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The Role of Peer Effects in Firms' Usage of R&D Tax Exemptions

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Abstract

Survey evidence suggests that firms are insufficiently aware of newly introduced R&D support measures due to the complexity of the public support landscape. As a result, adoption is slow and incomplete, implying that eligible firms leave money on the table. We hypothesize that a key coping mechanism involves firms relying on their peers' behaviour to inform their own adoption decision. We test this hypothesis by analysing firms' first use of a newly-introduced R&D tax exemption scheme in Belgium. We identify endogenous peer effects in industry- and location-based peer groups by exploiting the intransitivity in firms' networks as well as variation in peer group size. The results show that firms' decisions to use R&D tax exemptions are influenced by the choices of their peers. The findings suggest that the efficacy of R&D policy can be improved by accounting for the structure of firm networks in the communication of new support initiatives.

Keywords: peer effects; information diffusion; R&D tax exemptions; innovation policy

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1. Introduction

Over the past decades, public support for R&D has become a major policy tool to promote business R&D in a large majority of developed economies (OECD, 2018). However, many innovative firms do not use support measures for which they are eligible. This holds not only for R&D subsidies, which may require the firm to pass a potentially intensive screening procedure, but also for fiscal incentives, for which adoption costs tend to be modest. For example, in Belgium, the administrative cost of applying for an R&D tax exemption is negligible, while in addition the tax exemption is implemented as a wage subsidy for R&D workers, which means that a firm doesn't even need to report positive profits to benefit from the measure. Dumont (2015), reporting descriptive evidence on the uptake of the fiscal incentives for researchers introduced in Belgium in 2005, finds that most R&D-active companies do not use the measure four years after its introduction. Our representative sample of 1,981 R&D-active companies in the same country shows that even by 2011, hardly 40% of the firms eligible for the tax exemption scheme use it. Similar evidence has been reported for other countries. For example, 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 do not receive it still surpasses one in three companies. For Belgium, Dumont (2017) reports that in the year 2011, only half of the firms that are eligible for R&D tax exemption or R&D subsidies take advantage of this. In Austria, Falk et al. (2009) found that companies lack awareness of the structure of tax incentives and point towards insufficient information as a reason for non-adoption.

These low adoption rates are counterintuitive, since not using an R&D tax exemption scheme while being eligible comes down to leaving money on the table. While policy makers have been primarily concerned with the assessment of the effectiveness of support for firms that use it, the group of firms that doesn’t adopt R&D support - despite being eligible - has received much less attention. The policy concern for low absorption of support mechanisms can be expected to increase, given recent changes in policy evaluation frameworks. For example, the recently updated EU State Aid guidelines require counterfactual impact assessments for large-scale public R&D support (European commission, 2014). The evaluation plans that R&D funding agencies will have to draw up to comply with these guidelines have to mention the risks that may affect the expected impact of the support scheme, including lower than expected

usage rates. Furthermore, if support measures are not taken up by a substantial share of the targeted firms then the consequences are not limited to 1st order effects such as (a lack of) input or output additionality, but also 2nd order (higher overall firm performance as a consequence of higher R&D intensity) and 3rd order effects (broader socio-economic benefits, such as increased employment and FDI inflows into the region). This latter social return of R&D support has been estimated to be up to 2 times higher than the private gains (e.g. see the review in Hall, Mairesse & Mohnen, 2009). In other words, low absorption of public support for R&D implies substantial losses for society.

As a potential explanation for low adoption rates, it has been argued that mature innovation support systems tend to become overly complex, which implies that firms have imperfect information about potential R&D support. For example, an audit of the portfolio of support mechanisms for innovation in Flanders (Belgium) 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).A survey conducted in 2011 by the Belgian Federal Science Policy Office gauged firms' awareness of the R&D tax exemption scheme that we analyse in this paper and found that, five years after the launch of the measure, one out of six (quasi-) permanent R&D active firms still do not know the measure, confirming that knowledge about the measure was not widely available at the time of its introduction and only spread slowly afterwards. Using a more comprehensive survey, Boucq & López Novella (2018) investigate the reasons for non-take-up of employer tax exemptions in Belgium. They report that the complexity of legislation and unawareness of the existence of support measures are the most common reasons for non-take-up. Up to 52% of firms cite unawareness of a tax exemption scheme as a key reason for not using it despite being eligible, with smaller firms more likely to be uninformed.

A central tenet in competitive cognition theory is that managers operate under conditions of bounded rationality when processing signals from their environment, and that they cope with this limitation by relying on cognitive frameworks that shape their attention and interpretation (Daft & Weick, 1984; Nadkarni and Barr, 2008). Relevant for our analysis is the early work by Hannan & Freeman (1977) who argued that decisions by rival firms legitimize a certain path of action. Later research on the diffusion of information among firms has aimed to identify those cues embedded in competitors' actions that managers are likely to notice and respond to (Haveman, 1993; Rogers, 1983). For example, environmental scanning has been found to be directed primarily toward information that is considered strategically important (Boyd & Fulk,

1996), while firms are more likely to also interpret actions as relevant if they are initiated by firms that are seen as legitimate, strategically similar or competing in common markets (Smith *et al.*, 1991; Baum & Haveman, 1997; Gimeno & Woo, 1996; Osborne *et al.*, 2001). In other words, competitive cognition theory views the characteristics of competitors and their actions as important drivers for firms' behaviour, especially under circumstances of bounded rationality. This process of social recognition has been shown to lead to imitation behaviour for decisions as diverse as market entry (Gort & Konakayama, 1982; Kennedy, 2002; Lu, 2002; Debruyne & Reibstein, 2005; Gielens & Dekimpe, 2007), investment banking (Haunschild & Miner, 1997), corporate financial policy (Leary & Roberts, 2014) and compensation of top management (Albuquerque, 2009). More generally, a comprehensive assessment of firm decision-making necessitates looking beyond the individual firm to include social feedback effects (Hall, 2004). This paper ties into this literature by investigating the premise that social interaction is an important mechanism for firms to learn about R&D support. More particularly, we analyse whether firms' adoption of wage-based R&D tax exemptions can be attributed to decisions of peers, rather than to own firm characteristics or unobserved shocks pushing whole groups of companies towards adoption of the tax credit. The insights from competitive cognition theory provide a valuable theoretical lens to understand why firms are likely to follow suit if more of their peers adopt a newly introduced R&D support measure, which they may fail to detect in the overcrowded R&D policy landscape. Furthermore, the findings on what information sources firms consider as legitimate contribute to our rationale for which firms should be included in the focal firm's peer group. As discussed further in section 2, we hypothesize that these effects occur within well-delineated peer groups defined by industry and geography, inspired by prior work which has shown that geographically-bound social capital influences firms' R&D strategy (Laursen *et al.*, 2016).

Our paper makes three contributions. First, consistent with the theory that low adoption rates of public R&D support can be attributed to firms' lack of information, this paper informs innovation policy by showing, using an innovative instrumental variables approach, that peers influence firms' use of public support schemes. This is important because 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. We demonstrate the mechanism of social interaction with only limited information on the composition of peer networks, showing that social interaction occurs in peer groups that follow industry- and distance-based default lines. Second, the establishment of peer effects as a factor driving firms' selection into support

schemes informs the methodological literature on selection bias in program evaluation (Imbens & Wooldridge, 2009)[1] since it confirms the importance of looking beyond the individual firm to explain selection into support programs. Third, the paper uses recent methodological advances to identify peer effects (Bramoullé *et al.*, 2009; De Giorgi *et al.*, 2010) by relying on a 'nearest neighbours' peer group definition. Given that many empirical networks exhibit the clustering that gives rise to the intransitivity that we exploit in this paper (e.g. Fleming & Marx, 2006), our empirical analysis demonstrates how the method can be used to identify peer effects in innovation networks.

