatial IV estimator, which is implemented in the R package *sphet* (Piras, 2010). The estimator permits spatial correlation between the error terms i.e. they are modelled as:[22]

$$u_i = \theta M u + \epsilon_i. \qquad (3)$$

The resulting SARAR[23] model is fairly general in its specification and has been used in prior work that estimates spatial peer effects, e.g. Helmers & Patnam (2014) used it to estimate

[22] As in many applications, we set the spatial weight matrix $M = W$.

[23] The spatial autoregressive model with autoregressive disturbances (SARAR) is a generalized version of the basic Cliff & Ord (1973) model, which contains spatial lags of the dependent variable plus a disturbance term.

spatial interactions among children with respect to cognitive skill formation. The generalized spatial two-stage least-squares (GS2SLS) estimator of Kelejian and Prucha uses a two-stage procedure, where the first stage instruments the endogenous peer effect Wy. Kelejian and Prucha (1998) have shown that the linearly independent columns of WX and WX^2 can be used as valid instruments for Wy. The linear independence of the instruments is ensured, in our data, by the intransitivity present in peer groups (Bramoullé et al., 2009).

As a benchmark for the SARAR estimates, we also report the results of an OLS model, which represents a naïve approach to the estimation of peer effects, in the sense that it ignores the reflection and endogeneity problems discussed above.[24]

4 Analysis of Peer Effects in R&D Tax Credit Adoption

4.1 Data

Our data set is based on the repository of R&D active firms in Belgium, managed by the Belgian Science Policy Office, and based on the sampling procedures of the biannual OECD Business R&D survey. It includes all companies known to be R&D active and it is updated on a regular basis. The dataset contains R&D-related information based on the OECD Business R&D survey and is enriched with public support measures in the form of R&D tax credits (provided by the Federal Public Service Finance) and R&D subsidies (provided by the regional governments). The business R&D survey is organized by the regional administrations (Brussels-Capital Region, Flemish Region, Walloon Region) according to a harmonized methodology and there is no a reason to suspect spatial bias. General company characteristics are provided by the Federal Public Service Finance, among which main sector of activity, employment and financial variables. As mentioned in section 2, we observe the approximate location of each firm down to municipality level. Belgium contains 589 municipalities, of which nineteen in the Brussels-Capital Region, 308 in Flanders and 262 in Wallonia.

We use three waves of the survey to create our analysis sample. Due to the fact that only a minority of firms answer two consecutive surveys, and questions related to R&D personnel

[24] Naturally, the usage of the SARAR model amounts to a linear probability model. We believe the robustness of the IV estimator proposed by Kelejian & Prucha (2010), which allows for spatial autocorrelation in the residuals, outweigh its disadvantages. Recent work (De Giorgi et al., 2010; Claussen, Engelstätter, & Ward, 2014; Leary & Roberts, 2014) has also employed linear probability models to estimate peer effects in a binary choice setting.

cover the two years preceding each survey, our sample is effectively a pooled cross section. We exclude from our sample firms that have not employed any researchers in *t* and *t-1*, where *t*=2007, 2009 and 2011, as they are not eligible for tax credits, which are awarded as a partial tax exemption on the wages of researchers, as explained in more detail in the next section. We also restrict the sample to firms that have at least one peer in the same industry, which removes 93 observations from the sample. This implies that we only analyse peer effects for those firms where those effects can occur, conditional on our peer group definition. The estimation sample contains 699, 961 and 1,018 observations on a total of 1,981 firms, for the respective years 2007, 2009 and 2011.

4.2 Dependent variable

Our dependent variable is a binary indicator of whether a company has received tax credits for researchers for the first time in a given year.[25] The measure is a partial wage withholding tax exemption and was introduced in 2006 for companies employing R&D personnel with PhD degrees and has been extended as of 2007 for Master degrees (except those in social sciences), across all industries. Initially, the tax exemption started at 25% of taxes on wages, but has been raised to 65% in 2008 and 75% from 2009 onwards. We focus on first-time adoption since this state transition is the change in the firm's behaviour that we want to explain, not its repeated use of the measure after initial adoption.[26]

The data we have at our disposal contains the population of users of the tax credit for researchers. However, the coverage of our sample is reduced due to the use of different sources for R&D data, fiscal data, and financial and employment data. As a result, our estimation data set is a sample of R&D tax credit users. Section 2 already discussed the implications for peer group definition.

Table I.2 illustrates the evolution over time of the population of companies using the tax exemption and compares them with our sample. There is a clear upward trend in the number

[25] The partial tax exemption can thus be seen as a wage subsidy. Given that it only applies to taxes on wages, it clearly differs from other R&D tax credits, such as for fixed asset investments.

[26] There are about 100 firms that abandon the tax credit after initially using it and we cannot attribute this change of behaviour to any observed characteristic, such as stopping R&D activity or bankruptcy. We are agnostic as to why they stop using the tax credit given our focus on explaining first-time adoption. We do drop these firms from the data in the years they stop using the tax credit. The rationale is that, given initial adoption, they know about the measure and can transfer information about it to other firms. Keeping them in the data after they abandon the tax credit would artificially lower the average peer group adoption rate.

of firms that use tax credits for R&D, especially between 2007 and 2009, with up to 1,131 companies using the measure in 2009. However, the number further increases only slightly in 2011 – to 1,330 users, suggesting a possible ‘saturation’ in the sense that the majority of R&D active firms have already become aware of and decided whether to use or not tax credits.[27] Consequently, the number of first-time adopters has grown from 245 to 395, only to decline afterwards to 167 new users in 2011. In terms of percentages, the rate of first-time users sees a steady decline from 42% of all users to 35% in 2009, and even 13% in 2011. The pattern in our sample is similar, although the difference in first-time adoption rates is almost zero between the first two periods. However, the sample does capture the drop in first-time adoption in 2011, from 26% to 7% of firms using the tax credit. Similarly, we see a larger increase in overall adoption in 2009 from 151 to 319 firms, followed by a more modest increase to 408 users in 2011.

Table I.2 Comparison of sample and population of tax credit users

	2007	2009	2011
Tax credit users (pop.)	578	1,131	1,330
First-time users (pop.)	245	395	167
% first-time users (pop.)	42%	35%	13%
Tax credit users (sample)	151	319	408
First-time users (sample)	40	83	28
% first-time users (sample)	26%	26%	7%

a) The difference between total users and first-time users comprises past users, irrespective of when in the past they have used the measure. To this effect, the first two rows are not cumulative.

4.3 Peer effects

Our explanatory variable measures, for each company and in each year, the average use of tax credits among its ten (geographically) closest peers active in the same 3-digit NACE industry.[28]

We define the elements of the spatial weighting matrix W described previously as follows:

[27] A back-of-the-envelope calculation shows that firms that employ R&D personnel and do not receive tax credits forego on average 37.6 K Euros in 2007, 65.9 K Euros in 2009 and 79.5 K Euros in 2011. The maximum amounts foregone by a company vary between 2.9 M Euros in 2007 and 7.3 M Euros in 2011. Reported to turnover, the average represents 0.7% and the maximum up to 60% of turnover.

[28] Our choice of 3-digit NACE codes to define peer groups follows Leary and Roberts (2014).

$$w_{ij} = \begin{cases} 0 \text{ if firms } i \text{ and } j \text{ are not active in the same industry or if firm } j \text{ is not among the ten closest peers of firm } i \\ 1 \text{ if firm } j \text{ is active in the same industry as firm } i \text{ and is also among the ten closest peers of } i \end{cases}$$

Next, we row-standardize W by averaging w_{ij} over the number of peers j of each firm i. Consequently, we construct our explanatory variable by multiplying W by the vector y' containing the binary variable indicating which companies have used tax credits in the previous year. Note that this is different from y, our dependent variable which indicates whether a firm is using tax credits for the first time. As explained in section 4.2, the rationale is that firms after their initial adoption know about the measure and can transfer information about it to other firms. Hence, we test whether the increase in overall use of tax credits among a firm's peers results in an increase in the firm's probability to start using the same fiscal exemption.

In order to calculate distances between companies, we use data on their approximate locations based on geographical coordinates of the town hall of the municipality each firm is located in.[29] Due to this setup, there can be more firms with the same coordinates and in the same industry, in which case we randomize the attribution of firms to peer groups in those municipalities with more companies than the size of a peer group.[30] For example, suppose we define firm A1's peer group as the ten closest firms in the same industry. In cases where a municipality contains more than eleven companies active in the same industry (say 15 firms, A1-A15), we randomly attribute ten peers for firm A1 from the remaining A2-A15 firms in that municipality, and so forth.

We lag the endogenous peer effect variable by one year for three reasons. First and foremost, the data does not allow to distinguish, within a year, when each firm has used tax credits. In other words, we do not know if a firm uses the measure before or after its peers in a given year. By lagging the variable we make sure the peers' use precedes the focal firm's decision. Second, it is unlikely that information reaches firms instantaneously, but rather needs time to diffuse

[29] The coordinates locate town halls with a precision of 2 km.

[30] This is a very minor issue since, as explained in section I.2, the average number of firms per municipality is 3.18 with a standard deviation of 4.23 and a maximum of 45. Hence, for the main analysis with $K = 10$, the peer groups are larger than the number of firms in the same municipality.

within peer groups. Moreover, there may also be a lag between the time information reaches a firm and its decision to act. And third, this alleviates the reflection problem by ensuring that a firm's decision does not econometrically influence the average decision of its peer group.[31]

4.4 Other determinants of R&D tax credit use

Given the volume-based nature of the R&D tax credit, the main explanatory variable is the R&D intensity of a firm, measured by the ratio of researchers to overall employees. The higher this ratio, the higher the relative savings on personnel cost and therefore we expect this variable to have a positive impact on the probability to start receiving tax credits.

The size of a firm can affect the probability to receive tax credits in the sense that larger firms may have dedicated staff to follow up on changes in R&D support measures and may therefore be quicker to adopt newly introduced measures (Blanes & Busom, 2004; Neicu et al., 2016b). Prior research has found that larger firms are more inclined to use tax credits (Czarnitzki et al., 2011). We control for firm size by the number of employees in full-time equivalent.

Since the R&D tax credit initially provided a higher exemption for young and innovative companies – a rate of 50% from 2006 to mid-2008, while also being able to use it for R&D support personnel), we include a YIC binary indicator.[32] The YIC indicator also captures the potentially higher propensity of YICs to use public support for R&D, given that innovation is at the heart of their value proposition, even more so than for the other R&D active companies in the sample. Because of this strategic emphasis on innovation and because they are more financially constrained than more mature and/or less innovative firms, YICs may learn about the R&D tax credit sooner than other companies, in particular because they may have their roots in government-sponsored R&D projects. Also, investors and/or members of the management team for such companies may be well versed in accessing the public support system for innovation, based on prior experience and therefore do not have to learn about the existence of specific support measures in the way other companies need to. Hence, we expect YICs to be early adopters while being less prevalent among late adopters.

[31] While the use of excluded peers addresses the reflection problem, as explained in section 3, for a minority of firms the data does not allow specifying excluded peers, depending on the precise peer group definition. Therefore, the lagging of the peer group variable still plays a role in identification.

[32] We follow the Belgian Science Policy Office's definition, which states that a YIC is less than ten years old, has less than 50 employees, an annual turnover lower than 7.3 million Euros, total assets of maximum 3.65 million Euros, and spends more than 15% of its total cost on R&D.

In order to avoid a spurious attribution of the usage of R&D tax credits to peer effects, the empirical analysis must control for all sources of correlation between the focal firm and the adopting peers that may explain the adoption decision. In other words, one needs to be careful claiming that a focal firm's decision to apply for the R&D tax credit is inspired by the behaviour of its peers while in fact it may be due to some underlying shared characteristic. A crucial attribute in this respect is a firm's savviness in using public support for R&D, which we proxy by an indicator of whether the company has received regional subsidies for R&D in the previous year. As for YICs, we expect that R&D subsidy use makes firms less likely to be late adopters. Table I.3 illustrates the descriptive statistics for the main variables in the estimation sample. Correlations between individual characteristics are presented in Appendix in Table I.10.

Table I.3 Summary statistics of dependent and independent variables

	2007		2009		2011	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
First-time use[a]	0.06	0.23	0.09	0.28	0.03	0.17
Overall tax credit use	0.22	0.41	0.33	0.47	0.40	0.49
R&D intensity	18.00	23.50	17.70	22.40	19.40	23.30
Employees	185.00	484.00	147.00	414.00	147.00	379.00
YICs	0.06	0.24	0.04	0.21	0.05	0.22
Subsidy	0.24	0.42	0.18	0.38	0.24	0.43
W*Tax credit use	0.22	0.22	0.33	0.23	0.40	0.23
W*R&D intensity	16.80	14.10	16.90	13.70	18.60	13.00
W*Employees	3.92	0.99	3.78	0.90	3.80	0.82
W*YIC	0.07	0.13	0.06	0.11	0.05	0.10
W*Subsidy	0.24	0.23	0.20	0.18	0.20	0.18
Observations		699		961		1018

a) The percentage of first-time users is relative to the number of R&D active firms in the sample. In order to obtain the values from Table I.2, row one needs to be divided by row two (slight differences will occur due to trimming decimals).

4.5 Results

Table I.4 illustrates the estimation results of equation (1) through the GS2SLS procedure[33] with (columns 1c, 2c, 3c) and without (columns 1b, 2b, 3b) contextual effects. As a benchmark, we compare the latter results with the ones of a 'naïve' OLS model (models 1a, 2a, 3a), in which we do not instrument the endogenous peer effect.[34] We perform a yearly cross-sectional analysis due to the fact that we expect peer effects to behave differently in the first period after the introduction of the tax credit, when fewer companies knew of its existence, suggesting a greater potential for peer effects. We also assume that this different behaviour cannot be captured solely by year indicators.[35] The first row shows the coefficient of the endogenous peer effect β from equation (1), while the subsequent rows show, respectively, the coefficients of the focal firm characteristics δ, and the parameter θ capturing the spatial correlation between the error terms from equation (3). Since the primary purpose of the contextual peer effects is to distinguish this influence from the endogenous peer effects, which capture the influence emanating from peers' decisions and where our main interest lies, we omit them from the results presented here, but they are reported in Appendix in Table I.8.

---

[33] For the estimation of our model through GS2SLS, we use the R package *sphet* (Piras, 2010) and define endogenous peer effects as the (lagged) general use of tax credits by a firms' peers, and also include lagged contextual effects.

[34] We estimate an OLS model for comparability with our main GS2SLS specification, in line with our linear probability model. Alternatively, we have estimated the benchmark through a probit model, the results being highly similar in terms of significance and magnitude with the basic OLS estimation.

[35] We have also estimated the model on the pooled cross-section, but failed to find significant endogenous peer effects. We hypothesise that this is due to the effects weakening as the tax credit becomes pervasive in time.

Table I.4 Estimations of endogenous peer effects from the closest ten peers

	2007			2009			2011		
	OLS	GS2SLS		OLS	GS2SLS		OLS	GS2SLS	
	1a	*1b*	*1c*	*2a*	*2b*	*2c*	*3a*	*3b*	*3c*
Endogenous peer effect	0.106**	0.282***	0.586**	-0.006	-0.043	1.122**	-0.018	0.016	0.103
	(0.046)	(0.106)	(0.259)	(0.045)	(0.072)	(0.562)	(0.023)	(0.046)	(0.136)
Log(Employees)	0.015**	0.012**	0.012**	0.019***	0.019***	0.020***	-0.001	-0.001	0.0003
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.004)	(0.003)	(0.003)
YIC	0.059	0.05	0.043	0.013	0.012	0.026	-0.027	-0.029***	-0.029***
	(0.038)	(0.040)	(0.039)	(0.044)	(0.050)	(0.055)	(0.025)	(0.009)	(0.010)
Subsidies	0.012	0.006	0.005	-0.039	-0.038	-0.060**	-0.019	-0.021*	-0.027***
	(0.022)	(0.023)	(0.023)	(0.024)	(0.024)	(0.028)	(0.014)	(0.012)	(0.015)
R&D Intensity	-0.0005	-0.001**	-0.001**	0.001**	0.001**	0.001	-0.0002	0.000	-0.0002
	(0.0005)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.000)	(0.0002)
Spatial error θ		0.058	0.233***		0.015	0.298**		-0.025	0.020
		(0.080)	(0.091)		(0.054)	(0.120)		(0.024)	(0.048)
Observations		699			961			1,018	

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Intercept estimated but not shown in table.
c) Standard errors in parentheses.
d) Models 1c, 2c and 3c include contextual peer effects not shown in table – see Table I.8 in Appendix.

The GS2SLS estimates that include contextual and correlated effects (columns 1c, 2c, 3c) show positive and significant endogenous peer effects in 2007 and 2009, although we cannot reject the null hypothesis of no effects in 2011. The results indicate that a firm's decision to start using R&D tax credits is positively influenced by the (lagged) average use of tax credits of up to ten of its closest peers within the same 3-digit NACE industry code, but primarily so in the first few years following the introduction of the measure.

With respect to firm characteristics explaining adoption of the R&D tax credit, we find that, on average, larger firms have a higher probability of being first-time users, while young innovative companies are less likely to adopt the tax credit in the latter period, as are subsidy users in 2009 and 2011. As argued in section 4.4, the result for YICs is consistent with the expectation that YICs are at the forefront to adopt new R&D support measures. Our data seems to capture periods when YICs are mostly general users of tax credits rather than adopters. Out of 43 YICs present in the data set in 2007, 15 were already using the tax credit and only 3 were using it for the first time. Similarly, we observe 24 and 31 users and only 4 and 1 new adopters in 2009 and 2011 respectively.[36] This numbers suggest that we might fail to capture YIC adoption behaviour in years not covered by our data.[37] The same observation is true for subsidy users. In 2011, only 2 firms that had received subsidies one year before become adopters of tax credits, whereas there were 12 and 14 in 2007 and 2009 respectively.[38]

Somewhat contrary to expectations, more R&D intensive firms are also less likely to be adopters in the immediate period after introduction of the measure, although the coefficient's magnitude is rather small. Moreover, since we are analysing a sample of R&D active firms that are, in principle, all eligible for the R&D tax credit, this variable acts a control rather than a fundamental driver of tax credit adoption.[39]

---

[36] The numbers are similar in terms of lagged YIC status, as the variable is used in our estimations. Moreover, of the adopters in 2011, none were YICs a year before.

[37] Our data is based on the biannual Belgian OECD business R&D survey. Due to the low sample overlap between two consecutive surveys and the fact that we lag our explanatory variables, we decided to estimate cross sectional models on the periods with most coverage – 2007, 2009 and 2011.

[38] The difference between adoption and general usage behaviour can also be seen in a pooled OLS estimation presented in Appendix in Table I.9. The first column shows that (lagged) YIC status and subsidy use do not explain adoption behaviour (without accounting for peer effects), but they do significantly and positively influence overall use of tax credits (column two).

[39] We also observe in Table I.9 in Appendix that the R&D intensity coefficient is significant at 1% in a simple OLS (excluding any peer effects) of general use of tax credits (column 2). Similarly, it positively affects adoption in 2009 (again, without considering peer effects), while in the other two periods – as well as in the pooled cross sections – it has very limited impact and no statistical significance at 10%.

In most studies implementing spatial estimators, interpreting the magnitude of the endogenous effect – or spatial lag – is cumbersome due to feedback loops – i.e. peers' decisions affect the focal firm's decision, which in turn affects its peers and so on. However, because our endogenous effect variable – average peer tax credit use – is measured prior to the dependent – first-time tax credit use – we avoid this issue of circularity. This facilitates the interpretation of the magnitude of the coefficients. In 2007, a 10% increase in the number of peers having used tax credits the year before increases the probability that the focal firm becomes a user by 5.86 percentage points (model 1c). Similarly, the effect amounts to 11.22 percentage points in 2009 (model 2c) and 1.03 percentage points in 2011 (model 3c), although the latter is not significantly different from zero. The magnitude of peer effects is quite large given that less than 10% of the sampled firms adopt the tax credit in any given year. From a policy perspective, these results indicate the presence of an important multiplier effect. More practically, they suggest that geographically-targeted information campaigns can be very effective at increasing the take-up of tax credits. For example, ensuring that one in every ten firms knows about – and uses – the fiscal measure can increase adoption by as much as 11 percentage points, converting two out of ten firms doubles the take-up, and so forth.

4.6 Robustness checks

As mentioned in section 2, the definition of interactions between firms is based on their industry membership and geographical proximity. Notwithstanding that the definition is informed by theory, it is an assumption that we need to make in the absence of interaction patterns between firms.[40] Thus, the network structure used for the analysis might only partially capture the true peer network. The spatial econometrics literature provides little guidance on the potential bias due to a misspecified spatial weights matrix W and the resulting measurement error in the instruments. For the related SAR model without spatially correlated errors, Lee (2009) found bias from over-specification of the spatial weights matrix to be lower than bias from under-specification in both maximum likelihood and 2SLS estimations. To investigate potential implications of a misspecified peer network for our results, we perform the following robustness tests. First and foremost, following Helmers & Patnam (2014), we randomize peer

[40] Note that the network structure might still be misspecified even if self-reported firm data were available, due to perception bias and other (un)intentional misreporting by firms on whether they were affected by other firms in their decisions to start using the R&D tax credit.

groups by performing a permutation of firms over the two peer group dimensions, i.e. locations and industries, and then re-estimate the model. This falsification test serves to verify that our result on peer effects is not obtained when considering any random peer group network. Second, we re-run the analysis for different peer group sizes to verify whether the results are not driven solely by the choice of a ten nearest-neighbour network. Finally, we introduce additional controls in the model to check for industry-wide and regional effects on adoption behaviour that are not accounted for by the industry and location dimension of the peer group definitions.

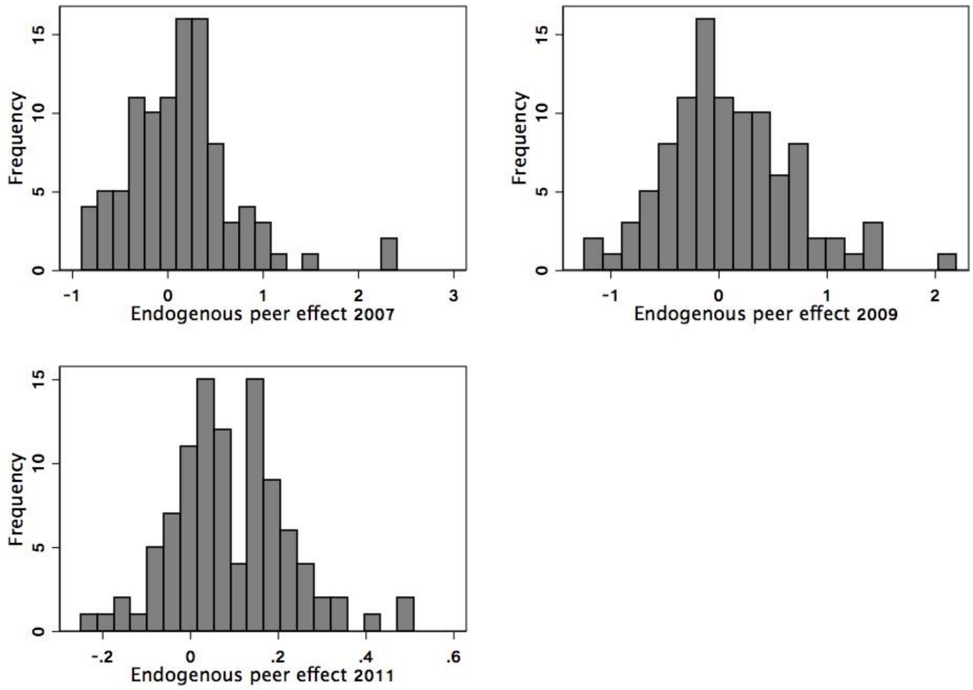
Random peer assignment

To test the assumption of our industry and location-based peer groups, we randomly assign ten peers to each firm in the sample by shuffling the locations and 3-digit NACE industry codes across firms. Although this method ensures that peers are random, it also maintains the basic structure of the sample – that is, each industry and municipality will keep the true number of firms, but firms are randomly along these dimensions.

As for the main results, we estimate equation (1) using the GS2SLS method and we repeat the procedure 100 times, each repetition generating a new random network structure. The histograms in Figure I.3 show the distribution of point estimates of the endogenous peer effects obtained in the 100 replications for each time period.[41]

[41] We performed the same procedure for the model without the contextual effects γ. The results are consistent with the ones reported here, and are shown in Figure I.4 in Appendix.

Figure I.3 Histograms of point estimates of endogenous effects from 10 random peers



a) Estimations include contextual peer effects.

The mean estimate of the endogenous peer effect is 0.139 (with a standard deviation of 0.560) for 2007, a mean of 0.105 (s.d. 0.590) for 2009, and a mean of 0.091 (s.d. 0.130) in 2011. These results imply that we cannot reject the null of zero endogenous peer effects in the randomised networks. Furthermore, 99% of point estimates are statistically insignificant at 10% level.

We interpret this as reassuring evidence that our main model captures the underlying network structure of peer groups rather than some empirical artefact arising from a misspecified network.

Misspecification of peer group size

As explained in section 2, the empirical upper bound on the peer group size implied by our data is about ten peers, as this allows the identification of social effects by intransitivity for the majority of firms in the sample, while for a minority of firms identification is based on variation in the peer group size.[42]

[42] Note that specification is flexible enough to permit peer groups to be industry-specific.

We now restrict the maximum group size to five and seven firms and present the GS2SLS estimation results of endogenous peer effects in Table I.5. The complete results – including exogenous effects and individual characteristics are included in Appendix in Table I.11.

Table I.5 Endogenous peer effects for different peer group sizes (K)

	2007	2009	2011
K=10	0.586**	1.122**	0.103
	(0.259)	(0.562)	(0.136)
K=7	0.536*	2.325*	0.235
	(0.309)	(1.245)	(0.227)
K=5	0.453	-1.234	-0.152
	(0.364)	(1.867)	(0.183)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Standard errors in parentheses.

We observe that the endogenous effect for groups of seven peers follows our main results by having a positive and significant coefficient in the first two periods, followed by a non-significant and smaller effect in 2011. The same patterns arise in the case of contextual and correlated effects. However, when defining peer groups of five firms, we are unable to robustly identify the endogenous or exogenous effects.

These results indicate that groups of 10 peers are sufficiently broad containers of firm interaction while progressively smaller peer groups fail to capture peer effects.[43] Combined with the network scramble test, we are confident that the used peer groups capture the real network structure of firms sufficiently accurately. Similar patterns arising from under- and over-specification are noted by Lee (2009) and Helmers and Patnam (2014).

Furthermore, we have defined peer groups within 3-digit NACE industries. Although we have based our choice on previous empirical evidence (e.g. Leary & Roberts, 2014), we now test whether choosing different definitions of industry boundaries also allow identify peer effects. Table I.6 shows the results of GS2SLS estimations for K=10 and peers defined in the same 2 and 4-digit NACE sectors respectively. We observe that none of the endogenous peer effect coefficients are significant at 10% level, although they are similar in magnitude and yearly

[43] Similar patterns arising from under- and over-specification of peer groups are reported by Lee (2009) and Helmers and Patnam (2014).

variation to our main results. These results build confidence in the fact that peer effects operate at 3-digit NACE sector level, as lower or higher granularity does not seem to capture any interaction between firms. Indeed, 2-digit NACE sectors may be too wide a definition, coupling together firms that in practice do not have any links, whereas 4-digit sectors are too narrow, which implies that there are missing links in networks defined at this level.

Table I.6 GS2SLS estimations with groups defined in 2 and 4-digit NACE sectors

	2007		2009		2011	
	2-digit NACE	4-digit NACE	2-digit NACE	4-digit NACE	2-digit NACE	4-digit NACE
	1	*2*	*3*	*4*	*5*	*6*
Endogenous effect	0.371	0.405	1.781	0.271	0.261	-0.090
	(0.467)	(0.316)	(1.682)	(0.499)	(0.191)	(0.142)
ln(employees)	0.012**	0.012*	0.022***	0.016***	0.000	-0.002
	(0.006)	(0.006)	(0.008)	(0.006)	(0.003)	(0.004)
YIC	0.049	0.031	0.019	-0.010	-0.027***	-0.023**
	(0.041)	(0.037)	(0.060)	(0.051)	(0.010)	(0.010)
Subsidy	0.014	0.005	-0.071**	-0.051*	-0.026**	-0.016
	(0.022)	(0.025)	(0.030)	(0.027)	(0.012)	(0.012)
R&D intensity	-0.001	-0.0008*	0.001*	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Standard errors in parentheses.
c) Contextual effects, spatial errors and intercept estimated but not shown - see Table I.12 in Appendix.

Omitted control variables

Finally, we test how robust our results are to omitted variable bias. We have mentioned in the Data section that we do not specifically control for industry and geographical region because these two dimensions are part of the definition of peer groups. Since there may exist region- and industry-wide influences that extend beyond the reach of the peer group and that may lead firms to adopt the tax credit, we now re-estimate the spatial model by including binary indicators for the three geographical-administrative regions – Brussels (baseline), Wallonia and Flanders – as well as for industries aggregated into four groups – high- and low-tech manufacturing and services. Although including these covariates reduces the identifying variation of the endogenous and exogenous effects, the coefficients remain robust and show similar values and significance to the main specification, as can be seen in Table I.7. Moreover, the included region indicators are not significant, with one exception, strengthening our trust in our main specification. Similarly, industry affiliation seems to matter little in firms' use of tax credits, as we only find some evidence in 2009 of firms in high-tech services and low-tech manufacturing sectors having higher probability of adopting R&D tax credits.

Table I.7 GS2SLS estimations of peer effects from the closest ten peers

	2007	2009	2011
Endogenous effect	0.672**	1.350*	0.177
	(0.313)	(0.798)	(0.156)
R&D intensity	-0.001*	0.001	0.000
	(0.000)	(0.001)	(0.000)
Log(Employees)	0.010	0.022***	-0.001
	(0.007)	(0.008)	(0.004)
YIC	0.035	-0.026	-0.026**
	(0.039)	(0.060)	(0.013)
Subsidies	0.004	-0.044	-0.036**
	(0.024)	(0.028)	(0.016)
Flanders Region	-0.008	0.000	-0.008
	(0.030)	(0.040)	(0.025)
Wallonia Region	-0.059	-0.031	-0.043*
	(0.041)	(0.066)	(0.026)
High-tech services	0.029	0.287*	0.004
	(0.050)	(0.152)	(0.021)
Low-tech manufact.	0.082	0.241**	0.004
	(0.056)	(0.116)	(0.017)
Low-tech services	0.006	0.149	0.025
	(0.045)	(0.093)	(0.022)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Intercept, contextual effects and spatially-lagged errors θ estimated but not shown in table – see Table I.13 in Appendix for full results.
c) Standard errors in parentheses.

5 Conclusions

While our analysis does not directly answer the puzzling question why firms seem reluctant to make use of a public support measure that clearly benefits them, it shows how peer influence among firms fosters the adoption of R&D tax credits. Our empirical application uses a methodologically innovative approach to identify these peer effects: by making the plausible assumption of not fully overlapping peer groups based on distance and industry, this paper is the first to show how peer effects play a role in firms' response to R&D public support schemes in the absence of clear peer group information. In particular, we show that firms optimize their R&D costs through public support as information from their peers reaches them. Consistent with a bounded rationality perspective, we interpret this as a way for firms to cope with the multitude of public support measures they face, and which are not always efficiently marketed by public authorities. We have also shown that a critical mass of peers is required to find such effects. Using intransitivity in the network structure to separate endogenous peer effects (peers' decisions) from exogenous peer effects (peers' characteristics), the results show that these are two separate channels through which peers influence peers influence firms' decision-making.

Second, positive peer effects in firms' decisions to adopt public support for R&D are important given the tenacious proliferation and fragmentation of public support schemes, which is believed to create a situation that bewilders some firms. In particular, while our findings do not imply policy interventions with respect to R&D support schemes as such, they are suggestive of opportunities to foster adoption of public support for R&D. For example, these insights can be used to set up more effective government communication initiatives, such that early adopters in different industries are involved in promoting the measures to their respective peers. Adoption by eligible firms could be expedited by communicating the measure to sufficiently fine-grained sectors and in a geographical distributed way. As opposed to broad policy communications, 'narrowcasting' would help to reach many localized firm clusters, or peer groups, allowing rapid peer-to-peer influence, once initial adoption has taken place.

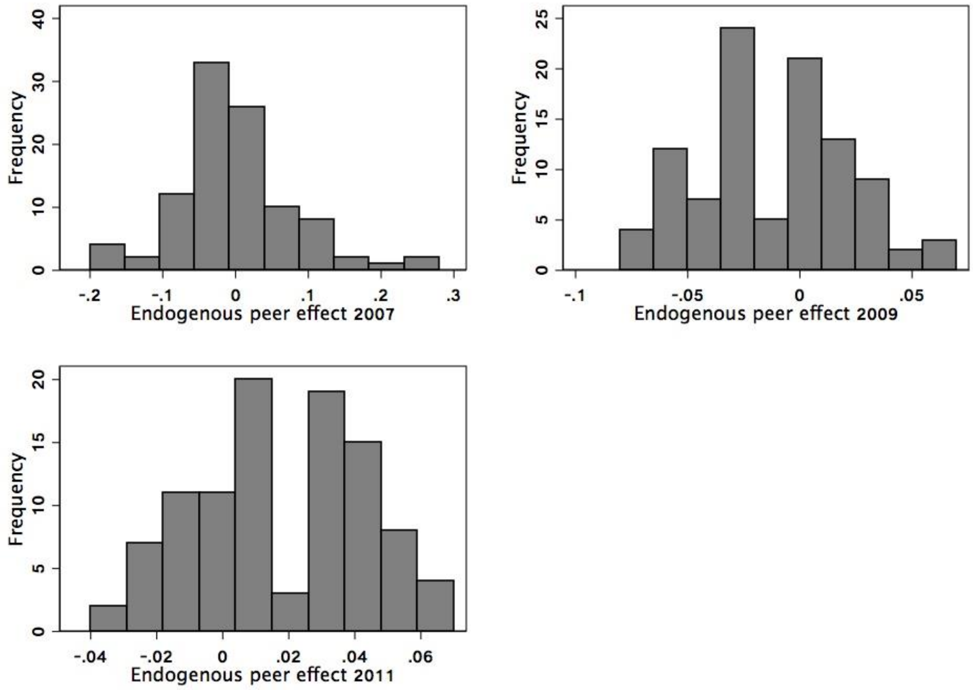
Third, the establishment of peer effects as a significant factor driving firms' selection into support schemes informs the methodological literature on selection bias in program evaluation (Imbens & Wooldridge, 2009). Namely, the existence of peer effects calls for looking beyond the individual firm to explain selection into support programs. Peer effects should be accounted for in the selection equation when estimating the effects of policy interventions in R&D, especially in contexts where there is reason to believe information about support measures has not reached all potential users. Including peer effects as an explanatory factor for firm participation in a programme will then help to satisfy the conditional independence assumption underlying matching estimators, or to identify the parameters of the selection equation in two-step estimations.

Finally, this paper contributes to the broader literature on peer effects between firms. Given the high degree of clustering in many 'small world' firm networks (Fleming & Marx, 2006), our approach of exploiting intransitivity in firms' networks is more generally applicable to identify peer effects in other settings. While we have strived to be as rigorous as possible in our identification strategy, it is possible that due to data limitations (omitted variables, sample of tax credit users) the analysis misattributes some other driver of tax credit adoption to peer effects. For example, although prior studies have found that group membership can affect the use of public support for R&D, our data does not allow including a good control for a firm's membership to a corporate group. This is relevant for our analysis in the sense that the peer effects measure may pick up information flows between entities of the same corporate group, rather than between competitors. Further, there is a remaining risk of a misspecified network structure due to sampling and other sources of measurement error. However, we think the array of robustness checks instils sufficient confidence in the findings and ascertains that the identified peer effects are not dependent on a particular peer group definition. Finally, the simple information diffusion framework that provides the rationale for peer effects does not seem to fully explain the observed time pattern. In particular, the peer effect disappears in 2011, without, it seems, a clear rationale why non-adopters at that stage would cease to be influenced by their peers. Nevertheless, the framework accommodates the fading of peer effects provided a saturation effects occurs. This could occur as follows. In 2006, year of the introduction of the R&D tax credit, little is known about its existence. However, a small number of 'fiscal pioneers' – mostly larger firms – have already benefited from the measure from its introduction. One year later, in 2007, information spills from these pioneers to the 'followers', which are situated in close proximity to the former and are active in the same industries. This phenomenon continues through 2009, three years after the introduction of the new tax credit. However, by 2011, local groups of firms are saturated with the aforementioned information, thus the peer effect loses its significance. Although it is still possible that knowledge still travels the inter-company space to larger distances – and thus in larger peer groups – the size of our sample does not allow to investigate whether the effect would persist in more broadly defined peer groups.

Our work triggers several avenues for further research. First, recent work on firms' combination of R&D support measures shows evidence of complementarities between R&D grants and fiscal support in terms of R&D additionality (e.g. Neicu et al., 2016b). In the light of the finding of peer effects for the adoption of R&D tax credits, this begs the question whether those companies that are driven by peer effects in their adoption decision show the same additionality effects as early adopters. Second, the hypothesis of firm heterogeneity in peer effects could be explored further, by a more comprehensive analysis of the strength of the effect conditional on individual characteristics, or on who are the leaders and followers in peer groups, similarly to Leary & Roberts (2014) or Claussen et al. (2014). However, due to the relatively low numbers of first-time users in our data, split-sample analyses would suffer from lack of variation in the dependent variable, which would render identification of endogenous and exogenous effects more difficult in the GS2SLS framework.

6 Appendix

Figure I.4 Histograms of point estimates of endogenous effects from 10 random peers



a) Estimations exclude contextual peer effects.

Table I.8 GS2SLS estimation results of main models including exogenous peer effects

	2007	2009	2011
	1c	*2c*	*3c*
Endogenous peer effect	0.586**	1.122**	0.103
	(0.259)	(0.562)	(0.136)
Log(Employees)	0.012**	0.020***	0.0003
	(0.006)	(0.007)	(0.003)
YIC	0.043	0.026	-0.029***
	(0.039)	(0.055)	(0.010)
Subsidies	0.005	-0.060**	-0.027***
	(0.023)	(0.028)	(0.015)
R&D Intensity	-0.001**	0.001	-0.0002
	(0.001)	(0.001)	(0.0002)
W*R&D Intensity	-0.002	-0.011**	0.0004
	(0.002)	(0.005)	(0.001)
W*log(employees)	-0.042*	-0.133**	-0.013
	(0.024)	(0.066)	(0.017)
W*YIC	-0.159	0.019	-0.108*
	(0.104)	(0.160)	(0.060)
W*Subsidies	0.014	-0.267	-0.017
	(0.074)	(0.170)	(0.044)
Spatial error θ	0.233***	0.298**	0.020
	(0.091)	(0.120)	(0.048)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Intercept included but not shown in table.
c) Standard errors in parentheses.

Table I.9 OLS estimations of tax credit adoption and general usage

	Adoption	Usage	Adoption 2007	Adoption 2009	Adoption 2011
	1	*2*	*3*	*4*	*5*
ln(employees)	0.011***	0.133***	0.017***	0.019***	-0.001
	(0.003)	(0.006)	(0.006)	(0.007)	(0.004)
YIC	0.020	0.200***	0.065*	0.013	-0.027
	(0.021)	(0.036)	(0.038)	(0.044)	(0.025)
Subsidy	-0.015	0.162***	0.015	-0.040*	-0.020
	(0.011)	(0.020)	(0.022)	(0.024)	(0.014)
R&D intensity	0.000	0.006***	0.000	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2009	0.033***	0.144***			
	(0.011)	(0.020)			
2011	-0.027**	0.205***			
	(0.011)	(0.020)			
Intercept	0.010	-0.460***	-0.011	0.002	0.042**
	(0.017)	(0.029)	(0.028)	(0.029)	(0.018)
Observations	2678	2678	699	961	1018
R^2	0.02	0.26	0.02	0.01	0.00

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Standard errors in parentheses.
c) Columns 1 and 2 are OLS estimations of first-time use ('Adoption') and overall use ('Usage') of tax credits on the pooled cross sections.

