R&D Subsidies & External Collaborative Breadth: Differential Gains and the Role of Collaboration Experience

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Abstract

External collaboration breadth is important for firms to acquire the knowledge needed to innovate. In this paper, we combine cross-sectional and longitudinal data from the Spanish Panel of Technological Innovation Survey (PITEC) to examine the indirect impact of R&D subsidies on firm external collaboration breadth. We contribute to understanding of the indirect impacts of R&D subsidies by first providing strong evidence of an economically significant average positive impact of R&D subsidies on firm external collaboration breadth. Second, our results advance understanding of the differential impacts of R&D subsidies by revealing the vast heterogeneity of the impact at the firm level, where approximately only half of treated firms experience a positive collaboration impact from R&D subsidies, while the remainder experience no impact or a negative effect. Finally, we advance understanding of the characteristics explaining the differential impact of R&D subsidies on external collaboration breadth by utilising the organisational learning literature to demonstrate the important role of firm collaboration experience.

Keywords: External Collaboration Breadth, R&D Subsidies, Differential Effects; Collaboration Experience, Innovation Policy, Treatment Effects.

1. INTRODUCTION

Governments commit substantial resources to R&D subsidies to stimulate firm innovation activities, for example, in Spain (the context of this study) more than 3 billion Euros were allocated between 2011 and 2013 (Fernandez-Zubieta, 2014; 2015). Consistent with the direct aim of R&D subsidies, vast empirical research has emerged showing that R&D subsidies stimulate firm R&D expenditure (e.g., Czarnitzki and Lopes-Bento, 2013; Dimos and Pugh, 2016). Beyond directly intended impacts, interventions typically also have *indirect* (unintended) impacts on organisations. While the behavioural additionality literature has postulated that R&D subsidies, through for example stimulating learning processes, induce important indirect impacts on organisations alongside their intended effects, we know little about the nature of these *indirect* impacts (Autio et al, 2008; Clarysse et al, 2009; Cunningham et al, 2016). Particularly, while the indirect impact on external collaboration has attracted some attention (Afcha, 2011; Busom and Ferandez-Ribas, 2008), reflecting its importance for innovation, our understanding of this relationship remains limited.

This paper advances understanding through examining the *indirect* impact of R&D subsidies on firm external collaboration *breadth* (Busom and Fernandez-Ribas, 2008), which we define as the number of partner types with which firms collaborate (e.g., Laursen and Salter, 2006). It is well established that as the knowledge needed for innovation has become increasingly complex and distributed across the innovation value chain (Chesbrough, 2006; Lakhani et al, 2013), that external collaboration *breadth* is central for firms to acquire the knowledge needed to innovate (e.g., Dahlander and Gann, 2010; Laursen and Salter, 2006). As such, we first examine the (average) indirect impact of R&D subsidies on external collaboration breadth, arguing that R&D subsidies, through enhancing firm absorptive capacity, generating new technological opportunities, and easing firm access to external finance, help stimulate firm external collaboration breadth. Second, we drill further into this relationship by explicitly considering both the *average* and *differential* impact. Existing research has predominately focused on the average effect, however, this is an important limitation since it is unlikely most participants obtain this effect, or close to it, given inherent differences in underlying firm characteristics (Cunningham et al, 2016; Lee, 2011). As such, by considering both the *average* and *differential* impact we advance the literature toward more nuanced understandings of the (in) direct impacts of R&D subsidies. Finally, we advance understanding of the characteristics explaining the differential (collaboration) impacts of

R&D subsidies by examining the important influence of collaboration experience, which existing research shows is an important antecedent of firm collaboration behaviour (Badilo and Moreno, 2016; Belderbos et al, 2012; Gulati, 1999). We argue that collaboration experience, through developing firm alliance formation capabilities, search capabilities, and signalling their quality, magnifies the *indirect* impact of R&D subsidies on external collaboration breadth.