The rest of the paper is organized as follows. Section 2 clarifies the theoretical arguments that underpin the role of peer groups in the diffusion of information and explains how we define firms' peer groups, given that we cannot directly observe them. The definition of peer groups ties into the identification strategy and empirical model, both of which are explained in section 3. The section continues with a discussion of the main features of the tax credit system for researchers in Belgium, followed by the empirical analysis of peer effects in firms' adoption decisions, including various robustness checks. Section 4 concludes and reflects on the implications for policy.

2. Peer groups and the diffusion of information

2.1. Defining peer groups: what do we learn from the literature?

As explained above, the lack of perfect information about available R&D support creates the basis for peer-to-peer diffusion of this information, i.e. less informed firms that have not (yet) adopted the support measure can learn from better-informed firms that are already using it.

Any identification of peer effects in firms' decision-making therefore needs to start from the definition of peer groups. This constitutes a key challenge, since a 'connection' between firms through which they may learn about R&D support can take various forms. Learning about R&D support may not even take place within formal arrangements such as R&D alliances or other contractual relations, which makes the connections hard to trace empirically. While some settings in the social interaction literature provide an institutional dimension that makes peer groups observable, e.g. class allocations of students, it is not clear a priori which firms jointly constitute a peer group for the purpose of our analysis. We draw on the cluster literature, which

[1] Imbens and Wooldridge (2009, p. 14) point out that social interactions have only recently become an important point of attention in program evaluation, rather than merely a nuisance.

has explained the geographical agglomeration of firms in terms of (knowledge) spillovers between complementary economic activities (Delgado *et al.*, 2014; Audretsch & Feldman, 1996a). Considering industry and geographical location to determine a firm's network also follows the long-standing observation in the economic geography literature that economic activity tends to be clustered in relatively small geographic areas (Krugman, 1991; Baptista & Swann, 1998). We follow these insights and elaborate upon those two dimensions and their relevance for defining peer groups of firms.

First, regarding the geographical proximity dimension, Porter (1990) argued that innovation dynamics in clusters are stimulated by local competition and peer pressure among firms, suggesting that firms within clusters are aware of their peers' activity, and, by extension, initiatives such as accessing public R&D support.[2] In addition, securing access to R&D support during financial and economic difficult times (period 2008-2010) serves as a signal of creditworthiness to external investors (Stinchcombe, 1965), which might be picked up by competitors. Geographical proximity also is prominent in the social interaction literature since short distances favour contacts and facilitate knowledge exchange, and especially uncodified knowledge (Lundvall, 1988; Bell & Song, 2007; Hauser *et al.*, 2007; Nam *et al.*, 2007). Several empirical studies have shown the geographically-bounded nature of (technological) knowledge spillovers (Jaffe *et al.*, 1993; Almeida & Kogut, 1999; Audretsch & Feldman, 1996b; 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 peer firms, such as social relations between employees. Moreover, social capital from a geographical region can enhance firms' access to knowledge or information (Laursen *et al.*, 2016). Bell and Zaheer (2007) highlight the facilitating role of location for knowledge access, comprising both formal and informal knowledge exchange. In such a bounded geographical setting, in particular personnel relations are the drivers for knowledge exchange (Storper & Venables, 2004). This can be explained by the highly tacit character of knowledge related to R&D, which is largely contextual and difficult to codify,

[2] While our analysis does not aim to identify specific mechanisms of information exchange, firms may try to shield - rather than share - information that provides a competitive advantage to rivals. However, competition for most firms in a very open economy like the Belgian one extends beyond the boundaries of their domestic peer group so we expect deliberate non-sharing of information to play a minor role. Furthermore, use of the tax exemption scheme in Belgium does not require public disclosure of R&D projects so this should not hinder the sharing of information about the scheme among peers. Finally, even if the information on the existence and use of R&D tax benefits were not be shared directly between R&D managers, firms can still be expected to closely monitor the financial position of peer companies. This is plausible given that firms benefitting from the tax exemption scheme have to report it in their annual accounts by means of an extra-ordinary R&D revenue booking, making it visible to outsiders.

requiring direct face-to-face interactions, regular meetings and conversations (Gertler, 2003). These knowledge interactions in the field of R&D supposedly bring in their wake an exchange of more codified information regarding the availability and use of R&D tax credit schemes.

The second dimension in the cluster literature that is relevant for defining peer groups is the composition of economic activities (Porter, 1990; Barro & Sala-i-Martin, 1991). Clusters group firms with related economic activities (Baptista & Swan, 1998) or that belong to the same or related industries (Saxenian, 1996), which implies reduced cognitive distance (Boschma, 2005) and easier sharing of common knowledge and cluster-specific inputs and outputs (Delgado *et al.*, 2014). Simmie (2002) argues that regional specialization in a particular industry facilitates knowledge spillovers, with a prominent role for researchers as the transmission channel. Porter (1994) and Delgado *et al.* (2014) emphasize that localisation effects may occur due to a common local customer base, because firms produce complementary goods and/or due to the presence of specialized institutions and suppliers. Finally, the preferential attachment of firms to peers with similar activities is also a central tenet in the social network literature (Boschma & Frenken, 2010). Empirical work has indeed found industry to be a defining feature of the context where different types of inter-firm influencing take place. For example, financing decisions by peer firms in the same industry, in particular competitors, are found to influence the focal firm's own decisions (Graham & Harvey, 2001). Measuring firms' industry membership at 3-digit SIC level, Leary and Roberts (2014) show how within-industry peers affect firms' financial policies, such as leverage ratios, rather than changes in firm-specific characteristics. These latter studies show how peer effects play a role in corporate decision making, particularly in situations of high uncertainty and costly optimization. Such conditions – which arguably also hold in our empirical setting where firms need to navigate a complex R&D support landscape - induce managers to attach more weight to the decisions of others (Banerjee, 1992).

Based on these theoretical arguments, the intersection of industry and geography provides an intuitive perspective on peer groups with respect to adoption externalities (Baptista, 2000). In other words, information does not spread homogenously throughout the firm population and social interaction does not occur between random pairs of firms. Rather, a firm is typically only connected to a subset of all other firms (i.e. the firm network has low density), with preferential connections to those firms that are nearby and active in the same industry. Hence, we hypothesize that social interaction takes place primarily within peer groups. In order to assess

the validity of the peer group definition, we will carry out robustness checks of the structure, size and scope of peer groups.

2.2. Defining peer groups: what do the descriptive statistics tell us?

As a first indication of the potential role of distance as a determinant of peer groups, we report descriptive statistics for our sample of Belgian firms, considering their adoption decisions for the R&D tax exemption scheme introduced in 2005-2006. Figure 1 relates firms' usage of R&D tax exemptions to location in 2007, the earliest year in which any peer effect emanating from early adopters (in 2006) was possible. Controlling for the agglomeration of innovative firms, it shows the share of tax exemption users among eligible (i.e. R&D active) firms by municipality, the finest level of detail at which we observe firms' locations.[3] The pattern indicates that R&D tax exemptions use is not spread uniformly, but rather that locations with higher shares of tax exemption users tend to be clustered.[4]

[Figure 1 here]

Based on the insights from previous work on firm interactions and knowledge spillovers discussed in section 2.1, we define peer groups using a nearest-neighbour logic. More specifically, we define a firm's peers as the K closest firms (KNN) within the same 3-digit NACE sector.[5] This definition allows for intransitivity in the network of firms, i.e. the peers of a firm's peers are not necessarily peers of the focal firm itself. This network structure plays a critical role in the identification of the peer effects, as explained in section 3.

While conceptually grounded in prior research, several empirical issues may threaten the validity of this peer group definition. We discuss them here and indicate how they are addressed later in the paper.

[3] Technically, we observe a firm's location by 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. For 37 out of 589 municipalities our sample does not contain observations on R&D active firms (marked as "no data" in Figure 1). These municipalities are mostly located in the South of the country where the prevalence of R&D active firms is lower.

[4] Note that firms may be considered randomly allocated to a location with respect to their use of R&D tax exemptions. In other words, it is unlikely that firms would co-locate for reasons that drive their decision to use R&D tax exemptions. The analysis will control for other R&D-related factors that may explain co-location of firms, such as R&D intensity.

[5] 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 network.