Table I.10 Correlation between dependent and independent variables

	Adopters	Users	Empl.	YIC	Subsidy
2007					
Users	0.46				
Employees	0.12	0.30			
YIC	0.02	0.08	-0.28		
Subsidy	0.06	0.30	0.06	0.18	
R&D intensity	-0.05	0.22	-0.41	0.39	0.29
2009					
Users	0.44				
Employees	0.07	0.33			
YIC	0.01	0.11	-0.24		
Subsidy	-0.03	0.24	0.08	0.09	
R&D intensity	0.02	0.23	-0.38	0.36	0.20
2011					
Users	0.21				
Employees	0.01	0.30			
YIC	-0.01	0.09	-0.27		
Subsidy	-0.04	0.24	0.10	0.04	
R&D intensity	-0.03	0.17	-0.38	0.25	0.14

a) 'Adopters' refers to first-time use of tax credits; 'Users' refers to general use.

Table I.11 GS2SLS estimations of peer effects from the closest 5 and 7 peers

	5 peers			7 peers		
	2007	2009	2011	2007	2009	2011
Endogenous effect	0.453	-1.234	-0.152	0.536*	2.325*	0.235
	(0.364)	(1.867)	(0.183)	(0.309)	(1.245)	(0.227)
W*R&D intensity	-0.003	0.010	0.001	-0.003	-0.019*	-0.002
	(0.003)	(0.015)	(0.001)	(0.002)	(0.010)	(0.002)
W*log(employees)	-0.033	0.160	0.016	-0.040	-0.270*	-0.033
	(0.037)	(0.234)	(0.023)	(0.029)	(0.145)	(0.027)
W*YIC	-0.056	0.137	-0.002	-0.113	-0.115	-0.224**
	(0.084)	(0.268)	(0.084)	(0.095)	(0.256)	(0.104)
W*Subsidies	0.012	0.231	0.071	0.014	-0.635**	-0.054
	(0.069)	(0.391)	(0.054)	(0.074)	(0.330)	(0.071)
Spatial error θ	0.235*	0.148	-0.077*	0.245***	0.538***	0.099**
	(0.136)	(0.113)	(0.054)	(0.096)	(0.099)	(0.043)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Standard errors in parentheses.
c) Intercept estimated but not shown.

Table I.12 GS2SLS estimation with groups defined in 2 and 4-digit NACE sectors

	2007		2009		2011	
	2-digit	4-digit	2-digit	4-digit	2-digit	4-digit
	1	*2*	*3*	*4*	*5*	*6*
Endogenous effect	0.371	0.405	1.781	0.271	0.261	-0.090
	(0.467)	(0.316)	(1.682)	(0.499)	(0.191)	(0.142)
ln(employees)	0.012**	0.012*	0.022***	0.016***	0.000	-0.002
	(0.006)	(0.006)	(0.008)	(0.006)	(0.003)	(0.004)
YIC	0.049	0.031	0.019	-0.010	-0.027***	-0.023**
	(0.041)	(0.037)	(0.060)	(0.051)	(0.010)	(0.010)
Subsidy	0.014	0.005	-0.071**	-0.051*	-0.026**	-0.016
	(0.022)	(0.025)	(0.030)	(0.027)	(0.012)	(0.012)
R&D intensity	-0.001	-0.0008*	0.001*	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
W*ln(employees)	-0.015	-0.034	-0.184	-0.030	-0.033	0.017
	(0.053)	(0.026)	(0.208)	(0.064)	(0.023)	(0.018)
W*YIC	-0.032	-0.004	-0.111	0.134	-0.161*	0.014
	(0.117)	(0.104)	(0.388)	(0.105)	(0.091)	(0.061)
W*Subsidy	0.040	-0.029	-0.462*	-0.086	-0.083	0.010
	(0.068)	(0.074)	(0.258)	(0.131)	(0.073)	(0.039)
W*R&D intensity	-0.002	-0.002	-0.014	-0.003	-0.002	0.001
	(0.004)	(0.001)	(0.014)	(0.004)	(0.001)	(0.001)
Spatial error θ	-0.007	0.094	0.709***	0.119	0.103	-0.034
	(0.162)	(0.089)	(0.131)	(0.103)	(0.129)	(0.022)
Intercept	0.039	0.123	0.593	0.109	0.123**	-0.006
	(0.220)	(0.116)	(0.684)	(0.226)	(0.058)	(0.041)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Standard errors in parentheses.

Table I.13 GS2SLS estimation of peer effects from the closest ten peers

	2007	2009	2011
Endogenous effect	0.672**	1.350*	0.177
	(0.313)	(0.798)	(0.156)
R&D intensity	-0.001*	0.001	0.000
	(0.000)	(0.001)	(0.000)
Log(Employees)	0.010	0.022***	-0.001
	(0.007)	(0.008)	(0.004)
YIC	0.035	-0.026	-0.026**
	(0.039)	(0.060)	(0.013)
Subsidies	0.004	-0.044	-0.036**
	(0.024)	(0.028)	(0.016)
W*R&D intensity	-0.002	-0.012*	-0.001
	(0.002)	(0.007)	(0.001)
W*log(employees)	-0.051*	-0.156*	-0.024
	(0.028)	(0.089)	(0.021)
W*YIC	-0.207*	-0.369	-0.141*
	(0.109)	(0.306)	(0.084)
W*subsidies	0.028	-0.186	-0.042
	(0.074)	(0.153)	(0.052)
Flanders Region	-0.008	0.000	-0.008
	(0.030)	(0.040)	(0.025)
Wallonia Region	-0.059	-0.031	-0.043*
	(0.041)	(0.066)	(0.026)
High-tech services	0.029	0.287*	0.004
	(0.050)	(0.152)	(0.021)
Low-tech manufact.	0.082	0.241**	0.004
	(0.056)	(0.116)	(0.017)
Low-tech services	0.006	0.149	0.025
	(0.045)	(0.093)	(0.022)
Spatial error θ	0.248***	0.308***	0.048
	(0.090)	(0.122)	(0.063)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Intercept included but not shown in table.
c) Standard errors in parentheses.

II. Mix and match: evaluating the additionality of an R&D policy mix

Abstract

This paper analyses the additionality of a policy mix of R&D tax credits and subsidies on firms' R&D investment. Using non-parametric matching models and instrumental variables estimations on a rich dataset of R&D-active companies from Belgium, the results reveal that tax credits and subsidies have different effects on firms' budgetary decisions regarding basic and applied research and development. First, although both support measures increase private R&D spending, the effect of subsidies is only significant when they are combined with tax credits. Second, tax credits outperform subsidies in every comparison, showing positive additionality on all parts of R&D. On the other hand, subsidies do not affect development spending, while they do have an impact on research when combined with fiscal stimuli. Mitigating to some extent hidden treatment effects and selection bias, I demonstrate that there are complementarities between direct and indirect R&D support.

Keywords R&D policy mix, output additionality, behavioural additionality, tax credits, subsidies.

JEL Codes D01 – D03 – D04 – D78 – O30.

Acknowledgements Financial support from KU Leuven – HU Brussels (ZKC7171) and the National Bank of Belgium is gratefully acknowledged. The author would also like to thank the Belgian Federal Public Service Finance for providing data used in this paper.

1 Introduction

The role of public intervention in private R&D stems from the link between research, innovation and economic growth (Mansfield, 1972). Underinvestment in R&D hinders growth, which paves the way for governments to support firms' efforts in research and development in order to achieve a 'social optimum' of R&D and innovation activity.

Underinvestment in R&D is based on two market failure arguments (Arrow, 1962). First, because knowledge is a non-rival and non-exclusive good, firms cannot fully appropriate the returns on their R&D investments; this stems from knowledge having high fixed costs of production and low marginal costs of utilisation. Secondly, uncertainty is a defining characteristic of innovative activity. When firms engage in R&D, they cannot fully predict the output by the inputs they employ. If economic actors are risk averse, they will discriminate against risky projects (Arrow & Lind, 1970).

The latter argument is aggravated for types of R&D projects that are farther away from the market, as is the case for basic or even applied research, compared to development. As uncertainty about returns is higher for these projects, firms encounter more barriers to financing them externally and thus need to rely more on internal funds (Czarnitzki & Hottenrott, 2011).

Higher returns' uncertainty of basic and, to some extent, applied research arises from their characteristics. Both basic and applied research comprise activities geared towards acquiring new knowledge, whereas development builds on existing knowledge to create new or improved products or processes. The difference between basic and applied research stands in that the former creates knowledge that is not directed at practical use, unlike the latter (OECD, 2002).

Whichever the reason for the market failure, governments saw the need to provide incentives to firms in order to bridge the gap between the private and social returns to investment in R&D. Over the decades, this has usually been done by directly subsidising research projects. R&D grants have, at least in theory, the advantage of directly addressing market failures by allowing policy makers some control over which type of research they finance. However, information asymmetries, bureaucracy or political pressure can result in the mismanagement of public funds and an aggravation of the market failure that required intervention in the first place.

More recently, countries have started to implement various systems of tax credits for firms engaging in R&D. Among OECD member states, the percentage of governments offering some form of tax credits doubled between 1995 and 2011, reaching 75% of countries implementing such policies (OECD, 2013). The attractiveness of tax credits to governments stands mainly in their administrative simplicity and lower information asymmetries, while also providing firms with a more predictable policy than subsidies (Haegeland & Møen, 2007a).[44]

With the increasing use of R&D tax credits alongside subsidies comes the risk that different policies might crowd each other out, thus the need to properly assess the effects and interactions between these measures. Indeed, most empirical studies to date assess solely the impact – or additionality – created by one of these tools, rather than their combined effects[45]. However, a growing literature on the combined use of different policies is emerging. On the one hand, studies compare the effects of tax credits with those of subsidies on firms' total or private R&D expenditure (Haegeland & Møen, 2007b; Dumont, 2015; Guerzoni & Raiteri, 2015; Marino, Parrotta, & Lhuillery, 2015). On the other hand, there are a few studies distinguishing the impact of subsidies on either research or development spending (Czarnitzki, Hottenrott, & Thorwarth, 2011; Hottenrott, Lopes Bento, & Veugelers, 2014). However, to the best of my knowledge, there are no studies analysing both input and behavioural additionality of subsidies and tax credits when used solely and combined.

Therein the contribution of this paper. I evaluate whether subsidies and tax credits increase R&D spending in firms that are using either measure or combining them in a policy mix. Moreover, the analysis goes beyond the classical input additionality approach and studies if the two policies crowd each other out in terms of total R&D expenditure, but also whether they have different effects on basic research, applied research, or development activities.

I find strong evidence of input additionality from tax credits used alone or combined with subsidies, but cannot rule out crowding out for subsidies alone. Moreover, I show some evidence that both policies induce a behavioural change away from development and towards research. From an econometric perspective, I mitigate possible bias arising from hidden treatments and selection of firms into programmes, two hot issues in contemporary policy evaluation research.

---

[44] Although fiscal policy may be on average more predictable than subsidy budgets, the reverse can also be true – in Belgium, for example, wage-based tax credit rates have been constantly raised on an almost yearly basis from 2006 to 2013.

[45] See García-Quevedo (2004) for a meta-analysis of the impact of public funding on private R&D.

2 Theory and hypotheses

In this section I will briefly sum up the main existing empirical findings on the effectiveness of direct grants and tax credits for R&D, based on which I formulate my research hypotheses.

2.1 R&D grants and tax credits as separate policies

In a survey of econometrical studies on the impact of direct R&D grants on firms' R&D expenditure, David et al. (2000) argue that most previous research can be criticised for not accounting correctly for the selection of firms into subsidy programmes. Consequently, results were inconclusive, either showing that direct grants substitute or complement private R&D spending. More recently, positive additionality of public grants on firms' R&D expenditure has been found in Germany (Czarnitzki & Licht, 2006), France (Duguet, 2004), Germany and Flanders (Aerts & Schmidt, 2008; Czarnitzki & Lopes-Bento, 2013), Italy (Carboni, 2011) and Spain (González & Pazó, 2008).[46] However, crowding-out can sometimes still take place, as Görg and Strobl (2007) find to be the case of Irish firms. Although they find positive additionality of small grants on firms' R&D expenditure, larger subsidies appear to finance projects that would have been implemented even without public support.

On the other hand, because tax credits have been introduced by governments later than grants, econometric evaluations of their effectiveness are more scarce. Nevertheless, in a comprehensive analysis of econometric evidence on US and non-US tax credit systems, Hall and Van Reenen (2000) found that most results point towards a dollar-for-dollar increase in firms' R&D spending due to tax credits. They do, however, find that the effects are smaller in the first years after the introduction of each measure.

More recent studies have generally confirmed the positive effects of R&D tax credits on R&D inputs, for example Haegeland and Møen (2007), Corchuelo and Martínez-Ros (2009), Duguet (2010), or Czarnitzki, Hanel, & Rosa (2011). Lokshin and Mohnen (2012) perform an analysis of the Dutch R&D tax incentive introduced through the Wage Tax and Social Insurance Act. The level-based tax deduction is applied to R&D labour costs, similarly to the Belgian system analysed in the current paper. They find that the Dutch programme stimulates R&D investment and the bang-for-the-buck is larger for small firms than for larger ones.

[46] Most recent studies address in some way the selection bias, overcoming the issues signalled in David et al. (2000).

In Belgium, Dumont (2013, 2015) analyses the same tax credit on researchers' wages and subsidy system that are the focus of my paper. Splitting the tax credit into its four components – wages of researchers involved in collaboration with universities, those with master degrees, PhD degrees, or employed in young innovative companies – he finds that results vary with the estimation method. Without controlling for (self-) selection, three of the four parts of the tax credit show positive effects on firms' private R&D expenses, the exception being the fiscal exemption for young innovative companies. Controlling for selection into programmes by using instrumental variables fails to mimic those results, and the only robust effect remains that of the tax exemption on wages of researchers with a Master's degree, although using a matching estimator does produce significant average treatment effects for all exemption categories. Similarly, results for additionality of subsidies on private R&D expenditure vary with the econometric method employed, and their economic impact seems smaller than (parts of) the wage withholding tax exemption. Apart from methodological differences, my paper diverges from his analysis in that I investigate the overall impact of the wage-based fiscal exemption, rather than focusing on each specific line. I do so in the belief that the mechanism through which the measure affects firms is common for all its components – targeting employment of highly-skilled researchers to increase investment in R&D in firms. I also offer more robust econometric evidence concerning the separate additionality on research and on development spending, as I discuss in Section 2.3.

Ientile and Mairesse (2009) conclude, after analysing over 30 studies on the effectiveness of tax credits, that evidence is scattered based on the methodology used and on the design of the incentive scheme itself. A more recent meta-analysis for the European Commission confirms that additionality depends on the design of the measure and econometric results are highly country-specific, but also that tax credits have varying effects on different groups of firms. However, most evidence does point towards a stimulating effects on R&D expenditure (Straathof et al., 2015).

In light of this – although somewhat varying – evidence of the additionality created by R&D tax credits and subsidies, I build the first hypothesis as follows:

Hypothesis 1: Subsidies and tax credits increase firms' private R&D spending.

2.2 The policy mix

As I have already signalled, there is a lack of empirical evidence of the interaction between direct and indirect – and, more generally between different levels of – support for R&D, which has been signalled multiple times in recent years (Flanagan et al., 2011; Aranguren et al., 2014). A study for the European Commission concludes: "*the limited empirical evidence indicates that interactions between different policy measures probably exist*" (Straathof et al., 2015). Furthermore, the interaction between (inter-)national and regional policy is even more opaque, in the context of distribution of authority from national level 'downstream' – to regional level – but also 'upstream' – to international structures (Flanagan et al., 2011; Lanahan & Feldman, 2015; Martin, 2016). Federal systems of governance provide an ideal context to study interactions between policies at different levels of administration (Lanahan & Feldman, 2015, p. 1387). Although incomparable in size to the US, Belgium does offer fertile ground for study by having numerous R&D policies spread across federal and regional governmental agencies, and my analysis provides evidence that federal fiscal exemptions and regional subsidies do seem to interact in ways that increase firms' response to receiving them – but that also depend on how responses are defined.

Although empirical evidence is not yet abundant, the theoretical consensus seems to be that different policies will interact with one another, sometimes in unpredictable ways. Martin (2016, p. 167) provides a useful analogy with healthcare, where drugs used to treat different ailments may interact in complex manners. Even though each drug may be the best treatment for its target illness, other drugs may counteract its effect and vice-versa; as physicians need to take all these interactions into account, policy makers should also design R&D instruments without neglecting how they may affect each other.

The reasons to expect such interactions stem both from the characteristics of direct and indirect support and from the possibility of their simultaneous use.

Grants have been the main policy tool used to provide up-front financing to companies pursuing R&D projects, while tax credits are comparatively new on the public agenda. Whereas subsidies allow granting agencies some form of control over how firms use the public funds, tax credits impose lower administrative costs on both the firm and the policy maker. Moreover, receiving a grant can act as a signal to other financing bodies and thus indirectly increase firms' attractiveness to venture capitalists or private lenders (Takalo & Tanayama, 2010), while tax credits may oftentimes only apply to profit-making companies.[47] Furthermore, direct grants are usually earmarked for use within a specific R&D project, while tax incentives can be redirected to non-R&D activities, in certain fiscal environments – including the one analysed in this paper. Clearly, different policies not only have different goals, but also function in different ways at a managerial level. Thus the need to better understand the interactions between the more rigid – in terms of application process and destination – direct R&D grants, on the one hand, and the more flexible R&D tax credits, on the other, is paramount to new evaluation studies for innovation policy (Diez, 2002; Aranguren et al., 2013).

In this vein, more recent research has focused on how firms simultaneously use direct R&D subsidies and tax credits, either by measuring the impact on private R&D inputs (Haegeland & Møen, 2007a; Carboni, 2011), on innovative output (Bérubé & Mohnen, 2009), or by exploring the drivers behind the choice of each support policy (Busom et al., 2014).

Hall and Maffioli (2008) review a number of direct and indirect R&D subsidy programmes in Latin America and generally find positive additionality on firms' R&D expenditure. Moreover, they show that the effects differ by type of financing mechanism, tax credits being more effective than direct grants. Haegeland and Møen (2007) find that both subsidies and tax credits prompt Norwegian firms to invest more in R&D, again finding that tax credits outperform grants. Carboni (2011) reports similar results from Italian firms. On the other hand, direct support has been found to have greater impact than tax credits in a panel of 19 members states of the OECD (Westmore, 2013). Recently, Guerzoni & Raiteri (2015) have used matching estimators to find that additionality of tax credits used as a single measure decreases when controlling for other support that firms use, while it disappears altogether in the case of subsidies. On the other hand, combining the two in a policy mix results in positive additionality on R&D expenditure. Similarly, Marino et al. (2015) find substitution effects in firms that combine subsidies with tax credits, although complementarity cannot be ruled out at medium levels of support. A drawback of these analyses is the fact that they are based on matching estimators, which heavily rely on the conditional independence assumption. Should there be

[47] However, in some cases, tax credits are not related to the overall tax position of companies. My analysis involves a partial exemption on the wage-withholding tax in Belgium, and thus applicants are not restricted to profit-making firms.

unobserved characteristics that play a part in firms' choice of policies, treatment effects will be biased.

As empirical findings seem to be country- or at least policy-specific, my hypothesis regarding the effect of the policy mix needs to be constructed in view of existing evidence from Belgium. In an analysis of the Belgian R&D support system, Dumont (2013) showed that some financing lines of wage-based tax credits display higher additionality on R&D expenditure than subsidies. Although additionality decreases (but remains positive) when the estimation controls for the possible simultaneous use of direct and indirect support, this cannot be interpreted as a substitution effect, but rather as a reduction in bias resulting from controlling for 'hidden treatments'. Guerzoni and Raiteri (2015) find a similar behaviour of the estimates, arguing that this is due to confounding factors in a system of multiple R&D policies, an issue that most previous studies have not tackled.

In an update to Dumont (2013) covering the period 2003-2011, Dumont (2015) finds some evidence that subsidies and part of the wage withholding tax exemption are substitutes, although the magnitude of the effect is limited. However, his specification is based on ordinary least squares and does not consider possible selection of firms into different policies nor combination of policies, which can produce biased estimates of additionality on private R&D expenditure. Furthermore, because his data includes subsidies received as of 2001 and tax exemptions started in 2006, there is a strong possibility that the positive additionality effect of subsidies is driven by the period before the wage-based tax credits were introduced – i.e. before 2006. In this sense, the interaction between the two support measures may not be completely captured in the panel. I diverge from this part of his research by estimating the effect of the policy mix – defined the simultaneous use of tax credits for researchers and subsidies – while controlling for (self-) selection into policies and their combination, in an attempt to reduce the inherent bias. I describe the identification strategy in Section 3.3. Moreover, I analyse tax exemptions and grants throughout the same period – i.e. when both measures were available to firms.

The interaction between direct and indirect support can emerge for different reasons and in various ways, and it stems from the characteristics of the policies. Tax credits have the main advantage – from the market's perspective – or disadvantage – from the policy maker's perspective – of leaving the decision on what R&D projects to pursue up to the firms. Moreover, in some policy designs, firms are not required to invest the exempted amount in

R&D activities. Subsidies, however, are funds directly provided by public authorities, usually after a selection procedure based on the perceived quality of the proposed R&D project and track record of performing R&D, among others. Complementarity can arise as a simple volume effect – pooling together more resources allows firms to engage in larger R&D projects, which in turn require more private investment.[48] Substitution, on the other hand, can occur when firms choose to redirect resources to activities unrelated to R&D when they receive more than one type of support. It can arise, for example, when tax credits and subsidies can be combined on the same R&D project and their amount covers the necessary funds, the firm not needing to top-up with private cash for the project to take place. This points to a possible upper bound to how much firms can invest in R&D – that is, once they assure funding for a portfolio of projects, they do not have incentives to seek additional investment opportunities. An alternative explanation – albeit with similar effects – is that financial constraints do not allow companies to increase their portfolio through private funds.

As existing empirical research on the issue of mixing policies is rare and results that point to substitution among support measures lack both robustness and magnitude, I choose to test the hypothesis that their interaction is positive, although this is purely for exposition reasons in this part of the paper, and whether the hypothesis holds or policies are substitutes will be decided by the empirical analysis.

> *Hypothesis 2: Each policy used alone generates smaller additionality on private R&D expenditure than the policy mix.*

2.3 Effects of R&D support on basic, applied research, and development spending

Focusing on private R&D expenditure as an input in the innovation process, although undoubtedly informative, does not capture the inner workings of how firms combine direct grants with tax stimuli in managing their R&D.

[48] Note that I use the word 'complementarity' to define rather loosely the interaction between different policies that does not result in them crowding each other out. Different meanings of this term exist and have been analysed, such as policies having varying targets and scopes – for example, subsidies being more useful for SMEs facing financing constraints (Busom, Corchuelo, & Martínez-Ros, 2014).

When evaluating public policy, it is oftentimes forgotten that R&D is not a monobloc. Instead, it has different components that make up the entity, and these components might be very different in their characteristics. The Frascati Manual (OECD, 2002) distinguishes three separate activities within the R&D process: basic research, applied research, and development.

The market failures inherent to R&D might affect disproportionately each of its components. Outcome uncertainty plays a bigger role when firms engage in basic research, as the intrinsic characteristics of this activity make it more prone to risk and distance it from a potential market. Externally financing basic research is thus more difficult than projects which are closer to the market, i.e. applied research and development projects. Furthermore, knowledge created in basic and applied research is harder to appropriate than knowledge created by development activities. Coupled with the larger contribution of basic research to innovation, this translates into private rates of return from research being smaller than the social rates of return (Rosenberg, 1990; Mansfield, 1991).

Current empirical evidence shows that research activities are more sensitive to operating liquidity than development activities, as firms need to rely more on internal funds to finance basic and applied research and thus cash-strapped firms will have less resources for research, whereas they should find it easier to finance development through market loans (Czarnitzki et al., 2011). In this vein, the Flemish regional government has devised specific policies to directly subsidise firms' research and development activities separately. Hottenrott et al. (2014) analyse this framework and find that the policy has direct effects on private spending – i.e. research (development) subsidies increase private spending on research (development) – but also cross-effects, from research grants to private development expenditure and vice-versa. In earlier work, Clausen (2009) found that subsidies for projects farther from the market do stimulate additional spending in Norwegian firms, while those granted for projects closer to the market crowd out private funding. My paper differs from the latter two in two significant ways. First, both studies only analyse subsidies' impact on R&D, without accounting for other support firms might use simultaneously. This 'hidden treatment' can induce upward bias in the estimation of treatment effects, as previous research has shown (Dumont, 2013; Guerzoni & Raiteri, 2015). My results also point towards complementarity between subsidies and tax credits, another feature that is not present in the aforementioned papers.

In his analysis of the Belgian R&D support system, Dumont (2015) briefly addresses the question of additionality on the orientation of R&D activities. He finds that subsidies shift firms' activities from development towards basic research, while tax credits for YICs seem to move activities towards applied research. His analysis does not measure the amount of funds spent on each activity, but rather the percentage, thus does not capture input additionality for each component of R&D. Moreover, the results are likely to suffer to some extent from selection bias, which is not accounted for in this part of his analysis, whereas I will try to mitigate this issue through robust econometric techniques.

These previous findings lead to the construction of the following hypothesis:

> *Hypothesis 3: Subsidies increase firms' spending on basic and applied research, but their additionality is smaller or insignificant on development.*

On the other hand, tax credits can usually be freely spent by firms, and are more likely to be used to finance projects with high private rates of return (David et al., 2000). Czarnitzki et al. (2011) evaluate the Canadian tax credit system and bring empirical support for this argument. They find that firms that use tax credits do invest more in R&D, but some investment is in short-term projects that lead to incremental innovations. It can thus be argued that firms use tax credits to invest more on development, rather than basic or even applied research. On the other hand, fiscal exemptions can also finance marginal projects which might be deemed too risky to be subsidized.

The Belgian tax credit I analyse is granted to firms that employ highly-skilled researchers, which are more prone to engage in basic and applied research than development. The argument of the federal authorities for introducing the fiscal exemption was that it would increase R&D investments and contribute to achieving the Lisbon strategy's objective of spending 3% of GDP on R&D. Dumont et al. (2015) find that using the tax credit induces an increase of PhD-holders in firms' research departments. Considering this, it could well be the case that the tax credit increases research rather than development spending, a hypothesis partially supported by Dumont (2015). He finds that only one of the four lines of exemption produces a shift from development to applied research. However, the finding could be biased by selection of firms into treatment categories, which is not accounted for. As the balance between the two theories is unclear, I do not have a specific hypothesis regarding the effect of tax credits on research versus development activity and will let the results shed light onto this matter.

Recently, Neicu et al. (2016b) have shown that there are important differences in how firms respond to receiving a policy mix rather than a single measure. They find that direct grants increase the effects that tax credits have on the speed and scale of R&D projects. Moreover, using the policy mix allows firms to spend more resources on research rather than development, compared to what they would have spent had they received only tax credits. However, their data do not allow to assess the effect of tax credits alone, nor to calculate the magnitude of additionality. They can only observe the complementarity or extra effect brought on by subsidies to firms that already receive tax credits. Following this work, my fourth hypothesis states:

> *Hypothesis 4: The policy mix increases (basic and applied) research more than development spending.*

3 Data and method

3.1 R&D subsidies and tax credits in Belgium

R&D subsidies in Belgium are granted by regional authorities in each of the three administrative regions – Brussels, Flanders and Wallonia. Firms pass through a selection procedure at the end of which projects are either funded or rejected by the granting authority. They can also be specifically earmarked for research or development projects (research grants and development grants). The Region of Flanders subsidises research, development or mixed (R&D) projects to varying degrees, offering extra incentives for SMEs, as do the other two regions. Moreover, Flanders and Brussels also sponsor feasibility studies, while Flanders and Wallonia target specific industries based on their economic needs.

Tax credits are a federal measure which applies to all firms within the country. The specific tax credit I analyse is a partial wage withholding tax exemption on researchers' salaries and has been introduced in October 2005, at first only for researchers working on collaborative R&D projects with universities or other research centres. In 2006 it has been extended to all employees with a PhD degree in science and all R&D personnel employed in young innovative companies (YICs), and from 2007 it is applicable to researchers with a Master degree too. It is thus somewhat different from the more common R&D tax credits used in other countries – and also to lesser extent in Belgium – and which are dependent on turnover or profits. The amount exempted started at 50% of wage withholding tax for YICs and collaborative projects and 25% for PhD and MA holders, but the rate was raised to 65% in 2008 and 75% from 2009 for all categories. The Belgian measure can be freely spent by firms on any activity, be it related to

R&D or not. This specific provision is in contrast with subsidies, which are grants with a specific destination in R&D activities within pre-approved projects.

It is important to note that the tax exemption has been implemented to replace a previous – somewhat similar – fiscal measure which applied only to newly-hired researchers, and that forced beneficiaries to return the exempted amounts when ending the contracts of the researchers receiving the tax credit. The importance of examining the effects of regional (direct) and federal (indirect) measures together stems from such an institutional context in which authorities at different levels amend and replace existing policy. It is reasonable to believe that, in this case, federal authorities decided to introduce the new tax credit in 2006 while being fully aware not only of the fiscal instruments they would replace or work in parallel with, but also of the R&D subsidies granted by regional governments. New policy was thus introduced in the context of pre-existing policies, which paves the way for interactions between the former and the latter (Uyarra, 2010; Lanahan & Feldman, 2015; Martin, 2016).

In Table II.1 I briefly illustrate the evolution over time of the population of users of tax credits, subsidies and the policy mix. We see an abrupt increase in the uptake of tax credits in 2006 and 2007, as the measure opened to more categories of researchers, but also in 2009, when the percentage of exempted tax was raised to 75%. This increase is also visible in the average tax credit per firm, which raises steadily before 2008 from 36 to 92 thousand Euros, then encountering a more abrupt rise for two years up to 217 thousand Euros, only to slightly drop in 2010 and 2011. This decline is mostly due to a larger number of users, as the total amount of foregone tax in the economy remained at similar levels in 2009-2011, at around 290 million Euros. Subsidies, on the other hand, show a steadier trend, mostly due to a more even policy over time. Subsidy users remain around or above 800 firms per year, with a drop in 2009 and 2010, possibly correlated with the downturn in world financial markets. Regarding the amount of subsidies received on average by firms, it started almost four times the average tax credit, at 133 thousand Euros. There is no clear trend though, as it raises and drops in an apparently disordered fashion up to 2011, when it surges by almost 80 thousand Euros to 259 thousand. The last panel displays firms combining tax credits and subsidies in the same year. As expected, the trend follows the lines of the singular policies, but we mostly see a steady increase in the number of firms choosing the mix and the average amount received. The average amount of the policy mix in 2005 was 870 thousand Euros, many times higher than the average tax credit and subsidy amounts combined. This is most probably due a few firms with very large R&D

departments, given that only 33 companies used the mix in that year. Moreover, the tax exemption in 2005 only applied to researchers hired on collaborative projects and stood at 50% of their wage withholding tax. The drop to almost half the average amount in 2006 follows from almost six times more users. There is also a large increase in 2009 of about 200 thousand Euros, on average, which is matched by an increase in the overall budget spent on firms combining the two by almost 65 million Euros.

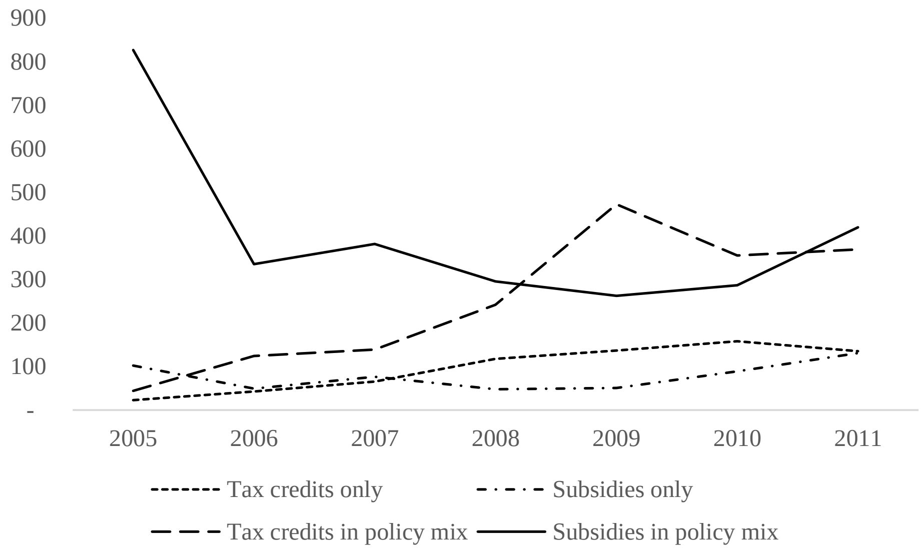
Table II.1 Population statistics by support type and period

	Tax credits			Subsidies			Policy mix		
	Users	Average	Total	Users	Average	Total	Users	Average	Total
2005	52	36	1,875	778	133	103,000	33	870	28,700
2006	427	78	33,200	856	110	94,500	184	459	84,500
2007	673	92	62,000	844	164	139,000	243	521	127,000
2008	887	158	140,000	813	136	110,000	288	537	155,000
2009	1242	217	270,000	703	141	98,900	299	735	220,000
2010	1402	207	290,000	776	178	138,000	350	641	224,000
2011	1459	198	289,000	885	259	229,000	394	788	311,000

a) Numbers refer to the entire population of public support users.
b) Tax credits and subsidies categories include users of the policy mix.
c) Average and total columns in thousand Euros.

Figure II.1 illustrates the evolution of the average amounts received per company split into four groups: firms that receive only tax credits or only subsidies, and those receiving both measures simultaneously. It reveals that policy mix users receive on average larger amounts of both tax credits and grants compared to single policy users. The difference in average subsidies starts off high and diminishes in time, while tax credits follows the opposite trend – similar amounts for single policy and mix users, followed by a jump in 2008, simultaneous with the raise in exemption rates.

Figure II.1 Evolution of average amounts by policy



a) Categories are mutually-exclusive, thus numbers are not identical to, but based on Table II.1.
b) Average amount received expressed in thousand Euros.

3.2 Data

I use a dataset comprising the 2008, 2010 and 2012 OECD Business R&D surveys on Belgian firms, coupled with employment, financial, fiscal and subsidy information from the Belgian Federal Public Service Finance[49]. Although non-R&D data is a panel, the OECD Business R&D surveys have been applied to different samples of companies over the years, rendering the data usable in the form of repeated cross sections.[50]

As I am interested in the effect of each type of public support on the private R&D intensity of firms, the main dependent variables are extracted from survey questions where firms were asked the amounts spent on internal R&D. However, rather than focusing solely on total R&D expenditure, I also consider the allocation of R&D budgets over different activities. Thus, I use survey questions regarding the share of R&D expenditure by type of activity – basic research,

[49] The dataset is a collection of data managed by the Belgian Federal Public Service Finance and collected from the following sources: the Belgian Federal Public Service Finance (tax credit data), the National Bank of Belgium (financial data), the Belgian Federal Science Policy Office (R&D survey), and the regional agencies involved in R&D subsidy allocation – the Walloon government's R&D services, the Flemish governmental Agency for Innovation by Science and Technology (IWT) and the Institute for Scientific Research and Innovation of Brussels (IRSIB).

[50] Only around 220 firms have full data covering the three waves of the survey.

applied research, and development – to test whether different types of public support for R&D have (dis)similar, if any, effects on the R&D budget allocation decision of firms.[51] The three different waves of the survey provide data on the outcome variables for the years 2007, 2009 and 2011.

Data on subsidies granted by the regional governments and on the federal tax credit for researchers is exhaustive and comprises the amounts received by the complete population of recipients. Firm characteristics – employment, location, financial data, etc. – are available as a panel, thus I am able to use lags of most independent and control variables in order to tackle possible simultaneity biases.

After checking the data for consistency, the sample contains 2,650 observations on 1,809 firms.[52]

3.3 Method

The main issue present in evaluation studies of public policy is the fact that funds are not randomly attributed to firms. In the case of subsidies, public authorities decide which projects, and thus firms, to finance from limited funds. On the other hand, firms using tax credits for R&D do not have to go through such an evaluation process, but have their own considerations when deciding whether or not to demand such tax breaks. Be it third party selection or self-selection, this issue implies that firms using some type of public support for their R&D differ ex ante from firms that do not use such measures, and the differences might be hidden to the researcher. Heckman et al. (1999) provide an overview of estimation strategies under the presence of selection bias, among which matching estimators and instrumental variables regressions. The former is a non-parametric method that relies on the assumption that selection into programs is based on observable characteristics of participants. The IV method requires that selection be tackled by exogenous instruments that only affect outcomes through their

[51] Respondents to the survey are given guidelines and examples on how to attribute expenses to each category, based on the Frascati Manual (OECD, 2002). While it is plausible that for some companies this distinction might not be obvious, I suspect that firms active in high-tech sectors have good knowledge of the difference between these categories. For the former, the guidelines, definitions and examples provided to them should offer enough information to mitigate measurement issues stemming from subjective interpretations.

[52] Only firms that have responded to the survey are analysed (estimated values by the Science Policy Office have been removed). Moreover, firms that report no internal R&D expenditure or a number that is higher than total costs (R&D intensity higher than 100%) are removed the sample.

impact on the treatment variables. Trade-offs need to be made when choosing either method, as none is robust to all possible bias.

Matching estimator

In order to measure the effects each different policy has on the design of R&D budgets, I first perform nearest-neighbour matching using a flexible definition of treated and control groups on a pooled cross section of firms. For each outcome, I create four mutually-exclusive groups of firms: users of tax credits, users of subsidies, users of both tax credits and subsidies (policy mix), and firms that do not receive any public support. The fact that groups are mutually exclusive deals with the 'hidden treatment' issue – when multiple policies are used as treatments, they can have a confounding effect on each other (Guerzoni & Raiteri, 2015).

Based on the methodology developed by Gerfin and Lechner (2002), I consider grants, tax credits and the policy mix as heterogeneous treatments and analyse their effect on each outcome as the average treatment effect on the treated, $\alpha^{t,c}$, as

$$E(\alpha^{t,c}) = E(Y^t|S = t) - E(Y^c|S = t) \qquad (1)$$

where Y^t and Y^c denote the outcomes for the 'treatment' and the 'counterfactual' states.

I form pairwise comparisons of t and c states with the types of firms described above (policy mix users, tax credit users, subsidy users, non-users of public funds) as shown in Table II.2.

Table II.2 illustration of the different definitions of treated and control groups

		Treatment		
		Policy mix	Tax credits	Subsidies
Counterfactual	No funding	Definition 1	Definition 2	Definition 3
	Policy mix		Definition 4	Definition 5
	Tax credits	Definition 6		Definition 7
	Subsidies	Definition 8	Definition 9	

a) 'Definition 1' analyses the effect on each outcome variable of the policy mix (tax credits and subsidies), versus the counterfactual of not having used any public funding. Analogously, 'Definition 7 analyses the additionality of subsidies compared to the counterfactual of using tax credits.

This method allows the direct comparison of policies with each other, but also disentangling each individual effect that policies have compared to the counterfactual of not using any public funding. However, in this part of my analysis I only define treatment groups by simple dummy variables denoting whether a firm has received tax credits or subsidies (or both) for R&D.

I employ a two-step matching procedure, as follows: first, I estimate the propensity scores as the probability of being in each of the four groups. In order to do so, I employ a multinomial probit model on the four treatment groups – being a policy mix user, a tax credit user, a subsidy user, or not receiving any support – and condition on company characteristics that might play a role in the use of each of these policies.

In order to make sure that a comparison between the estimated effects of each treatment definition is valid, I restrict the entire sample to common support so that all firms have the possibility of participating in all four states. This comes down to keeping only those observations with probability of being observed in state t (P^t) larger than the highest minimum and smaller than the lowest maximum of all probabilities P^t observed for each state t=1..4.

In a second step, for each combination of states t and c, for each firm in state t, a similar firm in state c is found based on the smallest Mahalanobis distance calculated on the propensity scores P^t and P^c. Furthermore, given that I use a pooled cross section, an exact match on the year in which the outcomes are measured is required. When a match is found, the firm in state t is taken out of the sample, while the one in state c is kept as a possible control for the remaining firms in state t (matching with replacement). When all firms in state t have been matched, the treatment effects are estimated using the matched firms in states t and c.