We believe advancing this understanding is important for several reasons. First, while research suggests R&D subsidies directly stimulate R&D expenditure (Beck et al, 2016), the beneficial effects are small (Dimos and Pugh, 2016) and we know little about the *indirect* behavioural additionality impacts, particularly for external collaboration, despite its importance for innovation (Busom and Fernandez-Ribas, 2008; Clarysse et al, 2009). Considering policymakers' finite resources (Gupta and Guerguil, 2014; Mazzucato, 2013) and existing alternative interventions to R&D subsidies (e.g., R&D tax credits (Guerzoni and Raiteri, 2015), obtaining more comprehensive understanding of the (in)direct impacts of R&D subsidies is important for informing future innovation policymaking. Second, the established innovation benefits of external collaboration have stimulated policymaker attention and programmes focused on encouraging external collaboration (Chesbrough et al, 2011; Fabrizi et al, 2016). Given the significant resources currently devoted to R&D subsidies, advancing understanding of their utility to indirectly stimulate external collaboration, alongside their intended impacts, could inform and aid policymaker efforts to design effective policy mixes for stimulating external collaboration. Third, despite the importance of external collaboration breadth for firms to access the knowledge needed to innovate (Beck and Schenker-Wicki, 2014; Dahlander and Gann, 2010; Laursen and Salter, 2006;), the limited existing research has focused on the *indirect* impact of R&D subsidies on firm propensity to collaborate (Busom and Fernandez-Ribas, 2008), with little attention to the impact on the *breadth* of external collaboration. Finally, despite some attention to the differential impacts of R&D subsidies (Cunningham et al, 2016; Lee, 2011), empirical evidence on both the *extent* and *drivers* remains extremely limited (Beck et al, 2016; Clarysse et al, 2009; Hottenrott and Lopes-Bento, 2014). Redressing this is important to obtaining more nuanced understandings of who experiences the (in) direct impacts of R&D subsidies and what characteristics magnify (or weaken) the impacts. This understanding could inform policymakers about the types of participants for which R&D subsidies could be a useful instrument to stimulate greater external collaboration breadth.

To examine our questions, we utilise data from the PITEC on Spanish manufacturing and service firms, and a two-stage methodology. In the first stage, we use data from 2007 to 2013 in estimating a matching procedure to examine the *average* and *differential* impact of R&D subsidies on external collaboration breadth, while accounting for selection bias on observables. The robustness of the matching results to selection on unobservables is examined using instrumental variable regression. In the second stage, we use further data from 2002 to 2010 on firm collaboration experience in estimating OLS regressions examining whether collaboration experience magnifies the indirect impact of R&D subsidies on external collaboration breadth. In additional models, the *extent* and *age* of the collaboration experience are also considered.

This paper proceeds as follows. In section 2, we outline our conceptual framework, which considers the average and differential impact of R&D subsidies on external collaboration, and the role of collaboration experience in magnifying this impact. Section 3 overviews our data and methods. Section 4 overviews our key empirical findings and section 5 discusses our contributions to the literature and the implications of our findings for policymakers, organisations and future research.

2.0 EXTERNAL COLLABORATION, INNOVATION & R&D SUBSIDIES

External collaboration is a crucial innovation search strategy for organisations to acquire novel technologies and knowledge to sustain, enhance and accelerate their innovation efforts (Belderbos et al., 2004; Chesbrough, 2006). Existing research has shown external collaboration with a *breadth* of external partners is particularly important for innovation (Beck and Schenker-Wicki, 2014; Laursen and Salter, 2006; Roper et al, 2017). The importance of breadth stems from the technology and knowledge needed for innovation becoming increasingly complex and spread across the innovation value chain, such that collaborating with a breadth of diverse partners increases the odds firms will acquire the technology and knowledge needed to innovate successfully (Leiponen and Helfat, 2010). A significant body of empirical evidence has amassed demonstrating the innovation benefits of external collaborative breadth (e.g., Beck and Schenker-Wicki, 2014; Laursen and Salter, 2006; Love et al, 2014; Roper et al, 2017).