First, it is common for empirical work using social network data to observe only a sample of all nodes in the network. Our work is no exception: the data we use for the peer group definition and the estimation is a sample of users (and non-users) of the R&D tax exemption, namely those firms for which characteristics from the OECD business R&D survey are available. If there are firms in the population that are not part of the observed sample but that are in the (true) peer groups of sampled firms, this would introduce measurement error. Given that firms are not selected into the business R&D survey sample based on location, it is a reasonable assumption that missing links in peer groups are random.

Second, we adopt a conservative approach and conduct a series of robustness checks regarding the specification of peer groups in section 3.7 to ascertain that any identified peer influence is not conditional on the precise measurement of peer groups. First, we apply a network randomization test, in which we scramble the peer groups by reshuffling the sample 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 group 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, finally, include additional industry and regional controls in the model.

3. Analysis of peer effects in R&D tax credit adoption

3.1. 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*, means in our empirical setting that it is hard to disentangle whether a firm's decision to use the R&D tax exemption causes its peers to do the same, or whether the firm does so as a consequence of its peers' actions. In other words, the identification of peer effects suffers from a simultaneity problem. The second problem in identifying peer effects consists of endogeneity issues due to endogenous peer group formation and unobserved correlated shocks. Both 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 exemption scheme.

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 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 exemption[6], 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 and excludes firm i. $E(x|G_i)$ are the average characteristics of firm i's peers. A firm's peers are defined by the 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. the '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 where peer groups overlap perfectly such that, if firm i and firm j are in the same peer group, their peers coincide, i.e. $G_i = G_j$. As Manski (1993) already argued, in this case the endogenous effect β cannot be identified separately from the exogenous effect γ.[7] A less ambitious approach is to estimate a single parameter for the combination of endogenous and exogenous

[6] Although our dependent variable (adoption of the R&D tax credit) is binary, we opt for a linear model. This allows for a clearer exposition of the identification strategy, in line with De Giorgi *et al.* (2010), who study the binary choice of majors in higher education and also estimate a linear probability model (LPM). Some work has been done on identifying peer effects in binary choice models, exploiting non-linearity to separate endogenous from exogenous effects (e.g. Brock & Durlauf, 2007). However, strict multivariate distributional assumptions needed to identify the model do not allow controlling for aspects like spatially correlated errors and heteroscedasticity, which are common in spatial models (Klier & McMillen, 2008). Since accounting for unobserved peer group characteristics that may drive firms' adoption decisions is paramount to properly identify the endogenous peer effect, we choose to estimate a robust (spatial) linear probability model. It has been noted in the literature that LPM-based estimates of coefficients in binary choice models are consistent (e.g. Claussen *et al.*, 2015) and provide good approximations to true marginal effects, even if they do not fit choice probabilities perfectly (Angrist & Pischke, 2009). A LPM may underestimate standard errors, which is why the results should be interpreted with some caution although statistical significance levels are consistent with the OLS and probit estimates we report as benchmarks in section 3.6.

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

effects, without separating them.[8] However, in our empirical framework, the KNN-based peer groups are not fixed across firms, hence $E(y|G_i)$ varies *within* peer groups, which allows separating endogenous and exogenous peer effects. Consider the following simple example that illustrates how intransitivity in peer networks 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 neighbors, but, given the geographical distribution of firms in the industry, firms A and C are not (see Figure 2). This layout results in 'excluded peers', i.e. firms who are not in a firm's peer group but are part of its peers' peers. Firm A is excluded from firm C's peer group, and vice versa, while B's peer group includes both A and C.

[Figure 2 here]

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

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

with j a member of i's peer group, and G_j never identical to G_i. With respect to the preceding example, we can write the peer groups, 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:

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

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

[8] In this case, one assumes the absence of either endogenous peer effects or contextual peer effects (see e.g. Klier & McMillen, 2008).

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

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.[9] 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 section 2, it is 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:

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

with g denoting the peer group (of A, B or C in the preceding example), μ_i an individual fixed effect, θ^g a group fixed effect, such as the aforementioned 'common accountant' effect,[10] and ϵ_i an 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 exemption use, making μ_i negligible or zero.[11] The more serious concern leading to endogeneity is the existence of unobserved correlated effects at the group level, θ^g. 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 the endogenous peer effect. 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

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

[10] 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 exemptions through the TTO or a scientific entrepreneurship program run by the university.

[11] 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.

uncorrelated with θ^A since C is not a peer of A – affects y_C and the latter affects y_B since C is a peer of B. For our peer group definition based on distance and industry, the excluded peers of firm i include the firms in the same industry not among its K nearest neighbours. Table 1 shows for various peer group sizes K, the share of firms that has *at least* K nearest neighbours in their industry. These are the firms for which the aforementioned identification strategy – which requires the existence of excluded peers in the focal firm's industry – is empirically feasible in our sample. As Table 1 shows, the share of firms with excluded peers decreases with peer group size. We consider $K = 10$ the empirical upper bound for peer group size since below this number we still have a majority of firms for which peer groups do not encompass all other firms within the same 3-digit NACE industry. 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 et al. (2009) have shown that peer effects are also identified if at least two 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 a 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. For the remainder of the paper, we use the 3-digit NACE industry level and 10 nearest neighbours as the main peer group definition. We instrument the endogenous peer effect Wy by Wx and, using information of excluded peers, WX^2.

[Table 1 here]

To estimate the model in (1), we use Kelejian and Prucha's (2010) spatial IV estimator. The estimator permits spatial correlation between the error terms, i.e. they are modelled as:[12]

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

The resulting SARAR[13] model is fairly general in its specification and has been used in prior work that estimates spatial peer effects, such as in Helmers & Patnam (2014), who use it to estimate 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

[12] As in most applications of this model, we set the spatial weight matrix $M = W$.

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

two-stage procedure, where the first stage instruments the endogenous peer effect Wy. Kelejian and Prucha (1998) have shown that the linearly independent columns 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 of 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.[14]

3.2. 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 biannual OECD Business R&D survey. It includes all companies known to be R&D active and is updated on a regular basis. The dataset contains R&D-related information and is enriched with information on public support measures in the form of R&D tax exemptions (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, thus there is no reason to suspect bias in terms of the three regions' relative representation in the sample. General company characteristics are provided by the Federal Public Service Finance, comprising the main sector of activity, employees, 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 OECD business R&D survey (2007, 2009 and 2011) to create our sample. Because only a minority of firms answer two consecutive surveys, our sample is effectively a pooled cross section. We exclude those firms that have not employed any researchers in *t* or *t-1*, as they are not eligible for tax exemptions, which are awarded as a partial tax exemption on the wages of researchers, and thus require employment of researchers rather than taxable profits, as explained in more detail in the next section. Given the identification strategy, we also first restrict the sample to those firms that have at least one peer in the same

[14] The SARAR model is a linear probability model in which the dependent variable capturing the firm's adoption decision is binary. We believe the robustness of the IV estimator proposed by Kelejian & Prucha (2010), which allows for spatial autocorrelation in the residuals, outweighs the disadvantage of not accounting for the dependent variable's distribution. Recent work (De Giorgi *et al.*, 2010; Claussen *et al.* 2015; Leary & Roberts, 2014) has also employed linear probability models to estimate peer effects in a binary choice setting.

industry, which removes 93 observations from the sample. The estimation sample contains 699, 961 and 1,018 observations of 1,981 unique firms, for the respective years 2007, 2009 and 2011.

3.3. Dependent variable

The R&D tax exemption scheme is implemented as a partial wage withholding tax exemption[15] and was introduced in 2006 for companies employing R&D personnel with PhD degrees and has been extended as of 2007 to Master degrees (except those in social sciences), across all industries. The initial tax exemption tariff was 25%, but was raised to 65% in 2008 and to 75% from 2009 onwards. Our dependent variable is binary and indicates when a company has received tax exemptions for researchers for the first time.[16] We focus on first-time adoption since this transition indicates the firm's learning about the measure, which is – as argued in section 2 – the change in the firm's behaviour that we want to explain, rather than its repeated use of the measure.[17]

Our data contains the population of firms that use the tax exemption for researchers. However, the sample coverage is reduced due to the merging 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 exemption users, which we assume to be random, as argued in section 2.