Next, I employ categorical matching for analysing whether the effects of treatment differ by the amount received, similarly to Görg & Strobl (2007) or Marino et al. (2015). I split each treatment at the median, creating the following categories: small and large tax credits (cut-off at 49,520 Euros), small and large subsidies (cut-off at 36,968 Euros), and small and large policy mix (cut-off at 280,084 Euros). Although a finer cut could provide better depth of the analysis, I split each policy into two groups due to the relative small sample size and in order to obtain proper balance between each treatment – counterfactual groups. The matching is done by first estimating probit models for each categorical comparison (e.g. small subsidy versus large policy mix) and obtaining propensity scores that are used to match treated and control groups. For each comparison, a common support restriction is applied, unlike the general matching where common support is defined to ensure that all firms could in theory receive any treatment. Although the common support restriction in this second part of categorical matching is less strict due to data restrictions, it nevertheless ensures each control used to compute ATT's has a theoretical probability of receiving the treatment category.

Instrumental variables regressions

In order for the matching estimators to be valid, all characteristics affecting selection into subsidy or tax credit programs must be observed. In other words, potential outcome and participation in a programme must be independent given the observed set of characteristics X – the conditional independence assumption (Rubin, 1977). As this assumption cannot be tested empirically, I also estimate the treatment effects by other methods which are robust to selection on unobserved characteristics.

The main concern is that, although the dataset is quite extensive, some variables that have been previously used in similar studies are not available. The main unobserved factor in most studies is the intrinsic quality of the firm and of its R&D projects. Authorities base their selection of grant winners on comprehensive description of the proposed projects, the past achievement of candidates and other characteristics that are not available in my data base. Among them, group ownership of a firm has been used to capture the lower incentives such firm might have due to lower subsidy budgets made available to them, but also the fact that network structures within a group may allow members to be better informed about funding sources (Czarnitzki & Lopes-Bento, 2013). Successful innovators might also have higher chances of receiving support, and the patent stock of a firm has been used as a proxy in previous studies (Hussinger, 2008). Due to the confidential character of my data, I cannot use external sources for these variables – e.g. Amadeus for group ownership or EPO/PATSTAT for patent statistics.

Furthermore, matching estimators only provide a general view of the effects of policies on outcomes. Even though I try to solve this issue by matching on different categories of treatment, this solves the issue only partially. Dose response methods based on a generalised propensity score have been employed to some effect in literature in order to assess whether treatment effects vary with treatment level (Hottenrott et al., 2014; Marino et al., 2015). Nevertheless, such models only allow comparisons between different levels of the same treatment, rather than between different treatments.

Taking all of the above into consideration, I test the robustness of the results from the matching estimation through methods that deal with unobserved heterogeneity among firms and that model parametrically the effect of the amount of each treatment received controlling for each other type of treatment.

Should selection not be an issue – for example if firms were randomly attributed public funds for R&D – then regressing the outcome variables on the subsidy and tax credit amounts by ordinary least squares would provide an unbiased estimation of the effects of each policy measure on private R&D. However, in the presence of (self-) selection, the subsidy and tax credit amount variables are endogenous and need to be instrumented. Valid instruments should be correlated with subsidy and tax credit use, but uncorrelated with any unobserved factors influencing outcome – R&D intensity, total and split by activity. A robust instrument would thus be the amount of subsidies and tax credits that each firm could potentially receive (Lichtenberg, 1987). I use two distinct features of subsidies and tax credits in Belgium to identify the endogenous variables.

First, subsidies are granted by regional governmental agencies with budgets that are fixed prior to the payment period. Thus, the overall subsidy budget for each agency is exogenous to firm characteristics. However, following Wallsten (2000), one cannot assume that the entire budget of an agency is potentially available to each firm. Therefore, I calculate the average amount of subsidies received by a firm per year, administrative region, industry defined by 4-digit NACE codes, and size class – indicated by an SME dummy. I also calculate the number of firms supported by subsidies within these groups. These two instruments together capture the variation over time of the overall budgets of granting agencies, the variation of the budgets of different agencies, and also the availability of subsidies to different industries.

Second, tax credits differ from subsidies in that there is no fixed budget available to firms. Thus, in theory, the amount of tax credits can vary from zero to infinity. However, following work by Neicu, Kelchtermans, & Teirlinck (2016a), I rely on the existence of peer effects in the spread of new policy for R&D. Analysing the same tax credit for Belgian firms, they show that firms have a higher propensity of using the measure if their peers – firms within the same industry and geographical location – use it too. By defining the average amount of tax credits per firm and the number of users by year, region, industry and size class, I construct an instrument that is correlated with each firm's amount of tax credits used, while exogenous to its R&D spending.[53]

[53] However, there might be instances where theoretical arguments can be made against the exogeneity of my instruments. For example, in a Cournot model, competitors' use of public support lowers their cost of R&D and improves their competitive position. This, in turn, can have two effects: first, it can reduce incentives to engage in R&D if these activities are strategic substitutes; on the other hand, if R&D results in innovations that lower the

3.4 Variables

Dependent variables

In order to assess the effects of each policy on firms' R&D activity, I first employ a standard dependent variable used in input additionality literature – the log of private R&D intensity (*LN R&D NET*). I define private R&D intensity as intra-mural R&D expenditure, net of any public support received. I select my sample to include only firms that have non-negative private R&D expenditure, and positive total R&D. That is to say that I only analyse R&D-active firms. Although this might drive down some of the significance of the results, I consider it appropriate to exclude firms in periods when they do not report any R&D activity.

Further, I split total R&D expenditure by type of activity: basic research, applied research, and development. Firms were asked in the OECD Business R&D Survey what percentage of their total internal R&D expenses make up each category. I multiply each percentage with the total R&D expenditure to create a variable that captures the overall volume of R&D by activity (*LN BASIC RES*, *LN APPLIED RES*, *LN DEVELOPMENT*). Lastly, I test the effects of policies on the percentage of development in total R&D (*DEVELOPMENT INT*), and, by extrapolation, the percentage of total research as (1-*DEVELOPMENT INT*). The difference between the last two sets of outcome variables stands in that the former allow to examine the input additionality that policies create in terms of increasing or decreasing the volume of basic, applied research or development activities of a firms, while the latter allows an analysis of the behavioural additionality induced by policies. In other words, one shows us if receiving public subsidies or tax credits has lead firms to increase their private expenditure in either of the three categories, while the other will indicate if firms have shifted funds from development to research as a result of using public support for R&D. Note that it is entirely possible that a company that receives support increases its private expenditure on both research and development, but the increase is less for one category than the other; in this case, the effect of the support used by

---

cost of production, increased investment in R&D is a competitive response. Both results illustrate that my instruments are possibly correlated with the outcome. Nevertheless, the issue is somewhat mitigated by the non-significant Hansen J tests. Under H_0, all instruments are uncorrelated with the error term of the main equation. My estimations show that the null cannot be rejected at 10%, which provides assurance that the Cournot effects are minimal.

the firm would be positive on all log-level variables, but negative on either development or research intensity.

Treatment variables

The variables used to define treatment status in the matching estimators are binary variables indicating whether a firm has received a 'treatment' comprising only subsidies (*SUBS*), only tax credits (*TAX*), both subsidies and tax credits (*MIX*), or no support (*NOSUP)* during the years covered by each survey (i.e. 2007, 2009 and 2011).[54] This specification allows to estimate the average effect of each treatment on the outcomes, irrespective of the amount of support received. Indeed, it assumes that, on average, the amounts are the same between the three treatment statuses.

I then use the available data on the amount of tax credits and subsidies received by firms in the categorical matching and the instrumental variables estimation. By taking the natural logarithm of these amounts, I can interpret the coefficients in terms of the effect of percentage increases in the independent variables on the dependent one. Because the model is parametric, I am able to model the impact of both the amount of subsidies (*LN SUBS*) and tax credits (*LN TAX*) received simultaneously. This allows establishing the marginal effect each policy has on the outcomes. In a second step, I define the total amounts for firms that both policies (*LN MIX*). This definition allows me to examine, similarly to the matching estimator, whether subsidies and tax credits show more (or less) additionality when combined in a policy mix.

Instrumental variables

As mentioned before, I instrument each endogenous variable by two exogenous instruments: the average of that variable by size class (SME or large firms) year, region and industry, and the number of firms with a non-zero value for the variable. Thus, I instrument *LN SUBS* with *LNSUBSAVG* and *NRSUBS*, *LNTAX* with *LNTAXAVG* and *NRTAX*, *LNSUBSONLY* with

[54] This definition of each treatment is rather strict. An alternative would be to consider treatment over two-year periods – e.g. a policy mix user would have used tax credits and subsidies either in period *t* or *t*-1, and not necessarily both at the same time. As matching estimators require that treated and control groups be balanced before treatment receipt, this would imply matching on observed characteristics in *t*-2, which would drastically reduce the data set by requiring to observe each firm in two consecutive surveys.

LNSUBSONLYAVG and *NRSUBSONLY*, *LNTAXONLY* with *LNTAXONLYAVG* and *NRTAXONLY*, and *LNMIX* with *LNMIXAVG* and *NRMIX*.

Control variables

Based on previous findings regarding the determinants of R&D and of the probability of firms to enter public support programs, I employ a set of control variables both in the matching estimator – when calculating the propensity of each firm to use public support – and in the instrumental variables equations. In this section I explain each variable's role in each model.

The age and size of firms have been shown to capture experience effects in dealing with public support agencies. The logarithm of age (*LN AGE*) will capture such effects, as one expects older firms to rely on more past knowledge regarding the availability of public funding. Moreover, the variable should capture whether younger firms invest more in R&D than established firms in the instrumental variables regressions. The size of a firm is usually found to affect the probability of receiving public support either by capturing scale effects on the opportunity cost of applying or the specific targeting by funding agencies of categories of firms (Blanes & Busom, 2004; Neicu et al., 2016b). I include the lagged number of employees in logarithm in the estimation to account for size effects (*LN EMP*). At least in the Flanders region, there are explicit grants for small and medium enterprises (Hottenrott et al., 2014). I capture this by including an SME dummy (*SME*). Size effects might also play a role in determining a firm's R&D budget and how it is split between research and development

Capital-intensive firms have been found to have a higher probability of engaging in R&D, and, consequently, having higher chances of receiving public support for R&D (Blanes & Busom, 2004). I include a measure of capital intensity as the ratio of fixed assets to employees in logarithm (*LN CAPINT*).

Moreover, I control for a firm's financial health with its current ratio (*CURR*), defined as the ratio of current to total assets. Whether a company has enough financial resources can have an influence on its incentive to request public support, but also invest more (less) on R&D activities. Czarnitzki et al. (2011) have found that working capital – the difference between current assets and current liabilities – has a positive impact on total R&D spending, but also a larger impact on R than on D.

In order to capture sectorial patterns related to R&D activity and also the possible targeting of specific industries by policy makers, I define high- and low-tech service and manufacturing industries, and include binary variables for each in the estimation.

Given that subsidies in Belgium are managed by the regional governments, while tax credits are managed by the federal government, I include dummy variables for firms located in Flanders and Wallonia, keeping Brussels as baseline. Year dummies are included to account for the different waves of the business R&D survey covered by the sample.

I also include in the parametric estimation of R&D expenditure, total and per activity, the financial leverage (*LEVER*), denoting a firm's debt to equity ratio in order to capture firms' access to the credit market. Czarnitzki et al. (2011) find that this variable has a significant impact on R&D activity, as firms with higher debt rates perform less research, while the impact on development is insignificant.

The control variables – with the exception of age, industry and region dummies – are measured in the year prior to the measurement of outcomes. This ensures, to the extent possible given the data, maximum sample size and addresses possible simultaneity concerns.

3.5 Descriptive statistics

Table II.3 displays mean values and standard deviations for the control and outcome variables before the matching procedure. They are aggregated by treatment, i.e. by type of support received. In the 3 pooled cross sections, 1,363 firms did not receive any public funding for R&D, 644 only received tax credits, 237 received only subsidies, and 406 used a mix of both.

Table II.3 Summary statistics

	No support (N=1363)		Tax credits only (N=644)		Subsidies only (N=237)		Policy mix (N=406)	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Tax credits[a]	0.00	0.00	188	883	0.00	0.00	482	1,444
Subsidy[a]	0.00	0.00	0.00	0.00	140	550	466	1,219
Policy mix[a]	0.00	0.00	0.00	0.00	0.00	0.00	948	2,458
R&D exp. [a]	531	2,521	4,341	30,000	1,537	6,821	9,151	34,500
Basic R exp. [a]	22	172	196	1,825	130	779	1,044	7,639
Applied R exp. [a]	224	824	1,213	3,332	805	2,711	3,971	13,400
Develop. exp. [a]	285	2,331	3,119	29,800	742	6,000	5,083	23,300
% basic R.	5.82	15.54	5.50	13.07	7.72	15.42	8.22	14.39
% applied R.	50.73	37.02	53.27	33.73	57.66	33.72	52.61	30.94
% develop.	43.45	37.40	41.23	33.80	34.62	32.96	39.17	31.67
Age	25.16	17.63	24.13	18.10	22.75	17.25	26.29	24.78
Employees	86.58	232.97	197.43	512.41	99.96	305.35	349.32	640.16
SME	0.92	0.27	0.81	0.39	0.92	0.28	0.69	0.46
Leverage	3.87	21.22	148.14	2757.19	38.22	532.63	3.12	8.58
Current ratio	2.22	3.01	2.70	5.11	2.21	2.47	2.98	4.64
Capital intensity	187	1,630	283	1,982	157	795	184	418
High-tech man.	0.19	0.39	0.24	0.43	0.29	0.45	0.38	0.49
High-tech serv.	0.25	0.43	0.30	0.46	0.31	0.46	0.32	0.47
Low-tech man.	0.33	0.47	0.26	0.44	0.21	0.41	0.18	0.39
Low-tech serv.	0.17	0.38	0.15	0.36	0.16	0.36	0.09	0.28
Brussels	0.07	0.26	0.08	0.27	0.07	0.26	0.09	0.28
Flanders	0.68	0.47	0.65	0.48	0.84	0.37	0.83	0.37
Wallonia	0.24	0.43	0.27	0.45	0.09	0.29	0.08	0.27

a) Amounts in thousand Euros.

The first three rows paint a similar picture to the one seen in Table II.1 and Figure II.1. As in the population statistics, policy mix users receive almost three times the amounts of subsidies and tax credits than the users of single-measures. They receive the two measures in almost equal quantities – 482,000 Euros in tax credits and 466,000 Euros in grants.

We also observe that receivers of public support have higher net R&D expenditure than non-receivers. Subsidy users spend three times more, tax credit users up to eight times more, while firms receiving the policy mix spend on average seventeen times more on R&D from private sources. All treatment groups show higher average spending on basic and applied research, but also on development.

Firms that use the policy mix are older and larger than the other categories. On the other hand, SMEs are better represented in the subsidy-only users group, which was expected due to the specific grants for these firms offered by all regional authorities. However, only 69% of policy mix users are SMEs, significantly lower than the other groups. Leverage shows the debt to equity ratio of firms, and we can see that single policy users have higher leverage ratios, although the number are driven by a few outliers.

The industry split shows that most firms receiving any type of support are active in high-tech sectors, and policy mix users are more concentrated in high-tech manufacturing. Finally, we note an over-representation of firms from Flanders in the sample, which can either be a missing data issue or an effect of the region harbouring relatively more R&D active firms.

These statistics already show some interesting facts about the distribution of firms into each treatment group by their characteristics, and their relative clustering is in line with the different policies implemented by each funding agency (e.g. subsidies being targeted at SMEs).

4 Results

4.1 Estimated propensities of receiving treatment

In a first step, I estimate a multinomial probit model on the four (mutually exclusive) categories denoting the receipt of each treatment (only tax credits, only subsidies, and a policy mix) or not receiving any support. The sample comprises 2,650 firm-year entries, of which around half (1,363) have not received any treatment ('no support').[55]

The results presented in Table II.4 indicate that, as expected from the distribution of characteristics over the four treatment groups, larger and younger firms in high-tech industries have a higher probability of receiving tax credits or using the policy mix. Somewhat surprising, being an SME translates into a lower propensity of accessing R&D subsidies, although regional governments have a pro-SME policy in Belgium (Hottenrott et al., 2014). Instead, high-tech firms from Brussels and Flanders have a higher propensity of receiving subsidies from the respective regional governments. Furthermore, the financial resources of a firm, measured by the current ratio, have a positive impact on their propensity to receive the policy mix.

[55] The sample only includes firms that report positive intra-mural R&D expenditure.

Table II.4 Multinomial probit estimation of treatment categories

	MIX	SUBS	TAX
	a	*b*	*c*
LN AGE	-0.52***	-0.12	-0.39***
	(0.09)	(0.09)	(0.07)
LN EMP	0.34***	-0.06	0.34***
	(0.05)	(0.05)	(0.04)
SME	-0.62***	-0.36	-0.21
	(0.21)	(0.23)	(0.18)
CURR	0.01*	-0.03	0
	(0.01)	(0.02)	(0.01)
LN CAPINT	0.16***	0.09***	0.12***
	(0.03)	(0.03)	(0.03)
HITECH M	1.03***	0.79***	0.53**
	(0.3)	(0.25)	(0.23)
HITECH S	0.99***	0.63**	0.70***
	(0.3)	(0.25)	(0.23)
LOWTECH M	-0.07	0.11	0.02
	(0.31)	(0.25)	(0.22)
LOWTECH S	0.16	0.29	0.32
	(0.32)	(0.26)	(0.24)
FLANDERS	0.38*	0.31	0.18
	(0.22)	(0.22)	(0.17)
WALLONIA	-0.58**	-0.54**	0.31
	(0.25)	(0.26)	(0.19)
2009	0.11	-0.38***	0.55***
	(0.1)	(0.12)	(0.1)
2011	0.36***	-0.14	0.83***
	(0.1)	(0.11)	(0.1)
Wald chi-square	467.76***		

a) Base category = unsupported firms.
b) Robust standard errors clustered by firm.
c) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
d) Intercept term not shown.

Following these results, I use the estimated propensity scores and apply a ‘common support’ restriction that drops 407 companies with estimated probabilities of being in treatment group *t* larger than the lowest maximum probability over the four treatment groups *t*, or smaller than the highest minimum probability over the same groups.

Consequently, for each combination of treatment *t* and control group *c*, each treated firm in group *t* (where *t* is based on each definition of treatment – policy mix, only tax credits, only subsidies) is matched to the most similar firm in group *c* (comprising the three treatments and the firms not using any policy), based on the Mahalanobis distance between the two firms' propensities to be in groups *t* and *c* (P^t and P^c). Furthermore, exact matches are required on the year in which the measurements are taken.

4.2 Average treatment effects on private R&D expenditure

The method allows for the average treatment effect on the treated (ATT) to be calculated for each combination of treatment *t* and counterfactual *c*. The estimations of the effects of each policy on private R&D expenditure are presented in Table II.5. Due to the fact that the group of firms only receiving subsidies is only half the size of tax credits and policy mix user groups, the procedure does not result in proper balance between treatment and counterfactual groups when the latter comprises subsidy users, even though the matching is done with replacement. The Wald chi-square statistics for the tax credits-subsidies and policy mix-subsidies are significant at 1% level, so the ATT's are not reported in the table below as they violate the method's main assumption – i.e. that the only difference between treated and non-treated firms comes from the treatment itself, conditional on covariates.[56] However, when treatment is subsidy receipt, the control groups are larger than the treatment group, thus the estimation of ATT's is implemented on groups that are balanced on the covariates. Throughout the paper I only report ATT's on balanced groups post-matching, i.e. for which the matching procedure produces reliable results.

[56] I calculate the Wald chi-square statistic of a probit on the binary variable indicating treatment receipt, where the sample includes only firms that have been matched. The statistic tests the balance between treated and control groups, the null being that the observed characteristics do not explain treatment receipt, i.e. groups are balanced on covariates.

Table II.5 ATT on log-levels of private R&D expenditure

		Actual state		
		Policy mix	Tax credits	Subsidies
Counterfactual	No support	1.45***	0.96***	0.02
	Policy mix		-0.47***	-0.89***
	Tax credits	0.40***		-0.80***
	Subsidies			

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Tax credits and subsidies groups refer to use of each policy as a single measure.
c) The first row displays additionality of each treatment compared to the counterfactual of not receiving support. Each column benchmarks treatments with each other.

The first row of the table shows the effect of each policy compared to the counterfactual of not having used any support. The results indicate that using tax credits solely or combined with subsidies has a positive effect on the private R&D of recipient firms compared to the counterfactual of not having received any support. On average, policy mix users spend 1,45 times more on R&D from their own funds, while tax credits users spend 96% more than firms that do not receive any support. However, the results also show that subsidies users do not spend a significantly different amount of own funds on R&D than they would have spent without having received any public support.

The comparison of different policies reveal that the policy mix outperforms both tax credits (by 40% extra R&D expenditure) and subsidies (by 89%) that are used separately.[57] Moreover, subsidy recipients spend 80% less of their own funds on R&D than they would have spent had they received tax credits instead.

My first hypothesis is only partially confirmed, as only tax credits show positive and significant additionality on the private R&D expenditure of firms.

Overall, it is the combination of subsidies and tax credits that induces the larger effect on how much firms spend on R&D, which confirms my second hypothesis.

[57] Note that due to the different sizes of treatment groups and the fact that matching is done with replacement, the ATT's are not symmetrical – e.g. the difference between the policy mix treatment and the tax credits counterfactual is different than the tax credits treatment versus the policy mix counterfactual. However, the differences are small in absolute value (0.49 vs. 0.31). Because the tax credit users group is larger than the other two treatment groups, the ATT's calculated when this group is the counterfactual are more significant and thus preferred in the analysis.

In order to analyse whether treatment effects vary with the volume of public support received, I perform categorical matching by size of treatment as described in section 3. Table II.6 illustrates the ATT's of each treatment category on the log-levels of private R&D expenditure.

Table II.6 ATT on log-levels of R&D expenditure by size

	Actual state					
	Policy mix S	Policy mix L	Tax credits S	Tax credits L	Subsidies S	Subsidies L
No support	0.55***	2.20***	0.30***	1.39***	0.06	0.39

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.

As expected, larger amounts of support received show higher positive additionality on the private R&D of firms across treatment categories, although the results for subsidies are not significant at 10%. Yet again, compared to the counterfactual of not receiving any support, the policy mix users have the higher levels of private R&D than firms not receiving support by 55% for small amounts of the mix and up to 2.44 times higher for firms receiving larger amounts of the mix, while large tax credits amounts increase private spending in R&D 1.39 times and small amounts by 30%.

The key takeaway from this analysis is that subsidies seem to have no significant effect on private R&D, while significant, positive effects are seen from small amounts of tax credits and continue to grow sequentially to small amounts of the policy mix, and reaching the largest additionality from the use of large volumes of tax credits and of the policy mix.

4.3 Average treatment effects on basic research

I now switch my analysis to the behavioural additionality of each policy on the different components of R&D expenditures. I first compute the average treatment effect on the treated on basic research expenditure. But before interpreting the results, a note on the distinction between this analysis and the previous one is in order. Because the OECD Business R&D survey does not ask firms to provide numbers on private expenditure on R&D divided by its three components, I can only assess whether there has been any additionality of public support in the sense of changing a firm's budgets for basic or applied research and development irrespective of how they finance their R&D. Thus, it is entirely possible that, for example, an increase in basic research spending can be induced by a specific subsidy that a firm has received for a basic research project. This may increase R&D spending on basic research only by the amount of the subsidy without creating any input additionality, i.e. without increasing the firm's private spending on basic research. That being said, if that firm or a similar one had spent less resources on basic research prior to receiving the subsidy, this does imply that the subsidy itself has induced a behavioural change in the user (controlling for the propensity to receive subsidies based on observed characteristics). The difference between input and behavioural additionality is relevant up to the point of the policy maker's interest in disentangling all the possible effects a policy may have.

With this in mind, I shift attention to analysing whether policy had any effect on the behaviour of supported firms and whether different policies had different effects, if any. The results are presented in Table II.7.

Table II.7 ATT on basic research

		Actual state		
		Policy mix	Tax credits	Subsidies
Counterfactual	No support	3.15***	1.03***	1.52***
	Policy mix		-1.90***	-0.38
	Tax credits	1.49***		0.72
	Subsidies			

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Tax credits and subsidies groups refer to use of each policy as a single measure.
c) The first row displays additionality of each treatment compared to the counterfactual of not receiving support. Each column benchmarks treatments with each other.

All policies have a positive effect on the amount that firms spend on basic research activities. On average, a recipient of the policy mix spends 3.15 times more on basic research than what they would have spent without receiving support. Tax credits users spend 1.03 times more on basic research, while subsidy users 1.52 times more, compared to the counterfactual of not having used support. The policy mix also outperforms tax credits by a factor of 1.49 or more, but the difference in additionality between subsidies and the policy mix is not significant. This might imply that subsidies drive most of the effect, or that the volume of support may play a role, such that when faced with greater volumes of financial slack, firms are more inclined to use it on farther-from-the-market research activities. In order to test if this is the case, I estimate ATT's by category of treatment, similarly to the previous section and present the results in Table II.8.

Table II.8 ATT on basic research spending by size of treatment

	Actual state					
	Policy mix S	Policy mix L	Tax credits S	Tax credits L	Subsidies S	Subsidies L
No support	2.32***	4.65***	0.56	2.08***	1.20**	2.56***

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.

The positive and significant ATT's of the policy mix and tax subsidies are present at both levels of the policies, while the additionality of tax credits seems to rely mostly on large treatment volumes. Contrary to total private R&D expenditure, subsidies do show significant effect on basic research budgets.

4.4 Average treatment effects on applied research

Subsequently, I analyse the effect of each policy on the expenditure on applied research in order to verify whether there is any difference in additionality on the two components of research. Table II.9 shows that all types of public support have a positive effect on this outcome, compared to the counterfactual of not receiving public support for R&D (row one).

Table II.9 ATT on applied research

		Actual state		
		Policy mix	Tax credits	Subsidies
Counterfactual	No support	3.48***	1.90***	1.20***
	Policy mix		-1.43***	-1.19***
	Tax credits	1.35***		-0.20
	Subsidies			

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Tax credits and subsidies groups refer to use of each policy as a single measure.
c) The first row displays additionality of each treatment compared to the counterfactual of not receiving support. Each column benchmarks treatments with each other.

On average, the policy mix increases spending on applied research activities 3.48 times, while tax credits only 1.9 times and subsidies by a factor of 1.2. The difference between tax credits and subsidies, on the one hand, and the combination of the two, on the other hand, is significant at 1%. Indeed, policy mix users spend 1.35 times more on applied research than tax credit users and 1.19 times more than subsidy users, while the difference between the latter two groups is not significant, albeit negative in favour of tax credits.

These results suggest that the effect of policy on applied research spending is purely based on the amount received, irrespective of the type of policy. I set out to further test this in the categorical treatment analysis presented in Table II.10.

Table II.10 ATT on applied research spending by size of treatment

	Actual state					
	Policy mix S	Policy mix L	Tax credits S	Tax credits L	Subsidies S	Subsidies L
No support	2.78***	4.68***	1.20***	3.25***	0.03	1.75***

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.

Overall, it does indeed seem that size effects drive to some extent the ATT's on applied research. The larger the amount of support received, the larger the effect compared to smaller levels of support, this results being seen across all treatments. The fact that small grants show no additionality is in line with my previous findings, as these types of support positively affect spending on basic research. The effect of subsidies on applied research is thus driven by large grants, firms that receive them spending on average 1.75 times more on this activity than non-receivers. The ATT's provide evidence that firms use small grants for their basic research, while larger grants are used for both types of research.

The greatest effect stems from using large amounts of the policy mix, a finding which is in line with the volume-driven explanation of the results shown in Table II.9.

4.5 Average treatment effects on development

Lastly, the policy effects on development spending are analysed and the results presented in Table II.11. Users of the policy mix experience positive additionality on their development budgets by a factor of 1.51 compared to firms receiving no support, while those using tax credits increase spending 1.04 times. On the other hand, subsidies do not show any significant effect, and, moreover, firms using subsidies spend, on average, significantly less on development than policy mix or tax credit users.

Table II.11 ATT on development spending

		Actual state		
		Policy mix	Tax credits	Subsidies
Counterfactual	No support	1.51***	1.04***	-0.55
	Policy mix		-0.55	-1.68***
	Tax credits	0.65		-1.55**
	Subsidies			

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Tax credits and subsidies groups refer to use of each policy as a single measure.
c) The first row displays additionality of each treatment compared to the counterfactual of not receiving support. Each column benchmarks treatments with each other.

Combined with my previous results, these numbers point towards a significant difference in how subsidies and tax credits influence firms' spending on R&D. One cannot rule out subsidies crowding out private spending on development, and it might be the case that users shift their research orientation towards basic and applied research when receiving this type of support. On the other hand, combining subsidies with tax credits in a policy mix has a positive effect on all three components of R&D.

The non-significant effect of subsidies confirms my third hypothesis and the intuition behind it, namely that subsidies crowd-out private spending on development projects, which that are closer to the market than research.

The amount of support seems to mitigate the effects of policy on development spending too. The results in Table II.12 reveal that the positive effects of the policy mix and of the tax credits are solely due to larger treatment values, while smaller amounts of treatment show no effect. Subsidies, on the other hand, show no effects on development spending at both levels of treatment.

Table II.12 ATT on development spending by size of treatment

	Actual state					
	Policy mix S	Policy mix L	Tax credits S	Tax credits L	Subsidies S	Subsidies L
No support	0.16	3.41***	-0.11	1.35**	0.49	0.18

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.

In order to verify the implication that stems from the previous results, namely that the policies provoke a shift in R&D budgets away from development and towards (basic and applied) research, I calculate the ATT's on the percentage of total R&D that firms spend on development activities (development intensity). The results are presented in Table II.13.

Table II.13 ATT on development intensity

		Actual state		
		Policy mix	Tax credits	Subsidies
Counterfactual	No support	-7.35**	-4.18	-8.67*
	Policy mix		4.56	-1.97
	Tax credits	-5.03*		-9.97*
	Subsidies			

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.

Because the outcome is measured as the percentage of R&D devoted to development, the results can be interpreted as evidence of the shift of funds between development and research activities. The average effect of subsidies is an 8.67 percentage points decrease in development intensity, which implies that the same amount is shifted towards (an increase in) research spending. The effect of the policy mix stands at 7.35 percentage points, while tax credit users show not significant change of behaviour.

The combined results show that tax credits and the policy mix increase firms' spending on basic and applied research, and, to a smaller extent, on development. The more interesting conclusion is that the policy mix also creates behaviour changes in firms, leading them to focus more resources on research activities compared to development. Combined with the positive effect the policy mix has on research spending, this proves my forth hypothesis.

Subsidies, on the other hand, show an even stronger behavioural effect, as they do not increase spending in development altogether, but they also cause a shift in funds from development towards research. However, as I mentioned previously, firms can receive subsidies either for research or development projects. This is the case of the IWT, the Flemish funding agency, which grants higher percentages of project costs for research than for development projects. In 2007, research subsidies amounted to around 35% of total subsidies granted by the IWT, while development grants over 50%. In 2009, the difference between the two contracted to under 10% (Hottenrott et al., 2014). Given that 83% of subsidy-only recipients in my sample are Flemish firms, the effects could well be driven by this specific policy design. Hottenrott et al. (2014) do find positive and significant direct effects of both types of subsidies on research and development, but they also find cross-effects from research subsidies to development and vice-versa. However, they do find larger effects on research for the period between 2005 and 2009, which corresponds to a policy shift towards targeted support. As I analyse three periods – 2007, 2009 and 2011, it could well be that the driver behind my results is an increase in research grants relative to development grants post 2009, combined with higher direct additionality of research grants would explain my findings that on average, subsidies increase spending on research but not on development.

4.6 Instrumental variables estimation

Because the matching procedure only accounts for selection of firms into treatments based on observed characteristics, it may provide biased estimates if this assumption does not hold. One can think of a number of ways this could happen, as the researcher rarely has extensive data on (self-) selection procedures. For example, firms might have a better chance of receiving larger subsidies if they have used them to good effect in the past, whatever 'good effect' might mean to the policy maker. Similarly, a firm's decision to request tax credits might lay in the hands of its overseas headquarters. As I mentioned in the Data section, there are a few variables that have been used in similar previous studies that are not comprised in my data set. Among them, firms' patent stock or group affiliation might play a role in selection into programmes.

Moreover, the categorical matching analysis only goes so far in to capturing size effects of tax credits or grants on firms' internal R&D. A parametrisation of some sort is needed in order to obtain better insight into how the amounts received affect firms' budgetary choices.

In order to do so I introduce the instruments described in section 0, but also a new variable (*LEVER*) denoting a firm's debt to equity ratio in order to capture firms' access to the credit market. Czarnitzki et al. (2011) find that this variable has a significant impact on R&D activity, as firms with higher debt rates perform less research, while the impact on development is insignificant.

I estimate the effect of the level of tax credits and subsidies, used separately and combined, on the private R&D spending and on the basic and applied research and development spending of firms by a series of instrumental variables regressions presented in Table II.14.

I test the instruments' relevance with Anderson's canonical correlation statistic and their over-identification with Hansen's J test. The former confirms that the instruments are relevant in explaining the endogenous regressors in all equations, while the latter's insignificance confirms that the instruments are exogenous in the main equations. However, if I would instrument policy mix use with the excluded variables used to instrument tax credits and subsidies, the over-identification would fail in the policy mix equations. This is a direct consequence of the fact that I would exclude part of the effect of tax credits and subsidies from the estimation, passing them to the error term, which becomes correlated with the excluded instruments used for the endogenous variable of the policy mix. The solution of estimating in the same equation the coefficients of subsidies, tax credits and the policy mix is not viable, as I do not have a specific set of instruments for tackling endogeneity of the policy mix variable. In consequence, the estimates of the policy mix coefficient will be biased. In order to circumvent this issue, I construct instruments for the policy mix variable similar to those used for tax credits and subsidies: the average amount of policy mix received and the number of firms receiving it per year, industry and size category. The two instrumental variables are valid in that they are correlated with the amount of policy mix received and uncorrelated with the error term of the main equation[58]. The results of the first-stage estimations on the amount of each treatment received is presented in Table II.17 in Appendix.

The results are presented in Table II.14, where the first two rows show the average effects of tax credits and of subsidies, and the following three rows disentangle their impact when used as single measures from that of the policy mix.

[58] Note that average amount of policy mix received and number of users are not linear combinations of the average amounts of tax credits and subsidies and the number of users of each.

Table II.14 Instrumental variables (2SLS) estimations of policy effects

	LN R&D NET		LN BASIC RES		LN APPLIED RES		LN DEVELOPMENT	
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*
LN TAX	0.15***		0.18***		0.23***		0.20***	
	(0.02)		(0.06)		(0.05)		(0.06)	
LN SUBS	0.04**		0.15**		0.14***		0.05	
	(0.02)		(0.06)		(0.05)		(0.06)	
LN MIX		0.18***		0.32***		0.36***		0.22***
		(0.02)		(0.07)		(0.05)		(0.06)
LN TAX ONLY		0.14***		0.19**		0.20***		0.17**
		(0.02)		(0.07)		(0.07)		(0.08)
LN SUBS ONLY		0.01		0.18		0.06		0.00
		(0.04)		(0.13)		(0.12)		(0.13)
LN AGE	-0.12**	-0.12**	0.15	0.17	-0.00	0.01	0.05	0.03
	(0.05)	(0.05)	(0.20)	(0.20)	(0.14)	(0.14)	(0.20)	(0.20)
LN EMP	0.63***	0.63***	0.18	0.17	0.44***	0.44***	0.56***	0.58***
	(0.04)	(0.04)	(0.13)	(0.12)	(0.11)	(0.10)	(0.13)	(0.13)
SME	-0.04	-0.04	-0.69	-0.67	0.17	0.18	-0.56	-0.60
	(0.14)	(0.14)	(0.53)	(0.53)	(0.37)	(0.37)	(0.47)	(0.47)
LEVER	0.00***	0.00***	0.00	0.00	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CURR	0.00	0.00	-0.01	-0.01	0.01	0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LN CAPINT	0.11***	0.11***	0.17**	0.16**	0.01	0.01	0.25***	0.26***
	(0.02)	(0.02)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
HITECH M	0.37**	0.38**	-0.77	-0.81	0.82*	0.85*	-0.12	-0.05
	(0.15)	(0.16)	(0.55)	(0.56)	(0.48)	(0.49)	(0.48)	(0.49)
HITECH S	0.85***	0.87***	-0.68	-0.71	1.04**	1.08**	-0.15	-0.08
	(0.16)	(0.17)	(0.57)	(0.57)	(0.50)	(0.51)	(0.51)	(0.51)
LOWTECH M	-0.19	-0.18	-0.44	-0.43	0.55	0.56	-0.15	-0.14
	(0.15)	(0.15)	(0.52)	(0.52)	(0.45)	(0.46)	(0.44)	(0.43)
LOWTECH S	0.33**	0.35**	-0.07	-0.08	-0.20	-0.15	0.31	0.35
	(0.16)	(0.16)	(0.56)	(0.56)	(0.50)	(0.51)	(0.48)	(0.48)
FLANDERS	-0.34**	-0.34**	1.13**	1.12**	0.28	0.27	0.47	0.48
	(0.13)	(0.13)	(0.50)	(0.50)	(0.42)	(0.43)	(0.48)	(0.48)
WALLONIA	-0.19	-0.19	-0.06	-0.05	-0.43	-0.44	1.22**	1.20**
	(0.15)	(0.15)	(0.52)	(0.52)	(0.48)	(0.49)	(0.54)	(0.53)
Observations	2650	2650	2650	2650	2650	2650	2650	2650
Firms	1809	1809	1809	1809	1809	1809	1809	1809
Hansen J	0.56	0.55	0.62	1.23	1.77	1.57	0.98	4.92
Hansen J (df)	2	3	2	3	2	3	2	3
Anderson u-id	238.10	108.40	238.10	108.40	238.10	108.40	238.10	108.40
Anderson u-id(df)	3	4	3	4	3	4	3	4

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by firm in parentheses.
c) Intercept term and year dummies included but not shown in table.
d) All Hansen's J over-identification tests insignificant at 10% level.
e) All Anderson under-identification tests significant at 1% level.
f) Base category for industry indicators comprises firms that do not fit in high- or low-tech groups. Base categories for region is Brussels.
g) Instruments include the number of users of each policy and average amount received by 4-digit NACE industries, year and size group. Details of first-stage regressions are provided in Table II.17 in Appendix.

Additionality on private R&D expenditure

Both policies have, on average, a positive and significant impact on firms' private R&D expenditure (first column), while tax credits also show a significantly larger coefficient than subsidies. As the variables are measured in natural logarithms, the interpretation is the following. Increasing the amount of tax credits by 10% would increase private R&D spending by 1.5%, while the same increase in subsidies only brings a 0.4% increase in spending. However, the effects are averaged over all firms that receive each type of support. In order to estimate whether they have a different impact when used as a single policy, I estimate the equation by separating the amounts received as a single treatment from the amount received in a policy mix. The second column reveals that subsidies do not significantly increase private R&D spending if they are used alone, whereas tax credits add an extra 1.4% for each 10% increase in their volume if used without subsidies, comparable to their average effect we saw before. Finally, increasing by 10% the amount of the policy mix causes firms to raise their private spending by 1.8%.

The results are similar to the ATTs reported in section 4.2. However, the parametric specification allows estimating the different effects of each instrument when it is used alone or combined. This was not possible in the matching framework without possibly including 'hidden treatment' bias by ignoring the existence of both types of support. This results in the interesting finding that subsidies do increase private R&D spending only if they are used together with tax credits, which I interpret as evidence of complementarity between the two measures. Haegeland and Møen (2007b) also found evidence of complementarity in Norway, although Dumont (2015) provided some indication that Belgian subsidies and tax credits are substitutes. Although based on the same data set, the latter finding can be the effect of selection bias that is unaccounted for, as the analysis does not consider the endogeneity of support measures. Moreover, the negative effect of combining the policies is economically small, albeit highly significant in his study.