2.1 THE INDIRECT IMPACT OF R&D SUBSIDIES ON EXTERNAL COLLABORATIVE BREADTH

We argue that R&D subsidies indirectly stimulate increases in firm external collaboration breadth drawing on three mechanisms. First, through providing greater access to additional financial resources. Existing research shows that R&D subsidies, through providing a 'certification effect' about the quality of subsidized firms, enable them to more easily obtain additional finance from private investors (e.g., banks) (Cerulli et al., 2016; Kleer, 2010; Meuleman and Maeseneire, 2012). Participating in a breadth of external collaboration imposes significant financial costs for firms because it requires companies to expand their alliance management skills, which affects their cost structure (Cassiman and Valentini, 2016; Faems et al., 2010; Hottenrott and Lopes-Bento, 2016). Thus, we argue that by relaxing financial constraints, R&D subsidies can help firms expand their external collaboration breadth (Busom and Fernandez-Ribas, 2008; Cano-Kollmann et al, 2016). For example, the greater access to external finance could be used to fund the costs of acquiring and developing the personnel and internal structures needed to support and expand their external collaboration breadth (Belederbos et al, 2012; Faems et al., 2010; Leiponen, 2005). Empirically, Park et al (2002) demonstrate the importance of financial resources in increasing external collaboration breadth.

Second, firms gain new R&D experiences through performing their R&D subsidy-funded project, which increase supported firms' stocks of knowledge (Buisseret et al, 1995). The formation of these stocks provides supported companies with greater ability to identify, assimilate and apply external knowledge that is associated with the technological fields related to these stocks (Lee, 2011). This idea is coherent with the concept of absorptive capacity, according to which the degree of external knowledge utilisation is a function of the level of prior related knowledge a firm accumulates (Cohen and Levinthal, 1990). Additionally, as R&D subsidies typically fund far from market projects (Clausen, 2009; Santamaria et al., 2010), while managers prefer those closer to market, the knowledge gained in R&D subsidies is likely to be novel to firms' current knowledge stocks, thus increasing their diversity. Moreover, R&D subsidies encourage firms to perform more technologically challenging projects (DITRA, 2006; Falk, 2007; Hsu et al, 2009), which through learning processes can further increase the diversity of their knowledge stocks. The increased diversity of knowledge stocks is associated with improved absorptive capacity, with firms' ability to identify external knowledge being a function of their absorptive capacity (Lee, 2011; Cohen and Levinthal, 1990).

Thus, we argue that through increasing firm absorptive capacity R&D subsidies enhance their ability to identify diverse external collaborative partners. Enhanced absorptive capacity extends the knowledge and technological landscape within which firms can recognize and assimilate knowledge (Cohen and Levinthal, 1990). As such, firms can search and monitor knowledge and technological developments across multiple fields and recognise (potentially) valuable new developments that offer opportunities for collaboration (Zhang et al, 2007; Zhang, 2016). Thus, absorptive capacity can increase firms' availability of opportunities for external collaboration. Absorptive capacity also favours external collaboration breadth because it promotes firms to enlarge their knowledge bases by forming collaborations with organizations having different attributes, such as industry focus, routines, organizational structures and technologies (Lavie and Rosenkopf, 2006). This occurs because absorptive capacity reduces the costs of communicating, understanding and assimilating external knowledge, thus favouring effective collaboration with diverse partners (De Jong and Freel, 2010; Lane et al., 2001). Empirically, existing research supports our argument for absorptive capacity, showing that R&D intensity, a typical proxy of absorptive capacity, positively influences firm propensity to collaborate and their external collaborative breadth (Belderbos et al, 2004; Chun and Mun, 2012; Laursen and Salter, 2014; Segarra-Blasco and Arauzo-Carod, 2008).

Third, the experience and results of R&D subsidy projects may provide new technological opportunities (e.g., solutions to existing innovation problems) that firms subsequently pursue in new R&D projects (Lee, 2011). For example, Hottenrott et al (2017; 1120) note that the results of firms' R&D subsidy funded research (development) projects inform and direct their subsequent development (research) projects toward promising opportunities. This idea is also consistent with innovation persistence research that suggests current innovation projects generate opportunities pursued in subsequent projects (e.g., Peters, 2009; Triguero and Córcoles, 2013). We argue that the opportunities discovered through R&D subsidy projects may stimulate firms to expand their external collaborative breadth to exploit discovered opportunities. Our reasoning is as follows. Considering R&D subsidies fund different types of projects (e.g., far from market and/or more technologically challenging) than firms typically perform themselves (DITRA, 2006; Santamaria et al., 2010), the resources required to exploit the discovered opportunities may not reside within the firm, but instead be spread across multiple organisations (Lakhani et al., 2013; Rothaermel and Deeds, 2004). Consequently, to successfully exploit the opportunities firms need to form collaborations with diverse partners to acquire and access the necessary resources (Grant and Baden-Fuller, 2004; Lee and Wong, 2009), leading to enhanced external collaboration breadth (Cerulli et al, 2016; Kang and Park, 2012).