Table 2 shows the evolution over time of our sample companies using the tax exemption, and compares these numbers with the population of R&D tax exemption users identified by the Belgian Federal Public Service Finance. The pattern in our sample shows an increase in overall adoption in 2009 from 151 to 319 firms, followed by a more modest increase to 408 users in 2011. The first-time adoption rate equals 26% in 2007 and 2009, after which it drops to 7% in 2011, suggesting a possible 'saturation' in the sense that the majority of R&D active firms have

[15] The partial tax exemption can be seen as a wage subsidy. Given that it applies to taxes on wages, it clearly differs from other types of R&D tax credits, such as for fixed asset investments, which permit a tax deduction from the firm's taxable income.

[16] Note that we do observe the population of R&D tax exemption users in every year (as opposed to other firm characteristics that are drawn from the biannual R&D survey) so we accurately observe whether a firm is a first-time adopter in a given year.

[17] There are about 100 firms that abandon the tax exemption after initially using it and we cannot attribute this change to obvious reasons, such as stopping R&D activity or bankruptcy. We are agnostic as to why they stop using the tax exemption given our focus on explaining first-time adoption. We drop these firms from the data in the years they stop using the tax exemption since keeping them in the data after they abandon the tax exemption would lower the average peer group adoption rate while these firms were demonstrably aware of the tax exemption.

already become aware of and decided whether to use tax exemptions.[18] The population shows comparable numbers with a large jump from 2007 to 2009, which then levels off in 2011. While the rate of first-time users is higher in the population than in the sample for the years 2007 and 2009, it shows a similar relative decline in 2011.

[Table 2 here]

3.4. Peer effects

Our main explanatory variable measures, for each company and in each year, the average use of tax exemptions among its ten (geographically) closest peers active in the same 3-digit NACE industry.[19]

We define the elements of the spatial weighting matrix W, defined in section 3.1, as follows:

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

Next, we row-standardize W by averaging w_{ij} over the number of peers j of each firm i. Consequently, we construct the peer effects variable by multiplying W by the vector y' containing the binary variable indicating which companies have used tax exemptions in the previous year. Hence, we test whether a higher average use of tax exemptions among a firm's peers increases its likelihood of adoption.

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.[20]

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

[19] Our choice of 3-digit NACE codes to define peer groups follows other work on peer effects in firm decision making, such as Leary and Roberts (2014).

[20] The coordinates locate town halls with a precision of 2 km. Due to this setup there can be more than one firm with the same coordinates and in the same industry. If the number of same-industry and same-location firms is greater than the chosen peer group size, this raises the issue which of those firms should be included in the focal firm's peer group, which we address by a random selection process. 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, say, 15 firms in the same industry (A1-A15), we randomly attribute ten peers for firm A1 from the remaining A2-A15 firms in that municipality. Note that this is a minor issue since, as explained in section 2, the average number of firms per

We lag the endogenous peer effect variable by one year for three reasons. First, the data does not allow distinguishing, within a year, when each firm has used tax exemptions. 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 within peer groups. Moreover, there may also be a lag between the time information reaches a firm and its decision to act. Third, lagging alleviates the reflection problem by ensuring that a firm's decision does not econometrically influence the average decision of its peer group.[21]

3.5. Other determinants of R&D tax exemption use

The size of a firm can affect the probability to receive tax exemptions in the sense that larger firms may have dedicated staff to follow up on changes in R&D support measures, in absolute terms have a potentially larger advantage of the tax exemption, and may therefore be quicker to adopt newly introduced measures (Blanes & Busom, 2004; Neicu *et al.*, , 2016). 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 equivalents.

Besides firm size, we also control for R&D intensity, measured by the ratio of researchers to overall employees, since firms with higher shares of researchers are more likely to adopt the R&D tax exemption, all else equal.

Since the R&D tax exemption 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 indicator.[22] This variable 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 (Czarnitzki & Hottenrott, 2011), YICs may learn about the R&D tax exemption sooner than other companies, or because they

municipality is 3.18 with a standard deviation of 4.23 and a maximum of 45. Hence, on average, for the main analysis with $K = 10$, the peer groups are larger than the number of firms in the same municipality.

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

[22] We follow the criteria for a YIC as defined by the Belgian Science Policy Office: a YIC is less than 10 years old, has less than 50 employees, an annual turnover lower than 7.3 million Euro, total assets of maximum 3.65 million Euro, and spends more than 15% of its total cost on R&D.

may have their roots in government-sponsored R&D projects. On the other hand, young firms have less experience and less resources to scan complex policy environments such as the one we study because they lack the internal routines and management skills of incumbent firms (Stinchcombe, 1965). Thus, we would expect YICs to be prone to early adoption, but only if they manage to overcome the 'liability of newness' (Stinchcombe, 1965; Laursen *et al.*, 2016). If they do, a positive YIC effect is likely in the early years after the introduction of the tax exemption, while in the latter periods YICs may be less likely to adopt than non-YICs, as most YICs would have started using tax exemptions earlier.

To avoid a spurious attribution of the usage of R&D tax exemptions to peer effects, the empirical analysis must control for sources of correlation between the focal firm and the adopting peers that may explain the adoption decision. In other words, a firm's decision to apply for the R&D tax exemption may not be triggered by its peers but rather due to some underlying shared characteristic of the focal firm and its peers. A crucial determinant in this respect is firms' savviness in using public support for R&D, as this may explain the propensity of tapping into newly introduced measures for both the focal firm and its peers, rather than any peer-to-peer learning taking place. We proxy firms' familiarity with the support landscape by a binary 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.

We also estimated a specification including additional firm characteristics, such as firm age (instead of firm size) and financial variables like capital intensity and the current ratio to account for the possibility that a firm's financial situation may explain why it seeks R&D tax exemptions. However, the coefficients of these variables were insignificant. Furthermore, the inclusion of these variables in the model reduces the sample substantially due to limited data availability, and the peer effect becomes insignificant.

Descriptive statistics for the estimation sample are provided in Appendix. Table 7 reports the shares of (first time) R&D tax exemption users and firm characteristics, comparing users and non-users of the R&D tax exemption. Average peer group characteristics are summarised in Table 8 and correlations are reported in Table 9.

3.6. Results

Table 3 shows the estimation results of equation (1) with the GS2SLS procedure[23] 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.[24] We estimate separate models for each of the three observed years as this allows us to study whether peer effects behave differently in the first period after the introduction of the tax exemption, when fewer companies knew of its existence, suggesting a greater potential for peer effects.[25] 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 the full results are reported in Appendix in Table 10.

[Table 3 here]

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 exemptions is positively influenced by the (lagged) average use of tax exemptions 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. The softening of endogenous peer effects in the last year of the observation period may be due to the fact that the number of users increases every year, lowering the remaining potential of first-time adopters who can learn from their peers. This pattern is in line with studies on regional

[23] 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 exemptions by a firms' peers, and also include lagged contextual effects.

[24] 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.

[25] We have also estimated the model on the pooled cross-section including year dummies, but failed to find significant endogenous peer effects. We hypothesise that this is due to weakening of the effects as use of the tax exemption becomes more widespread over time.

knowledge diffusion that find that learning effects in the adoption of new technologies are strongest in the early stages of diffusion (Baptista, 2000).

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 exemption use – is measured prior to the dependent – first-time tax exemption use – we avoid this circularity. This facilitates the interpretation of the magnitude of the coefficients. In 2007, a 10% increase in the number of peers having used tax exemptions 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 exemption in a given year.

With respect to firm characteristics explaining adoption of the R&D tax exemption, we find that, on average, larger firms have a higher probability of being first-time users, in line with the hypothesized slack resources of larger firms to follow up on policy innovations and the larger absolute benefit from adopting.