Other firm characteristics that influence the amount spent on R&D include age, size, debt, capital intensity and industry affiliation, but also geographical location. Younger and larger firms spend more on R&D net of public support, as do firms with higher debt-to-equity ratios and capital intensity values. Similarly, companies in high-tech industries record higher amounts spent on R&D, but also – surprisingly – firms in low-tech service sectors.

Additionality on components of R&D

Both instruments show positive additionality on basic and applied research spending. Increasing tax credits by 10% boosts basic and applied research expenditure by 1.8% and 2.3% respectively, while the same increase in subsidies raises them by 1.5% and 1.4% respectively.

The average effect of subsidies seems to be driven again by complementarity with tax credits, as additionality is not significant in firms that only receive grants. Tax credits do 'work alone', too, but their effect is smaller than that of the policy mix, which increases basic and applied spending by 3.2% and 3.6% respectively, for a 10% raise in the amount received.

Tax credits and the policy mix also show positive additionality on development spending to the ratio of 2-to-10 in percentages. On the other hand, subsidies do not seem to affect this category in neither setting. This result should nevertheless be interpreted with caution, as it might be the effect of more grants for research projects than for development being awarded to firms in my sample. Nevertheless, Hottenrott et al. (2014) report that in 2007 and 2009 over 50% of subsidies for Flemish companies were for development projects, 30% to 40% for research, and 15% to 20% mixed. Mixed and development grants are also significantly larger than research grants. The study finds positive overall additionality of each type of subsidy on net R&D intensity, direct additionality (of research grants on research intensity and development grants on development intensity), but also cross additionality from research grants to development intensity and vice-versa. On the other hand, Dumont (2015) finds that Belgian R&D grants increase the basic research intensity while decreasing the percentage of development projects firms pursue. Again, his results do not account for selection of companies into the subsidy programme. Compared to their analyses, I diverge by analysing grants provided by all three regional governments – Brussels, Flanders and Wallonia – and by mitigating (self-)selection bias. Considering the detailed description of the amounts and number of research and development grants by Hottenrott et al. (2014), it does not seem that my results are driven by a larger share of research subsidies being granted to firms. The only way this distribution would drive the insignificant effect on development expenditure from Table II.14 would be if my sample were skewed, containing substantially less recipients of development grants. However, due to data confidentiality, I cannot check whether this is the case, nor extend the data to include details on the type of grants awarded.

Finally, I find that size and leverage have a positive and significant effect on applied research and development spending, although the size of the coefficient of debt-to-equity ratio is of the magnitude 10^{-4}. More capital intensive firms spend more on basic research and development, while those active in high-tech sectors record higher spending on applied research.

In general, the instrumental variables estimators produce similar results as the non-parametric matching method. However, some differences do exist – such as a loss of significance of the effect of subsidies on basic and applied research spending, when they are used as a single policy. This result can have two causes. First, it can be inherent to applying a parametric function to firms' expenditure on research, resulting in a loss of efficacy. Alternatively, it points to a possible violation of the CIA assumption of the matching estimator, which can bias the average treatment effect. By performing both parametric and non-parametric analyses, I try to mitigate, to the extent possible, the known issues that are integral to each method and provide robust comparisons of the effects of direct and indirect support for R&D.

Variation in the effects of policies

In this section I explore whether the effects of tax credits, subsidies and the policy mix vary in different samples of firms. I have shown that, on average, the policy mix creates positive additionality on firms' R&D expenditure, either aggregate or split by activity. The effect seems to be larger than the impact of tax credits alone, which is still positive. On the other hand, subsidies do not seem to spur additional R&D unless alongside tax credits. This sort of interaction between direct and indirect support measures deserves further scrutiny, as policies are frequently created with the intention to attenuate issues encountered by particular sectors or types of firms. For example, Belgian regional subsidies come in wide variety, and all three administrative regions offer specific grants for SMEs, but also for industries deemed to underperform in terms of R&D.

A number of studies have analysed whether policies have different effects on SMEs than on larger firms. The intuition behind this assumption resides in the difficulties encountered by SMEs to access external finance for their R&D, but also in the ability of direct and indirect support to address different sources of underinvestment in R&D. For example, Busom et al. (2014) find that Spanish SMEs are more prone to use subsidies than tax credits if they face financing constraints, but the same is true for large firms. Also in Spain, tax credits were not found to increase innovation activity in small firms by Corchuelo & Martínez-Ros (2009). In the Netherlands however, SMEs have invested more in R&D than large companies if they received wage-based fiscal incentives (Lokshin & Mohnen, 2012). In Belgium, Dumont (2015) has shown that the most impact of subsidies on private R&D is encountered in either small or large firms, while wage-based tax credits seem to spur spending in small firms more than in large ones. Overall, the effects seem to be country- and policy-dependent, but there is variation in how different firms respond to receiving direct and indirect support (Castellacci & Lie, 2015).

In order to assess whether subsidies and tax credits – combined or not – have different effects according to firm size, I estimate the same 2SLS models from section 4.6 on two subsamples split by SME status. The coefficients of the amounts of support received are presented in Table II.15.[59]

Table II.15 IV estimation of additionality: SMEs vs. large firms

	SME (N=2,275)				LARGE FIRMS (N=375)			
	LN R&D NET	LN BASIC R	LN APPLIED R	LN DEVELOP	LN R&D NET	LN BASIC R	LN APPLIED R	LN DEVELOP
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*
LN TAX	0.15***	0.11	0.22***	0.09	0.14***	0.25***	0.22***	0.33***
	(0.02)	(0.07)	(0.06)	(0.07)	(0.03)	(0.09)	(0.07)	(0.09)
LN SUBS	0.04	0.11	0.16**	-0.04	0.04*	0.23**	0.07	0.19***
	(0.03)	(0.09)	(0.07)	(0.08)	(0.02)	(0.09)	(0.06)	(0.07)
LN MIX	0.19***	0.25***	0.40***	0.03	0.18***	0.45***	0.27***	0.48***
	(0.03)	(0.09)	(0.07)	(0.09)	(0.03)	(0.10)	(0.07)	(0.09)
LN TAX ONLY	0.13***	0.11	0.18**	0.07	0.13***	0.32***	0.24**	0.3**
	(0.03)	(0.09)	(0.08)	(0.09)	(0.03)	(0.11)	(0.10)	(0.12)
LN SUBS ONLY	0.01	0.09	0.08	-0.08	0.01	0.5**	0.13	0.07
	(0.05)	(0.15)	(0.14)	(0.15)	(0.07)	(0.25)	(0.22)	(0.29)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by firm in parentheses.
c) Each column presents coefficients from two different estimations. LN TAX and LN SUBS are estimated simultaneously through 2SLS, and LN MIX, LN TAX ONLY and LN SUBS ONLY are grouped in another 2SLS estimation, similarly to section 4.6.
d) Control variables included but not shown in table.
e) All Hansen's J over-identification tests insignificant at 10% level.
f) All Anderson under-identification tests significant at 1% level.
g) Instruments include the number of users of each policy and average amount received by 4-digit NACE industries, year and size group.

[59] For ease of exposition control variables are not shown; full tables of structural equations are available in Table II.18 and Table II.19 in Appendix.

Columns *a* and *e* illustrate the additionality of each policy on total private R&D spending in SMEs and large firms respectively. There seems to be little difference in the workings of the policies – either used separately or in a mix – between firms of different sizes, when looking at aggregated R&D activity. On the other hand, there is some variation in additionality on its components, showing that the 2,275 sampled SMEs respond differently from large firms in terms of research behaviour. For example, SMEs increase basic research spending only if they use the policy mix, as column *b* shows a 2.5% increase in basic research due to increasing the amount of the mix by 10%. In contrast, column *f* shows that large firms significantly increase basic research spending no matter which policy measure they receive, although the largest effect comes from subsidies (a 5% increase in spending arising from a 10% increase in subsidies received) and the policy mix (for each 10% extra received, spending is increased by 4.5%). The effects on applied research are similar for both types of firms, but columns *d* and *h* paint a different picture regarding development activities. SMEs are not affected in a significant manner by the receipt of public support, while large firms respond positively to tax credits and the policy mix especially.

The overall picture seems to show that, while policies work similarly on aggregate R&D for SMEs and large firms, the former are more responsive to the policy mix in terms of basic research and also increase applied research spending when using any measure, while large firms are more varied in their responses across all three R&D activities. Finally, it is worth noting that subsidies, if used alone, only increase basic research spending of large firms and have little significant effect on other activities for any type of firm. Corroborated with the fact that SMEs only increase basic research if they receive the policy mix, it seems that there is indeed a scale effect in the sense that firms need to reach a certain threshold of funding in order to increase investment in this activity. Larger firms can arguably receive larger amounts of both policies – due to engaging in bigger projects – whereas small companies need to combine them in a mix in order to achieve the same impact on basic research.

The way in which tax credits and subsidies affect firms may be related to the financial health of the latter. I have argued in the introduction that scale effects arising from mixing two policies may be countered by a lack of financial resources to pursue larger projects. If this were the case, one would expect the additionality created by the policy mix to be similar in size and significance to that of separate policies. In other words, there may be an upper limit to how much firms can invest in R&D. The comparison between SMEs and large firms has not revealed such an effect, although it has shown that small and medium firms only respond to single policies by increasing applied research spending, while using the policy mix also increases basic research. This result may have two underlying explanations. First, it may be that subsidies received by SMEs are awarded for applied research projects to start with, but the data does not contain the information required to check this supposition. Second, basic research is farther from the market and thus small firms may find it harder to access external financing or indeed be more reluctant to invest own funds in riskier activities (Czarnitzki & Hottenrott, 2011). Using a policy mix decreases the need for additional funds and thus allows these firms to engage in more applied research.

If the latter explanation is true for the average SME and if indeed the effects of policies relate to financing constraints, one would expect evidence to show up in larger companies with funding barriers too. In order to test this assumption, I perform a split-sample analysis comparing firms with lower debt levels to those that show higher values than the median leverage in the sample. The results are presented in Table II.16.[60]

[60] For ease of exposition control variables are not shown; full tables of structural equations are available in Table II.20 and Table II.21 in Appendix.

Table II.16 IV estimation of additionality: low vs. high leverage

	LOW LEVERAGE (N=1,325)				HIGH LEVERAGE (N=1,325)			
	LN R&D NET	LN BASIC R	LN APPLIED R	LN DEVELOP	LN R&D NET	LN BASIC R	LN APPLIED R	LN DEVELOP
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*
LN TAX	0.15***	0.14*	0.21***	0.14*	0.15***	0.20**	0.25***	0.26***
	(0.02)	(0.07)	(0.08)	(0.08)	(0.02)	(0.08)	(0.07)	(0.08)
LN SUBS	0.06**	0.27***	0.25***	0.05	0.02	0.03	0.01	0.07
	(0.03)	(0.09)	(0.07)	(0.08)	(0.02)	(0.09)	(0.07)	(0.08)
LN MIX	0.21***	0.39***	0.44***	0.19**	0.15***	0.21**	0.27***	0.25***
	(0.02)	(0.09)	(0.07)	(0.08)	(0.03)	(0.09)	(0.07)	(0.09)
LN TAX ONLY	0.12***	0.15*	0.18**	0.11	0.15***	0.22*	0.25**	0.26**
	(0.03)	(0.09)	(0.09)	(0.09)	(0.03)	(0.12)	(0.10)	(0.12)
LN SUBS ONLY	-0.02	0.30	0.14	-0.01	0.03	0.07	0.01	0.09
	(0.08)	(0.21)	(0.16)	(0.20)	(0.05)	(0.17)	(0.16)	(0.18)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by firm in parentheses.
c) Each column presents coefficients from two different estimations. LN TAX and LN SUBS are estimated simultaneously through 2SLS, and LN MIX, LN TAX ONLY and LN SUBS ONLY are grouped in another 2SLS estimation, similarly to section 4.6.
d) Control variables included but not shown in table.
e) All Hansen's J over-identification tests insignificant at 10% level.
f) All Anderson under-identification tests significant at 1% level.
g) Instruments include the number of users of each policy and average amount received by 4-digit NACE industries, year and size group.

The two groups of firms behave similarly, with the exception of how they respond to subsidies that are used in a mix (row two). Companies with higher debt ratios do not increase their R&D when receiving subsidies, whereas firms with lower leverage respond positively to this policy by spending more on basic and applied research, which results in higher private R&D spending overall. Comparing columns *a* and *e* shows that in terms of total private R&D investment is increased in a similar manner by both firms with low and high debt to equity ratios. However, subsidies only show significant additionality in the low-leverage sub-sample. Similarly, basic and applied research is increased, on average, in firms with low debt levels that receive subsidies, while this policy has no impact on development. On the other hand, tax credits seem to increase development spending of firms with higher debt ratios (column *h*). The policy mix seems to provide enough resources for both types of companies all across the board. It increases R&D overall and per component with between 1.5% and 4.4% for each extra 10% of the amount of grants and tax credits received. These results suggest that combining policies in a mix provides 'critical mass' that allows even debt-ridden firms to increase investment in both research and development activities, but that this effect rests mostly on tax credits and less on subsidies.

5 Conclusions

This paper contributes to the scarce empirical evidence on the additionality of R&D subsidies and tax credits, while at the same time providing a much needed multiple-treatment analysis of this policy mix. Using a rich dataset of R&D-active Belgian firms, I perform multiple matching and instrumental variable estimations in order to trace how using tax credits and grants allows companies to change how they manage internal R&D processes.

First, I cannot exclude crowding out of overall private R&D expenditure by subsidies if they are used alone. I find robust evidence that firms that only receive grants do not spend more of their own funds than what they would have spent without support. This result is in line with similar findings by Guerzoni and Raiteri (2015), but conflicts with previous analyses on Flemish firms by Aerts and Schmidt (2008), Czarnitzki and Lopes-Bento (2013), or Hottenrott et al. (2014). Although Dumont (2015) finds some indication that Belgian subsidies have a positive impact, the effect is not robust to different estimation techniques accounting for selection of firms into treatment. Moreover, as he uses a longer panel for subsidies, results could be driven by effects of grants received before tax credits were introduced in their current form in 2006. The latter three studies, on the other hand, do not control for possible 'hidden treatment' effects – such as the use of tax credits alongside subsidies. Both Guerzoni and Raiteri (2015) and Dumont (2013) show that failure to account for this issue can bias estimates by increasing the apparent treatment effect of the observed policy. My analysis is partially robust to this bias by controlling for the simultaneous use of subsidies and wage-based tax credits. However, other support measures available to Belgian firms are not accounted for, such as tax credits for new R&D investments, patent boxes, European subsidies or public procurement, all of which have been shown to affect private R&D (see e.g. Czarnitzki & Lopes-Bento, 2014; Dumont, 2015; Guerzoni & Raiteri, 2015).

Second, I find that subsidies can increase private R&D spending if they are used together with tax credits and vice-versa, concluding that there is some interaction between the two policies. Similar effects are found by Guerzoni and Raiteri (2015), while the opposite is concluded by Dumont (2015), although the latter does not properly control for selection into multiple treatments. Tax credits, whether used separately or together, increase R&D spending of firms compared to what they would have spent had they not received any support and substantially outperform subsidies, confirming a part of extant evidence (Haegeland & Møen, 2007b;

Carboni, 2011). Moreover, combining tax credits and subsidies in a policy mix further increases spending in R&D, excluding complete substitution effects between the two policies.

Third, I show that the two policies have different action zones in terms of firms' expenditure on basic and applied research and development. Subsidies show a positive effect on basic and applied research only in combination with tax credits, but do not impact development activities. Tax credits, on the other hand, are more potent and increase all categories of R&D whether used in isolation or combined. Similar to the effects on total expenditure, the policy mix also shows higher additionality than subsidies or tax credits alone on the three subcategories or R&D.

An interesting finding is that using grants or the policy mix changes the way firms behave in their R&D. I find some evidence of a behavioural additionality effect of turning firms away from development and towards research. I emphasize 'some evidence' because the effect might be due to a specific policy design in which Belgian regional authorities provide separate grants for research and for development projects, and the amount of each of these could drive the effect I mentioned. Without more refined subsidy data, I cannot clearly state whether this is the case or whether the effect can be called 'additionality'.

Fourth, my results also complement recent analyses by comparing the impact of policy through two estimation techniques. Similarly to Dumont (2013, 2015) and in line with Guerzoni and Raiteri (2015), I find that parametric estimators point to less stringent effects than non-parametric methods. This result may point to a possible upward bias driven by selection on unobservables. In other words, there might be company characteristics that matter in authorities' choice of subsidy recipients, but that are unobserved by the researcher. As more econometric evidence of policy impact is being produced, such method effect should always be addressed.

The key takeaway for policy makers is that wage-based tax credits seem to outperform subsidies in increasing private R&D in the Belgian context. Even though – contrary to subsidy recipients – firms benefitting from the wage-based tax credit I analyse are not restricted in the destination of the amounts made available by the measure, the analysis points to increased investment in R&D activities. This result is interesting by itself, as it suggests that market forces work towards more research and development, once access to funding barriers are lowered. On the other hand, one cannot conclude that subsidies should be scrapped from the support system altogether. Not only do they seem to positively interact with tax credits and create an increased effect on private R&D, but they may also serve complementary purposes – for example providing aid to specific industries, regions or types of firms that require it at a given point.

Finally, I end this paper with a renewed call for better data. Although my data set is rather rich research-wise, I have already mentioned some of its shortcomings. The fact that I can use the amounts of grants and tax exemptions is a step forward compared to most previous studies, which have to settle for binary treatment indicators. However, the fact that subsidy data is not systematically gathered in a similar fashion across administrative boundaries, corroborated with over 15 different subsidy schemes, poses issues with the interpretation of their impact on research versus development activities. The fact that the average effect of all these different grants is not significant does not imply that, for example, research subsidies do not increase research spending, as other papers have been able to show (Hottenrott et al., 2014). Moreover, the wage-based tax credits are also split into four different categories, and Dumont (2015) shows solid evidence that only one of the four actually increases R&D spending. In light of all these, policy makers would be well advised to either simplify the support environment, which would benefit both firms and themselves, or streamline the data gathering process in order to have better analyses in their drive for evidence-based policy – where such drive exists.

6 Appendix

Table II.17 First stage of 2SLS estimations

	LN TAX	LN SUBS	LN MIX	LN TAX ONLY	LN SUBS ONLY
	a	*b*	*c*	*d*	*e*
LN AVG MIX			0.24***	-0.16***	-0.12***
			(0.02)	(0.02)	(0.02)
# MIX RECEIVERS			0.71***	-0.18**	-0.15**
			(0.10)	(0.08)	(0.07)
LN AVG TAX	0.50***	-0.03	0.02	0.46***	-0.08***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
# TAX USERS	0.06***	-0.11***	-0.15***	0.13***	-0.05***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
LN AVG SUBS	-0.01	0.36***	0.10***	-0.14***	0.20***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
# SUBS USERS	-0.07**	0.18***	-0.23***	-0.07*	0.18***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
LN AGE	-1.00***	-0.55***	-0.52***	-0.49***	0.02
	(0.18)	(0.17)	(0.16)	(0.15)	(0.09)
LN EMP	1.13***	0.29***	0.52***	0.60***	-0.20***
	(0.10)	(0.10)	(0.08)	(0.08)	(0.06)
SME	-1.06**	-2.16***	-1.36***	0.47	-0.62***
	(0.43)	(0.42)	(0.41)	(0.39)	(0.22)
LEVER	0.00	-0.00***	-0.00***	0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CURR	0.02	0.03	0.03	-0.01	-0.00
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
LN CAPINT	0.34***	0.35***	0.24***	0.10	0.08**
	(0.08)	(0.07)	(0.06)	(0.07)	(0.04)
HITECH M	0.73	1.09**	-0.14	0.53	0.85***
	(0.47)	(0.48)	(0.38)	(0.43)	(0.27)
HITECH S	0.57	0.09	-0.43	0.97**	0.48
	(0.53)	(0.51)	(0.41)	(0.48)	(0.31)
LOWTECH M	-0.37	-0.38	-0.79**	0.27	0.23
	(0.45)	(0.44)	(0.33)	(0.41)	(0.24)
LOWTECH S	0.29	0.27	-0.34	0.50	0.49*
	(0.49)	(0.46)	(0.34)	(0.44)	(0.26)
FLANDERS	-0.59	-0.87**	-0.69*	0.16	-0.16
	(0.44)	(0.42)	(0.38)	(0.37)	(0.29)
WALLONIA	0.10	-1.68***	-1.04***	1.15***	-0.63**
	(0.46)	(0.39)	(0.36)	(0.40)	(0.28)
Obs.	2650	2650	2650	2650	2650
Firms	1809	1809	1809	1809	1809

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by firm in parentheses.
c) Intercept term and year dummies included but not shown in table.
d) Base category for industry indicators comprises firms that do not fit in high- or low-tech groups. Base categories for region is Brussels.
e) Instruments include the number of users of each policy and average amount received by 4-digit NACE industries, year and size group.

Table II.18 Structural equations (2nd stage) on SME sub-sample

	LN R&D NET		LN BASIC R		LN APPLIED R		LN DEVELOPMENT	
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*
LN TAX	0.15***		0.11		0.22***		0.09	
	(0.02)		(0.07)		(0.06)		(0.07)	
LN SUBS	0.04		0.11		0.16**		-0.04	
	(0.03)		(0.09)		(0.07)		(0.08)	
LN MIX		0.19***		0.25***		0.40***		0.03
		(0.03)		(0.09)		(0.07)		(0.09)
LN TAX ONLY		0.13***		0.11		0.18**		0.07
		(0.03)		(0.09)		(0.08)		(0.09)
LN SUBS ONLY		0.01		0.09		0.08		-0.08
		(0.05)		(0.15)		(0.14)		(0.15)
LN AGE	-0.18***	-0.16***	-0.09	-0.05	-0.05	-0.01	-0.47**	-0.49**
	(0.06)	(0.06)	(0.22)	(0.21)	(0.19)	(0.18)	(0.23)	(0.22)
LN EMP	0.61***	0.60***	0.30**	0.28**	0.48***	0.46***	0.77***	0.78***
	(0.04)	(0.04)	(0.14)	(0.13)	(0.12)	(0.11)	(0.14)	(0.14)
SME [a]	0.25	0.25	-4.46*	-4.32*	-0.12	-0.05	-2.69***	-2.81***
	(0.29)	(0.31)	(2.49)	(2.56)	(0.68)	(0.82)	(0.64)	(0.62)
LEVER	-0.00	-0.00	0.00***	0.00**	0.00	-0.00	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CURR	0.00	0.00	-0.00	-0.01	0.01	0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LN CAPINT	0.11***	0.10***	0.23***	0.22***	0.03	0.02	0.29***	0.30***
	(0.03)	(0.03)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
HITECH M	0.34**	0.35**	-0.54	-0.58	0.99*	1.01*	-0.01	0.05
	(0.17)	(0.17)	(0.58)	(0.58)	(0.54)	(0.55)	(0.50)	(0.50)
HITECH S	0.78***	0.79***	-0.19	-0.24	1.33**	1.34**	0.05	0.11
	(0.18)	(0.18)	(0.61)	(0.60)	(0.55)	(0.56)	(0.52)	(0.52)
LOWTECH M	-0.14	-0.13	-0.23	-0.22	0.76	0.79	-0.46	-0.46
	(0.16)	(0.16)	(0.52)	(0.53)	(0.50)	(0.51)	(0.45)	(0.45)
LOWTECH S	0.33**	0.35**	0.17	0.17	0.05	0.09	0.19	0.22
	(0.16)	(0.17)	(0.56)	(0.57)	(0.55)	(0.56)	(0.49)	(0.49)
FLANDERS	-0.40***	-0.41***	1.03**	0.98*	0.43	0.38	0.72	0.73
	(0.14)	(0.14)	(0.52)	(0.52)	(0.49)	(0.50)	(0.58)	(0.58)
WALLONIA	-0.28*	-0.29*	-0.35	-0.35	-0.24	-0.27	1.24**	1.23**
	(0.15)	(0.15)	(0.53)	(0.54)	(0.54)	(0.54)	(0.61)	(0.61)
Obs.	2275	2275	2275	2275	2275	2275	2275	2275
Firms	1594	1594	1594	1594	1594	1594	1594	1594
Hansen J	0.56	0.35	1.61	2.20	0.58	0.40	2.37	4.75
Anderson u-id	149.16	90.63	149.16	90.63	149.16	90.63	149.16	90.63

a) Lagged SME status included as control.
b) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
c) Robust standard errors clustered by firm in parentheses.
d) Intercept term and year dummies included but not shown in table.
e) All Hansen's J over-identification tests insignificant at 10% level.
f) All Anderson under-identification tests significant at 1% level.
g) Base category for industry indicators comprises firms that do not fit in high- or low-tech groups. Base categories for region is Brussels.

Table II.19 Structural equations (2nd stage) on large firms' sub-sample

	LN R&D NET		LN BAISC R		LN APPLIED R		LN DEVELOPMENT	
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*
LN TAX	0.14***		0.25***		0.22***		0.33***	
	(0.03)		(0.09)		(0.07)		(0.09)	
LN SUBS	0.04*		0.23**		0.07		0.19***	
	(0.02)		(0.09)		(0.06)		(0.07)	
LN MIX		0.18***		0.45***		0.27***		0.48***
		(0.03)		(0.10)		(0.07)		(0.09)
LN TAX ONLY		0.13***		0.32***		0.24**		0.30**
		(0.03)		(0.11)		(0.10)		(0.12)
LN SUBS ONLY		0.01		0.50**		0.13		0.07
		(0.07)		(0.25)		(0.22)		(0.29)
LN AGE	0.13	0.13	0.58	0.58	0.32	0.32	1.07**	1.08**
	(0.13)	(0.13)	(0.53)	(0.52)	(0.31)	(0.31)	(0.46)	(0.46)
LN EMP	0.85***	0.85***	-0.34	-0.31	0.13	0.15	0.22	0.23
	(0.13)	(0.12)	(0.42)	(0.42)	(0.43)	(0.43)	(0.42)	(0.41)
SME [a]	0.60	0.60	-0.41	-0.41	-0.07	-0.05	-0.72	-0.67
	(0.37)	(0.38)	(1.68)	(1.68)	(0.99)	(0.99)	(1.57)	(1.56)
LEVER	0.00**	0.00*	0.00	-0.00	0.00	0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CURR	0.02	0.02	-0.10	-0.09	-0.10	-0.10	0.17**	0.17**
	(0.02)	(0.02)	(0.10)	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)
LN CAPINT	0.17***	0.17**	0.12	0.09	-0.01	-0.02	0.47**	0.48**
	(0.06)	(0.07)	(0.23)	(0.22)	(0.17)	(0.17)	(0.21)	(0.21)
HITECH M	0.41	0.41	-2.34	-2.47	-0.67	-0.69	0.79	0.83
	(0.43)	(0.44)	(1.75)	(1.62)	(0.64)	(0.65)	(1.74)	(1.76)
HITECH S	1.58***	1.60***	-3.82**	-4.01**	-2.17*	-2.21*	0.60	0.66
	(0.52)	(0.53)	(1.86)	(1.72)	(1.28)	(1.31)	(2.02)	(2.05)
LOWTECH M	-0.29	-0.31	-2.34	-2.19	-1.59***	-1.56**	1.92	1.84
	(0.41)	(0.43)	(1.70)	(1.61)	(0.60)	(0.62)	(1.62)	(1.66)
LOWTECH S	0.50	0.50	-1.25	-1.23	-2.74**	-2.74**	2.89	2.87
	(0.53)	(0.54)	(2.00)	(1.90)	(1.14)	(1.13)	(1.88)	(1.89)
FLANDERS	0.05	0.06	1.36	1.29	-0.86	-0.88	0.17	0.22
	(0.37)	(0.37)	(1.23)	(1.22)	(0.83)	(0.84)	(0.83)	(0.82)
WALLONIA	0.38	0.41	1.75	1.54	-1.61	-1.69	1.66	1.72
	(0.48)	(0.49)	(1.69)	(1.64)	(1.31)	(1.33)	(1.39)	(1.39)
Obs.	375	375	375	375	375	375	375	375
Firms	230	230	230	230	230	230	230	230
Hansen J	3.88	5.23	1.29	1.94	0.70	0.80	0.92	1.15
Anderson u-id	71.49	21.15	71.49	21.15	71.49	21.15	71.49	21.15

a) Lagged SME status included as control.
b) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
c) Robust standard errors clustered by firm in parentheses.
d) Intercept term and year dummies included but not shown in table.
e) All Hansen's J over-identification tests insignificant at 10% level.
f) All Anderson under-identification tests significant at 1% level.
g) Base category for industry indicators comprises firms that do not fit in high- or low-tech groups. Base categories for region is Brussels.

Table II.20 Structural equations (2nd stage) on low leverage sub-sample

	LN R&D NET		LN BAISC R		LN APPLIED R		LN DEVELOPMENT	
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*
LN TAX	0.15***		0.14*		0.21***		0.14*	
	(0.02)		(0.07)		(0.08)		(0.08)	
LN SUBS	0.06**		0.27***		0.25***		0.05	
	(0.03)		(0.09)		(0.07)		(0.08)	
LN MIX		0.21***		0.39***		0.44***		0.19**
		(0.02)		(0.09)		(0.07)		(0.08)
LN TAX ONLY		0.12***		0.15*		0.18**		0.11
		(0.03)		(0.09)		(0.09)		(0.09)
LN SUBS ONLY		-0.02		0.30		0.14		-0.01
		(0.08)		(0.21)		(0.16)		(0.20)
LN AGE	-0.17*	-0.14	0.17	0.19	-0.01	-0.01	-0.14	-0.13
	(0.09)	(0.09)	(0.29)	(0.29)	(0.23)	(0.23)	(0.29)	(0.28)
LN EMP	0.65***	0.63***	0.17	0.16	0.38**	0.38**	0.70***	0.70***
	(0.06)	(0.06)	(0.18)	(0.18)	(0.16)	(0.16)	(0.18)	(0.18)
SME	-0.05	-0.04	-0.87	-0.85	0.34	0.34	-1.00*	-1.00*
	(0.20)	(0.20)	(0.73)	(0.73)	(0.53)	(0.54)	(0.60)	(0.60)
LEVER	-0.00*	-0.00***	0.00***	0.00***	-0.00**	-0.00**	-0.00***	-0.0***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CURR	-0.00	-0.00	-0.01	-0.01	0.01	0.01	-0.02	-0.02
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LN CAPINT	0.10***	0.10***	0.15	0.15	0.10	0.11	0.19*	0.19*
	(0.03)	(0.03)	(0.10)	(0.10)	(0.09)	(0.09)	(0.11)	(0.11)
HITECH M	0.17	0.20	-0.89	-0.93	0.75	0.82	-0.92	-0.89
	(0.24)	(0.24)	(0.76)	(0.76)	(0.72)	(0.72)	(0.63)	(0.63)
HITECH S	0.61**	0.63**	-1.28*	-1.32*	0.89	0.97	-0.73	-0.70
	(0.25)	(0.25)	(0.77)	(0.77)	(0.75)	(0.75)	(0.67)	(0.67)
LOWTECH M	-0.37	-0.36	-0.79	-0.78	0.66	0.67	-1.31**	-1.30**
	(0.23)	(0.23)	(0.69)	(0.69)	(0.69)	(0.69)	(0.58)	(0.58)
LOWTECH S	0.24	0.30	-0.52	-0.53	-0.60	-0.52	0.25	0.29
	(0.25)	(0.25)	(0.81)	(0.82)	(0.81)	(0.82)	(0.63)	(0.64)
FLANDERS	-0.45**	-0.50**	1.35**	1.36**	-0.00	-0.04	0.73	0.69
	(0.19)	(0.21)	(0.62)	(0.62)	(0.57)	(0.59)	(0.68)	(0.67)
WALLONIA	-0.24	-0.28	0.40	0.41	-0.53	-0.60	1.52**	1.50**
	(0.23)	(0.24)	(0.67)	(0.69)	(0.69)	(0.70)	(0.73)	(0.73)
Obs.	1325	1325	1325	1325	1325	1325	1325	1325
Firms	970	970	970	970	970	970	970	970
Hansen J	1.15	0.66	1.65	2.06	3.26	3.53	2.44	4.28
Anderson u-id	143	41.7	143	41.7	143	41.7	143	41.7

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by firm in parentheses.
c) Intercept term and year dummies included but not shown in table.
d) All Hansen's J over-identification tests insignificant at 10% level.
e) All Anderson under-identification tests significant at 1% level.
f) Base category for industry indicators comprises firms that do not fit in high- or low-tech groups. Base categories for region is Brussels.

Table II.21 Structural equations (2nd stage) on high leverage sub-sample

	LN R&D NET		LN BAISC R		LN APPLIED R		LN DEVELOPMENT	
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*
LN TAX	0.15***		0.20**		0.25***		0.26***	
	(0.02)		(0.08)		(0.07)		(0.08)	
LN SUBS	0.02		0.03		0.01		0.07	
	(0.02)		(0.09)		(0.07)		(0.08)	
LN MIX		0.15***		0.21**		0.27***		0.25***
		(0.03)		(0.09)		(0.07)		(0.09)
LN TAX ONLY		0.15***		0.22*		0.25**		0.26**
		(0.03)		(0.12)		(0.10)		(0.13)
LN SUBS ONLY		0.03		0.07		0.01		0.09
		(0.05)		(0.17)		(0.16)		(0.18)
LN AGE	-0.08	-0.08	0.15	0.15	0.09	0.10	0.18	0.16
	(0.07)	(0.07)	(0.26)	(0.26)	(0.18)	(0.18)	(0.26)	(0.26)
LN EMP	0.62***	0.62***	0.22	0.22	0.51***	0.51***	0.51***	0.54***
	(0.05)	(0.05)	(0.17)	(0.17)	(0.14)	(0.14)	(0.18)	(0.18)
SME	-0.09	-0.08	-0.73	-0.73	-0.13	-0.07	0.02	-0.11
	(0.19)	(0.19)	(0.76)	(0.76)	(0.48)	(0.47)	(0.71)	(0.70)
LEVER	0.00***	0.00**	-0.00	-0.00	0.00	0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CURR	0.05*	0.05	0.03	0.03	0.13*	0.13	0.25***	0.24***
	(0.03)	(0.03)	(0.12)	(0.12)	(0.08)	(0.08)	(0.09)	(0.09)
LN CAPINT	0.10***	0.10***	0.18*	0.18*	-0.10	-0.11	0.29**	0.30**
	(0.03)	(0.03)	(0.11)	(0.11)	(0.10)	(0.10)	(0.12)	(0.12)
HITECH M	0.53***	0.53***	-0.70	-0.70	0.90	0.87	0.55	0.64
	(0.19)	(0.19)	(0.79)	(0.79)	(0.63)	(0.65)	(0.70)	(0.70)
HITECH S	1.06***	1.05***	-0.14	-0.14	1.05	1.06	0.28	0.34
	(0.20)	(0.20)	(0.81)	(0.81)	(0.64)	(0.66)	(0.71)	(0.72)
LOWTECH M	-0.04	-0.04	-0.15	-0.16	0.49	0.51	0.89	0.86
	(0.18)	(0.18)	(0.76)	(0.76)	(0.58)	(0.59)	(0.61)	(0.61)
LOWTECH S	0.43**	0.42**	0.14	0.13	-0.14	-0.12	0.60	0.58
	(0.19)	(0.19)	(0.78)	(0.78)	(0.63)	(0.64)	(0.67)	(0.68)
FLANDERS	-0.23	-0.24	0.90	0.88	0.46	0.47	0.18	0.16
	(0.16)	(0.16)	(0.69)	(0.70)	(0.59)	(0.60)	(0.64)	(0.66)
WALLONIA	-0.12	-0.12	-0.45	-0.47	-0.40	-0.36	0.98	0.90
	(0.18)	(0.18)	(0.71)	(0.71)	(0.66)	(0.66)	(0.73)	(0.74)
Obs.	1325	1325	1325	1325	1325	1325	1325	1325
Firms	989	989	989	989	989	989	989	989
Hansen J	0.023	0.35	0.64	0.96	0.30	2.41	0.69	4.03
Anderson u-id	129	66.2	129	66.2	129	66.2	129	66.2

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by firm in parentheses.
c) Intercept term and year dummies included but not shown in table.
d) All Hansen's J over-identification tests insignificant at 10% level.
e) All Anderson under-identification tests significant at 1% level.
f) Base category for industry indicators comprises firms that do not fit in high- or low-tech groups. Base categories for region is Brussels.

III. Do R&D subsidies foster behavioural additionality effects of R&D tax credits?[61]

Abstract

We analyse how behavioural additionality effects of wage-based R&D tax credits are influenced by the firm's joint use of R&D subsidies. Using matching estimators and a multivariate probit analysis of cross-sectional survey data on Belgian firms, we find that R&D subsidies induce tax credit users to focus more strongly on research relative to development and to accelerate the execution of R&D projects. To a slightly lesser extent, we also find size effects, firms scaling up current R&D or initiating additional projects. Overall, these findings suggest that companies that benefit from the 'policy mix' respond more strongly to R&D tax credits and use the tax-exempted resources to adopt a more strategic approach to R&D.

Keywords Behavioural additionality, tax credits, subsidies, policy mix.

JEL Codes D01 – D03 – D04 – D78 – O30.

Acknowledgements Financial support from KU Leuven – HU Brussels (ZKC7171) and FWO (V416713N) is gratefully acknowledged. The authors would also like to thank the Belgian Federal Science Policy Office and the Belgian Federal Public Service Finance for providing data used in this paper.

---

[61] This chapter is based on Neicu, D., Teirlinck, P., and Kelchtermans, S. (2016). Dipping in the policy mix: do R&D subsidies foster behavioral additionality effects of R&D tax credits? *Economics of Innovation and New Technology*, 25(3), 218-239.

1 Introduction

Tax credits have been used as enablers of R&D activity in a growing number of countries for a few decades now. The number of OECD countries offering some form of tax exemptions for R&D more than doubled between 1995 and 2011, up to 75% of members offering such indirect support. At the same time, the ratio of indirect versus direct support through subsidies (R&D grants) increased in almost half of the OECD countries and tax credits are now equally important as R&D subsidies in over one third of the member states (OECD, 2013).

As more data became available, the number of studies on the effects of indirect R&D support increased markedly in the past few years. The effects of R&D tax credits have been considered in recent studies in terms of input and output additionality (Köhler et al., 2012), but also in terms of economic performance (Cappelen, Raknerud, & Rybalka, 2007; Czarnitzki et al., 2011). However, in spite of a large and growing body of empirical work, the effects of such policies are not yet fully understood (Köhler et al., 2012; Lokshin & Mohnen, 2012; Zúñiga-Vicente et al., 2014). Our paper complements the literature on additionality of public funding for R&D by analysing how R&D subsidies moderate behavioural additionality effects of R&D tax credits.

Behavioural additionality has so far been largely ignored when studying the effects of R&D tax credits. The concept refers to the difference made by policy intervention in the supported firm's approach to R&D (speed, scale, risk, etc.), rather than the effect on R&D investment or R&D performance (Buisseret et al., 1995; Georghiou, 2002). The interest in behavioural additionality stems from the potentially restrictive view on impact attributed to the input and output additionality concepts (Georghiou, 2002; Falk, 2007). In the wage-based R&D tax credit scheme in Belgium, which is the one we study, additional financial resources generated by an R&D tax exemption can be freely used by the firm for any purpose, hence our interest in examining behavioural outcomes.

The focus of our paper is not on behavioural additionality of R&D tax credits as such. The novelty of the paper stems from studying whether firms' behavioural response to receiving R&D tax credits differs if they also enjoy direct support through R&D subsidies, versus using only indirect support. Gauging the combined effects on firms who benefit from such a policy mix is of great interest to policy makers who aim to design effective support schemes and wish to understand the potential synergies between R&D support measures. So far, different R&D incentives have largely been analysed in isolation (Falk et al., 2009), with a few notable exceptions (Bérubé & Mohnen, 2009; Busom et al., 2014; Dumont, 2013, 2015; Guerzoni & Raiteri, 2015). The potential for interaction effects between multiple (types of) support measures stems from the inherent differences between them. In particular, while R&D subsidies provide the benefit of targeted support, tax credits are comparatively easier to integrate in the firm's long-term financial planning and impose a lower administrative burden (Köhler et al., 2012).