R&D intensity is significant only in the GS2SLS models in 2007 and – for the model without contextual peer effects – in 2009, with opposing signs but a very small effect.[26]

For young innovative companies, we find no significant effect in 2007 and 2009. However, they are less likely to adopt the R&D tax exemption in 2011. As argued in section 3.5, the result for YICs is consistent with the expectation that YICs are at the forefront to adopt new R&D support measures and have thus mostly adopted the measure prior to our observation years. The data is consistent with this explanation: out of 43 YICs present in the data set in 2007, 15 were already using the tax exemption and only 3 were using it for the first time. Similarly, we observe 24 using YICs and 4 adopting YICs in 2009, and 31 using versus 1 newly adopting YIC in 2011.[27]

[26] We also observe that the R&D intensity coefficient is significant at 1% in a simple OLS model (excluding any peer effects) of general use of tax credits (column 2 in Table 11 in Appendix). 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%.

[27] The numbers are similar for lagged YIC status, which we use in our estimations. Moreover, of the adopters in 2011, none were YICs a year before.

We find no evidence that firms who are familiar with the R&D support system as evidenced by prior use of R&D subsidies are more prone to adopt R&D tax exemptions in 2007. Conversely, we find they are less likely to be first-time adopters in 2009 and 2011. It can be argued again that these firms are inclined to be early adopters of tax exemptions – i.e. from their introduction in 2006. Corroborated with the fact that subsidy use is stable over time, it implies that firms that use subsidies are less likely to become users of tax exemptions in later periods. In 2011, only 2 firms that had received subsidies one year before become adopters of tax exemptions, whereas there were 12 and 14 in 2007 and 2009 respectively, which confirms our intuition regarding the trend of subsidy use and tax exemption adoption.[28]

Finally, although the small sample limits the degrees of freedom, we explore whether - building on the theoretical arguments in section 2.1 - smaller firms are more sensitive to peer effects than large firms. Building on Stinchcombe's (1965) seminal idea of the liability of newness and prior research that has shown that small firms are more resource-constrained in their innovation activities (e.g. Czarnitzki & Hottenrott, 2011), we hypothesize an interaction effect between peer effects and firm size. More specifically, we expect that smaller firms are more sensitive than larger firms when it comes to their reliance on their peers' decisions to adopt R&D support measures in order to cope with a lack of information. To test this additional hypothesis, we interact the endogenous peer effect with industry-specific size quartiles and re-estimate the GS2SLS model (see Table 12 in appendix). Besides a main effect for size (positive and significant, as in the main model in the paper), the results for 2007 show a positive and statistically significant endogenous peer effect for the firms in the smallest size quartile, which acts as the reference group (coefficient 0.632, p-value 0.081) and which contains about 10% of the first-time adopters in that year. Interestingly, firms in the largest size quartile (which account for 40% of the first-time adopters in 2007) are less sensitive to peer effects (coefficient -0.512, p-value 0.082),[29] suggesting that larger firms are more able to keep track of new policy support measures, in line with the aforementioned survey evidence (e.g. Boucq & López Novella, 2018). If we omit the YIC-dummy from the specification - which may capture part of

[28] The difference between adoption and general usage behaviour can be seen in a pooled OLS estimation presented in Appendix in Table 11. 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).

[29] Although the interaction coefficient for the largest firms is negative, these firms still experience peer effects, but to a lesser extent. The effect for the largest firms is the linear combination of the general peer effect (coefficient 0.632) and the interaction of the endogenous effect with the corresponding size dummy (-0.512), thus a total effect of 0.120, which is smaller than that on the smallest firms. These results are robust to alternative definitions of firm size quantiles.

the size effect - the peer effect for the smallest firms becomes slightly more significant (coefficient 0.72, p-value 0.066). As was the case for the main results in Table 3, results are less outspoken for the later years. To provide additional robustness for this finding, we estimated similar models interacting the peer effect with firm age and, alternatively, the R&D intensity of the focal firm, again distinguishing between 4 industry-specific quartiles. These results are very similar to the ones for firm size.

3.7. Robustness checks

As we mentioned in section 2, firms' peer groups are defined based on 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 direct observation of firm interaction.[30] In other words, 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.[31] To investigate potential implications of a misspecified peer network, we therefore perform several robustness tests. First, following Helmers and Patnam (2014), we randomize peer 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 with 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 any remaining cross-industry and regional effects on adoption behaviour that are not accounted for by the industry and location dimension of the peer group definitions.

3.7.1. Misspecification of peer group structure

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. This method ensures that a firm's peers are randomly assigned while maintaining

[30] 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 exemption.

[31] For the SAR model without spatially correlated errors, a simpler version of the SARAR specification we use, 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.

the basic structure of the sample – that is, each industry and municipality will keep the true number of firms, keeping the distribution of firms over industries and locations intact.

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 3 show the distribution of point estimates of the endogenous peer effects obtained in the 100 replications for each period.[32]

[Figure 3 here]

The results show that we cannot reject the null of zero endogenous peer effects in the randomised networks.[33] In addition, we checked that 99% of the bootstrapped point estimates are statistically insignificant at the 10% level. The absence of peer effects in randomized networks confirms our definition of peer groups based on distance and industry.

3.7.2. Misspecification of peer group size

As explained in section 3.1, the empirical upper bound on the peer group size imposed 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.

As a robustness check, we restrict the maximum group size to respectively five and seven firms. The GS2SLS estimation results of endogenous peer effects are presented in Table 4. The complete results – including exogenous effects and individual characteristics - are included in Appendix in Table 13.

[Table 4 here]

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. However, when defining peer groups of five firms, we are unable to robustly identify endogenous peer effects.

[32] 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 4 in Appendix.

[33] 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 indicate that groups of ten peers are sufficiently broad containers of firm interaction while progressively smaller peer groups fail to capture peer effects.[34] Combined with the network scramble test, we are confident that the used peer groups sufficiently accurately capture the real network structure of firms.

3.7.3. Misspecification of industry scope in peer groups

Another issue in the peer group definition is the sensitivity of our findings to the aggregation level of the industry dimension. Underlying our main model, we defined peer groups within 3-digit NACE code industries. Although this choice is consistent with prior empirical studies on peer effects in firm decision making (e.g. Leary & Roberts, 2014), we test alternative definitions of industry boundaries. Table 5 shows the results of GS2SLS estimations for K=10, the same peer group size as in the main model, but using 2 and 4-digit NACE sectors, respectively. None of the endogenous peer effect coefficients are significant at 10% level, although they are similar in magnitude to our main results. These results indicate that peer effects operate at 3-digit NACE sector level, as lower or higher granularity does not seem to appropriately capture 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 the defined peer groups do not contain all relevant links.[35]

[Table 5 here]

3.7.4. Common shocks at peer group level

In our model, we do not specifically control for industry and geographical region because these two dimensions are part of the definition of peer groups. However, there may exist region- and industry-wide influences that extend beyond the reach of the peer group and that may lead both the focal firm and (excluded) peers to adopt the R&D tax exemption. More specifically, there may be government-initiated communication campaigns about new R&D support policies at the regional level since this is where the authority over R&D policy resides in Belgium, rather

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

[35] For example, NACE code 26 (*Manufacture of computer, electronic and optical products*) groups fairly heterogeneous firms, encompassing 3-digit industries like NACE code 26.3 (*Manufacture of communication equipment*) and 26.7 (*Manufacture of optical instruments and photographic equipment*). Conversely, going beyond the 3-digit level, the relatedness of industries is very high, e.g. NACE code 26.11 (*Manufacture of electronic components*) and 26.12 (*Manufacture of loaded electronic boards*), justifying a single peer group.

than at the national level. Analogously, firms are linked in cross-industry associations, such as the Belgian Federation for the Technology Industry that groups all high-tech firms, regardless of their precise industry. Such federations may also serve as vehicles for diffusion of information on new R&D policies, operating at a higher level of aggregation than the peer groups as we defined them. As a robustness check, we therefore re-estimate the spatial model including binary indicators for the three geographical-administrative regions – Brussels (baseline), Wallonia and Flanders – and four broad groups of industries – high- and low-tech manufacturing and high- and low-tech services. Although including these covariates reduces the identifying variation of the endogenous and exogenous effects, the coefficients generally remain robust and show similar values and significance to the main specification, as can be seen in Table 6. Moreover, the included region indicators are not significant, with one exception. Similarly, industry affiliation seems to matter little in firms' use of tax exemptions, 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 exemptions. Jointly, these results show the robustness of our main specification and the adopted peer group specification.

[Table 6 here]

4. Conclusions

Both at the level of OECD countries and within the European Union, R&D tax measures have become increasingly popular over the past decade (OECD, 2017). Although an increasing number of studies investigate the additionality effects of these support instruments, hardly any evidence exists why a substantial number of eligible firms does not make use of them (Falk *et al.*, 2009; Soete, 2012; Bozio *et al.*, 2014; Dumont, 2017).

We draw on competitive cognition theory to argue that imperfect information explain delayed adoption by eligible firms and that these circumstances create the potential for peer-to-peer diffusion of information and imitation of early adopters. The basic premise of the paper is that this imitation behaviour does not occur randomly but within well-delineated peer groups defined by industry and geography Using an identification strategy that exploits the network characteristic of incompletely overlapping peer groups, our empirical analysis provides

evidence that peer influence among nearby firms in the same industry fosters the adoption of R&D tax exemptions.

Consistent with a bounded rationality perspective and with survey evidence of firms' unawareness of innovation support measures, we interpret imitation of peers' decisions as a way for firms to cope with the multitude of public support measures they face, which are not always efficiently 'marketed' by public authorities. To our knowledge, this paper is the first to take a behavioural perspective on firms' decisions to use public R&D support. We also contribute to the growing empirical evidence of peer effects in firm decision making, which has so far primarily focused on applications in finance and corporate strategy. As a methodological contribution, the establishment of peer effects as a significant factor driving firms' selection into support schemes informs the literature on selection bias in program evaluation (Imbens & Wooldridge, 2009) and calls for looking beyond the individual firm to explain selection into support programs. Including adoption by a firm's peers as an explanatory factor for firm participation in a programme would help to satisfy the conditional independence assumption underlying matching estimators, or to identify the parameters of the selection equation in two-step estimations. Furthermore, our approach of exploiting intransitivity in firms' networks is more generally applicable to identify peer effects in other settings, which are potentially numerous given the high degree of clustering in 'small world' networks (Fleming & Marx, 2006).

From a policy perspective, the finding of positive peer effects in firms' decisions to adopt public support for R&D is important in the light of the tenacious proliferation and fragmentation of public support schemes, which is generally believed – and reported by firms themselves - to create a situation that bewilders the intended beneficiaries. Our results suggest the presence of important multiplier effects of targeted communication to foster adoption of public R&D support. In particular, wider adoption by eligible firms could be expedited by communicating the measure to sufficiently fine-grained sectors and in a geographically-distributed way. The model estimates indicate that ensuring that one in every ten peer firms knows about – and uses – the fiscal measure can increase adoption by as much as 11 percentage points. As opposed to broad policy communications, such better targeted 'narrowcasting' to clusters of firms would trigger peer-to-peer influence and promote adoption.

Of course, our work is not without limitations given the numerous empirical challenges. While we have strived to be as rigorous as possible in our identification strategy, it is possible that due to data limitations the analysis misattributes an unobserved driver of tax exemption

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 measure of peer effects may fail to pick up information flows between entities of the same corporate group, such as between the corporate headquarters and its local affiliates in Belgium.

Further, the lack of direct observation of peer groups and the sampling of firms – even if fully random – still allow for residual measurement error and thus a misspecified network structure (Chandrasekhar & Lewis, 2011). However, virtually all studies of peer effects suffer from potential measurement error in the definition of peer groups, since the precise mechanism that underlies the interaction is typically not known, and the type and degree of interactions are specific to the empirical context (De Giorgi *et al.*, 2010). However, this paper puts forward an array of robustness checks in terms of structure, size, industry scope, and common shocks of the peer groups that warrant confidence in the findings.

Finally, while the simple information diffusion framework underlying peer interaction accommodates the fading of the effect, it is hard to formally test for saturation effects due to short time frame of the data.

Our work triggers several avenues for further research. First, recent work on firms combining multiple types of R&D support measures shows evidence of complementarities between R&D grants and fiscal support (e.g. Neicu *et al.*, 2016). One interesting question in this respect is whether late adopters of R&D support who are driven by peer effects show the same additionality effects as early adopters. Second, given that our results suggest that smaller firms are more susceptible to peer effects than large firms, firm heterogeneity could be explored further in order to better understand the interaction with firm characteristics, and we hope future work can address these ideas in larger datasets.

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Figures

Figure 1: Share of R&D tax exemption users among eligible firms, by municipality in 2007

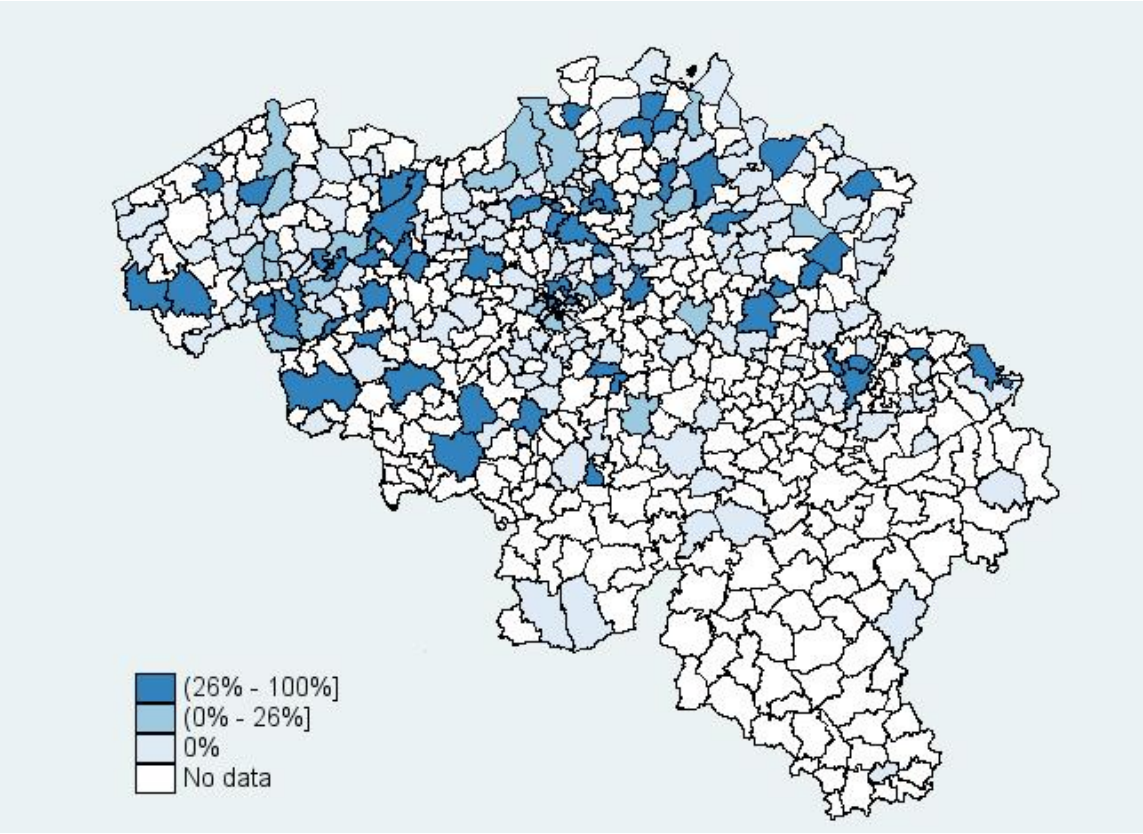
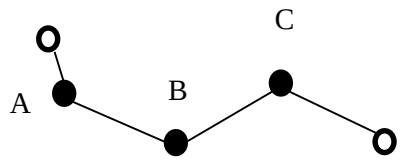
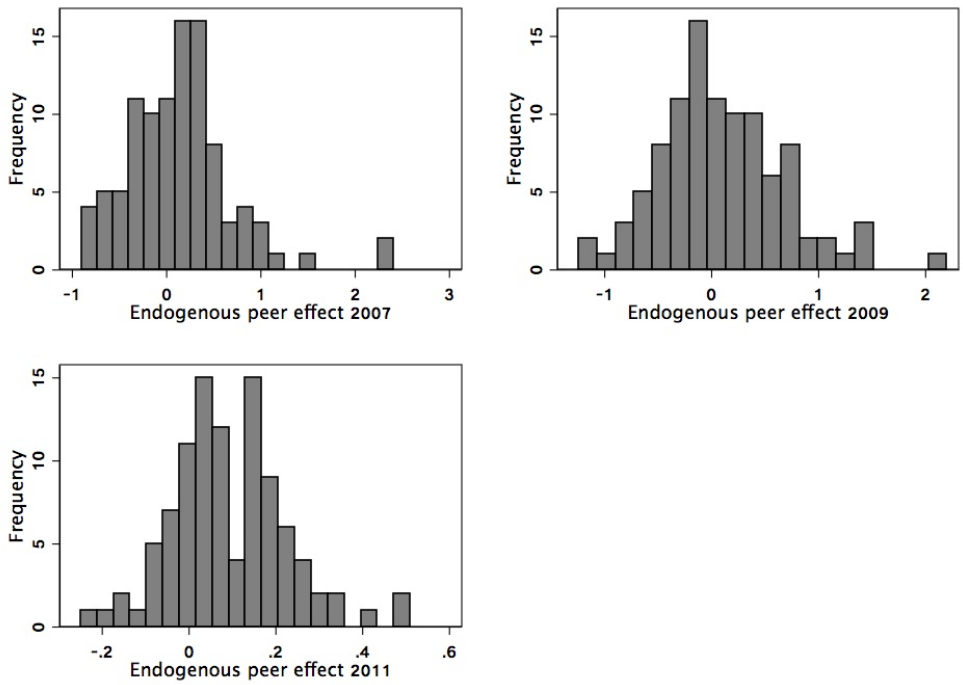