The remainder of the paper is structured as follows. The next section reviews the literature on behavioural additionality in support of our central hypothesis on the effect of R&D subsidies on firms also benefiting from R&D tax credits. The third section provides background information on the availability and use of R&D subsidies and tax credits in Belgium. It also discusses the survey data and our empirical approach. The fourth section presents the results and reports on various robustness checks. We conclude with a reflection on the main insights of our analysis for policy, and indicate avenues for further research.

2 Literature review

In this section, we provide a more elaborate motivation for our focus on behavioural additionality and clarify how this paper builds on prior research. We first explain the concept of behavioural additionality and the way we measure it. Next, we relate it to the importance of tax credits and to the R&D policy mix.

2.1 Behavioural additionality

The concept of behavioural additionality refers to permanent changes in firm processes and behaviour, such as newly acquired competences, the entry into new business areas or a change in working procedures, occurring as a result of policy intervention. Such changes may arise due to, among others, learning effects and knowledge spillovers (Clarysse, Wright, & Mustar, 2009).

The growing interest in behavioural additionality resulted from the fact that the traditional input and output additionality concepts can be questioned in terms of their ability to fully and adequately capture the impact of public intervention on the innovation process (Falk, 2007). More specifically, it has been argued that government support can be motivated not only based on the neoclassical market failure argument, i.e. the aim to address underinvestment in knowledge production (Nelson, 1959; K. Arrow, 1962), but can alternatively be prompted from an evolutionary-systemic policy perspective (Flanagan et al., 2011; Magro & Wilson, 2013).

This perspective provides an alternative rationale for policy intervention in the sense that the primary purpose shifts to modifying (in a permanent way) the firm's approach to R&D. This view naturally translates into behavioural additionality as a complementary way to evaluate policy measures, besides the classical input and output additionality approaches. Attention for behavioural additionality as an evaluation concept has further been justified by the argument that persistent changes in firm behaviour create the necessary condition for a policy's ability to eventually induce output additionality (Georghiou, 2002). Moreover, it is methodologically challenging to judge the effectiveness of public support in terms of output additionality, e.g. due to long lags before 'sleeper technologies' find a productive use (Luukkonen, 2000).

Behavioural additionality fits within an evolutionary-structuralist perspective if the policy intervention ultimately leads not only to adjustments in the approach to R&D, but also to a change in cognitive capacity of the firm (Bach & Matt, 2002).

The OECD (2006) report on behavioural additionality highlights for example that Finnish companies that had received R&D funding for specific projects assessed that this permitted them to focus on long-term and riskier research. In Japan, national research funding allowed companies to engage in large-scale research projects and, to a greater extent, improve the efficiency of R&D. Another series of case studies presented in the report investigate the impact of government support on R&D activities of firms, including accelerating projects or setting-up projects with higher technological challenges. However, their results only refer to the direct effect of public grants for R&D, rather than the moderating effect of subsidies on tax incentives – as is the case of our study.

To measure behavioural additionality, (Falk, 2007) integrates previous insights and addresses scope additionalities – expanded coverage of an activity to a wider range of markets, applications or players, advancement into new research areas – possibly reflected in a greater risk profile of the innovation projects, new partnerships between the realms of business and academe – resulting in cognitive capacity additionality (Bach & Matt, 2002), the timing of projects – acceleration additionalities which, if going hand in hand with scope additionality, can also result in long-term projects geared towards strategic objectives, and scale additionalities – engagement in larger innovation projects. Her paper also emphasizes that different aspects of behavioural additionality can and should be addressed in order to draw conclusions about the effectiveness of a policy measure. The UK Department of Trade and

Industry uses the subcategories of scale, acceleration and scope to measure behavioural additionality (Georghiou, 2002).[62]

In our paper, we analyse the following dimensions of a firm's R&D activities: scale, speed of execution, the ratio of R (research) versus D (development),[63] and the number of projects that the firm is engaged in (details will be given in the third section and their relation with tax credits will be made clear at the beginning of the next section). These R&D descriptors allow assessing key aspects of behavioural additionality as they have been put forward in the literature. While not all four outcome variables at our disposal map clearly onto one of these dimensions, we believe the set of outcomes available in the survey allows for a meaningful analysis of the behavioural additionality effects of R&D tax credits, as moderated by R&D subsidies.

2.2 Behavioural additionality of tax credits

Behavioural additionality of R&D tax credits is not guaranteed and, if it occurs, may manifest in different ways. Research by Goolsbee (1998) with US data and Haegeland & Møen (2007) on Norwegian firms indicates an important influence of R&D tax credits on raising researchers' wages, but also on the probability of firms starting to invest in R&D where they have not done so preceding the introduction of tax incentives. However, related to the tax credit in the Netherlands, Lokshin & Mohnen (2012) find that small firms have a larger R&D cost elasticity, whereas there seems to be a crowding out effect on larger firms. Such deadweight loss is a distinct possibility if the firm can freely spend the tax exempted financial resources. Alternatively, they might be (partially) channelled back to R&D activities, but in ways that do not represent a fundamental departure of the firm's usual way of doing R&D. In particular, the firm may increase the staffing of current projects, which may affect the scale and/or speed of execution, without really changing the firm's R&D agenda.[64] Conversely, a firm may also take decisions that more fundamentally affect its R&D strategy, such as taking on additional R&D projects or changing the balance between research and development. The changes in the firm's approach to R&D are ultimately determined by the decisions it makes in response to the slack

[62] More dimensions of behavioural additionality have been proposed in the literature, such as the expansion of a firm's network. In our empirical analysis we do not have measures for such outcomes, so we necessarily leave them out of scope.

[63] Zúñiga-Vicente et al. (2014) argue that studies that consider the impact of public support on research and development separately provide inconclusive results.

[64] Note that a firm may also respond by replacing employees who work on R&D projects but who are not eligible for the tax credit with people who do meet the formal requirements in terms of e.g. educational qualification.

resources freed up by the R&D tax credit. For example, if the firm decides to replace R&D workers who are not eligible for the measure by highly-qualified people who do comply with the requirements – such as replacing non-PhDs with PhD holders – then this may have an impact on the composition of the firm's skill base rather than the total available R&D (wo)manpower. Assuming that a different and more diverse set of competences represents an incentive to undertake projects in which those skills are put to use, one may expect an upward influence on the ratio of research versus development and/or the number of projects. An alternative response could be that the firm does not increase the share of highly qualified R&D workers, but instead chooses to hire more people to help executing R&D work, e.g. lab technicians, which does not represent a substantial expansion of the firm's expertise. In that case, one would expect an effect on the scale and speed of R&D activities, rather than on more scope-oriented outcomes. While the actual reaction of a given firm will end up somewhere along the spectrum of skill-upgrading versus pure capacity-building, these alternatives provide a useful framework for making sense of differential effects across the sub-dimensions of behavioural additionality.

2.3 Behavioural additionality of R&D tax credits in the presence of R&D subsidies

There is long-standing interest in the interactions that may arise in a 'mix' of policy instruments: Cunningham et al. (2013) trace the emergence of the policy mix concept in the policy-oriented literature back to the 90s. Supported by the growing emphasis on a systemic view of innovation, scholars and policy makers have banked on the concept to better understand the complexities in stimulating innovation. Despite the need for a more comprehensive approach to evaluating interactions between different support measures (Diez, 2002; Aranguren et al., 2014), the policy mix concept remains a rather ill-defined and under-conceptualized term (Flanagan et al., 2011). In this paper we operationalize the policy mix as the joint use of R&D tax credits and subsidies, which are by far the two most important policy instruments used to stimulate private R&D activity. We briefly introduce the key differences between these instruments in terms of their objectives and usage by firms.

In general, subsidies provide up-front financing independent of the firm's tax position and are more interesting for firms facing appropriability difficulties. Subsidies may also help to attract additional funding, since they produce a certification effect, unlike tax credits (Takalo & Tanayama, 2010). On the other hand, tax incentives typically require less administrative burden and do not suffer from winner-picking by government agencies, but require that the firm has the capacity to appropriate the returns of its innovation to benefit from the measure (Busom et al., 2014). Related to the latter argument, tax incentives are more likely to benefit stable R&D performers, whereas subsidies tend to increase the number of R&D performers (Arqué-Castells & Mohnen, 2015).

In terms of criteria, subsidies are typically awarded based on the innovative content of the proposal, technical ability of the firm and potential market (Busom et al., 2014). Conversely, R&D tax credits do not require the approval of a specific government agency and funding is provided irrespective of the quality of the project. An advantage of tax-based support is that it leaves the choice of how to conduct and pursue R&D programs in the hands of the private sector and thus avoids inefficiencies due to uninformed steering of firms' R&D (Hall & Van Reenen, 2000). At the same time, this allows firms to fund R&D projects that yield the highest private return rather than the ones with the highest social value (David et al., 2000). Conversely, the existence of tax deductibles may tempt firms to game the system, for example by labelling expenses as research activities while in fact they are related to other kinds of business activities unrelated to R&D (Antonelli & Crespi, 2013). R&D subsidies that impose conditions on the execution of R&D may, in principle, improve allocation decisions, but issues like asymmetric information, lobbying and red tape may lead to suboptimal funding decisions (Hall & Van Reenen, 2000).

Given that the policy goals and granting mechanisms of tax credits and subsidies are quite different, it is not trivial to predict the results when they are used jointly. In fact, little is known about the interaction between R&D tax incentives and direct subsidies for R&D. More generally, which particular form of public support should be used to correct for market failures is not clear, nor is the question whether or not there exists an optimal mix of tax credits and subsidies (Busom et al., 2014).

Most existing input or output additionality studies that consider multiple instruments do not analyse interactions. (Cunningham, Gök, & Larédo, 2012) report higher success levels of firms that combine direct and indirect support. Haegeland & Møen (2007) find that both subsidies and tax credits lead to input additionality but they don't explicitly study interactions. Carboni (2011) studies Italian firms and finds evidence of input additionality, tax incentives seemingly being more effective than direct grants, although grants encouraged the use of funding sources internal to the firm. Corchuelo & Martínez-Ros (2009) find evidence of a stepping stone logic, subsidised Spanish firms being more likely to take advantage of tax credits. Finally, Falk (2007) reports evidence that firms enjoying a mix of direct and indirect support have a higher likelihood to innovate radically. Bérubé & Mohnen (2009) apply matching estimators to show that Canadian firms using a mix of tax credits and subsidies have a higher innovative performance than firms using only tax credits. We will follow a similar set-up in this paper, albeit we will zoom in on behavioural additionality rather than innovation output. More specifically, we analyse whether subsidies moderate the behavioural additionality effects of wage-related tax credits. The intuition for such a treatment effect is the following: while R&D subsidies are generally targeted towards long-term research projects, there may be spillovers with respect to the way R&D tax credits are used by the firm. In order to justify the existence of such spillovers, one needs to analyse how the subsidy (i.e. R&D project) changes the R&D environment such that the firm uses the tax credit differently. We argue that it may be a very real possibility that subsidized firms direct the financial resources freed up by the tax exemption towards the subsidized project(s), and as such provide direction for the use of the R&D tax credit. In other words, those financial resources may find a productive home within the context of the subsidized project.[65] More specifically, the subsidized R&D projects may serve as a roadmap, pointing to a more productive way for allocating additional R&D resources. For example, the tax credit may create room for additional experimentation in the subsidized R&D activities that the firm would not have undertaken otherwise. We do not explicitly disentangle our hypothesis conditional on the outcome variable since prior work provides few, if any, handles to argue differential effects for scale, speed or the share of R versus D.

> *Hypothesis: The use of R&D tax credits together with R&D subsidies creates stronger behavioural additionality effects than the use of R&D tax credits alone.*

3 Background, Data & Method

3.1 R&D subsidies and R&D tax credits in Belgium

While the discussion will yield insights that extend to other countries, our empirical analysis is constructed on Belgian data. Therefore, we start by highlighting the main features of the wage-based R&D tax credits and the R&D subsidy system implemented in Belgium. First, it should be noted that R&D tax credits are a federal authority, whereas R&D subsidies are predominantly awarded – EU subsidies aside – by the three regional governments in Belgium,

[65] Note that nothing prevents the firm from using the tax credit for activities related to subsidized projects.

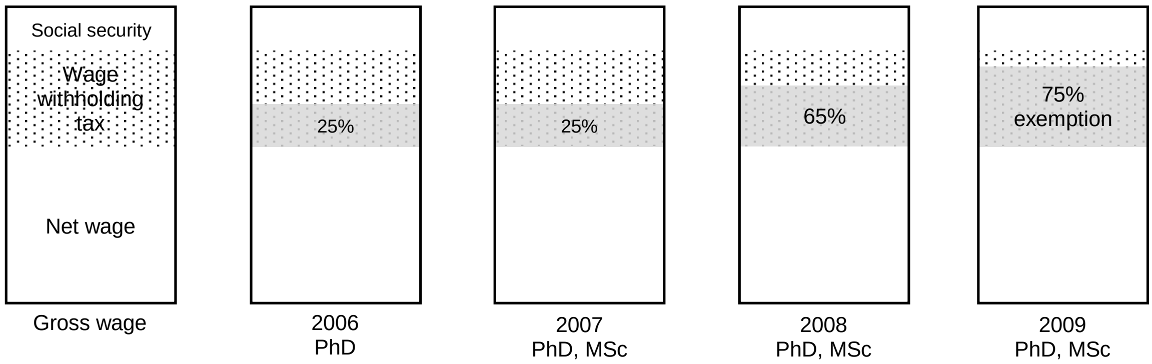
i.e. the Flemish Government, the Walloon Government and Government of the Brussels Capital Region. While this is not of primary importance from the perspective of firms, it does have ramifications for policy making as any coordination on these R&D support measures requires interaction between different governments.

As in many other countries (Busom et al., 2014), R&D subsidies have long been the most important source of funding for R&D in Belgium. Subsidy policies are largely inspired by a bottom-up approach, meaning that they are tailored to the specificities of the enterprises located in the region. Important aims of subsidy programs include fostering co-operative research and other forms of networking in order to stimulate knowledge spillovers. R&D subsidies are typically geared to address firms' risk averseness, some subsidies being specifically earmarked for small and medium sized enterprises who face stronger financial constraints for R&D (Czarnitzki & Hottenrott, 2011; Teirlinck & Spithoven, 2012). In Belgium, firms pass through a selection procedure at the end of which projects are funded or rejected by the public authority. The Region of Flanders subsidises research, development or mixed (R&D) projects, offering extra incentives for SMEs, as do the other two regions.[66] Moreover, Flanders and Brussels also sponsor feasibility studies, while Flanders and Wallonia target specific industries based on their economic needs.

The Belgian R&D tax credit we analyse operates as a wage subsidy for R&D workers, which sets it apart from tax credit systems in many other countries. More accurately, it offers companies a partial exemption of the wage-withholding tax for highly qualified R&D personnel. Note that this implies that a firm needn't generate profits in order to benefit from the tax credit. The operation of the measure is illustrated in Figure III.1.

[66] The balance between the specific Flemish subsidy schemes for research or development (or mixed) may drive part of our results in terms of research orientation. However, as our data does not offer any information regarding the type of subsidies firms receive, we rely on observations by Hottenrott, Lopes Bento, & Veugelers (2014) related to the amounts of each measure granted over time. Before 2009, development subsidies were more prominently handed out to firms, whereas research grants were lagging behind. However, there has been a steady shift in policy to increase the latter, and by 2009 they became almost as important in value as development subsidies, while mixed grants faded.

Figure III.1 Operation of the R&D tax credit as a wage subsidy



The tax credit was introduced in January 2006 for researchers holding PhDs in exact or applied sciences, (veterinarian) medicine, or civil engineering. At the beginning of 2007 it was extended to researchers with a master's degree, with the exception of masters in the social sciences and humanities. The rate of the tax exemption amounted to 25% and was increased to 65% in July 2008, to 75% in January 2009, and (out of scope of our analysis) augmented to 80% from June 2013 onwards. Young innovative companies (YICs) have benefited of the 75% rate since 2006. For them, R&D support personnel has also been eligible for the tax credit since the introduction of the system. For these reasons, we will control for the YIC status of firms in the analysis.

There is high persistence in tax credit usage, with a very limited number of companies abandoning the system once they start using it.[67] This implies that the vast majority of firms that report in 2011 that they have used the R&D tax credit (see details on the survey below) have enjoyed the maximum rate of 75%.

As stated in the previous section, the exempted amount of the wage-withholding tax can be freely used by the company. While a strict condition to channel this reduction in wage cost back to R&D is absent, the aim of the policy measure nevertheless is to stimulate R&D investment, mainly through the employment of highly qualified researchers. In sum, this wage-based R&D tax credit system in Belgium is different from tax-related incentive schemes for R&D in many

[67] Only 101 companies out of the cumulative population of 1,131 firms who used the tax credit at least once between 2006 and 2009 abandoned its use. The reasons for this are unknown, but seem mostly unrelated to bankruptcies or other forms of exit as we find evidence of continued activity for most of these 101 firms. Given that most of the 101 firms are relatively small in size, around 70% being SMEs, the main reason might be that changing the composition of their personnel or lack of substantial R&D made these firms no longer eligible.

other countries (Busom et al., 2014), which provide an ex-post stimulus through tax deductibles, effective only when the firm is profitable.

Both R&D tax credits from the federal government and R&D subsidies from regional governments represent sizeable public support for innovation in the business sector. In 2011, 1,459 companies benefited from the tax credit, representing a reduction in wage cost of 289 million Euros.[68] At the same time, R&D subsidies from regional governments amounted to 229 million Euros, benefiting 885 companies. The average tax credit per beneficiary firm was 198,000 Euros compared to 259,000 Euros for subsidies. On the other hand, 394 firms combined tax credits and subsidies in 2011, receiving an average mix of 788,000 Euros, and the overall budgetary effort for the policy mix was 311 million Euros.[69]

3.2 Data

In June 2011, the Belgian Science Policy Office (Belspo) conducted an electronic survey aimed at evaluating the behavioural additionality effects of the wage-based R&D tax credit measure. It was sent to all R&D tax credit users in Belgium that were also included in the 2010 OECD business R&D survey, which draws on the exhaustive inventory of 2,706 (quasi) permanent R&D-active firms in the country. The electronic questionnaire yielded 412 responses. After internal consistency checks and removal of incomplete answers, a total of 177 firms provided information on all the variables necessary for the analysis conducted in this paper. Data from the survey was combined with firm characteristics from the Belfirst database (Bureau Van Dijk). The resulting sample for the empirical analysis thus consists of surveyed companies that have used the tax credit in any of the years between 2006 and 2010 (N=177). The treatment group is defined as those firms using both subsidies and tax credits (N=105), while the control group consists of the firms that have used the tax credit but not subsidies (N=72).

Although the survey provided a cross-section of tax credit users, the respondents had to provide yearly figures (2006-2010) of the number of R&D employees and the number of researchers supported by the R&D tax credit measure. This allows us to observe when each firm has first

[68] These number refer to the wage withholding tax exemption for researchers with master and doctoral degrees and those employed by YICs, but also include a fourth line of the measure which is attributed to researchers engaged on collaborative R&D with universities and public research institutes.

[69] The numbers have been calculated based on a database comprising the population of tax credit and subsidy receivers from the Belgian Federal Public Service Finance.

used the R&D tax credit and construct the control variables for the matching procedure described in the next section.

To assess the representativeness of our sample of respondents for all R&D tax credit users, we have used data from the Federal Public Service Finance on the population of 1,131 R&D tax credit users in 2009 – the most recent year with complete data. The overall statistical tests of differences in means for a broad range of firm characteristics indicate that – while the sample is relatively small – it allows for a valid analysis.[70]

Four indicators of firms' R&D behaviour are investigated: scale, speed of execution, the ratio of R (research) versus D (development), and the number of R&D projects. The indicators reflect the outcome of tax credit use over the entire 2006 – 2010 period and cannot be split into separate periods. More specifically, firms were asked to indicate, on a 5-point Likert scale, the level of agreement with the following statements: '*1) The budget freed up by the partial wage withholding tax exemption has been used to: a) conduct more research (relative to development); b) start extra R&D projects. 2) Without the R&D tax credit measure*[71]*: a) R&D activities would have gone through at a slower pace; b) R&D activities would have gone through on a smaller scale.*' The survey relies on firms' capacity to assess the additionality effects of tax credits relative to the counterfactual of not having benefited from R&D tax credits. This approach may be prone to measurement errors and requires us to assume that firms' self-reporting qualitatively reflects the underlying data[72]. Although we acknowledge that this might not always be the case, prior work has shown that, in general, this is a legitimate assumption (Clarysse et al., 2009; Falk, 2007).[73] The Likert-scale responses have been recoded into

---

[70] We compared our sample of firms with the population of R&D tax credit users in terms of firm size, age, NACE sector, geographical region, current ratio, R&D intensity (defined as the share of researchers in all employees), the percentage of firms that have used the tax credit from 2006 ('tax leaders'). The only statistically significant differences concern low-tech manufacturing firms and tax leaders, which are slightly overrepresented in our sample.

[71] The actual formulation in the survey uses the wording 'fiscal measure' rather than 'R&D tax credit'. In order to avoid confusion with respect to terminology, we consistently use the term 'R&D tax credit' throughout the paper.

[72] Moreover, our research question refers to the additional effect of subsidies on whatever impact tax credits might have. Although the survey questions refer unambiguously to the latter, there might still be response bias present in the policy mix users group. We acknowledge that such bias might be present, but the design of the survey does not permit a more comprehensive analysis of its extent.

[73] Although the reliability of surveys can be put into question, they are a valuable tool to assess the impact of policy on issues that are not easily quantifiable nor observed in company accounts or similar data (Ientile & Mairesse, 2009). For example, the speed of execution of R&D projects, their scale or the exact use of the exempted amount are research questions which are very hard – if not impossible – to proxy through some variables. For such issues as the ones we address, we think that a survey of the direct users of fiscal measures is possibly the most reliable way of gathering the data needed for analysis.

dichotomous variables: '*strongly agree*' and '*agree*' were coded 1, while '*neither agree nor disagree*', '*disagree*', '*strongly disagree*' and '*N/A*' were coded zero.[74]

3.3 Method

In order to detect whether subsidies mitigate the effects of tax credits on companies' R&D, we adopt a non-parametric matching approach complemented by a parametric multivariate model. We use y_{im}^{T} to denote the behavioral outcome m of firm i if it receives both R&D subsidies and tax credits ($S = 1$), and y_{im}^{C} for the same outcome of the same firm if it uses only tax credits ($S = 0$). The effect for a firm i enjoying the policy mix of using both tax credits and subsidies instead of only tax credits is given by $E\left[y_{im}^{T} - y_{im}^{C} | S = 1\right]$. Empirically, the treatment effect for outcome m is then calculated as:

$$SATT_m = \frac{1}{N_T} \sum_{i|S=1} \left[y_{im}^{T} - y_{im}^{C}\right] \qquad (1)$$

with $SATT$ denoting the Sample Average Treatment Effect on the Treated and N_T the number of treated firms. It is not possible to directly calculate the effect of using both measures since a firm is only observed as either having received the treatment or as being in the control group, i.e. there is a missing data problem (Heckman et al., 1997). The idea behind a matching approach is to find a proxy for the missing case by finding another firm with similar characteristics $X_i^{matching}$ but that only uses tax credits. The matching on observable characteristics addresses the problem of a potentially non-random selection of firms into the treatment, provided that the conditional independence assumption holds (Rubin, 1977). This means that the treatment status and potential outcome are assumed independent for firms with the same set of exogenous characteristics:

$$y_{im}^{T}, y_{im}^{C} \perp \mathrm{S}_i | X_i^{matching} = x \qquad (2)$$

In addition, we impose a common support restriction, meaning that, for all treated firms, a valid counterpart should be present in the control group, and, conversely, every tax credit user should represent a potential subsidy recipient.[75]

[74] Using dichotomous outcomes serves the purpose of answering our research question, while sidestepping the issue of heterogeneous interpretation of the detailed answer levels by the respondents. In addition, the size of the dataset does not lend itself to analysing the fine-grained response levels.

[75] In practice, this comes down to discarding all treated firms with propensity scores larger than the maximum and smaller than the minimum in the control group.

Under these assumptions, we can rewrite the SATT as the mean difference of the matched samples:

$$SATT_m = \frac{1}{N}\sum_{i=1}^{N}\left[\left(y_{im}^{T}|S=1, X_i^{matching}=x\right)-\left(y_{im}^{C}|S=0, X_i^{matching}=x\right)\right] \qquad (3)$$

Note that due to the nature of the survey questions, the matching design effectively yields a difference-in-differences estimation of the treatment effect. In particular, companies were asked what the *additional* effect of the R&D tax credit was on the scale, speed, etc. of their R&D. Thus, the answers represent the difference between the pre-treatment period t_0 and the post-treatment period t_1, the latter being the moment when the survey was conducted, in 2011.

Different methods exist to match the treated firms with their most similar counterparts in the control group. We use propensity score matching, $P\left(S=1|X_i^{matching}\right)$, introduced by Rosenbaum & Rubin (1983), which is estimated using a probit regression. Subsequently, each treated company is matched to one firm from the control group based on the propensity score.[76]

After matching, we run follow-up regressions including, besides the treatment variable, the control variables employed in the matching probit to correct for any remaining imbalance between treated and control groups (Iacus, King, & Porro, 2011). We also include the following four variables: *years of tax credit use*, *average tax importance*, *demand pull* and *technology push*.[77] We provide further justification for their inclusion in section 4.2. Furthermore, we exploit the fact that we observe multiple behavioural outcomes in these adjustment regressions by estimating a multivariate probit model,[78] which allows for correlation between unobserved

[76] We employ single nearest-neighbour matching with replacement, i.e. control firms are not removed from the pool of potential controls after matching with a treated firm. We follow this approach to ensure good quality matches given the specific composition of our sample: the treatment group is larger than the number of possible controls because most companies that have accessed tax credits have also used subsidies. We use the Stata command *teffects psmatch* to perform the propensity score matching and calculate average treatment effects on the treated with robust standard errors.

[77] The reason for not including these variables when estimating the propensity to use both tax credits and subsidies is that they are not measured pre-treatment. The first two variables are, respectively, a count and average over the entire 2006-2010 period, thus spanning both pre- and post- treatment periods. The *demand pull* and *technology push* variables stem from answers provided by the survey respondents in 2011 without referring to a specific period, making it impossible to attribute the variables to the pre-treatment period. To avoid endogeneity of the matching variables, we only include in the matching estimation those variables that unambiguously apply to the pre-treatment period (see also section 4.1 for details on the matching).

[78] Leveraging the matching approach, the multivariate probit model is estimated using all firms on common support. As a robustness check, we also estimated the same model using only the matched sample, yielding a better balance but which leaves us with fewer observations (130 firms instead of 163). The results, presented in Table III.8 in Appendix, are very similar. We opted to report the findings using the larger dataset as the main results in the paper, and reckon that this approach represents a reasonable trade-off between achieving good quality matching and accommodating the drawbacks of the available data.

factors driving the behavioural outcomes of a single firm – while still requiring the error terms to be uncorrelated across firms – and hence permits a more efficient estimation.

We estimate the following 4-equation multivariate probit model:

$$y_{im}^{*} = \alpha_m + \beta^{subs'} X_i^{subs} + \beta^{matching'} X_i^{matching} + \beta^{controls'} X_i^{controls} + \varepsilon_{im}\ ; m = 1..4 \quad (4)$$

The observed binary outcome y_{im} equals 1 $if\ y_{im}^{*} > 0$, whilst it equals 0 $if\ y_{im}^{*} \leq 0$. y_{im}^{*} is the latent variable that captures the change in the outcome m (scale, speed, research orientation, number of R&D projects) for firm i.

$X_i^{matching}$ represent the matching variables, which are included to control for remaining imbalance. X_i^{subs} denotes whether firm i received a subsidy, $X_i^{controls}$include measures of the importance of the tax credit for firm i and dummies if the firms consider that their R&D is driven by demand pull or technology push factors.[79] The error terms ε_{im} are assumed multivariate normal[80] with mean 0 and variance-covariance matrix V where $\rho_{jj} = 1$ and the off-diagonal correlations are estimated from the data under the restriction that $\rho_{jk} = \rho_{kj}$.

Recall that the binary outcome variables y_{im} have been coded as 1 if the respondent at least agrees or strongly agrees that there is an effect on the corresponding behavioral outcome, which is consistent with the idea of a latent variable y_{im}^{*} exceeding a threshold value.

4 Empirical Analysis

4.1 Matching

To construct a control group for the firms who benefit from R&D subsidies and tax credits, we include a range of variables that may be expected to affect the probability of a firm using both types of support, compared to only tax credits. Note that since all firms in the sample use R&D tax credits, the groups may be expected to be relatively homogenous, as all firms use public R&D support. While prior work provides little guidance on the precise characteristics that may distinguish between subsidized and non-subsidized firms, conditional on tax credit usage, we

[79] The importance of the tax credit is measured via three indicators: the yearly average percentage of R&D personnel for which the firm received the tax exemption – taking into account the different levels of the exemption – whether the firm is a tax leader (if it used the tax credit from 2006), and the number of years each firm has benefitted from the tax credit.

[80] In our estimation of the model, we specified 30 random draws from the multivariate standard normal distribution to be used for calculating the simulated maximum likelihood function in each iteration. This exceeds the guideline of using at least $\sqrt{N}$ with N the number of observations (Cappellari & Jenkins, 2003).

will draw on related work that has relied on matching techniques to study the effects of R&D support.

To avoid endogeneity of the matching variables, they need to be measured prior to the firm receiving the treatment, i.e. the combination of R&D tax credits and subsidies. While we do not have information on the precise timing of subsidy use, we do observe in which years a firm uses tax credits. By definition, the year prior to the firm's first use of R&D tax credits is a pre-treatment year since at most one of the support measures (subsidies) is being used by the firm.[81] Therefore, we use the values of the matching variables in that year, if the data is available. However, due to the small sample size and incomplete data, for a number of companies (119 out of 177), some variables can only be measured in the first year of tax credit use.[82] Prior work using matching estimators has followed an analogous approach to deal with limited data availability (e.g. Czarnitzki & Lopes-Bento 2013). Table III.6 in Appendix details the year that is used for each variable in the empirical analysis.

As a first matching variable, we follow Lhuillery, Marino, & Parrotta (2013) and control for the firm's *R&D intensity*, measured as the percentage of researchers relative to the total number of employees. Given our focus on behavioural additionality, it is important to construct a control group of firms for which R&D plays a comparable role as for the treated firms. Firms' R&D investments are hence treated differently in our research set-up compared to studies that analyse input additionality, in which R&D investments are used as a dependent variable. An important methodological concern about using R&D intensity as a matching variable is that it may be endogenous to the receipt of R&D subsidies, as an R&D grant may allow a firm to hire additional researchers. In other words, we need the pre-treatment R&D intensity, net of R&D employees financed through subsidies. Since we do not have this information, we use the following approach to mitigate endogeneity concerns: we rely on the observation that there is high persistence among firms that benefit from R&D subsidies (Busom et al., 2014). Therefore,

---

[81] Given the purpose of the matching to construct a control group of tax credit users that is similar to the firms that also use subsidies, the matching variables in the pre-tax credit year should not be 'contaminated' by R&D subsidies. This condition is only met if the firm's first subsidy use *succeeds* its first R&D tax credit use. Conversely, if a firm benefits from an R&D subsidy prior to receiving R&D tax credits - which we cannot observe - then certain matching variables may be affected by the subsidy. For the matching variable most likely to be affected by this issue, we apply an additional correction to obtain a 'subsidy-corrected' R&D intensity (described later in the current section). In sum, while the approach we follow is not perfect, it strives to the maximum extent possible for an accurate matching of treated and untreated firms given the available data.

[82] This period was used to measure firm size in 24 cases, R&D intensity for 122 companies, and current ratio for 20 firms for which pre-treatment values were not available.

we corrected a (subsidized) firm's R&D intensity by using information in the survey on the relative importance (in terms of each firm's budget) of subsidies compared to tax credits at the time the survey was performed. Jointly with the information on the number of researchers the firms received tax credits for, this allowed us to correct for the number of R&D workers supported by subsidies, and hence to calculate a 'subsidy-free' R&D intensity in the year preceding the first time a company benefitted from the R&D tax credit.

Further, we match firms on *industry*, as industry affiliation has been shown to be a factor in the decision to grant subsidies to firms. For example, Hyytinen & Toivanen (2005) show that government funding disproportionately helps firms from industries that depend more on external financing. Due to the relatively small size of the dataset, we merely use an aggregate industry classification. In particular, we use dummies for high- and low-tech manufacturing and service industries, following Eurostat guidelines.[83] However, note that the inclusion of R&D intensity as a matching variable helps control for different propensities across industries to invest in R&D (Mathieu & de la Potterie, 2010).

Company size and *age* have been found to have an impact on the use of public R&D support, with larger and younger firms more likely to benefit from it, although the findings are mixed (Almus & Czarnitzki, 2003; Blanes & Busom, 2004; Dirk Czarnitzki & Licht, 2006; Aerts & Schmidt, 2008). We control for these firm characteristics by using the logarithm of the number of employees and the age of the company in the first year it uses tax credits.

A firm's *financial health* has been found to affect a firm's likelihood to apply for subsidies because financially constrained firms have a stronger incentive to acquire external financing (Caiumi, 2010; Czarnitzki & Hottenrott, 2011). At the same time, such firms might not be primary targets for policy makers because of their uncertain financial future, which is at odds with 'picking the winner' strategies that may be followed by public funding agencies. We use the current ratio, defined as current liabilities to current assets, a frequently used measure to capture the firm's short-term financial health (Bromiley, 1991; Latham & Braun, 2010).

The *Young Innovative Company* (YIC) status of a firm is included in the estimation, as such firms benefitted from special treatment from the tax authorities, as mentioned in section 3.

[83] The use of a more detailed industry classification is likely to be less relevant in our setting since only R&D-active companies are considered, and differences between sectors are found to be more related to the propensity to engage in R&D rather than the characteristics of the R&D active firm (Teirlinck, Dumont, & Spithoven, 2010).

Companies being part of a *corporate group*[84] may benefit from internal funding, and may be better informed about public support thanks to internal company information networks. Furthermore, group headquarters may enjoy reduced costs in applying for subsidies (Takalo, Tanayama, & Toivanen, 2013).

The experience of a firm in actively seeking and *using other forms of R&D support* may serve as a signal for its use of subsidies (Czarnitzki & Lopes-Bento, 2013). Hence, we include a dummy (*tax leader*) capturing whether the firm used tax credits in 2006, when the measure was introduced.

Furthermore, the *relative importance of the R&D tax credit* for a firm's R&D operations might also be correlated with the probability that a firm obtains R&D subsidies. We control for this via a *tax importance* variable, measuring the percentage of researchers for which the firm received wage-based tax credits.[85]

Finally,[86] given that *authority over R&D subsidy policy* accrues to the regional governments, we include dummies for the three Belgian regions – Flanders, Wallonia and the Brussels Capital Region. As studies in other countries have also found (Santamaría, Barge-Gil, & Modrego, 2010), the decentralization of policies leaves room for differentiation in terms of subsidy eligibility criteria, focus on specific industries, etc.

Means and proportions of the variables used for matching and the behavioural outcome variables are shown in the first and second panels of Table III.1, respectively.

---

[84] Using information from the Amadeus database, we define members of a group as firms which are either owned (with a share of over 50%) by another firm, or have themselves a stake of over 50% in another company.

[85] We also weigh the percentage of researchers supported by the measure by the percentage of the tax exemption, according to the 'treatment' year: 25% from 2006 to June 2008, 65% as of July 2008 and 75% as of 2009.

[86] We tried to be as complete as possible with respect to the inclusion of variables in the matching model given the available data sources i.e. the survey conducted by the Belgian Federal Science Policy Office combined with the Belfirst and Amadeus databases. Nevertheless, we could not add some controls that have been used in other studies on R&D support. For example, Czarnitzki & Lopes-Bento (2013) use CIS, Belfirst and IWT data for Flemish firms and include variables for exports and patents. We were not able to include such information due to limited possibilities to link to external data sources and confidentiality reasons. However, compared to their study, we were able to use a set of extra variables regarding firms' financial health (*current ratio*), their R&D intensity, a proxy of their knowledge of the R&D support system (*tax leader*, *tax importance*), as well as *regional dummies* that capture differences in public policies across the three administrative regions in Belgium (Flanders, Brussels and Wallonia). Among other possible characteristics that might play a role in firms' selection into subsidy schemes might be the education of their researchers, the wage base, but also the quality of research projects. However, we do not have data on either of these variables.

Table III.1 Descriptive statistics, pre-matching

Variable	Tax credits only N=72	Policy mix N=105	p-value[b]
R&D intensity	24.42%	24.74%	0.94
Log(employees)	3.85	3.00	0.00
Age	22.59	19.69	0.30
Current ratio	1.76	2.52	0.27
YIC dummy	18.06%	16.19%	0.75
Group dummy	55.56%	47.62%	0.30
Tax leader dummy	26.39%	42.86%	0.03
Tax importance	37.55%	37.06%	0.89
High-tech manuf.[a]	19.44%	20.00%	0.93
High-tech services	27.78%	41.90%	0.06
Low-tech manuf.	34.72%	25.71%	0.20
Low-tech services	12.50%	8.57%	0.40
Brussels	9.72%	8.57%	0.79
Flanders	65.28%	62.86%	0.74
Wallonia	25.00%	28.57%	0.60
Scale	51.39%	69.52%	0.02
Speed	41.67%	65.71%	0.00
R versus D	29.17%	57.14%	0.00
Nr. of projects	50.00%	68.57%	0.01

a) A small number of firms could not be classified in any of the four categories because their NACE codes are not on the Eurostat list used for the classification. This is why the percentages do not sum to 100%. In the regressions, these firms are included in the base category.

b) Equality of means between the two groups was tested by t-tests (continuous variables) and Pearson's chi^2 (categorical variables).

Users of tax credits only (second column) do not seem to differ very much in characteristics from users of the 'policy mix' (third column). This is not unexpected, as both groups are users of some form of public support. Indeed, in terms of R&D intensity, age, percentage of young innovative companies, financial health (measured by the current ratio), the importance of the tax credit, sector of activity, and regional distribution, the two groups are rather balanced. However, like Bérubé & Mohnen (2009), who also study the 'policy mix' for firms experienced in accessing public support, we find some significant differences. In particular, differences in firm size – policy mix users are on average smaller – and speed of adoption of tax credits – policy mix users are on average more likely to be early adopters – point towards the necessity of balancing the two groups.

The second panel in Table III.1 shows that there are significant differences in outcomes for the treated and potential control firms. On average, users of the policy mix reckon that the tax credit has increased the scale, speed, relative orientation towards research, as well as the number of concurrent projects than is the case for users of the tax credit only.[87] Table III.2 shows the results of the probit estimation of the propensity to use both tax credits and R&D subsidies, with a dummy indicating the use of subsidies as the dependent variable. As expected, companies that have used the tax credit since 2006 (*tax leader*) have a higher probability of also using subsidies. This confirms the intuition that these firms are more prone to use different types of public support measures for R&D. Further, the matching results indicate that larger firms have lower probability of using subsidies alongside tax credits. This is in line with the particular attention in many regional R&D subsidy programs towards providing support to SMEs (Teirlinck & Spithoven, 2012). Bérubé & Mohnen (2009) find similar results for company size in their matching study, using an analogous treatment definition. Note however that these results should not be interpreted as general predictors of using R&D subsidies, but rather serve to identify differences in observable characteristics between treated and control firms.

Although the other variables such as industry affiliation and region have no significant effect on the probability to use R&D subsidies, they contribute to the model fit and thus the overall balance between treated and control firms in the propensity score matching in the next step.

[87] We remind that we are interested in the *difference* in the answers between the control group (tax credits only) and the treated firms (tax credits & R&D subsidies). The survey data, with all respondents using R&D tax credits, does not allow assessing the effects of R&D tax credits alone.

Table III.2 Probit estimation of the joint use of tax credits and subsidies

	Coef.	s.e.
R&D intensity	-0.62	(0.43)
Log(employees)	-0.29***	(0.08)
Age	0.00	(0.01)
Current Ratio	0.03	(0.04)
YIC	-0.63	(0.39)
Group	0.14	(0.25)
Tax leader	0.69***	(0.24)
Tax importance	0.11	(0.54)
High-tech manuf.	0.09	(0.30)
High-tech services	0.37	(0.30)
Low-tech services	-0.34	(0.38)
Flanders	0.26	(0.38)
Wallonia	0.15	(0.40)
Constant	0.76	(0.59)
Observations	177	
LR $chi^2(9)$	28.78***	
Pseudo-R^2	0.12	
Log-likelihood	-105.20	

a) ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

The tests presented in Table III.3 confirm that none of the matching variables show significant differences in the means between the treated and control firms after matching, while balance indicators also reveal a reduction in bias after having performed the matching procedure.

Table III.3 Descriptive statistics of matched sample

Variable	Unmatched vs. Matched	Mean Treated	Mean Control	%bias	% reduction bias	t	p>t
R&D intensity	U	25%	24%	1		0.07	0.95
	M	25%	21%	11.9	-1041.8	0.84	0.40
Log(employees)	U	3.00	3.85	-48.6		-3.19	0.00
	M	3.22	3.53	-17.9	63.1	-1.25	0.21
Age	U	19.69	22.60	-15.8		-1.04	0.30
	M	19.88	20.41	-2.9	81.9	-0.2	0.84
Current ratio	U	2.52	1.76	18.5		1.12	0.27
	M	1.80	2.04	-5.8	68.7	-1.04	0.30
YIC dummy	U	16%	18%	-4.9		-0.32	0.75
	M	16%	11%	14.5	-194.6	1.07	0.28
Group dummy	U	48%	56%	-15.8		-1.03	0.30
	M	48%	45%	6.6	58.5	0.44	0.66
Tax leader dummy	U	43%	26%	34.9		2.26	0.03
	M	40%	41%	-2.3	93.3	-0.15	0.88
Tax importance	U	37%	38%	-2.1		-0.14	0.89
	M	37%	35%	10.2	-372.8	0.7	0.49
High-tech manufacturing[a]	U	20%	19%	1.4		0.09	0.93
	M	22%	14%	19.2	-1284.6	1.35	0.18
High-tech services	U	42%	28%	29.8		1.93	0.06
	M	35%	43%	-16.2	45.5	-1.06	0.29
Low-tech manufacturing	U	26%	35%	-19.6		-1.29	0.20
	M	29%	27%	2.4	87.8	0.16	0.87
Low-tech services	U	9%	13%	-12.7		-0.85	0.40
	M	10%	10%	0	100	0	1.00
Brussels	U	9%	10%	-4		-0.26	0.80
	M	9%	4%	15.2	-282	1.19	0.23
Flanders	U	63%	65%	-5		-0.33	0.74
	M	63%	66%	-6.8	-36.2	-0.46	0.65
Wallonia	U	28%	25%	8		0.52	0.60
	M	28%	30%	-2.5	69.2	-0.16	0.87

a) A small number of firms could not be classified in any of the four categories because their NACE codes are not on the Eurostat list used for the classification. This is why the percentages do not sum to 100%. In the regressions, these firms are included in the base category.
b) Equality of means between the two groups was tested by t-tests (continuous variables) and Pearson's chi^2 (categorical variables).

Table III.4 shows the average treatment effect on the treated (ATT) for each outcome. The share of firms reporting that the tax credit has allowed them to speed up R&D projects and/or increase the relative orientation on research versus development is substantially and significantly higher for recipients of the policy mix relative to those firms that only benefit from tax credits. Although the ATTs are also positive for the scale and number of R&D projects undertaken by firms, these effects are not significant at the 1% level, but merely at 5%. These results support our hypothesis that R&D subsidies strengthen the behavioural additionality of tax credits. Noteworthy is that the evidence on size-related R&D outcomes (scale, number of projects) is somewhat weaker than for the outcomes that bear a closer relation with the firm's efforts to safeguard its competitive position, both in the short run (speed) and in the long run (more emphasis on research).

Table III.4 ATT on behavioural variables

Variable	Treated - Control	s.e.	Z-score	p-value
Scale	19.78%	(0.09)	2.10	0.04
Speed	24.18%	(0.08)	2.90	0.00
R vs D	26.37%	(0.08)	3.24	0.00
Nr. of projects	20.88%	(0.09)	2.39	0.02

4.2 Regression analysis

We further ascertain the robustness of our main results in a multivariate probit regression framework, which allows for a closer identification of the role of subsidies in moderating the behavioural additionality of R&D tax credits. We trim the sample to include only observations on common support in the matching exercise, amounting to 91 treated firms and 72 controls. While the impact on the sample is modest, this correction serves to assure that none of the subsequent results are driven by atypical firms. The regression results are shown in Table III.5. Correlations between the explanatory variables are presented in Table III.7 in Appendix.

A first observation is that remaining imbalance is low, with only few of the matching variables showing significant effects. The indicator variables for the three regions reveal different effects on scale and speed of R&D, firms in the Brussels Capital Region being more responsive to tax credits. A possible reason is the strong presence in Brussels of small firms active in the IT sector (mainly software and consulting), for which R&D is arguably less science-based and more cantered on short lead-times, which may not be picked up by the aggregate industry dummies (Teirlinck & Spithoven, 2008). As explained in section 3, we supplement the variables used in the matching procedure with additional (post-treatment) controls. First, we add the number of years a firm benefits from the tax credit as a way to capture accumulated benefits from the measure, but this turns out to be insignificant. The importance of R&D tax credits is now included as the weighted average of the yearly percentage of researchers supported by the tax credit over 2006 – 2010.[88] It has a significant and positive effect on the number of R&D projects, but does not affect the other outcomes. We also add indicators for the role of demand-pull and technology-push: firms were asked in the survey whether these respective factors had an influence on the decision to perform additional R&D.[89] We do not find evidence that the commercial and technical environments have an impact on the R&D behaviour of firms in our sample, except for a positive and significant effect of technology push on the speed of R&D projects.

[88] We define yearly weights as the percentage of the wage withholding tax exemption available to companies: 25% in 2006 - 2007, 45% in 2008 and 75% in 2009 - 2010.
[89] In the survey, the two items are not mutually exclusive, for which reason we included both in the estimation.

Table III.5 Multivariate probit estimation

	Scale		Speed		R vs D		Nr. of projects	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Subsidy	0.43*	(0.23)	0.61***	(0.24)	0.87***	(0.23)	0.55**	(0.23)
R&D intensity	0.10	(0.48)	0.18	(0.48)	-0.41	(0.46)	0.78*	(0.47)
Log(employees)	-0.10	(0.10)	0.02	(0.10)	0.00	(0.10)	0.06	(0.10)
Age	0.00	(0.01)	0.00	(0.01)	-0.01*	(0.01)	-0.01	(0.01)
Current ratio	-0.05	(0.08)	0.06	(0.08)	-0.14*	(0.08)	0.00	(0.08)
YIC dummy	0.02	(0.36)	0.39	(0.37)	0.44	(0.36)	-0.22	(0.37)
Group dummy	-0.23	(0.26)	-0.02	(0.27)	-0.23	(0.25)	0.03	(0.29)
Tax leader	0.35	(0.35)	0.17	(0.36)	-0.01	(0.38)	0.19	(0.36)
Years of tax credit use	-0.12	(0.12)	-0.02	(0.11)	0.04	(0.12)	-0.09	(0.13)
Average tax importance	-0.12	(0.42)	-0.19	(0.39)	-0.30	(0.43)	0.91**	(0.42)
High-tech manuf.	-0.27	(0.31)	-0.36	(0.32)	0.37	(0.32)	0.41	(0.32)
High-tech serv.	-0.27	(0.30)	0.02	(0.30)	-0.16	(0.31)	-0.06	(0.29)
Low-tech serv.	0.03	(0.40)	-0.06	(0.37)	0.21	(0.40)	0.55	(0.41)
Demand pull	0.32	(0.30)	-0.11	(0.33)	-0.15	(0.32)	0.18	(0.32)
Tech. push	0.67	(0.42)	0.83**	(0.39)	0.13	(0.55)	0.06	(0.44)
Flanders	-1.43***	(0.43)	-1.08***	(0.42)	0.36	(0.38)	-0.22	(0.39)
Wallonia	-1.17***	(0.45)	-0.55	(0.44)	0.10	(0.40)	0.21	(0.42)
rho21			0.86***				(0.05)	
rho31			0.65***				(0.10)	
rho41			0.71***				(0.08)	
rho32			0.51***				(0.11)	
rho42			0.75***				(0.07)	
rho43			0.64***				(0.09)	
Observations				163				
Log pseudo-likelihood				-319.26				
Wald test (chi²)				125.19***				
LR test of all rho=0 (chi²)				141.26***				

a) ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

With respect to our central hypothesis, we find that firms benefiting from the policy mix are significantly more likely to increase the research orientation and speed of R&D projects than firms using only R&D tax credits, which is consistent with the average treatment effect on the treated estimated in section 4.1. While the design of the R&D tax credit as a reduction in the wage cost of R&D workers may be expected to encourage *all* tax credit users – i.e. also the ones not receiving R&D subsidies – to hire highly skilled workers who engage in research rather than development, the policy mix may create a more favourable context for this to effectively happen. Possible reasons are that firms with subsidized R&D projects – which typically require a clear risk/research component to be funded – are likely to stumble upon tough scientific challenges when executing those projects. Furthermore, R&D grants often involve collaboration with external partners such as universities, which may put eligible researchers on the hiring radar of the firm. Further, subsidized R&D projects may provide a 'map function' for the financial resources made available through the R&D tax credit. More specifically, once a firm is awarded an R&D grant, the project may perform as a focal point to which additional R&D resources can be productively allocated.

This map function of subsidized projects also offers an explanation for the observed effect of shorter R&D lead times by avoiding wasteful R&D efforts. In addition, an important underlying mechanism that would explain faster execution of R&D is the learning effect stemming from competing for R&D grants. Specifically, there may be a 'disciplining role' performed by the subsidy application process. While firms may have their own structured approach to initiate R&D projects, in order to obtain an R&D grant, firms need to write a proposal that forces them to think through the entire project, anticipate external reviewer comments, establish connections with potential R&D partners, etc. This constitutes a rigorous learning experience, which the firm may not be able to reproduce entirely in internal processes and which creates a fertile basis for the use of tax credits by expediting R&D activities that would otherwise take longer to complete.

5 Conclusions

This paper addresses behavioural additionality effects of a policy mix of R&D subsidies and tax credits on companies' R&D strategy. Within the policy mix, we investigated the treatment effect of R&D subsidies for companies that also benefit from tax credits. The key contribution of our analysis is that it considers behavioural additionality effects of tax credits and subsidies, complementing the literature on input and output additionality. We find that subsidies enforce behavioural effects that tax credits might have on specific dimensions of firm decision-making in R&D. Our results indicate that firms that obtain R&D subsidies are more likely to further adjust their approach to R&D using funds made available through tax credits than when they benefit from tax credits alone. In particular, the combination causes firms to speed up their research projects, but also orient their R&D proportionally more towards research (versus development) activities. To a lesser extent, we also find that firms supported by means of a mix of tax credits and subsidies use the tax-exempted amounts to increase the scale and/or number of R&D projects relative to their counterparts using solely tax credits.

Altogether, these results indicate that subsidies reinforce firms' response to indirect support like tax credits, which raises questions with respect to 'picking the winner' strategies R&D funding agencies are (accused of) following. In particular, one might ask whether high selectivity in allocating R&D subsidies does not result in great untapped potential given the positive interaction effects between subsidies and tax credits. At the time of the survey – 2011 – the average subsidy received by a Belgian firm stood at 259,000 Euros, compared to little under 200,000 Euros for the average tax credit.[90] Put into context, our results imply that public authorities 'receive' an almost 20% increase in the scale of R&D, a 24% increase in speed of execution, a 26% shift in activity towards research, and a 21% increase in the number of R&D projects, all for the average price of 259,000 Euros. However, in the same period, the average amount of policy mix per firm was 788,000 Euros. The large difference implies that there is a 'big user' profile of firms that receive high amounts of tax credits and subsidies simultaneously. For this reason, the 'price' payed by authorities for the additionality mentioned above may be higher at the tail end of the distribution of policy mix amounts.

On the other hand, whether the positive effect of subsidies on behavioural additionality of tax credits would hold if one expanded the set of subsidy beneficiaries is far from certain. In particular, while the effect may be due to the subsidized R&D projects acting as focal points in firms' resource allocation process, the subsidized firms may also be more oriented towards R&D in ways that our matching approach could not control for. In other words, because of selection issues, firms that are currently not being granted subsidies might not use tax credits as productively if they also received a grant. Prior research has indeed shown that 'picking the winner' strategies are not necessarily a bad choice since they may result in a 'virtuous Matthew effect' (Antonelli & Crespi, 2013). Another concern with respect to adopting a policy mix is that such a comprehensive R&D policy requires communication between the public authorities managing different measures. Especially in the case of multi-level policy-making, such as in our setting where federal and regional governments are responsible for different support frameworks, such alignment may not be trivial.

Leaving aside feasibility issues of implementing and exploiting the policy mix, a key takeaway from our results is that firms seem to act purposefully if given more resources for R&D through a combination of different R&D support mechanisms. This insight mitigates concerns about the effectiveness of tax credits that have been raised in the literature, such as opportunistic

[90] The figures have been calculated based on the database of tax credit and subsidy recipients obtained from the Belgian Federal Public Service Finance.

relabelling of expenses as research activities (Antonelli & Crespi, 2013). After all, initiating additional projects or tipping the R&D-balance more towards research are decisions that firms arguably do not take overnight and may be expected to have a lasting impact on the firm's R&D processes.

Naturally, the specific nature of our survey data presents clear limitations to the analysis. One caveat is that the survey relied on firms' capacity to assess the additionality effects of tax credits relative to the counterfactual of not having benefited from them, an approach which may be prone to measurement errors. Further, we asked a very specific question and can only assess whether firms using the policy mix respond more strongly to wage-based tax credits, without allowing any judgment on the effectiveness of subsidies compared to tax credits or the effectiveness of any of these policies in isolation. Instead, the analysis is confined to assessing, conditional on an R&D tax policy being in place, whether its effects in terms of firms' R&D approach can be augmented by means of a subsidy policy. Clearly, we cannot make any statement about whether subsidies outperform tax credits or the policy mix altogether. More complete data on the timing of subsidy use and on R&D active firms that do not use any form of support would be needed to answer such questions.

While our results establish that subsidies affect the way tax credits are utilized, further research is called for to better understand the interaction effects between different policy measures. For example, complementary effects between policies may be related to firms' access to external finance (Busom et al., 2014). Avenues for future research include the construction of larger datasets in order to more accurately estimate behavioural additionality effects. Such datasets could give us more empirical traction in estimating the optimal policy mix by using information on the amounts of subsidies and tax credits. This goal could be achieved by the introduction of additionality-related surveys in more OECD or EU countries, following the example of the Belgian Science Policy Office's survey providing us with the data analysed in this paper. Such an international effort would also allow assessing the external validity of the results we presented, since the country-specific design of R&D subsidy and tax credit schemes may cause results not to hold across different settings. Finally, the consideration of longer time periods beyond the period of economic and financial turbulence that characterized our analysis would strengthen the generalizability of the results.

6 Appendix

Table III.6 Overview of longitudinal variables

Variable	Source	Year used
R&D intensity	Belspo survey	Year before first tax credit use
Employees	Belfirst	Year before first tax credit use
Current ratio	Belfirst	Year before first tax credit use
YIC	Belfirst & Belspo survey	Year before first tax credit use
Tax leader	Belspo survey	Year of first tax credit use
Tax importance	Belspo survey	Year of first tax credit use
Age	Belfirst	Year of first tax credit use
Group membership	Amadeus	Last available year
Industry	Belfirst	Last available year
Region	Belfirst	Last available year
Subsidy dummies	Belspo survey	Single value covering 2006-2010
Years of tax credit use	Belspo survey	Single value covering 2006-2010
Average tax importance	Belspo survey	Single value covering 2006-2010
Demand pull	Belspo survey	Single value covering 2006-2010
Technology push	Belspo survey	Single value covering 2006-2010
Scale of R&D	Belspo survey	Single value covering 2006-2010
Speed of R&D	Belspo survey	Single value covering 2006-2010
R vs D	Belspo survey	Single value covering 2006-2010
Number of R&D projects	Belspo survey	Single value covering 2006-2010

Table III.7 Correlation between explanatory variables

	Subsidy	R&D intensity	Log(empl)	Age	Current ratio	YIC	Group	Tax leader	Tax years	Avg tax impor-tance	High-tech manufacturing	High-tech services	Low-tech services	Demand pull	Technology push	Flanders
R&D intensity	0.00															
Log(empl)	-0.18	-0.51														
Age	-0.07	-0.31	0.47													
Current ratio	0.01	0.21	-0.15	0.02												
YIC	-0.02	0.52	-0.49	-0.41	0.03											
Group	-0.07	-0.30	0.54	0.26	-0.15	-0.47										
Tax leader	0.14	0.04	0.09	0.03	-0.01	0.05	-0.03									
Tax years	0.01	0.06	0.04	-0.02	-0.04	0.07	0.03	0.77								
Avg tax importance	-0.05	-0.12	-0.13	-0.11	-0.03	0.06	0.02	0.12	0.18							
High-tech manufacturing	0.03	-0.01	-0.01	-0.01	0.02	0.01	0.01	0.11	0.15	0.02						
High-tech services	0.08	0.42	-0.34	-0.34	0.15	0.32	-0.28	-0.13	-0.11	0.06	-0.35					
Low-tech services	-0.04	0.05	-0.15	-0.09	-0.05	0.00	-0.01	0.08	0.02	-0.01	-0.18	-0.24				
Demand pull	-0.16	-0.10	0.10	0.07	-0.16	-0.06	0.16	-0.07	-0.07	-0.10	0.03	-0.12	0.05			
Technology push	0.01	-0.05	0.05	-0.11	-0.08	0.06	0.13	0.04	0.02	-0.02	-0.04	-0.08	0.09	0.34		
Flanders	-0.03	0.01	0.01	-0.05	-0.03	0.07	0.01	-0.25	-0.32	-0.07	-0.15	-0.03	-0.02	0.11	0.10	
Wallonia	0.04	-0.06	0.01	0.07	-0.02	-0.06	0.06	0.21	0.21	0.02	0.20	-0.06	0.01	-0.03	0.00	-0.81

Table III.8 Multivariate probit model (treated and matched control firms only)

	Scale		Speed		R vs D		Nr. of projects	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Subsidy dummy	0.52*	(0.28)	0.48*	(0.28)	0.72***	(0.27)	0.54**	(0.27)
R&D intensity	0.22	(0.51)	0.20	(0.52)	-0.50	(0.49)	0.85*	(0.52)
Log(employees)	-0.09	(0.11)	0.02	(0.11)	0.01	(0.11)	0.08	(0.11)
Age	0.00	(0.01)	0.00	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Current ratio	0.02	(0.09)	0.14	(0.10)	-0.15	(0.10)	0.07	(0.09)
YIC dummy	0.00	(0.40)	0.27	(0.41)	0.59	(0.42)	0.05	(0.43)
Group dummy	-0.12	(0.29)	0.11	(0.30)	-0.18	(0.28)	0.03	(0.32)
Tax leader	0.37	(0.41)	0.12	(0.42)	0.24	(0.42)	0.52	(0.41)
Years of tax credit use	-0.09	(0.13)	0.01	(0.13)	-0.02	(0.14)	-0.14	(0.14)
Average tax importance	-0.24	(0.51)	-0.38	(0.47)	-0.33	(0.51)	0.98**	(0.50)
High-tech manuf.	-0.37	(0.36)	-0.43	(0.36)	0.57	(0.37)	0.17	(0.36)
High-tech serv.	-0.24	(0.33)	0.04	(0.31)	0.07	(0.33)	0.06	(0.31)
Low-tech serv.	-0.28	(0.45)	0.16	(0.43)	0.23	(0.44)	0.45	(0.46)
Demand pull	0.21	(0.35)	-0.16	(0.36)	-0.45	(0.39)	0.07	(0.37)
Tech. push	0.92**	(0.46)	1.26***	(0.45)	0.58	(0.66)	0.29	(0.52)
Flanders	-0.85	(0.57)	-1.34*	(0.77)	0.16	(0.48)	-0.14	(0.53)
Wallonia	-0.59	(0.58)	-0.83	(0.80)	-0.20	(0.49)	0.44	(0.55)
rho21		0.87				(0.05)		
rho31		0.62				(0.11)		
rho41		0.65				(0.11)		
rho32		0.54				(0.13)		
rho42		0.76				(0.08)		
rho43		0.55				(0.12)		
Observations				130				
Log pseudo-likelihood				-252.58				
Wald test (chi²)				116.07***				
LR test of all rho=0 (chi²)				105.92***				

a) ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

IV. Drivers of scientists' entry into new fields

Abstract

This paper analyses which individual and institutional factors encourage scientists to venture into research fields that are new to them. Using a ten-year panel of researchers in biomedical sciences and engineering from a large research university in Belgium, we find that higher scientific productivity and academic rank positively affect the probability of publishing in new fields and the degree of novelty of such change. Accounting for the endogeneity of funding, we also find that grants have a negative effect, driving research portfolios towards specialisation rather than diversification. Implications for university policy are discussed.

Keywords science funding, research behaviour, experimentation, scientific output.

JEL Codes I20 – I23.

Acknowledgements Financial support from KU Leuven (GOA/12/003), KU Leuven – HU Brussels (ZKC7171), FWO and the National Bank of Belgium is gratefully acknowledged. Publication data from ECOOM and data on similarity between scientific fields from Jian Wang are also gratefully appreciated. Other publication data are sourced from Thomson Reuters Web of Science Core Collection.

"Nature is not interested in our separations, and many

of the interesting phenomena bridge the gaps between fields."

The Feynman Lectures on Physics, volume I, lecture 35, 1964

"In this age of specialization, men who thoroughly know one field

are often incompetent to discuss another."

Richard Feynman, Caltech lunch forum, 1956

1 Introduction

Science is known to be a risky endeavour, where payoffs in terms of scientific success are highly uncertain (Arrow, 1962). Given that prestige sits at the core of the scientific reward system and that 'wrong turns' in one research trajectory may have long-lasting consequences, scientists arguably don't take the decision to enter a new field lightly. This paper aims to offer a better understanding of what motivates scientists to venture outside of familiar territory. To this end, we look at characteristics of the individual and her environment that influence the risk-reward trade-off and hence the decision to make 'sticky entries' into new fields, as shown by a scientist's repeated publication activity in fields they were previously not active in.

More specifically, we expect the response of a scientist to the risk-reward trade-off to depend on his research quality, his academic age and his track record in publications. We also study his past experience in entering new fields and the diversity of his research team as mechanisms to mitigate the risk of exploration. In addition, entry into new fields may be steered by institutional and policy-related factors, which establish a more or less favourable context for exploring new fields. Policy choices, in particular the award of grants, may be endogenous to new field entry as interdisciplinarity may be taken into account in funding decisions. While funding may grant the researchers the means to explore new territories, there is a concern that funding bodies are risk averse – shying away from grantees that venture outside their own research zone. We account for this by instrumenting the receipt of grants in our analysis.

Our work makes the following contributions. First, we exploit unique data that matches scientists' publication records with detailed administrative records from a large top research university in Europe – the University of Leuven. We combine a fairly rich characterization of the individual scientist's characteristics and career track with elements from her environment, most notably funding history to explain the scientist's research orientation. The perspective on funding as a driver of research orientation departs from the usual attention in prior work on the impact of research funding, which is mostly concerned with analysing the effects on productivity and collaboration (Bozeman & Gaughan, 2007; Goldfarb, 2008; Defazio et al., 2009; Auranen & Nieminen, 2010; Jacob & Lefgren, 2011; Grimpe, 2012; Hottenrott & Lawson, 2013; Kelchtermans & Veugelers, 2011, 2013; Whalley & Hicks, 2014). Conversely, this paper broadens the perspective by considering consequences of research grants on research orientation, furthering our understanding of funding mechanisms and their impact. In fact, little is known about what drives scientists to venture into new research areas. In one of the very few studies on the change in research direction due to grants, Azoulay et al. (2011) have shown that certain programs stimulate scientists to explore new lines of investigation within biomedical research, an effect strongly related to the specificity of the grant. Gush et al. (2015) find low impact of grants on research output in New Zealand, and argue that the low overall additionality effect may be due to a shift in focus of the grantees towards the subject area of the grant, in which a higher impact was observed. Ayoubi, Pezzoni, & Visentin (2016) study how researchers learn new areas from other members in their team. Learning occurs when a researcher cites journals that are new to her, but familiar to one of her team members. While they find more learning in bigger teams, they find no evidence for more learning in funded teams compared to non-funded ones.

We seek to build on this emerging empirical literature by analysing to what extent and under what circumstances researchers explore scientific areas that are new to them and what role research funding plays in this decision.

We analyse an unbalanced panel (1992-2001) of 757 researchers active in biomedical and exact sciences at the University of Leuven (KU Leuven) in Belgium to discover factors that are associated with scientists' motivation to enter and remain active in fields that are new to them. While previous studies are mostly focused on a single discipline, often the life sciences (Azoulay et al., 2011; Li & Agha, 2015), our dataset covers a wide range of fields within the domains of biomedical sciences and engineering.

We find that academics are less inclined to venture into new research fields if they obtain funding, and also that entry happens in fields more similar to the ones in which they have prior experience. Moreover, we show that rank and productivity play a positive role in diversification, as do higher numbers of PhD graduates that a scientist supervises. On the other hand, seniority seems to lead to specialisation, which, combined with the opposite effect of academic rank, implies that the positive effect is mostly present when higher-ranked scholars start their employment.

The remainder of the paper is organized as follows. The next section outlines the basic reasons why there is a trade-off between risk and reward in science, and puts forward a number of individual and institutional features that are expected to impact that trade-off and influence the decision to venture into new fields. Section 3 discusses the data and operationalizes the variables used in the analysis. Section 4 presents the results and robustness checks. Section 5 concludes.

2 Literature Review

2.1 Entry in new fields and the risk-reward trade-off

Choosing a risky road in one's own research direction involves trading off the lure of important breakthroughs for the cost of a higher risk of failing. The alternative of a beaten path avoids the higher risk of failure, but at the cost of lower chances for a breakthrough.

A number of intrinsic scientific knowledge-related reasons explain why research trajectories that have more potential for ground-breaking work also carry a higher risk. Literature on creative thinking has as a central tenet the fact that creativity, which is arguably underlying any major breakthrough in science, requires one to break away from prior experience (Simonton, 1999; Audia & Goncalo, 2007). A similar insight emerges from prior work that has looked at technological search as a process of recombination, such as the work of Fleming (2001) and Verhoeven, Bakker, & Veugelers (2016). They find that new combinations of knowledge components, while leading to less useful patented inventions on average, also come with increased variability in citation performance. Recent empirical evidence confirms the higher risks associated with novel research for the case of scientific output. For example, highly innovative scientific papers, making new combinations in cited knowledge sources, usually end up either in the high-end or low-end citation spectrum, and comparatively less often in the centre of the citation distribution (Azoulay et al., 2011; Stephan, Veugelers, & Wang, 2016). To the extent that making new combinations of knowledge components is associated with venturing outside one's own field to be able to make such new combinations, broadening the scope of research implies that a researcher will face a higher risk. Deciding on whether to enter new fields and how far away they should be from their past research involves a risk-reward trade-off. In other words, while there may be an exceptional payoff associated with boundary crossing, there is no certainty that one's existing expertise will be applicable in the new field or whether any productive cross-fertilization will take place. This concern is particularly acute for 'long jumps' to more remote fields, given that the way science is done differs substantially across areas (Becher, 1994).

The investment needed to become familiar with findings and techniques from fields outside one's core expertise come with an opportunity cost, in the form of foregone further specialisation within one's core fields. The ever-growing reservoir of knowledge, while acknowledged as a key foundation for economic growth, is a mixed blessing for scientists. In particular, it creates an accumulating educational burden to stay abreast of the findings in one's domain and it has been argued that they may respond with increased specialization. Jones (2009) found evidence that specialization has increased over time for technology inventors that received patents from the USPTO between 1963 and 1999, measured by the probability of switching technological areas between consecutive patent applications.[91]

There are other institutional reasons that may affect the risk-reward trade-off a researcher faces when contemplating charting into unknown territory. In particular, economics of science literature has argued that the competition that is an inherent feature of the scientific reward system induces scientists to pursue similar research strategies, that is, *"researchers tend to be drawn into duplicative races"* (Dasgupta & David, 1994, p. 507). The 'all or nothing' feature of scientific races may hold back a scientist from entering new fields in order to avoid the 'nothing'. But at the same time, it might prompt the researcher to enter new fields and vie for a breakthrough. Second, the governance model of academic institutions may interact with individual scientists' research orientation decisions. It is well documented that research evaluation based on bibliometric measures has become institutionalized in many establishments. Geuna (2001) already observed that many European universities had adopted a contract-oriented approach to funding, which includes an emphasis on research output. This

[91] Our data on scientists in biomedical sciences and engineering, using a similar measure of diversification, confirm to some extent this long-run trend for scientific output, as we see that the average number of publications in new (to the researcher) fields drops in our sample between 1992 and 2001 from 0.69 to 0.48.

evolution has provoked comments that the aim for scientific productivity may cause the science system to compromise other important values like diversity and novelty of research (Hicks, 2012; Alberts et al., 2014). Recently, the debate seems to have intensified, several stakeholders of the science system pondering the implications of a metrics-based approach to research evaluation and funding. For example, Bruce Alberts, the former editor-in-chief of Science argued that the use of impact factors to assess researchers' quality encourages 'me-too science' (Alberts, 2013). The argument is that the use of short term bibliometric indicators to evaluate individual scientists will drive them away from riskier trajectories. In other words, to the extent that classic bibliometric indicators bias against risky novel research (Stephan et al., 2016), the evolution towards metrics-based systems of research evaluation may not be helpful to encourage scientists to venture outside of their turf, but the contrary. Heavy reliance on bibliometric indicators may partially explain the perception that funding agencies and their expert panels are increasingly risk-averse. Selection procedures are accused of encouraging relatively safe projects which exploit existing knowledge at the expense of novel projects that explore untested approaches (Alberts, 2013; Walsh, 2013). Our paper ties into these concerns by considering the effect of grants on scientists' choices to publish in fields that are new to them, rather than funding's impact on scientific productivity in the classical sense.

2.2 Factors affecting the decision to enter new fields

Assessment of the risk-reward trade-off when considering to enter new scientific fields – that are also dissimilar from a researcher's track record – will vary among individuals and research environments. In this section we take a look at which characteristics of the individual and of his environment will influence his choice to venture into a new scientific field.

Taste for risk

A first intuitive factor is an individual's intrinsic risk aversion. Generally speaking, risk-averse scholars will mostly specialize in established areas (Jones, 2009), while those with a taste for risk will innovate more and possibly fail more in the process. The basic premise underlying our paper is that, while a scientist may have an idiosyncratic taste for risk, her attitude towards the risk-reward trade-off will be determined by her individual characteristics and the institutional context that shapes her research strategy. We consider taste for risk or experimentation to be ground zero in determining one's portfolio diversification, as other characteristics will build upon it and establish the overall profile of scientist *Lambda*.

Seniority

Whether a scientist chooses to engage in research that is dissimilar from what she has a proven track record in starts off with how comfortable she is with making such changes. But 'comfort' will arguably evolve during her tenure, as experience in a research environment plays an important part in professional choices. As such, senior scholars with a proven track record may have more appetite to explore new fields that may also be more different from what they are used to because they can afford to take more risk, 'riding the wave' of past career achievements. On the other hand, the 'experience trap' can lead them to continue the same research lines they are familiar with and that have proven efficient in the past. Junior scholars may behave in the opposite way: unburdened by an established reputation in a given field, they have more freedom to explore and stray farther away from their main research. Conversely, expectations to prove themselves in a relatively short time span may keep junior scientists within a well-defined research area without much incentives for excursions into new fields.

Life cycle effects may also be at play: the finite time horizon may not only induce more senior researchers to have less incentives to produce scientific output (Levin & Stephan, 1991), but may at the same time reduce the appetite to invest in mastering new fields, especially if the returns from these risky investments take a longer time to materialize and if the new fields are very different from their primary work.

Academic rank

Correlated with seniority, academic rank may affect the individual scientist's diversification decision. Whereas experience and seniority flow (almost) unrestricted, career advancement through rankings involves more red tape, evaluations and proven track records. For junior researchers, the 'carrot' of promotion may be a driver to bet on the riskier road towards higher probabilities for breakthroughs and consequent promotion. Moreover, research flexibility may be well regarded in early career stages, when juniors tend to be hired based on potential rather than track record. On the other hand, researchers having reached higher ranks may be missing this taste for risk-taking and venturing into uncharted waters.

Conversely, junior researchers may be more cautious and choose a less risky path, assuring performance, if the promotion process is not favourable to risk-taking and relies on bibliometric indicators focused on measuring short term success. Then, having reached the highest academic rank may result in a less risk-averse attitude and a greater appetite to enter new fields, being freed from the constraints of assuring performance for promotion. The bucket list only gets bigger throughout one's tenure, and, as they reach their career goals, time comes to cross off those eminent 'paper ideas' that have been put off because of constant pressure to perform.

Quality and productivity

No matter where they are or how they feel about taking risks in their careers, some scientists may simply be more productive in publishing their research. While publishing more, they may also create more novel ideas (Simonton, 2003). They may have the talent to recognize new approaches and navigate through the risks of combining their established skills in one field with learning new ones, avoiding the pitfalls and bringing them to breakthrough success (Stephan et al., 2016).

On the other hand, talented researchers with a thick track record face a higher opportunity cost when venturing into new fields. Past success can lead to path-dependency, 'riding the wave' patterns guaranteeing constant streams of publications (Audia & Goncalo, 2007). They are like Olympic athletes facing the choice of focusing on defending their titles or going for more glory. They face the choice of being the Michael Phelps or the Clara Hughes of academia; they can choose to specialise and be the most decorated summer Olympians or diversify and be one of only a handful to win medals at both summer and winter Games.

Past entry and scope of scientific fields covered

Unlike sports, the academic choice of whether to specialise or diversify does not come once every four years. Throughout their careers, researchers' portfolios will vary in depth and width – or productivity and diversity. Their history of venturing into new fields will influence their propensity to do so in the future. It is a testimony of their attitude towards risk and of the variation in intrinsic ability to spread across scientific fields. At the same time, experience from a larger scope of research allows them to exploit more synergies when venturing into new fields that are farther away from (scientific) home. On the other hand, because there is a limited number of research areas someone can publish in, past entry into new fields can also capture a saturation effect, where a scientist is less prone to enter new areas because she has already spanned the full spectrum of her individual portfolio.

Co-author network

So far our discussion has focused on individual characteristics that play a role in research behaviour. Arguably, with few exceptions – economics being one of them – research is not a one-(wo)man show anymore. Science is being performed in ever larger teams due to, among others, the increasing burden of knowledge and easier long-distance communication (Wuchty, Jones, & Uzzi, 2007; Jones, Wuchty, & Uzzi, 2008; Agrawal, McHale, & Oettl, 2013). An extreme example of the increasing size of research teams was observed with the discovery of the Higgs Boson in 2012, which was made by two independent CERN[92] teams, each comprising several hundred scientists. The implication of having a large network of co-authors for one's own research agenda is that such collaborations may provide a stepping stone for the individual researcher to enter new fields. Team interaction should allow for learning from each other's expertise (Ayoubi et al., 2016). Learning that comes from partnering with other researchers who are specialized in different fields may nudge the scientist to venture into new fields too (Lee, Walsh, & Wang, 2015). Moreover, diverse teams will be better catalysers for experimentation, while mono-disciplinary teams may trap scientists into continuing to do more of the same research.

Funding

The question to what extent funding encourages researchers to venture into previously uncharted territory is important because acquiring funding is central to performing research and can have a big impact on research agendas. Specifically, there are several mechanisms through which funding may incite researchers to go into – or avoid – new directions.

First, funding allows scientists to allocate resources to research avenues they want to exploit. Particularly if a grant is substantial and with a long timeframe, and if it is funding the researcher rather than a specific project, it allows her to go into new directions. This is why, as argued and demonstrated by Azoulay et al. (2011), HHMI[93] grants, in contrast to other type of funding, had positive effects on the novelty of the research produced *ex post*.

Furthermore, funding may affect the direction of research *ex ante*. Being involved in the competition for grants may lead researchers to enter fields they were previously not active in.

---

[92] The European Organization for Nuclear Research.
[93] The Howard Hughes Medical Institute.

The competitive nature of the funding process may push researchers to come up with novel elements to convince review panels that the proposed research is worthy of funding. A proposal that promises to bring together insights from different fields may have the cutting edge required to beat the competition. This stimulus effect from funding holds the more the funding selection criteria focus on high-risk / high-gain, as in the case of the HHMI grants or the more recent ERC[94] grants.

Conversely, one can think of reasons why funding may blunt scientists' willingness to venture into new fields. One reason is that performance-based funding systems award grants by considering past research performance, typically measured using classic bibliometric indicators which focus on short term impact (Jonkers & Zacharewicz, 2016; Wang, Stephan and Veugelers, 2016). Funding agencies may therefore be inclined to fund those proposals where the researcher and her team have a proven capacity to deliver results. These are the low-risk modes where the researcher continues on his existing path. Boudreau et al. (2012) analyse the role of novelty in research projects' evaluation by experts and find a penalty for novel proposals that deviate from existing research paradigms. Similarly, Banal-Estañol et al. (2016) show that more radical teams are less likely to be funded by the EPSRC[95] in the UK, but they find no correlation between the likelihood of receiving a grant and the interdisciplinary profile of individual researchers. While we do not consider novelty at project level and we study the impact on the individual researcher rather than the funding decision itself, this result suggests that scientists concerned about a steady funding stream may become locked-in in a field. Such path-dependency may have long-term effects on researchers' careers. Grants may impose expectations on the scientist in terms of delivering results, acting as an incentive to stay on familiar ground rather than experiment.

The effect that funding may have on research direction has been mostly analysed in studies that considered the effects of industry grants on academic research. Florida & Cohen (1999) argue that collaboration with industry can have an impact on the choice of research topics, and as such may shift academic agendas from basic towards more applied science, which was confirmed by empirical studies in Norway (Gulbrandsen & Smeby, 2005) and the US (Glenna et al., 2011). More recently, Banal-Estañol et al. (2015) find evidence that grants received for

[94] European Research Council.
[95] Engineering and Physical Sciences Research Council.

collaborating with industry increases academics' output of applied research papers, while general external grants increase the number of basic research publications. Banal-Estañol et al. (2013) show that scientists with an affinity for more applied research are a better match to collaborate with firms, but also that firms can use incentives in order to collaborate with scientists with an affinity towards basic research. In our paper, we only observe two related funding schemes of the Research Fund of the University of Leuven. In terms of scope, these grants make up a quarter of research funding at the university and are overwhelmingly attributed for basic scientific research. Industry grants, which we do not observe, represent an almost equal amount and may well drive research towards applied areas. We thus acknowledge that there is a possibility of 'hidden treatment' effects due to the unobserved impact that other types of grants may have on research behaviour. Nevertheless, we develop our empirical strategy in order to mitigate to the best extent possible any bias due to this effect.

Methodologically, taking into account selection effects when analysing the impact of funding on research direction is crucial if one wants to identify the true effects of funding on new field entry decisions. Given the aforementioned shift towards performance-based funding systems (Stephan, 2012), productivity and track record in entering new fields is one – but not the only, as discussed further below – factor to take into account when addressing the selection of who receives funding.

3 Data

Our data match scientists' publication profiles with detailed administrative records from a large university in Europe. The University of Leuven is the largest university in Belgium. It is a research-intensive, internationally-oriented university, consistently within the top 100 universities in world research rankings.[96]

We observe a data set of 757 researchers active in biomedical and exact sciences between 1992 and 2001 at the University of Leuven.[97] The data comprises individual and career-related characteristics, such as gender, age, year of employment at the university, full-time employment status, career age, rank, teaching duties, and a type of research grants received

[96] www.kuleuven.be/research.