Figure 2: Schematic representation of intransitivity in peer networks



Note: The dots show geographically distributed firms in the same industry. For a peer group defined on the basis of industry and the 3 nearest neighbours, firm A is excluded from firm C's peer group, and vice versa, while B's peer group includes both A and C.

Figure 3 Robustness check using randomized peer networks



Note: The histograms show the distribution of point estimates of the endogenous peer effect using peer groups of 10 randomly chosen peers and 100 replications for each period.

Tables

Table 1 Percentage of firms having at least K nearest neighbours in their 3-digit NACE industry

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%

Table 2 Comparison of in-sample tax exemption use with the population of tax exemption users

	2007	2009	2011
Sample			
Tax exemption users	151	319	408
First-time users	40	83	28
% first-time users	26%	26%	7%
Population			
Tax exemption users	578	1,131	1,330
First-time users	245	395	167
% first-time users	42%	35%	13%

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

b) The table does not comprise adoption rates in even years, which implies that first-time use and overall use are not cumulative.

Table 3 OLS and GS2SLS estimations of endogenous peer effects from the closest ten peers

	2007			2009			2011		
	OLS	GS2SLS	GS2SLS	OLS	GS2SLS	GS2SLS	OLS	GS2SLS	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)
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)
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)
Prior use of R&D 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)
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)
Intercept	-0.019	-0.031	0.140	0.003	0.009	0.472**	0.049**	0.037*	0.067
	(0.028)	(0.027)	(0.102)	(0.030)	(0.025)	(0.230)	(0.019)	(0.021)	(0.047)
Contextual effects	*no*	*no*	*yes*	*no*	*no*	*yes*	*no*	*no*	*yes*
Obs.		*699*			*961*			*1018*	

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Standard errors in parentheses.
c) Models 1c, 2c and 3c include contextual peer effects not shown in table – see Table 10 in Appendix for full results.

Table 4: Endogenous peer effect 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)
Observations	*699*	*961*	*1018*

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

Table 5 Endogenous effect from ten peers in groups defined by 2 and 4-digit NACE sectors

	2007	2009	2011
3-digit NACE	0.586**	1.122**	0.103
	(0.259)	(0.562)	(0.136)
2-digit NACE	0.371	1.781	0.261
	(0.467)	(1.682)	(0.191)
4-digit NACE	0.405	0.271	-0.090
	(0.316)	(0.499)	(0.142)

a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively. Standard errors in parentheses.
b) Contextual effects, spatial errors and the intercept are estimated but not shown: see Table 14 in Appendix for full results.

Table 6 GS2SLS estimations of endogenous and exogenous peer effects from the closest ten peers including industry and region indicators

	2007	2009	2011
Endogenous effect	0.672**	1.350*	0.177
	(0.313)	(0.798)	(0.156)
Log(Employees)	0.010	0.022***	-0.001
	(0.007)	(0.008)	(0.004)
R&D intensity	-0.001*	0.001	0.000
	(0.000)	(0.001)	(0.000)
YIC	0.035	-0.026	-0.026**
	(0.039)	(0.060)	(0.013)
Prior use of R&D 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 manufacturing	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)
Observations	*699*	*961*	*1018*

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 15 in Appendix for full results.
c) Standard errors in parentheses.

Appendix

Table 7 Summary statistics of dependent and independent variables

	2007		2009		2011	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
First-time use♦	0.06	0.23	0.09	0.28	0.03	0.17
Overall tax exemption use	0.22	0.41	0.33	0.47	0.40	0.49
Observations	*699*		*961*		*1018*	
Non-users of the R&D tax exemption						
Nr of employees (FTE)	117.80	265.17	79.21	193.43	79.21	202.73
R&D intensity	0.15	0.21	0.14	0.18	0.16	0.20
YIC	0.05	0.22	0.03	0.17	0.04	0.19
R&D subsidy user	0.17	0.37	0.11	0.32	0.15	0.36
Observations	*548*		*642*		*610*	
Users of the R&D tax exemption						
Nr of employees (FTE)	431.05	870.15	282.64	642.86	248.15	529.86
R&D intensity	27.84	26.50	24.96	27.12	24.33	25.79
YIC	0.10	0.30	0.08	0.26	0.08	0.27
R&D subsidy user	0.48	0.50	0.31	0.46	0.36	0.48
Observations	*151*		*319*		*408*	

♦ The percentage of first-time users is relative to the number of R&D active firms in the sample. To obtain the values in Table 2, row one needs to be divided by row two (differences are due to rounding).

Table 8 Summary statistics of average peer group characteristics and tax exemption use

	2007		2009		2011	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
W*Tax exemption 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) Estimations exclude contextual peer effects.

Table 9 Correlation between dependent and independent variables

	Adopters	Users	Log(Employees)	YIC	Subsidy	R&D intensity
			2007			
Adopters	1.00					
Users	0.46	1.00				
Log(Employees)	0.12	0.30	1.00			
YIC	0.02	0.08	-0.28	1.00		
Subsidy	0.06	0.30	0.06	0.18	1.00	
R&D intensity	-0.05	0.22	-0.41	0.39	0.29	1.00
			2009			
Adopters	1.00					
Users	0.44	1.00				
Log(Employees)	0.07	0.33	1.00			
YIC	0.01	0.11	-0.24	1.00		
Subsidy	-0.03	0.24	0.08	0.09	1.00	
R&D intensity	0.02	0.23	-0.38	0.36	0.20	1.00
			2011			
Adopters	1.00					
Users	0.21	1.00				
Log(Employees)	0.01	0.30	1.00			
YIC	-0.01	0.09	-0.27	1.00		
Subsidy	-0.04	0.24	0.10	0.04	1.00	
R&D intensity	-0.03	0.17	-0.38	0.25	0.14	1.00

a) ‘Adopters’ refers to first-time users of tax exemptions; ‘Users’ refers to general use.