[97] The data comprises the population of scientists in biomedical and exact sciences employed by KU Leuven between 1992-2001. We only observe scientists who publish at least once in that period, resulting in 5,009 observations. For the 757 active scientists we constructed full publication records while they are affiliated to the University of Leuven, including publications before 1992, from the Thomson ISI Web of Science (WoS).

from the university.[98] We complement this data with publication and citation numbers and scientific fields from Thomson ISI Web of Science (WoS).[99]

3.1 Dependent variables: entry into new scientific fields

We define entry into new research fields by first constructing, for each researcher, an indicator with the value one whenever a scientist publishes in a field in which she hasn't published before,[100] and follows-up with at least another publication in that field in subsequent years.[101] The latter means that we require a new field entry to achieve a minimum level of 'stickiness' and excludes a one-time only excursion into another field.[102]

To do so, we use historical publication data from Thomson ISI dating back to 1971 in order to accurately depict the fields in which each scientist has published in every year. The taxonomy of scientific fields defined in WoS has 247 unique fields, shown in Table IV.4 in Appendix. The fields cover all domains of science – science, social sciences, arts & humanities – and are attributed to journals and other publications. The researchers in our sample publish in 216 of these fields throughout their careers at the University of Leuven.[103]

Since some fields have many sub-classifications (e.g. chemistry is subdivided into analytical, applied, inorganic & nuclear) while others do not (e.g. microbiology is not further subdivided), usage of the complete taxonomy would imply that almost all entries in a subfield are classified as a 'new field entry'. In order to deal with this and remaining imbalances in the WoS taxonomy that may affect our measure of field entry, i.e. some fields may be more narrow than others

---

[98] The construction of the data set is described in Kelchtermans & Veugelers (2005).

[99] In order to retrieve each researcher's publication history, we have performed searches by name and affiliation at the University of Leuven. For the latter, we used the Organization-Enhanced field provided by Thomson Reuters, which links all possible variations of an organisation's name found in WoS publications. The search term 'KU Leuven' captures all the different names used in publications to refer to the university of Leuven; we also added the search term 'University Hospital Leuven' to retrieve all publications by scientists affiliated to the university's medical departments.

[100] We take into account the following types of publications: 'Article', 'Article; Book Chapter', 'Article; Proceedings Paper', 'Letter', 'Meeting Abstract', 'Note', 'Proceedings Paper', 'Review'.

[101] The first-ever publication while at KU Leuven is not counted as a new field entry.

[102] This restriction also partially addresses the concern that a field entry may be due to co-authorships. While this is not a problem *per se*, it exaggerates new field entry for the focal scientist if the co-author simply supplies own expertise without there being much interaction between co-authors.

[103] Researchers' publication records were retrieved from WoS using name and, to avoid false matches due to homonyms, affiliation. While we took into account spelling variations in both names and affiliation, the retrieved publications are restricted to those where the scientist mentions her University of Leuven affiliation. Although this may imply incomplete coverage of publication records, mobility of researchers is known to be very limited, especially in the time period we consider and it is reasonable to assume that the publication records are generally accurate.

and/or may differ less from neighbouring fields, we construct an alternative dependent variable. For each scientist, we define in each year *t* the maximum dissimilarity or distance between her main field – in which she published most before year *t* – and all new fields that she enters in year *t*.

We first calculate a yearly cosine similarity matrix between fields based on cross-citations between journals and their respective scientific fields attributed by Thomson Reuters.[104] Dissimilarity between each field pair is then defined as (1-similarity), and pairs of fields which are completely dissimilar have a distance value of one.[105] We finally calculate our dependent variable as the maximum dissimilarity or distance between each researcher's main field prior to year *t* and all fields that he publishes in for the first time in *t* (and at least once more afterwards).

Overall, the yearly average number of fields a researcher publishes in is 4.44 in the 1992-2001 period, while the average maximum number of fields per scientist and per year is 7.43. Three quarters of researchers enter new scientific fields at least once in the ten-year period, and the average maximum distance to new fields is 0.28, indicating that exploration happens mostly in closely related fields. However, the standard deviation of the maximum distance variable is 0.42, indicating a fair amount of variation between scientists.

Table IV.1 illustrates in its left panel the variation in entry percentages and overall number of new fields, and maximum distances and sum of distances to new fields in the right panel. The between-variation shows how much average behaviour differs from one scientist to another, while the within-variation illustrates individual behavioural differences across time. We observe that overall, both the entry indicators and the distances to new fields vary more across time than between scientists.

---

[104] For example, the most similar scientific fields in 1992 were 'Remote Sensing' and 'Imaging Science & Photo Technology', with a cosine similarity value of 0.692. The least similar in the same year (with a non-zero cosine value) are 'Astronomy & Astrophysics' and 'Biochemistry & Molecular Biology'. In 2002, 'Cell Biology' and 'Biochemistry & 'Molecular Biology' are most similar, while 'Astronomy & Astrophysics' and 'Health Policy & Services' are farthest apart.

[105] See Zhang et al. (2010) and Stephan, Veugelers, & Wang (2016) for a technical description of cosine calculation.

Table IV.1 Variation in field entry rates and distances from main fields

		Mean	s.d.			Mean	s.d.
Entry in new fields	overall	0.30	0.46	Maximum distance	overall	0.28	0.42
	between		0.27		between		0.25
	within		0.39		within		0.36
Sum of new fields	overall	0.55	1.07	Sum distances	overall	0.64	1.71
	between		0.60		between		0.86
	within		0.91		within		1.50

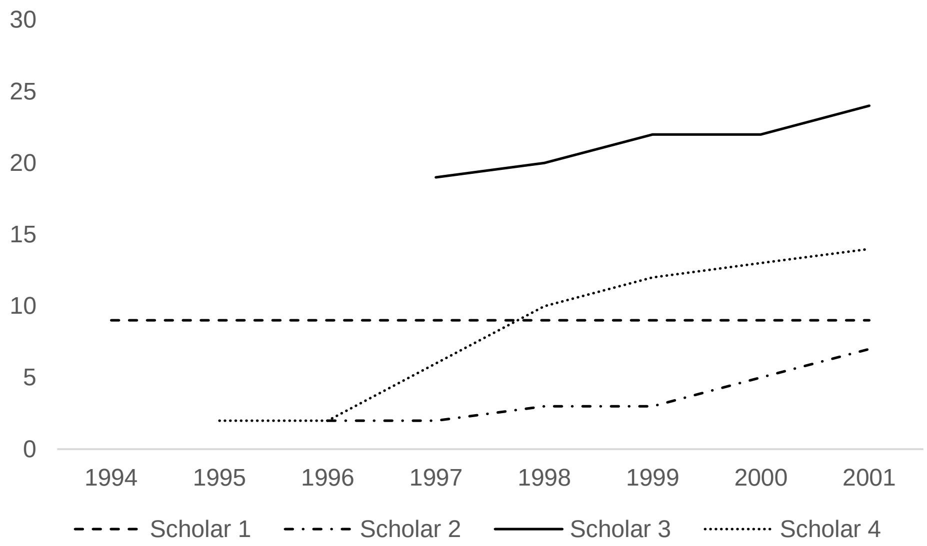
Looking closer at different entry patterns per main discipline in Table IV.6 in Appendix, we notice that Agriculture and Biology researchers are, on average, more prone to enter new fields in the observation period.[106] Researchers in these disciplines publish in new fields 40.3% and 37% of the time respectively, while, for example, the rate among mathematicians is 19%. Engineers and agriculture researchers have the highest averages of number of new fields entered per scientist and per year, at 0,76 and 0,79 respectively. Similarly, scientists with agriculture or biology as main disciplines stray farthest away from their fields when entering new ones, followed by engineers.

As the large standard deviations in Table IV.1 already indicate, there is still substantial heterogeneity within disciplines. As an example, Figure IV.1 displays the cumulative number of field entries of four bioscientists which are, to improve comparability, part of the post-1992 entry cohort. Different patterns occur: zero variation, modest and strong increase in the stock of field entries at low and high levels of output.[107]

[106] The classification of disciplines was developed by the Centre for Research & Development Monitoring (ECOOM) from the University of Leuven, independently from the Web of Science field classification. It distinguishes among 13 main disciplines, shown in Table IV.5 in Appendix. A researcher's main discipline is defined as the one in which she has the majority of her publications. Including it in the analysis allows controlling for both the fact that it may be 'easier' to enter new fields due to imbalances in the field taxonomy, as well as for different propensities between disciplines to enter new fields, e.g. due to scientific opportunities.

[107] Note that scientists enter the analysis from the moment they become professors at KU Leuven. Since we track their prior publications (as PhD & post-doc) the stock of field entries typically does not start at zero.

Figure IV.1 Cumulative number of new field entries for 4 bioscientists



3.2 Covariates

In this section we define the variables capturing the factors driving a researcher's venture into new fields that were discussed in section 2.2. The numbers we refer to are present in Table IV.7 in Appendix, unless stated otherwise.

We control for seniority through the number of years each person has been employed at the University of Leuven at least as an assistant professor. The average seniority in the sample is 8.91 years, with a standard deviation of 7.83. In Table IV.8 in Appendix we can observe that junior researchers – which have been employed at least at assistant professor level for at most seven years (the median value in our sample) – are on average more probable to enter new fields than senior scientists, and they also enter more new fields (0.63 versus 0.48 new fields entered per year).

To capture the talent of the researchers, we include a pre-sample measure of quality of research by dividing the average number of citations per publication before 1992 for each researcher by the average number of citations per publication in her main field in the entire Web of Science in 1991. The quality of her average pre-1992 publications is benchmarked to the world average research quality.

To capture researchers' track record of publishing, we compute a yearly productivity measure based on the scientists' comparative performance with colleagues who are active in the same main discipline using *k-means* clustering. We construct three mutually-exclusive binary indicators capturing the productivity cluster a scientist is in at each time period – low, medium and high productivity – considering the best performance over all disciplines she is active in. In the third panel of Table IV.8 in Appendix we observe that scientists in the medium and high productivity clusters enter more often new fields than the low-productivity group, with high performers almost twice as likely to do so than low performers. Moreover, the former also enter fields that are less similar to their main field.

To assess the impact of academic rank, we create binary indicators capturing whether a researcher is assistant professor, associate professor, professor or full professor in any given year. About one third of our researchers are assistant professors (30.4%). Panel 4 of Table IV.8 in Appendix illustrates the differences in entry behaviour by rank. We observe the differences are small in terms of entry in new fields, the average entry rate varying between 29.2% and 31.4% sequentially from lowest to highest rank. Similarly, the number of new fields entered during the sample period does not vary significantly. The difference is slightly larger in terms of maximum distance between new and main fields, more senior ranks adventuring farther than junior ones.

We next include the stock of fields in which the researcher has published. This variable counts the number of scientific fields each person has published in over their entire observed history up to one year before the current period. To the extent this reveals past entry decisions, it reflects appetite and experience in venturing outside of one's scientific comfort zone, which would have a more positive inclination to diversify into new areas. It may also reflect a larger scope for synergy effects. Conversely, as there is a limited number of feasible research areas someone can publish in, the stock effect may have diminishing effects.

To measure the size of a scientist's co-author network, we count the number of her co-authors in the previous year. The average scholar in our sample has 13.61 co-authors per year, with a standard deviation of 19.75. The relatively high numbers are mostly driven by a couple of disciplines – Biosciences and Clinical and Experimental Medicine. Researchers with more co-authors than the median in our sample enter new fields more often than those under the median, and they also venture farther in terms of maximum distance from their main field, as can be seen in panel 6 of Table IV.8 in Appendix.

We also look at the disciplinary composition of networks by adding a variable measuring the percentage of co-authors that are mostly active in the same main discipline as the academic. On average, 41% of co-authors register most of their publishing activity in the same discipline as the focal researcher, with the highest values present among Clinical and Experimental Medicine authors. We also compute the percentage of co-authors with the same funding status as the focal scientist – that is, if the scientist has (not) received a grant, we calculate the percentage of her co-authors that have (not) received grants. Furthermore, we control for the number of PhD graduates each scholar coordinated during the year in order to capture whether having a larger pool of disciples increases one's inclination of publishing in new fields: would PhDs be a bridge for incumbent senior advisors to be more adventurous or, on the contrary, are they a source of path dependency? If doctoral students are engaged in projects that the senior scientist has started prior to hiring PhDs, the propensity to enter new fields would be negatively affected by the variable. The average number of doctoral graduates per researcher and per year is 0.34 with a standard deviation of 0.52.

A number of other control variables are included, such as teaching duties. Academics with more teaching hours may have less incentives, given their restricted research time, to enter new fields, and so they will publish more in their established areas in order to reach evaluation goals based on productivity. We control for the amount of teaching by the average number of teaching hours per week. This variable captures the actual teaching load, i.e. we do not count teaching hours that are outsourced. The average researcher teaches 3.87 hours per week.

We also observe whether scholars are employed full-time at the university as a binary indicator. We observe that 90% of researchers are full-time employees. This can influence research portfolios in two ways. First, we expect a negative effect on entry in new fields for people that only work part-time at the university and the rest of their time is spent on other employment contracts unrelated to scientific research. Second, a positive impact would show up for researchers that are part-time at KU Leuven, but are also employed at other research institutions, giving them access to larger networks of peers and creative ideas. As we do not have detailed data on the amount of employment nor the activities external to the university, the effect captured by the binary indicator will depend on the average impact over all scientists in the sample. Next, we include a binary indicator signalling whether a scientist starts her contract with the university in or after 1992 to capture a hike in hiring that year and the fact that we do not observe full employment history for hirings prior to that date. This variable also corrects for new entrants in the sample for which we have less observations to calculate stocks.

A major factor of interest in our analysis is the funding status of researchers. Does funding make researchers more or less likely to venture into new scientific fields?

The funding scheme we observe is the University of Leuven's Research Fund (BOF), which represents a quarter of all research grants available at the university. The fund is financed by the Flemish government and its size is determined by the university's share in the overall Flemish quantity and quality of scientific publications. The university decides autonomously on how to allocate these funds to its researchers. To this end, it has established a Research Council that organises a competitive, international peer review assessment of the projects and the track records of applicants. Of the pre-screened proposals that are allowed to enter the competition, less than half obtain funding. Grants vary between 475,000 Euros for individual research grants and 1,625,000 Euros for research teams. Grants can last either four or five years, depending on the grant's type. In our sample, 314 researchers receive grants at least once, and the average number of funded researchers per year is 165.

Table IV.2 shows that funded researchers have a significantly higher likelihood than non-funded researchers to publish in new fields that are also less similar to their main fields. This positive correlation between funding and exploration may be driven by the selection process of the Research Council, as grant winners may also be *ex ante* more likely to be the types that venture into new fields, rather than funding leading them to venture into new fields *ex post*.

Table IV.2 Publication patterns by funding status (t-tests)

	Mean		t-test	
	Funded	Not Funded	t	p > t
Entry in new fields	0.37	0.27	7.01	0.00
Sum of new fields	0.70	0.49	6.37	0.00
Maximum distance	0.34	0.25	6.90	0.00
Sum of distances	0.77	0.59	3.32	0.00
Sum of fields	6.69	3.67	24.87	0.00
Stock of fields	17.91	12.09	21.99	0.00

Table IV.9 in Appendix illustrates the different profiles of funded and non-funded researchers. The former are more likely to be in the medium (45% to 28%) and high (21% to 10%) productivity clusters. Their score is also significantly higher on the pre-1992 quality of research. These numbers confirm that funding is granted mostly based on research performance. Grant receivers have, on average, higher ranks (professor and full professor) than the control group, while also being more senior, on average, by 2 years. The network of researchers that receive grants contains, on average, 22.62 co-authors, compared to 10.57 for non-funded scholars, although the difference is smaller in terms of percentage of co-authors with the same main discipline – 51% to 36%.

Overall, these statistics confirm the importance of correcting for the selection process of the grant in order to assess the impact of funding on the likelihood of entry into new fields. Our empirical specification, detailed in the following section, will deal with this issue.

4 Empirical analysis

4.1 Method

Our empirical strategy needs to take into account a few specificities of the data. As there are a number of researchers having multiple entries in new fields in a year, we use a binary indicator on whether or not a researcher has entered a new field as our main dependent variable. Second, we test whether the effects are similar if we take into account the dissimilarity of newly-entered fields with a researcher's main field via a continuous variable defined on the [0; 1] interval. Third, we instrument grant receipt in order to account for its endogeneity.

In order to maintain comparability between different specifications, we estimate a linear probability model and we formally define the following equation (omitting researcher subscripts for ease of exposition):

$$\boldsymbol{Y_t = \alpha + \beta_1 x_{grant(t-2)} + \sum \beta_k x_{k(t-1)} + \varepsilon} \quad (1)$$

Y_t indicates in a first instance whether a scientist enters new fields in year t, and in a second estimation denotes the maximum dissimilarity between the fields she enters in t and her main field prior to t. x_k is the vector of k individual characteristics described in section 3.2.

We lag all time-varying covariates by one year in order to mitigate endogeneity arising from simultaneity. For received funding we use a two-year lag because we expect that, once a grant is awarded, it takes time between the start of a research project and publishing its results. We subsequently test the robustness of our results when considering different lags of funding.

Receiving a grant may be endogenous with respect to entering new fields – exploration may be evaluated positively by the funding panel. However, the opposite argument can also be made – funding tends to reward a proven track record in a field. Proposals that would typically continue the proven research trajectory will be more likely to be granted, due to risk averseness and/or a 'winner picking' attitude of the funding panel. Either way, funding may not only steer scientists' research orientation, but there may be reverse causality with the (intention to) move into new research directions affecting the probability to receive funding. In addition, un- or imperfectly controlled heterogeneity, like research talent, may be driving both the funding decision and the decision to enter new fields. Therefore, we instrument the funding status variable with the percentage of peers who share the same main discipline with the focal researcher and who obtained grants in the same period. The instrument is individual-specific and correlated with the probability to get funding – positively, to the extent that it signals available budget; or negatively, if it implies that successful peers reduce one's own chances of securing the funding.

4.2 Results

Table IV.3 presents the results of estimating equation (1) through different procedures. Columns *a* and *b* report OLS estimates for the model with a binary dependent variable denoting entry in new fields, excluding and including a funding indicator, respectively; column *c* reports the coefficients estimated through two-stage least squares (2SLS), where in the first stage we instrument the funding indicator with the percentage of peers who are active in the same main discipline with the focal researcher and who obtained grants the same period.[108] Similarly, the second panel (columns *d* to *f*) reports the determinants of the maximum distance (dissimilarity) between newly entered fields and a scientist's main field.

[108] The excluded instrument is relevant in the sense that its first-stage impact on grant receipt is significant at 1% level (coef. 0.350; s.e. 0.065), and the F-test has a value of 29.08 with $p < 0.001$. The validity of the instrument rests on our assumption that the average funding rate of a scholar's peers (active in the same discipline) is correlated the scholar's own probability of receiving a grant, but uncorrelated with her decision to publish in fields she hasn't published in before.

Table IV.3 OLS and 2SLS estimations of determinants of entry in new fields

	New field entry $_t$ (0/1)			Maximum distance $_t$		
	OLS	OLS	2SLS	OLS	OLS	2SLS
	a	*b*	*c*	*d*	*e*	*f*
Grant $_{t-2}$		0.035*	-0.484**		0.031*	-0.542***
		(0.021)	(0.218)		(0.019)	(0.210)
Seniority $_{t-1}$	-0.014***	-0.014***	-0.015***	-0.013***	-0.013***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Quality $_{pre-92}$	-0.001	-0.002	0.015	0.000	-0.001	0.018
	(0.010)	(0.010)	(0.012)	(0.009)	(0.009)	(0.011)
High productivity cluster $_{t-1}$	0.088***	0.087***	0.098***	0.075***	0.074***	0.086***
	(0.027)	(0.027)	(0.031)	(0.025)	(0.025)	(0.031)
Medium productivity cluster $_{t-1}$	0.075***	0.073***	0.103***	0.064***	0.063***	0.096***
	(0.017)	(0.017)	(0.023)	(0.016)	(0.016)	(0.022)
Associate professor $_{t-1}$	0.028	0.025	0.074**	0.024	0.021	0.075**
	(0.023)	(0.023)	(0.034)	(0.022)	(0.022)	(0.033)
Professor $_{t-1}$	0.067**	0.062**	0.144***	0.056**	0.051*	0.143***
	(0.030)	(0.030)	(0.049)	(0.028)	(0.028)	(0.047)
Full professor $_{t-1}$	0.116***	0.108***	0.231***	0.105***	0.098***	0.233***
	(0.039)	(0.039)	(0.068)	(0.036)	(0.036)	(0.066)
Co-authors $_{t-1}$	0.000	0.000	0.001	0.000	0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Co-authors same disc. $_{t-1}$	-0.043**	-0.046**	-0.004	-0.044**	-0.046**	0.000
	(0.022)	(0.022)	(0.031)	(0.020)	(0.020)	(0.030)
Co-authors same grant status $_{t-1}$	0.036	0.038*	0.007	0.036*	0.038*	0.004
	(0.023)	(0.023)	(0.029)	(0.021)	(0.021)	(0.028)
PhD graduates $_{t-1}$	0.030***	0.029***	0.055***	0.029***	0.027***	0.057***
	(0.010)	(0.010)	(0.016)	(0.009)	(0.009)	(0.016)
Stock of fields $_{t-1}$	0.004***	0.004***	0.007***	0.004***	0.004***	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Start after 1992	0.025	0.026	0.011	0.017	0.018	0.001
	(0.025)	(0.024)	(0.031)	(0.023)	(0.023)	(0.030)
Gender (m)	0.028	0.029	0.011	0.028	0.029	0.009
	(0.029)	(0.029)	(0.036)	(0.027)	(0.027)	(0.036)
Full-time $_{t-1}$	0.005	0.002	0.058	0.003	0.000	0.063
	(0.031)	(0.031)	(0.040)	(0.029)	(0.029)	(0.038)
Teaching $_{t-1}$	0.002	0.003	-0.001	0.003	0.003	-0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Observations	5009					
Researchers	757					
Anderson under-id			28.21***			28.21***

a) Intercept and discipline dummies estimated but not shown in table.
b) Robust standard errors clustered by researcher in parentheses.
c) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.

While we found a positive correlation between funding and entry in the descriptive statistics, this positive correlation seems to be driven by selection. When we do not control for selection into funding, we find a positive effect (significant at 10% level) of funding on the probability to enter new fields (column *b*). When instrumented in the 2SLS estimation, the effect of funding is negative and significant at 5% level.[109] The size of the estimated coefficient implies that researchers that receive grants from the university's Research Council have a 48% lower probability of entering new fields two years after having received a grant compared to those that are not funded. Furthermore, columns *e* and *f* show that the same effects take place on how far away (from their main research) scientists venture when publishing in new fields. Receiving a grant is negatively (-0.542) and significantly (at 1% level) correlated with publishing in new fields that are less similar to the field where a scholar has published most in the past. These combined results support the hypothesis that this particular grant acts as a specialisation rather than a diversification tool.

Concerning the other independent variables, we find that the probability to enter new fields and the distance between them and the main field decrease with academic seniority. However, once correcting for academic age, we find that higher-ranked academics are more probable to publish in new fields that are also more distant. This shows that climbing the academic ladder has a significantly positive effect, rendering researchers less risk-averse and seeking to diversify their portfolios, possibly due to less achievement pressure that marks an early career. The effect is a 7.4% increase in the (linear) probability to enter new fields for associated professors, 14.4% for professors and 23.1% for full professors.

Productivity also drives experimentation, as shown by the positive and significant (at 1%) coefficients of the indicators for medium and high productivity clusters. This effect becomes stronger in the 2SLS results. Compared to academics in the low productivity group, those in the medium cluster have 10.3% higher chances of entering new fields, while those in the high productivity group 9.8% more. However, the pre-sample quality indicator is not significant at 10% level, which implies that the positive link between productivity and risk-taking is stronger over short periods, rather than reflecting a more permanent talent effect. The results are similar concerning the distance from his main field that a researcher 'travels' to enter new fields.

[109] The first-stage results in the first column of Table IV.10 in Appendix indicate that talent ($Quality_{pre\text{-}92}$) is an important determinant of receiving a grant. However, this is the full extent of conclusions we can reach regarding selection into funding, as the two-year funding lag precedes the one-year lag of all other covariates with the exception of talent.

Having more co-authors does not significantly increase entry in new fields but it does positively affect the distance of those entered from one's main field, although the magnitude of the effect is small, around 0.1% for each extra co-author. Having more PhD graduates increases the probability by 5.5% but also the distance between fields. This result points towards an interesting avenue for increasing diversification of portfolios by raising the number of doctoral students.

On the other hand, the percentage of co-authors that share the same main discipline as the focal scientist only has a significant (negative) effect in the OLS estimations; when we instrument the grant indicator, the effect from similar co-authors drops under the 10% significance level. This is rather surprising, as we would expect the variable to have a negative impact on entering new fields. One plausible explanation is that disciplines are defined too broadly to capture the impact of network similarity on the fine-grained field classification. Similarly, the percentage of co-authors with that have the same funding status – either receiving grants or not – as the focal researcher is not significant in our main 2SLS estimations. Again, more refined data regarding the percentage of co-authors that receive the same grant – i.e. on the same project – would be more suited to capture network effects.

The stock of fields in which a scholar has previously published has a positive and significant (at 1% level) effect, each extra field that she has already published in raising the probability of entering a new one by 0.7%, with a similar effect on the distance between her main field and the newly-entered ones. Although not large, the effect signals a certain trend that past behaviour can predict future diversification conduct.

We do not see any significant effect of gender, full-time employment status or the amount teaching hours. The former might be specially interesting for gender studies, as it shows that scientific exploration is not correlated with gender. Finally, academics that teach more classes have the same exploration behaviour as 'pure researchers', result which can be taken into account in internal evaluation policies that correlate research duties with productivity.

In order to test the conditions under which our results remain robust, we performed a number of additional estimations.

First, we test whether the choice of a 2-year lag for funding impacts our conclusions. We have re-estimated the 2SLS models by including different funding lags – from 1 to 5 years – and we present a summary of the grant effect in Table IV.11 in Appendix.[110] We see very similar patterns for 2 to 5 year lags, the negative effect of grants on entry in new fields and also on entry distance becoming even stronger over time. However, the 1-year lag of grants is not significantly different from zero at 10% level. We assert that this is due to the time required after receiving the grant to set up a team – including hiring doctoral students and postdocs – and performing research prior to publication.

Lastly, we re-define our dependent variable to relax the definition of new entry and include any publications in a new (to the researcher) field, disregarding whether she publishes again in the same field afterwards. The results in Table IV.12 in Appendix show that the effects of most covariates are highly similar to our main specification, reinforcing the latter. The two differences come as a decrease in significance (from 5% to 10% level) of the grant indicator, corroborated with an increase in significance to 10% level of the full-time employment indicators.

5 Conclusions

We provide empirical evidence of the drivers behind entry in scientific fields that are new to the researcher, including an analysis of the role of research grants. Our results show that academics who receive competitive grants are less inclined to venture into new research fields, and they also venture into fields that are more similar to their past publication activity. This negative effect from grants on new field entry is only obtained when we correct for selection into funding. We also find that productivity and exploration are positively correlated, scholars with higher publication output being more likely to enter new and more diverse fields. Moreover, past track record of entering new fields is a positive predictor of similar future behaviour. Career effects suggest that higher-ranked professors tend to venture more in new and distant fields, but they do so later after receiving a promotion. Finally, we find little evidence that peer networks affect diversification, the only channel seemingly being through doctoral students supervised by the researcher, their number increasing both the probability to publish in new fields and the diversity of those fields.

Our results suggest that grants lead researchers to stay within their established research fields rather than diversifying their portfolios by entering new and more diverse fields. Recent calls

[110] We capture the entire life-span of grants, as a project can be funded for maximum five years.

from prominent scientists show that there is a pressing need to improve the design of funding mechanisms, which has highlighted that we still do not fully understand the amalgam of incentives provided through grants (Lane, 2009). Funding agencies advertise the success of their support for science, but many fail to provide empirical evidence of any causal effects (Gush et al., 2015). In the economics of science literature, the main focus with respect to the effects of science funding has been on productivity. Although undoubtedly very informative for policy makers, output is only one product of the scientific process (Lane, 2009). Our paper reveals how funding affects the diversity of output by (not) stimulating scientists to enter new areas of research. We do not take a normative view on the scope of funding. To the extent that policy makers desire to increase diversity of research, we show that some types of competitive grants that are focused on productivity can have the reverse effect – leading scientists to specialise in order to secure output based on their past research experience. On the other hand, this effect is helpful if the goal of policy is to produce more specialised research.

Our study suggests a number of avenues for further analysis. First, the distribution of field taxonomy could be exploited further to distinguish whether entry in fields that are more different from one's past expertise is affected by funding in a different way than entry in more similar fields. Related to this, our results suggest that exploration varies across disciplines that comprise related fields. It may also be the case that the effect of funding varies with discipline or at a higher level, which could be analysed by estimating the effects in split samples. Moreover, we only analyse one type of research funding, which is specifically designed for basic research. A useful addition to the data would provide information on other grants, such as European Research Council funds or grants offered by the private sector. The latter would primarily offer evidence whether exploratory behaviour is driven by a push towards applied research.

6 Appendix

Table IV.4 List of Thomson Reuters ISI WoS scientific fields

Acoustics	Medical Ethics	Area Studies
Agricultural Economics & Policy	Medical Informatics	Business
Agricultural Engineering	Medical Laboratory Technology	Business, Finance
Agriculture	Medicine	Communication
Agronomy	Metallurgy & Metallurgical Engineering	Criminology & Penology
Allergy	Meteorology & Atmospheric Sciences	Demography
Anatomy & Morphology	Microbiology	Economics
Andrology	Microscopy	Education & Educational Research
Anaesthesiology	Mineralogy	Education
Astronomy & Astrophysics	Mining & Mineral Processing	Environmental Studies
Automation & Control Systems	Multidisciplinary Sciences	Ergonomics
Behavioural Sciences	Mycology	Ethics
Biochemical Research Methods	Nanoscience & Nanotechnology	Ethnic Studies
Biochemistry & Molecular Biology	Neuroimaging	Family Studies
Biodiversity Conservation	Neurosciences	Geography
Biology	Nuclear Science & Technology	Gerontology
Biophysics	Nursing	Health Policy & Services
Biotechnology & Applied Microbiology	Nutrition & Dietetics	History
Cardiac & Cardiovascular Systems	Obstetrics & Gynaecology	History & Philosophy of Science
Cell & Tissue Engineering	Oceanography	History of Social Sciences
Cell Biology	Oncology	Hospitality, Leisure, Sport & Tourism
Chemistry	Operations Research & Management Science	Industrial Relations & Labour
Clinical Neurology	Ophthalmology	Information Science & Library Science
Computer Science	Optics	International Relations

Construction & Building Technology	Ornithology	Law
Critical Care Medicine	Orthopaedics	Linguistics
Crystallography	Otorhinolaryngology	Management
Dentistry, Oral Surgery & Medicine	Palaeontology	Nursing
Dermatology	Parasitology	Planning & Development
Developmental Biology	Pathology	Political Science
Ecology	Paediatrics	Psychiatry
Education	Peripheral Vascular Disease	Psychology
Electrochemistry	Pharmacology & Pharmacy	Public Administration
Emergency Medicine	Physics	Public, Environmental & Occupational Health
Endocrinology & Metabolism	Physiology	Rehabilitation
Energy & Fuels	Plant Sciences	Social Issues
Engineering	Polymer Science	Social Sciences
Entomology	Psychiatry	Social Work
Environmental Sciences	Psychology	Sociology
Evolutionary Biology	Public, Environmental & Occupational Health	Substance Abuse
Fisheries	Radiology, Nuclear Medicine & Medical Imaging	Transportation
Food Science & Technology	Rehabilitation	Urban Studies
Forestry	Remote Sensing	Women's Studies
Gastroenterology & Hepatology	Reproductive Biology	Archaeology
Genetics & Heredity	Respiratory System	Architecture
Geochemistry & Geophysics	Rheumatology	Art
Geography, Physical	Robotics	Asian Studies
Geology	Soil Science	Classics
Geosciences, Multidisciplinary	Spectroscopy	Dance
Geriatrics & Gerontology	Sport Sciences	Film, Radio, Television
Health Care Sciences & Services	Statistics & Probability	Folklore

Haematology	Substance Abuse	History
History & Philosophy of Science	Surgery	History & Philosophy of Science
Horticulture	Telecommunications	Humanities, Multidisciplinary
Imaging Science & Photographic Technology	Thermodynamics	Language & Linguistics
Immunology	Toxicology	Literary Reviews
Infectious Diseases	Transplantation	Literary Theory & Criticism
Instruments & Instrumentation	Transportation Science & Technology	Literature
Integrative & Complementary Medicine	Tropical Medicine	Medieval & Renaissance Studies
Limnology	Urology & Nephrology	Music
Marine & Freshwater Biology	Veterinary Sciences	Philosophy
Materials Science	Virology	Poetry
Mathematical & Computational Biology	Water Resources	Religion
Mathematics	Zoology	Theatre
Mechanics	Anthropology	

Table IV.5 List of main scientific disciplines

Agriculture & Environment
Biosciences (General, Cellular & Subcellular Biology; Genetics)
Chemistry
Engineering
Geosciences & Space Sciences
Mathematics
Clinical and Experimental Medicine I (General & Internal Medicine)
Clinical and Experimental Medicine II (Non-Internal Medicine Specialized)
Neuroscience & Behaviour
Physics
Biomedical Research
Multidisciplinary Sciences
Biology (Organismic & Supraorganismic Level)

Table IV.6 Entry into and distance to new fields by main discipline

		Entry in new field[b)]	Sum of new fields[c)]	Maximum distance[d)]	Sum of distances[e)]
A	Agriculture	0.40	0.79	0.38	0.96
		(0.49)	(1.24)	(0.46)	(1.86)
B	Biosciences	0.30	0.51	0.27	0.55
		(0.46)	(0.95)	(0.41)	(1.20)
C	Chemistry	0.29	0.53	0.26	0.56
		(0.45)	(1.08)	(0.41)	(1.32)
E	Engineering	0.33	0.76	0.31	1.04
		(0.47)	(1.40)	(0.44)	(2.65)
G	Geosciences	0.28	0.47	0.26	0.74
		(0.45)	(0.84)	(0.41)	(2.53)
H	Mathematics	0.19	0.34	0.18	0.42
		(0.39)	(0.86)	(0.38)	(1.11)
I	Medicine I (general)	0.34	0.61	0.30	0.58
		(0.47)	(1.08)	(0.42)	(1.07)
M	Medicine II (specialised)	0.27	0.49	0.25	0.64
		(0.44)	(1.02)	(0.41)	(2.13)
N	Neuroscience	0.20	0.34	0.17	0.53
		(0.40)	(0.87)	(0.35)	(2.12)
P	Physics	0.27	0.46	0.25	0.51
		(0.44)	(0.94)	(0.41)	(1.21)
R	Biomedical	0.19	0.36	0.17	0.43
		(0.39)	(0.88)	(0.35)	(1.32)
Z	Biology	0.37	0.69	0.33	0.78
		(0.48)	(1.16)	(0.44)	(1.60)

a) Standard deviations in parentheses.
b) Entry in new to the researcher fields market by binary indicator (0/1).
c) Sum of new fields represents the average number of fields entered that were new to the researcher.
d) Maximum distance between main field prior to year *t* and newly entered fields in *t.*
e) Sum of distances between main field prior to year *t* and newly entered fields in *t*.

Table IV.7 Descriptive statistics at scholar level (yearly averages)

Variable	Mean	s.d.
Average entry in new fields	0.75	0.44
Avg. maximum distance from main field	0.28	0.25
Avg. sum of distances	0.63	0.86
Average # of fields	4.44	3.39
Maximum # of fields	7.43	4.77
Stock of fields	13.24	8.27
Co-authors (#)	13.61	19.75
Co-authors in same discipline (%)	0.41	0.31
Co-authors with same grant status (%)	0.37	0.26
Low productivity	0.54	0.39
Medium productivity	0.33	0.31
High productivity	0.13	0.25
PhDs	0.34	0.52
Seniority	8.91	7.83
Teaching load	3.87	3.75
Assistant professor	0.30	0.40
Associate professor	0.25	0.33
Professor	0.21	0.33
Full professor	0.24	0.40
Male	0.89	0.32
Full-time employment	0.90	0.28
Quality pre-92	0.84	1.03
Start after ‘92	0.47	0.50

Table IV.8 Average entry rates by covariate category

		New entry		Maximum distance	
		mean	s.d.	mean	s.d.
Seniority	Junior	0.347	(0.476)	0.315	(0.436)
	Senior	0.263	(0.440)	0.242	(0.408)
Talent	Low	0.315	(0.464)	0.288	(0.428)
	High	0.291	(0.454)	0.266	(0.419)
Productivity	Low	0.233	(0.423)	0.214	(0.391)
	Medium	0.371	(0.483)	0.338	(0.444)
	High	0.414	(0.493)	0.379	(0.455)
Academic rank	Assistant	0.292	(0.455)	0.265	(0.415)
	Associate	0.301	(0.459)	0.274	(0.420)
	Professor	0.304	(0.460)	0.279	(0.425)
	Full Prof.	0.314	(0.464)	0.291	(0.433)
Stock	Low	0.257	(0.437)	0.234	(0.401)
	High	0.343	(0.475)	0.315	(0.439)
Team size	Low	0.236	(0.425)	0.218	(0.395)
	High	0.366	(0.482)	0.333	(0.442)
Team similarity	Low	0.270	(0.444)	0.249	(0.412)
	High	0.334	(0.472)	0.303	(0.432)

a) Seniority, talent, stock, team size and similarity have been split at the median value in the sample.

Table IV.9 t-tests for independent variables by funding status

	Mean		t-test	
	Funded	Unfunded	t	p>t
Co-authors (#)	22.62	10.57	14.95	0.00
Co-authors same discipline (%)	0.51	0.36	11.62	0.00
Co-authors same grant status (%)	0.43	0.34	7.26	0.00
Low productivity	0.33	0.62	-19.61	0.00
High productivity	0.21	0.10	10.77	0.00
Medium productivity	0.45	0.28	12.53	0.00
PhDs	0.70	0.30	14.95	0.00
Seniority	11.41	9.34	8.79	0.00
Teaching	4.64	4.31	2.65	0.01
Assistant Professor	0.07	0.27	-16.48	0.00
Associate Professor	0.23	0.28	-3.58	0.00
Professor	0.27	0.22	3.41	0.00
Full Professor	0.43	0.22	15.22	0.00
Gender (m)	0.92	0.90	2.77	0.01
Full-time contract	0.98	0.89	10.41	0.00
Quality pre-92	1.20	0.80	12.24	0.00
Start after ‘92	0.25	0.41	-11.03	0.00

Table IV.10 Selection into funding and funding effect on entry – 2SLS

	First-stage	Structural
Grant $_{t-2}$		-0.484**
		(0.218)
Grant instrument $_{t-2}$	0.350***	
	(0.065)	
Seniority $_{t-1}$	-0.003	-0.015***
	(0.002)	(0.002)
Quality $_{pre-92}$	0.033***	0.015
	(0.010)	(0.012)
High productivity cluster $_{t-1}$	0.027	0.098***
	(0.030)	(0.031)
Medium productivity cluster $_{t-1}$	0.058***	0.103***
	(0.017)	(0.023)
Associate professor $_{t-1}$	0.079***	0.074**
	(0.027)	(0.034)
Professor $_{t-1}$	0.144***	0.144***
	(0.036)	(0.049)
Full professor $_{t-1}$	0.232***	0.231***
	(0.049)	(0.068)
Co-authors $_{t-1}$	0.001**	0.001
	(0.000)	(0.000)
Co-authors same disc. $_{t-1}$	0.080***	-0.004
	(0.026)	(0.031)
Co-authors same grant status $_{t-1}$	-0.058**	0.007
	(0.025)	(0.029)
PhD graduates $_{t-1}$	0.052***	0.055***
	(0.010)	(0.016)
Stock of fields $_{t-1}$	0.005**	0.007***
	(0.002)	(0.002)
Start after 1992	-0.05	0.011
	(0.033)	(0.031)
Gender (m)	-0.03	0.011
	(0.037)	(0.036)
Full-time $_{t-1}$	0.113***	0.058
	(0.025)	(0.040)
Teaching $_{t-1}$	-0.008***	-0.001
	(0.003)	(0.003)
Observations	5009	
Researchers	757	
Anderson under-id	28.21***	

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by researcher in parentheses.
c) Discipline indicators and intercept estimated but not shown in table.