Table 10 GS2SLS estimations of peer effects from the closest ten peers, with exogenous peer effects also shown (variables prefixed by *W*)

	2007 GS2SLS 1c	2009 GS2SLS 2c	2011 GS2SLS 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)
R&D Intensity	-0.001**	0.001	-0.0002
	(0.001)	(0.001)	(0.0002)
YIC	0.043	0.026	-0.029***
	(0.039)	(0.055)	(0.010)
Prior use of R&D Subsidies	0.005	-0.060**	-0.027***
	(0.023)	(0.028)	(0.015)
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*Subsidy use	0.014	-0.267	-0.017
	(0.074)	(0.170)	(0.044)
Spatial error θ	0.233***	0.298**	0.02
	(0.091)	(0.120)	(0.048)
Intercept	0.140	0.472**	0.067
	(0.102)	(0.230)	(0.047)
Observations	*699*	*961*	*1018*

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

Table 11 OLS estimations of tax exemption adoption and general usage without peer effects

	Adoption	Usage	Adoption 2007	Adoption 2009	Adoption 2011
	1	2	3	4	5
Log(Employees)	0.011***	0.133***	0.017***	0.019***	-0.001
	(0.003)	(0.006)	(0.006)	(0.007)	(0.004)
R&D intensity	0	0.006***	0	0.001**	0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
YIC	0.02	0.200***	0.065*	0.013	-0.027
	(0.021)	(0.036)	(0.038)	(0.044)	(0.025)
Prior use of R&D Subsidies	-0.015	0.162***	0.015	-0.040*	-0.02
	(0.011)	(0.020)	(0.022)	(0.024)	(0.014)
2009	0.033***	0.144***			
	(0.011)	(0.020)			
2011	-0.027**	0.205***			
	(0.011)	(0.020)			
Intercept	0.01	-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 exemptions on the pooled cross sections of 2007, 2009 and 2011. Columns 3-5 are estimations of first-time use on split samples by year.

Table 12 GS2SLS estimations with interaction between peer effects and firm size (quartiles)

	2007	2009	2011
	GS2SLS	GS2SLS	GS2SLS
	1c	2c	3c
Endogenous peer effect	**0.632***	**0.739**	**0.095**
	(0.362)	**(0.492)**	**(0.163)**
Endog. effect x size quartile 2	**-0.382**	**-0.427**	**-0.035**
	(0.258)	**(0.269)**	**(0.081)**
Endog. effect x size quartile 3	**-0.236**	**-0.526***	**-0.086**
	(0.275)	**(0.304)**	**(0.108)**
Endog. effect x size quartile 4	**-0.512***	**-0.632***	**-0.115**
	(0.294)	**(0.379)**	**(0.141)**
Log(Employees)	0.028**	0.052**	0.009
	(0.011)	(0.021)	(0.013)
R&D Intensity	-0.001*	0.001**	0.000
	(0.000)	(0.001)	(0.000)
YIC	0.051	-0.003	-0.034**
	(0.041)	(0.054)	(0.015)
Prior use of R&D Subsidies	0.016	-0.044*	-0.024*
	(0.023)	(0.025)	(0.013)
W*R&D Intensity	-0.001	-0.004*	0.000
	(0.002)	(0.002)	(0.001)

W*Subsidy use	0.022	-0.085	0.010
	(0.083)	(0.099)	(0.036)
W*Log(Employees)	-0.036	-0.067	-0.013
	(0.028)	(0.047)	(0.020)
W*YIC	-0.119	0.084	-0.079*
	(0.100)	(0.130)	(0.046)
Spatial error θ	0.114*	0.117	0.006
	(0.061)	(0.098)	(0.069)
Intercept	0.057	0.131	0.040
	(0.097)	(0.108)	(0.040)
Observations	*699*	*961*	*1018*

Table 13 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)
Log(Employees)	0.012*	0.014	-0.003	0.011*	0.018*	0.000
	(0.006)	(0.011)	(0.003)	(0.006)	(0.010)	(0.004)
R&D intensity	-0.001*	0.002*	0.000	-0.001**	0.000	0.000
	(0.001)	(0.001)	(0.000)	0.000	(0.001)	(0.000)
YIC	0.058	0.026	-0.021	0.052	0.019	-0.035***
	(0.039)	(0.062)	(0.013)	(0.039)	(0.070)	(0.013)
Prior use of R&D subsidies	0.005	-0.009	-0.015	0.003	-0.096**	-0.032*
	(0.023)	(0.060)	(0.014)	(0.023)	(0.043)	(0.017)
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*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*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)
Intercept	0.117	-0.517	0.017	0.138	0.942*	0.128*
	(0.157)	(0.778)	(0.057)	(0.122)	(0.503)	(0.069)
Observations	*699*	*961*	*1018*	*699*	*961*	*1018*

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

Table 14 GS2SLS estimations of peer effects with groups defined at 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)
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)
Log(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)
Prior use of R&D Subsidies	0.014	0.005	-0.071**	-0.051*	-0.026**	-0.016
	(0.022)	(0.025)	(0.030)	(0.027)	(0.012)	(0.012)
W*Log(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*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)
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)
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)
Observations	*722*	*645*	*984*	*908*	*1037*	*965*

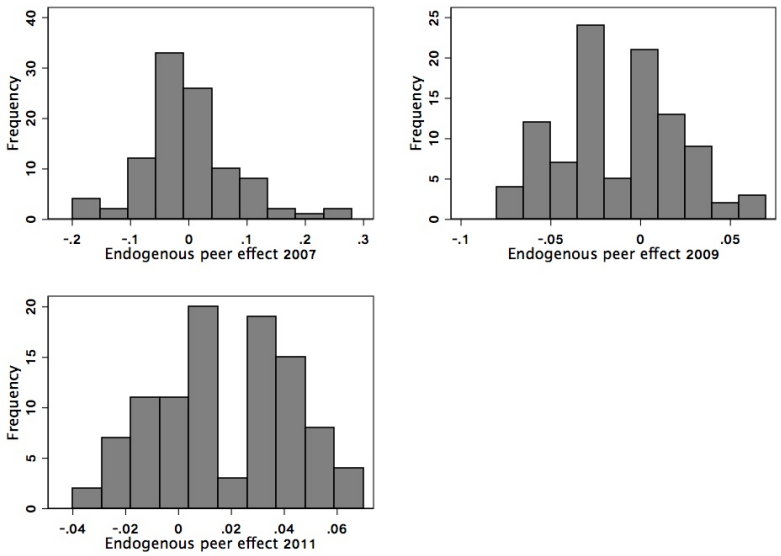
a) ***, **, and * indicate significance levels of 1%, 5% and 10%, respectively.
b) Standard errors in parentheses.
c) The number of observations used in estimations differs from one definition to the other because we restrict peer groups to at least two firms; this implies that more observations drop out because more 4-digit NACE sectors only contain one firm.

Table 15 GS2SLS estimations of endogenous and exogenous peer effects from the closest ten peers including industry and region dummies

	2007	2009	2011
Endogenous effect	0.672**	1.350*	0.177
	(0.313)	(0.798)	(0.156)
Log(Employees)	0.010	0.022***	-0.001
	(0.007)	(0.008)	(0.004)
R&D intensity	-0.001*	0.001	0.000
	(0.000)	(0.001)	(0.000)
YIC	0.035	-0.026	-0.026**
	(0.039)	(0.060)	(0.013)
Prior use of R&D Subsidies	0.004	-0.044	-0.036**
	(0.024)	(0.028)	(0.016)
W*Log(Employees)	-0.051*	-0.156*	-0.024
	(0.028)	(0.089)	(0.021)
W*R&D intensity	-0.002	-0.012*	-0.001
	(0.002)	(0.007)	(0.001)
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)
Intercept	0.147	0.361	0.107
	(0.115)	(0.239)	(0.074)
Observations	*653*	*943*	*986*

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

Figure 4 Robustness check using randomized peer networks for the model excluding contextual peer effects



Note: The histograms show the distribution of point estimates of the endogenous peer effect using peer groups of 10 randomly chosen peers and 100 replications for each period.