Table IV.11 Comparison of 2SLS coefficients for different lags of funding

	New field entry	Maximum distance
1-year lag	0.007	-0.079
	(0.236)	(0.221)
2-year lag	-0.484**	-0.542***
	(0.218)	(0.210)
3-year lag	-0.441**	-0.462**
	(0.220)	(0.208)
4-year lag	-0.883***	-0.883***
	(0.327)	(0.315)
5-year lag	-0.714**	-0.728**
	(0.320)	(0.308)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by researcher in parentheses.

Table IV.12 OLS and 2SLS estimates of determinants of 'non-sticky' entry

	Non sticky entry (0/1)		
	OLS	OLS	2SLS
	a	*b*	*c*
Grant $_{t-2}$		0.028	-0.399*
		(0.020)	(0.224)
Seniority $_{t-1}$	-0.012***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)
Quality $_{pre-92}$	-0.001	-0.002	0.012
	(0.009)	(0.009)	(0.011)
High productivity cluster $_{t-1}$	0.106***	0.105***	0.114***
	(0.028)	(0.028)	(0.030)
Medium productivity cluster $_{t-1}$	0.078***	0.077***	0.101***
	(0.019)	(0.019)	(0.025)
Associate professor $_{t-1}$	0.042*	0.039	0.079**
	(0.024)	(0.024)	(0.034)
Professor $_{t-1}$	0.085***	0.081***	0.148***
	(0.031)	(0.031)	(0.049)
Full professor $_{t-1}$	0.142***	0.136***	0.236***
	(0.040)	(0.040)	(0.068)
Co-authors $_{t-1}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Co-authors same disc. $_{t-1}$	-0.017	-0.019	0.015
	(0.022)	(0.022)	(0.031)
Co-authors same grant status $_{t-1}$	0.058**	0.059**	0.034
	(0.024)	(0.024)	(0.030)
PhD graduates $_{t-1}$	0.033***	0.032***	0.054***
	(0.010)	(0.010)	(0.016)
Stock of fields $_{t-1}$	0.006***	0.006***	0.008***
	(0.001)	(0.001)	(0.002)
Start after 1992	0.035	0.036	0.023
	(0.024)	(0.024)	(0.028)
Gender (m)	0.039	0.04	0.025
	(0.028)	(0.028)	(0.034)
Full-time $_{t-1}$	0.024	0.021	0.068*
	(0.032)	(0.032)	(0.041)
Teaching $_{t-1}$	0.002	0.002	-0.001
	(0.003)	(0.003)	(0.004)
Observations		5009	
Researchers		757	
Anderson under-id			28.21***

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Robust standard errors clustered by researcher in parentheses.
c) Discipline indicators and intercept estimated but not shown in table.

Conclusions

My research sheds light on the behavioural changes both firms and individuals go through when faced with an intricate R&D policy environment. In a first instance, I show that complexity leads companies to rely on their peers' decisions to adopt newly introduced tax exemptions. Then, responding to recent calls for a combined analysis of multiple policies, I analyse how separate policy measures and their mix affect the firms that adopt them. And finally, I focus on individual researchers and how they are changing their scientific behaviour when receiving competitive grants. By connecting these analyses, I adopt a systemic view of innovation policy at two different levels – scientific research and industrial R&D. Furthermore, I incorporate an often forgotten element of innovation environments – interaction between its users and between users and institutions (policy).

The first chapter makes the following contributions. First, it complements literature on support for R&D by showing how peer effects influence firms' usage of public support measures. An accurate understanding of the dynamics of firm choices is essential for reducing inefficiencies, such as the belated absorption of public support for R&D. My results suggest that firms develop strategies to cope with the complexity of the R&D support landscape by imitating firms who adopt earlier. The finding that imitation occurs in peer groups that follow industry and distance-based lines suggests possible policy interventions for reducing inefficiencies in usage of R&D support. More specifically, adoption by eligible firms could be expedited by communicating the measure to sufficiently fine-grained sectors and in a geographically-distributed way. As opposed to broad policy communications, 'narrowcasting' would help to reach many localized firm clusters, allowing rapid peer-to-peer influence, once initial adoption has taken place.

Second, the establishment of peer effects as a significant factor driving firms' selection into support schemes informs the methodological literature on selection bias in program evaluation (Imbens & Wooldridge, 2009). The existence of peer effects calls for looking beyond the individual firm to explain selection into support programs.

Using recent advances in identification strategy for peer effects (Bramoullé et al., 2009; De Giorgi et al., 2010), this chapter also contributes to the broader literature on peer effects. Given the high degree of clustering in many 'small world' firm networks (e.g. Fleming & Marx, 2006), exploiting intransitivity in firms' networks is more generally applicable to identify peer effects in other settings.

In the second and third chapters I analyse the additionality of subsidies and tax credits on firms' R&D activity. I provide empirical evidence that firms that mix direct and indirect support respond better to treatment than those using a single policy. My results also reveal that tax credits and subsidies have different effects on budgetary decisions regarding basic and applied research and development. I find that subsidies seem to mostly increase spending on research, whereas tax credits also positively affect development activities.

Furthermore, although I do not find any additionality of subsidies as a single treatment on R&D expenditure, my results do not indicate any substitution effects either. In other words, only receiving grants does not increase private expenses on R&D, nor does it decrease them. The central implication is that, should the goal of the government be to increase the overall volume of research and development in the economy, a subsidy-only policy might do the job. On the other hand, should the goal be to raise private funding of R&D, then using tax credits or a policy mix seems the more effective choice.

This part of my research also provides evidence that regional and national policies in Belgium reinforce each other. I show in the third chapter that subsidies – a regional measure – strengthen the effects of federal tax credits by further increasing the speed and scale of R&D for users of the policy mix. I thus build on recent literature on the mix of multi-level policy, as advocated by Martin (2016) and following empirical results from the US produced by Lanahan and Feldman (2015), among others.

Finally, I shift focus to the individual researcher to explore to what extent grants affect the diversity of scientific output. The competitive nature of funding leads researchers to stay within their established research fields rather than diversifying their portfolios by entering new and more diverse fields. Recent calls from prominent scientists show that there is a pressing need to improve the design of funding mechanisms, which has highlighted that we still do not fully understand the amalgam of incentives provided through grants (Lane, 2009). My research reveals how funding affects the diversity of output by (not) stimulating scientists to enter new areas of research. To the extent that policy makers desire to increase diversity of research, I show that some types of competitive grants that are focused on productivity can have the reverse effect – leading scientists to specialise in order to secure output based on their past research experience. On the other hand, this effect is helpful if the goal of policy is to produce more specialised research.

Combined, my findings have both policy and managerial implications. First, they provide much needed empirical evidence of the effects of funding on R&D. Second, they show that additionality goes beyond R&D inputs and outputs and touches research behaviour itself, both at firm and at individual level. And finally, they help understand what characteristics should be incorporated in funding schemes to avoid substitution and crowding-out, but also to reduce incremental research and encourage exploration.

Far from answering all the policy-relevant questions, my work triggers several avenues for further research. First, while I do show that firms that do not use tax credits can be influenced to do so by their peers, it would be interesting to explore which types of companies are leaders and which are followers in the take-up of policy support. Second, relating the speed of adoption to additionality might reveal whether firms that are slower to use support also respond less to it. And third, better data on inter-firm interactions would allow a more robust identification of peer groups and of the flow of information within them. Although my analysis seems robust to possible mis-specification of groups, it would benefit from comparing its results to a setting comprising observed networks of firms.

Regarding the multitude of policies available to companies performing R&D, more complete data sets are required in order to further mitigate hidden treatment effects stemming from unobserved support that firms may use simultaneously. Reinforcing recent evidence (Dumont, 2013, 2015; Guerzoni & Raiteri, 2015), I have briefly shown that failing to account for this effect can lead to an over-estimation of the impact of single policies. Similarly, in my analysis I aggregate various types of subsidies and tax credits due to data constraints. Dumont (2015) and Hottenrott et al. (2014) have shown that there is variation in the effect of these policies when they are split into finer components. However, their ability to do so rests again on the availability of data. The former paper does so for federal tax credits, while the latter analyses regional subsidies in Flanders. Aggregated national data – which I use in this thesis – is not systematically collected by local authorities in the same form, which renders it hardly usable if one tries to analyse it at high resolution. This being said, I applaud recent efforts by authorities at all levels of government to provide better access to more data for researchers, and I believe that they will be rewarded with more robust evidence for policy-making in the near future.

Finally, my fourth chapter shows how scientific grants can change individuals' research orientation by driving them towards specialisation. Although undoubtedly relevant, in my paper I only analyse one type of research funding, which is specifically designed for basic research. As such, its effect on exploration might be instrument-specific and, moreover, it may be simultaneously used with other types of grants and interact with them in ways not captured in my analysis. A useful addition to the data would provide information on other grants, such as European Research Council funds or grants offered by the private sector. The latter would primarily offer evidence whether exploratory behaviour is driven by a push towards applied research. Yet again, it comes down to more and better data.

References

Aerts, K., & Schmidt, T. (2008). Two for the price of one?: Additionality effects of R&D subsidies: A comparison between Flanders and Germany. *Research Policy*, *37*(5), 806–822.

Agrawal, A., McHale, J., & Oettl, A. (2013). Collaboration, Stars, and the Changing Organization of Science: Evidence from Evolutionary Biology. National Bureau of Economic Research Working Paper 19653. Retrieved from http://www.nber.org/papers/w19653

Alberts, B. (2013). Impact Factor Distortions. *Science*, *340*(6134), 787–787.

Alberts, B., Kirschner, M. W., Tilghman, S., & Varmus, H. (2014). Rescuing US biomedical research from its systemic flaws. *Proceedings of the National Academy of Sciences*, *111*(16), 5773–5777.

Albuquerque, A. (2009). Peer firms in relative performance evaluation. *Journal of Accounting and Economics*, *48*(1), 69–89.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, *45*(7), 905–917.

Almus, M., & Czarnitzki, D. (2003). The Effects of Public R&D Subsidies on Firms' Innovation Activities. *Journal of Business and Economic Statistics*, *21*(2), 226–236.

Antonelli, C., & Crespi, F. (2013). The' Matthew effect' in R&D public subsidies: The Italian evidence. *Technological Forecasting and Social Change*, *80*(8), 1523–1534.

Aranguren, M. J., de la Maza, X., Parrilli, M. D., Vendrell-Herrero, F., & Wilson, J. R. (2014). Nested Methodological Approaches for Cluster Policy Evaluation: An Application to the Basque Country. *Regional Studies*, *48*(9), 1547–1562.

Arqué-Castells, P., & Mohnen, P. (2015). Sunk costs, extensive R&D subsidies and permanent inducement effects. *The Journal of Industrial Economics*, *63*(3), 458–494.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The Rate and Direction of Inventive Activity* (R. Nelson, pp. 165–180). Princeton, NJ: Princeton University Press.

Arrow, K. J., & Lind, R. C. (1970). Uncertainty and the Evaluation of Public Investment Decisions. *American Economic Review*, *60*(3), 364–78.

Audia, P. G., & Goncalo, J. A. (2007). Past success and creativity over time: A study of inventors in the hard disk drive industry. *Management Science*, *53*(1), 1–15.

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review*, *86*(3), 630–640.

Auranen, O., & Nieminen, M. (2010). University research funding and publication performance—An international comparison. *Research Policy*, *39*(6), 822–834.

Ayoubi, C., Pezzoni, M., & Visentin, F. (2016). *At the Origins of Learning: Absorbing Knowledge Flows from Within or Outside the Team?* (Working Paper No. 2016-08). Groupe de Recherche en Droit, Economie, Gestion (GREDEG CNRS), University of Nice Sophia Antipolis. Retrieved from http://www.gredeg.cnrs.fr/working-papers/GREDEG-WP-2016-08.pdf

Azoulay, P., Graff Zivin, J. S., & Manso, G. (2011). Incentives and creativity: evidence from the academic life sciences. *The RAND Journal of Economics*, *42*(3), 527–554.

Bach, L., & Matt, M. (2002). Rationale for science & technology policy. In L. Georghiou, J. Righby, & H. M. Cameron (Eds.), *Assessing the Socio-economic Impacts of the Framework Programme*. Manchester: PREST.

Banal-Estañol, A., Jofre-Bonet, M., & Lawson, C. (2015). The double-edged sword of industry collaboration: Evidence from engineering academics in the UK. *Research Policy*, *44*(6), 1160–1175.

Banal-Estañol, A., Macho-Stadler, I., & Pérez-Castrillo, D. (2013). Endogeneous matching in university-industry collaboration: Theory and empirical evidence from the UK. Universitat Pompeu Fabra Working Paper Series. Retrieved from http://repositori.upf.edu/handle/10230/20968

Banal-Estañol, A., Macho-Stadler, I., & Pérez Castrillo, D. (2016). Key success drivers in public research grants: Funding the seeds of radical innovation in academia? (Barcelona

GSE Working Paper No. 890). Barcelona, ES: Barcelona GSE. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2774648

Becher, T. (1994). The significance of disciplinary differences. *Studies in Higher Education*, *19*(2), 151–161.

Bell, D. R., & Song, S. (2007). Neighborhood effects and trial on the Internet: Evidence from online grocery retailing. *Quantitative Marketing and Economics*, *5*(4), 361–400.

Bérubé, C., & Mohnen, P. (2009). Are firms that receive R&D subsidies more innovative? *Canadian Journal of Economics/Revue Canadienne D'économique*, *42*(1), 206–225.

Blanes, J. V., & Busom, I. (2004). Who participates in R&D subsidy programs?: The case of Spanish manufacturing firms. *Research Policy*, *33*(10), 1459–1476.

Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional Studies*, *39*(1), 61–74.

Boschma, R., & Frenken, K. (2010). The spatial evolution of innovation networks. A proximity perspective. In R. Boschma & K. Frenken (Eds.), *Handbook on Evolutionary Economic Geography* (pp. 120–135). Cheltenham: Edward Elgar.

Boudreau, K. J., Guinan, E. C., Lakhani, K. R., & Riedl, C. (2012). The novelty paradox and bias for normal science: evidence from randomized medical grant proposal evaluations. Harvard Business School Technology & Operations Mgt. Unit Working Papers, SSRN. Retrieved from http://papers.ssrn.com/sol3/Delivery.cfm?abstractid=2184791

Bozeman, B., & Gaughan, M. (2007). Impacts of grants and contracts on academic researchers' interactions with industry. *Research Policy*, *36*(5), 694–707.

Bozio, A., Irac, D., & Py, L. (2014). Impact of research tax credit on R&D and innovation: evidence from the 2008 French reform. SSRN Working Paper Series. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2544604

Bramoullé, Y., Djebbari, H., & Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, *150*(1), 41–55.

Brock, W. A., & Durlauf, S. N. (2007). Identification of binary choice models with social interactions. *Journal of Econometrics*, *140*(1), 52–75.

Bromiley, P. (1991). Testing a causal model of corporate risk taking and performance. *Academy of Management Journal*, *34*(1), 37–59.

Buisseret, T. J., Cameron, H. M., & Georghiou, L. (1995). What difference does it make Additionality in the public support of RD in large firms. *International Journal of Technology Management, 10*, *4*(5), 587–600.

Busom, I., Corchuelo, B., & Martínez-Ros, E. (2014). Tax incentives… or subsidies for business R&D? *Small Business Economics*, *43*(3), 571–596.

Caiumi, A. (2010). The evaluation of the effectiveness of tax expenditures: A novel approach. Institute for Studies and Economic Analysis (ISAE), Rome, Working Paper 126. Retrieved from http://leonardo3.dse.univr.it/home/documents/seminars/seminario_antonella_caiumi_20-11.pdf

Cappelen, A., Raknerud, A., & Rybalka, M. (2007). The effect of R&D tax credits on firm performance. Statistics Norway Reports Series No. 2007/22. Oslo, Norway.

Cappellari, L., & Jenkins, S. P. (2003). Multivariate probit regression using simulated maximum likelihood. *Stata Journal*, *3*(3), 278–294.

Cappellari, L., & Tatsiramos, K. (2011). Friends’ networks and job finding rates. University of Leicester Discussion Papers in Economics, 11/40.

Carboni, O. A. (2011). R&D subsidies and private R&D expenditures: evidence from Italian manufacturing data. *International Review of Applied Economics*, *25*(4), 419–439.

Card, D., & Giuliano, L. (2011). Peer Effects and Multiple Equilibria in the Risky Behavior of Friends (Working Paper No. 17088). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w17088

Castellacci, F., & Lie, C. M. (2015). Do the effects of R&D tax credits vary across industries? A meta-regression analysis. *Research Policy*, *44*(4), 819–832.

Chandrasekhar, A., & Lewis, R. (2011). Econometrics of sampled networks. MIT Working Paper 422. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.476.4060&rep=rep1&type=pdf

Charles, K. K., Hurst, E., & Roussanov, N. (2009). Conspicuous Consumption and Race. *The Quarterly Journal of Economics*, *124*(2), 425–467.

Clarysse, B., Wright, M., & Mustar, P. (2009). Behavioural additionality of R&D subsidies: A learning perspective. *Research Policy*, *38*(10), 1517–1533.

Clausen, T. H. (2009). Do subsidies have positive impacts on R&D and innovation activities at the firm level? *Structural Change and Economic Dynamics*, *20*(4), 239–253.

Claussen, J., Engelstätter, B., & Ward, M. R. (2014). Susceptibility and influence in social media word-of-mouth. ZEW-Centre for European Economic Research Discussion Paper 14-129. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2564065

Corchuelo, B., & Martínez-Ros, E. (2009). The Effects of Fiscal Incentives for R&D in Spain. Business Economic Series 02, Universidad Carlos III de Madrid, WP 09-23. Retrieved from http://orff.uc3m.es/handle/10016/3870

Corredoira, R. A., & Rosenkopf, L. (2010). Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal*, *31*(2), 159–181.

Cunningham, P., Edler, J., Flanagan, K., & Laredo, P. (2013). Innovation policy mix and instrument interaction: a review. NESTA working paper. London, UK.

Cunningham, P., Gök, A., & Larédo, P. (2012). The Impact of Direct Support to R&D and Innovation in Firms. NESTA working paper. London, UK.

Czarnitzki, D., Hanel, P., & Rosa, J. M. (2011). Evaluating the impact of R&D tax credits on innovation: A microeconometric study on Canadian firms. *Research Policy*, *40*(2), 217–229.

Czarnitzki, D., & Hottenrott, H. (2011). R&D investment and financing constraints of small and medium-sized firms. *Small Business Economics*, *36*(1), 65–83.

Czarnitzki, D., Hottenrott, H., & Thorwarth, S. (2011). Industrial research versus development investment: the implications of financial constraints. *Cambridge Journal of Economics*, *35*(3), 527–544.

Czarnitzki, D., & Licht, G. (2006). Additionality of public R&D grants in a transition economy. *Economics of Transition*, *14*(1), 101–131.

Czarnitzki, D., & Lopes-Bento, C. (2013). Value for money? New microeconometric evidence on public R&D grants in Flanders. *Research Policy*, *42*(1), 76–89.

Czarnitzki, D., & Lopes-Bento, C. (2014). Innovation subsidies: Does the funding source matter for innovation intensity and performance? Empirical evidence from Germany. *Industry and Innovation*, *21*(5), 380–409.

David, P. A., Hall, B. H., & Toole, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy*, *29*(4-5), 497–529.

Debruyne, M., & Reibstein, D. J. (2005). Competitor see, competitor do: Incumbent entry in new market niches. *Marketing Science*, *24*(1), 55–66.

Defazio, D., Lockett, A., & Wright, M. (2009). Funding incentives, collaborative dynamics and scientific productivity: Evidence from the EU framework program. *Research Policy*, *38*(2), 293–305.

De Giorgi, G., Pellizzari, M., & Redaelli, S. (2010). Identification of social interactions through partially overlapping peer groups. *American Economic Journal: Applied Economics*, 241–275.

Diez, M.-A. (2002). Evaluating New Regional Policies Reviewing the Theory and Practice. *Evaluation*, *8*(3), 285–305.

Dodgson, M., Hughes, A., Foster, J., & Metcalfe, S. (2011). Systems thinking, market failure, and the development of innovation policy: The case of Australia. *Research Policy*, *40*(9), 1145–1156.

Duguet, E. (2004). Are R&D subsidies a substitute or a complement to privately funded R&D? *Revue D'économie Politique*, *114*(2), 245–274.

Duguet, E. (2010). The Effect of the R&D Tax Credit on the Private Funding of R&D: An Econometric Evaluation on French Firm Level Data. SSRN Working Paper Series (1592988). Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1592988

Dumont, M. (2013). The impact of subsidies and fiscal incentives on corporate R&D expenditures in Belgium (2001-2009). Belgian Federal Planning Bureau Working Paper No. 1-13. Brussels, BE: Belgian Federal Planning Bureau.

Dumont, M. (2015). Evaluation of federal tax incentives for private R&D in Belgium: An update Belgian Federal Planning Bureau Working Paper No. 5-15. Brussels, BE: Belgian Federal Planning Bureau.

Dumont, M., Spithoven, A., & Teirlinck, P. (2015). Public Support for R&D and the Educational Mix of R&D Employees. CESifo Economic Studies.

Edquist, C. (2011). Design of innovation policy through diagnostic analysis: identification of systemic problems (or failures). *Industrial and Corporate Change*, *20*(6), 1725–1753.

Falk, R. (2007). Measuring the effects of public support schemes on firms' innovation activities:: Survey evidence from Austria. *Research Policy, 36*(5), 665–679.

Falk, R., Borrmann, J., Grieger, N., Neppl-Oswald, E., & Weixlbaumer, U. (2009). Tax Incentive Schemes for R&D. Evaluation of Government Funding in RTDI from a Systems Perspective (WP No. 4). Vienna, Austria: Austrian Institute for Economic Research.

Flanagan, K., & Uyarra, E. (2016). Four dangers in innovation policy studies–and how to avoid them. *Industry and Innovation*, *23*(2), 177–188.

Flanagan, K., Uyarra, E., & Laranja, M. (2011). Reconceptualising the 'policy mix' for innovation. *Research Policy*, *40*(5), 702–713.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science, 47*(1), 117–132.

Fleming, L., & Marx, M. (2006). Managing creativity in small worlds. *California Management Review*, *48*(4), 6–27.

Florida, R., & Cohen, W. M. (1999). Engine or Infrastructure? The University Role in Economic Development. In Branscomb, L. M., Kodama, F., & Florida, R. (Eds.), *Industrializing Knowledge: Universityv Industry Linkages in Japan and the United States*. MIT Press, London.

Fritsch, M., & Franke, G. (2004). Innovation, regional knowledge spillovers and R&D cooperation. *Research Policy*, *33*(2), 245–255.

García-Quevedo, J. (2004). Do public subsidies complement business R&D? A meta-analysis of the econometric evidence. *Kyklos*, *57*(1), 87–102.

Georghiou, L. (2002). Additionality and impact of R&D subsidies. *IWT-STUDIES*, *40*, 57–64.

Gerfin, M., & Lechner, M. (2002). A Microeconometric Evaluation of the Active Labour Market Policy in Switzerland. *The Economic Journal*, *112*(482), 854–893.

Geuna, A. (2001). The changing rationale for European university research funding: are there negative unintended consequences? *Journal of Economic Issues*, *35*(3), 607–632.

Gleason, C. A., Jenkins, N. T., & Johnson, W. B. (2008). The contagion effects of accounting restatements. *The Accounting Review*, *83*(1), 83–110.

Glenna, L. L., Welsh, R., Ervin, D., Lacy, W. B., & Biscotti, D. (2011). Commercial science, scientists' values, and university biotechnology research agendas. *Research Policy*, *40*(7), 957–968.

Goldfarb, B. (2008). The effect of government contracting on academic research: Does the source of funding affect scientific output? *Research Policy*, *37*(1), 41–58.

González, X., & Pazó, C. (2008). Do public subsidies stimulate private R&D spending? *Research Policy*, *37*(3), 371–389.

Goolsbee, A. (1998). Does Government R&D Policy Mainly Benefit Scientists and Engineers? *American Economic Review*, *88*(2), 298–302.

Görg, H., & Strobl, E. (2007). The effect of R&D subsidies on private R&D. *Economica*, *74*(294), 215–234.

Gort, M., & Konakayama, A. (1982). A Model of Diffusion in the Production of an Innovation. *American Economic Review*, *72*(5), 1111–20.

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics*, *60*(2), 187–243.

Grimpe, C. (2012). Extramural research grants and scientists' funding strategies: Beggars cannot be choosers? *Research Policy*, *41*(8), 1448–1460.

Guerzoni, M., & Raiteri, E. (2015). Demand-side vs. supply-side technology policies: Hidden treatment and new empirical evidence on the policy mix. *Research Policy*, *44*(3), 726–747.

Gulbrandsen, M., & Smeby, J.-C. (2005). Industry funding and university professors' research performance. *Research Policy*, *34*(6), 932–950.

Gush, J., Jaffe, A. B., Larsen, V., & Laws, A. (2015). The Effect of Public Funding on Research Output: The New Zealand Marsden Fund. *NBER Working Paper*, (w21652). Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2679690

Haegeland, T., & Møen, J. (2007a). Input additionality in the Norwegian R&D tax credit scheme. Statistics Norway Reports Series No. 47.

Haegeland, T., & Møen, J. (2007b). The relationship between the Norwegian R&D tax credit scheme and other innovation policy instruments. Statistics Norway Reports Series No. 45.

Hall, B. H. (2004). Innovation and diffusion. National Bureau of Economic Research Working Paper 10212. Retrieved from http://www.nber.org/papers/w10212

Hall, B. H., & Maffioli, A. (2008). Evaluating the impact of technology development funds in emerging economies: evidence from Latin America. *The European Journal of Development Research*, *20*(2), 172–198.

Hall, B., & Van Reenen, J. (2000). How effective are fiscal incentives for R&D? A review of the evidence. *Research Policy*, *29*(4–5), 449–469.

Haunschild, P. R., & Miner, A. S. (1997). Modes of interorganizational imitation: The effects of outcome salience and uncertainty. *Administrative Science Quarterly*, 472–500.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, *64*(4), 605–654.

Heckman, J. J., LaLonde, R. J., & Smith, J. A. (1999). The economics and econometrics of active labor market programs. *Handbook of Labor Economics*, *3*, 1865–2097.

Helmers, C., & Patnam, M. (2014). Does the rotten child spoil his companion? Spatial peer effects among children in rural India. *Quantitative Economics*, *5*(1), 67–121.

Hicks, D. (2012). Performance-based university research funding systems. *Research Policy*, *41*(2), 251–261.

Hottenrott, H., & Lawson, C. (2013). Fishing for complementarities: Competitive research funding and research productivity. KU Leuven - Faculty of Economics and Business Working Paper. Retrieved from https://lirias.kuleuven.be/bitstream/123456789/429644/1/MSI_1315.pdf

Hottenrott, H., Lopes Bento, C., & Veugelers, R. (2014). Direct and cross-scheme effects in a research and development subsidy program. SSRN Working Paper Series. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2506017

Hussinger, K. (2008). R&D and subsidies at the firm level: An application of parametric and semiparametric two-step selection models. *Journal of Applied Econometrics*, *23*(6), 729–747.

Hyytinen, A., & Toivanen, O. (2005). Do financial constraints hold back innovation and growth?: Evidence on the role of public policy. *Research Policy*, *34*(9), 1385–1403.

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

Ientile, D., & Mairesse, J. (2009). A Policy to Boost the R&D: Does the Tax Credit Work? European Investment Bank Paper, 14(1).

Imbens, G. W., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature*, *47*(1), 5–86.

Jacob, B. A., & Lefgren, L. (2011). The impact of research grant funding on scientific productivity. *Journal of Public Economics*, *95*(9), 1168–1177.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, *108*(3), 577–598.

Jones, B. F. (2009). The burden of knowledge and the ‘death of the renaissance man’: Is innovation getting harder? *The Review of Economic Studies*, *76*(1), 283–317.

Jones, B. F., Wuchty, S., & Uzzi, B. (2008). Multi-university research teams: Shifting impact, geography, and stratification in science. *Science*, *322*(5905), 1259–1262.

Jonkers, K., & Zacharewicz, T. (2016). Research Performance Based Funding Systems: a Comparative Assessment. Seville, Spain: Institute for Prospective Technological Studies, Joint Research Centre. Retrieved from https://www.researchgate.net/profile/Koen_Jonkers/publication/303488024_Research_Performance_Based_Funding_Systems_a_Comparative_Assessment/links/574556fd08ae9ace8421b154.pdf

Kelchtermans, S., & Veugelers, R. (2005). Top research productivity and its persistence. SSRN Working Paper 876904. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=876904

Kelchtermans, S., & Veugelers, R. (2011). The great divide in scientific productivity: why the average scientist does not exist. *Industrial and Corporate Change*, *20*(1), 295–336.

Kelchtermans, S., & Veugelers, R. (2013). Top research productivity and its persistence: Gender as a double-edged sword. *Review of Economics and Statistics*, *95*(1), 273–285.

Kelejian, H. H., & Prucha, I. R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The Journal of Real Estate Finance and Economics*, *17*(1), 99–121.

Kelejian, H. H., & Prucha, I. R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, *157*(1), 53–67.

Kennedy, R. E. (2002). Strategy Fads and Competitive Convergence: An Empirical Test for Herd Behavior in Prime-Time Television Programming. *The Journal of Industrial Economics*, *50*(1), 57–84.

Köhler, C., Laredo, P., & Rammer, C. (2012). The Impact and Effectiveness of Fiscal Incentives for R&D. NESTA Working Paper, NESTA: UK. Retrieved from http://www.nesta.org.uk/library/documents/TheImpactandEffectivenessofFiscalIncentives.pdf

Krugman, P. (1991). Increasing Returns and Economic Geography. *The Journal of Political Economy*, *99*(3), 483–499.

Lanahan, L., & Feldman, M. P. (2015). Multilevel innovation policy mix: A closer look at state policies that augment the federal SBIR program. *Research Policy*, *44*(7), 1387–1402.

Lane, J. (2009). Assessing the impact of science funding. *Science*, *324*(5932), 1273–1275.

Laranja, M., Uyarra, E., & Flanagan, K. (2008). Policies for science, technology and innovation: Translating rationales into regional policies in a multi-level setting. *Research Policy*, *37*(5), 823–835.

Latham, S. F., & Braun, M. R. (2010). Assessing the relationship between financial slack and company performance during an economic recession: an empirical study. *International Journal of Management*, *26*(1), 33.

Leary, M. T., & Roberts, M. R. (2014). Do peer firms affect corporate financial policy? *The Journal of Finance*, *69*(1), 139–178.

Lee, L. (2007). Identification and estimation of econometric models with group interactions, contextual factors and fixed effects. *Journal of Econometrics*, *140*(2), 333–374.

Lee, S.-Y. (2009). Bias from misspecified spatial weight matrices in SAR models: Theory and simulation studies. Department of Economics, San Francisco State University Working Paper.

Lee, Y.-N., Walsh, J. P., & Wang, J. (2015). Creativity in scientific teams: Unpacking novelty and impact. *Research Policy*, *44*(3), 684–697.

Levin, S. G., & Stephan, P. E. (1991). Research productivity over the life cycle: Evidence for academic scientists. *The American Economic Review*, 114–132.

Lhuillery, S., Marino, M., & Parrotta, P. (2013). Evaluation de l'impact des aides directes et indirectes à la R&D en France. Rapport pour le Ministère de l'Ensegnement Supérieur et de la Recherche. Paris, France.

Lichtenberg, F. R. (1987). The effect of government funding on private industrial research and development: a re-assessment. *The Journal of Industrial Economics*, 97–104.

Li, D., & Agha, L. (2015). Big names or big ideas: Do peer-review panels select the best science proposals? *Science*, *348*(6233), 434–438.

Lokshin, B., & Mohnen, P. (2012). How effective are level-based R&D tax credits? Evidence from the Netherlands. *Applied Economics*, *44*(12), 1527–1538.

Lu, J. W. (2002). Intra-and inter-organizational imitative behavior: institutional influences on Japanese firms' entry mode choice. *Journal of International Business Studies*, 19–37.

Lundvall, B. A. (2007). National innovation systems—analytical concept and development tool. *Industry and Innovation*, *14*(1), 95–119.

Luukkonen, T. (2000). Additionality of EU framework programmes. *Research Policy*, *29*(6), 711–724.

Magro, E., & Wilson, J. R. (2013). Complex innovation policy systems: Towards an evaluation mix. *Research Policy*, *42*(9), 1647–1656.

Mansfield, E. (1972). Contribution of R&D to Economic Growth in the United States. *Science*, *175*(4021), 477–486.

Mansfield, E. (1991). Academic research and industrial innovation. *Research Policy*, *20*(1), 1–12.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, *60*(3), 531–542.

Manski, C. F. (2000). Economic analysis of social interactions. National bureau of economic research Working Paper Series. Retrieved from http://www.nber.org/papers/w7580

Marino, M., Parrotta, P., & Lhuillery, S. (2015). An overall evaluation of public R&D subsidy on private R&D expenditure in absence or in combination with R&D tax credit incentives. DRUID15 Conference on The Relevance of Innovation, Rome, Italy. Retrieved from http://druid8.sit.aau.dk/acc_papers/arlixjutu74vl8ct298hi8fyc8ph.pdf

Marshall, A. (1920). Principles of economics: an introductory volume. London: Macmillan.

Martin, B. R. (2016). R&D policy instruments – a critical review of what we do and don't know. *Industry and Innovation*, *23*(2), 157–176.

Maskell, P., & Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge Journal of Economics*, *23*(2), 167–185.

Mathieu, A., & de la Potterie, B. van P. (2010). A Note on the Drivers of R&D Intensity. *Research in World Economy*, *1*(1), 56–65.

Nam, S., Manchanda, P., & Chintagunta, P. K. (2007). The effects of service quality and word of mouth on customer acquisition, retention and usage. SSRN Working Paper Series. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=969770

Nanda, R., & Sørensen, J. B. (2010). Workplace peers and entrepreneurship. *Management Science*, *56*(7), 1116–1126.

Neicu, D., Kelchtermans, S., & Teirlinck, P. (2016). Thanks, but no thanks: Companies' response to R&D tax credits. MSI Working Papers - FEB Research Reports No. MSI 1608. Leuven, Belgium: University of Leuven.

Neicu, D., Teirlinck, P., & Kelchtermans, S. (2016). Dipping in the policy mix: Do R&D subsidies foster behavioral additionality effects of R&D tax credits? *Economics of Innovation and New Technology*, *25*(3), 218–239.

Nelson, R. R. (1959). The simple economics of basic scientific research. *The Journal of Political Economy*, *67*(3), 297–306.

Noorderhaven, N., & Harzing, A.-W. (2009). Knowledge-sharing and social interaction within MNEs. *Journal of International Business Studies*, *40*(5), 719–741.

Ord, J. K., & Cliff, A. (1973). Spatial autocorrelation. London: Pion.

Organisation for Economic Co-operation and Development. (2002). Frascati Manual 2002: Proposed Standard Practice for Surveys on Research and Experimental Development. Paris: OECD.

Organisation for Economic Co-operation and Development. (2006). Government R&D Funding and Company Behaviour: Measuring Behavioural Additionality. Paris: OECD.

Organisation for Economic Co-operation and Development. (2013). Maximising the benefits of R&D tax incentives for innovation. OECD Policy Brief. Paris. Retrieved from http://www.oecd.org/sti/rd-tax-stats.htm

Partha, D., & David, P. A. (1994). Toward a new economics of science. *Research Policy*, *23*(5), 487–521.

Piras, G. (2010). sphet: Spatial models with heteroskedastic innovations in R. *Journal of Statistical Software*, *35*(1), 1-21.

Porter, M. E. (1990). The competitive advantage of nations. Free Press: New York.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55.

Rosenberg, N. (1990). Why do firms do basic research (with their own money)? *Research Policy*, *19*(2), 165–174.

Rubin, D. B. (1977). Assignment to Treatment Group on the Basis of a Covariate. *Journal of Educational and Behavioral Statistics*, *2*(1), 1–26.

Sacerdote, B. I. (2001). Peer Effects with Random Assignment: Results for Dartmouth Roommates. *Quarterly Journal of Economics*, *116*(2), 681–704.

Santamaría, L., Barge-Gil, A., & Modrego, A. (2010). Public selection and financing of R&D cooperative projects: credit versus subsidy funding. *Research Policy*, *39*(4), 549–563.

Simonton, D. K. (1999). Origins of genius: Darwinian perspectives on creativity. Oxford University Press: UK.

Simonton, D. K. (2003). Scientific creativity as constrained stochastic behavior: the integration of product, person, and process perspectives. *Psychological Bulletin*, *129*(4), 475.

Soete, L. (2012). Expertgroep voor de doorlichting van het Vlaams innovatieinstrumentarium. Retrieved from www.innovatiecentrum.be

Stephan, P. E. (2012). *How economics shapes science* (Vol. 1). Cambridge, USA: Harvard University Press.

Stephan, P. E., Veugelers, R., & Wang, J. (2016). Bias Against Novelty in Science: A Cautionary Tale for Users of Bibliometric Indicators. SSRN Working Paper Series. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2766556

Straathof, B., Gaillard-Ladinska, E., Kox, H., Mocking, R., Goldberg, I., Jensen, C., Lindholm, P., Sobolewski, M., Berg-Andersson, B., Kaseva, H., Rouvinen, P., Valkonen, T., Sellner, R., Schoenpflug, K., & Paterson, I. (2015). *A Study on R&D Tax Incentives*. Taxation Paper No. 52. Directorate General Taxation and Customs Union, European Commission: Brussels, BE.

Takalo, T., & Tanayama, T. (2010). Adverse selection and financing of innovation: is there a need for R&D subsidies? *The Journal of Technology Transfer*, *35*(1), 16–41.

Takalo, T., Tanayama, T., & Toivanen, O. (2013). Estimating the benefits of targeted R&D subsidies. *Review of Economics and Statistics*, *95*(1), 255–272.

Teirlinck, P., Dumont, M., & Spithoven, A. (2010). Corporate decision-making in R&D outsourcing and the impact on internal R&D employment intensity. *Industrial and Corporate Change*, *19*(6), 1741–1768.

Teirlinck, P., & Spithoven, A. (2008). The Spatial Organization of Innovation: Open Innovation, External Knowledge Relations and Urban Structure. *Regional Studies*, *42*, 689–704.

Teirlinck, P., & Spithoven, A. (2012). Fostering industry-science cooperation through public funding: differences between universities and public research centres. *The Journal of Technology Transfer, 37*(5), 676–695.

Uyarra, E. (2010). What is evolutionary about ‘regional systems of innovation’? Implications for regional policy. *Journal of Evolutionary Economics*, *20*(1), 115–137.

Verhoeven, D., Bakker, J., & Veugelers, R. (2016). Measuring technological novelty with patent-based indicators. *Research Policy*, *45*(3), 707–723.

Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research program. *The RAND Journal of Economics*, 82–100.

Westmore, B. (2013). R&D, Patenting and Growth: The Role of Public Policy. OECD Economics Department Working Papers No. 1047. OECD: Paris.

Whalley, A., & Hicks, J. (2014). Spending wisely? How resources affect knowledge production in universities. *Economic Inquiry*, *52*(1), 35–55.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*(5827), 1036–1039.

Zhang, L., Liu, X., Janssens, F., Liang, L., & Glänzel, W. (2010). Subject clustering analysis based on ISI category classification. *Journal of Informetrics*, *4*(2), 185–193.

Zúñiga-Vicente, J. Á., Alonso-Borrego, C., Forcadell, F. J., & Galán, J. I. (2014). Assessing the effect of public subsidies on firm R&D investment: a survey. *Journal of Economic Surveys*, *28*(1), 36–67.

Doctoral dissertations from the Faculty of Economics and Business, see:

http://www.kuleuven.ac.be/doctoraatsverdediging/archief.htm