Existing research supports our argument that R&D subsidies indirectly stimulate firm external collaboration breadth. Cano-Kollmann et al (2016), Cerulli et al (2016) and Chapman and Yacoub (2016), using data on European, Italian, and British firms respectfully, find that R&D subsidies stimulate increases in firm external collaborative breadth. Others (e.g., Afcha, 2011; Busom and Fernandez-Ribas, 2008; Kang and Park, 2012) show that R&D subsidies increase the likelihood of external collaboration with a range of partner types (e.g., universities, suppliers) in Spain, Italy and Korea. Taken together, the discussion suggests R&D subsidies *indirectly*, through enhancing absorptive capacity, generating new technological opportunities, and easing access to external finance, helps firms expand their external collaboration breadth.

2.2 DIFFERENTIAL GAINS FROM R&D SUBSIDIES

We proceed to explore the (potential) differential collaboration impact firms experience from R&D subsidies, both in terms of the extent and drivers. The concept of differential gains suggests that distinct types of firms experience different impacts from R&D subsidies, which could be in terms of the direction (i.e. positive/negative) and/or magnitude of the impact. However, while some research (e.g., Beck et al, 2016; Hottenrott et al, 2015) have provided initial empirical insight on the differential gains of R&D subsidies for R&D expenditure (showing only half of firms benefitted), guidance remains extremely limited, particularly for indirect impacts such as external collaboration (Cunningham et al, 2016). The existence of differential gains where the positive (negative) impact of an intervention is concentrated in only a subset of subsidised firms, casts doubt on the analytical value of *solely* considering the 'average effect'[1], as is predominately standard in existing research (Cunningham et al. 2016). This focus on the average effect is particularly problematic as most firms likely do not obtain

1 Nightingale and Coad (2014) recently made a similar observation relating to the skewed distribution of the contribution of 'entrepreneurial' firms, with the authors arguing for the need to consider more granular conceptualisations to obtain more useful and accurate insights.

this impact, or close to it. As such, it is necessary to consider the *extent* and *drivers* of differential impacts to obtain more nuanced insights into the (in)direct impacts of R&D subsidies and to whom they accrue. This paper advances in this direction by explicitly considering both the *average* and *differential* effect of R&D subsidies on external collaboration, and drawing on the organisational learning literature to shed light on the drivers, by postulating collaboration experience magnifies the indirect impact of R&D subsidies on external collaboration.

2.3 COLLABORATION EXPERIENCE

We argue that the indirect effect of R&D subsidies on external collaboration breadth will be greater for firms with collaboration experience. The significant value of 'experience' for organisations is well established in management literature (e.g., Argote et al, 1990; Levitt and March, 1988), with two main benefits of collaboration experience identified. First, that collaboration experience enhances firm ability to manage and appropriate value from collaborative relationships, such that the returns from a given set of partnerships are greater for firms with collaboration experience (e.g., Anand and Khanna, 2000; Love et al, 2014; Sampson, 2005). Second, that collaboration experience develops firm alliance formation capabilities, their search capabilities, and signals their quality, such that experience enhances firm efforts to grow and diversify their external collaborative activities (e.g., Badilo and Moreno, 2016; Belderbos et al, 2012; Gulati, 1999; Jacob et al, 2013; Powell et al, 1996; Simonin, 1997). As this paper focuses on the determinants of external collaboration breadth, we develop our argument drawing on the second benefit of collaboration experience.

First, we propose that collaboration experience magnifies the indirect effect as firms develop alliance formation capabilities, which eases the formation of new collaborations (Gulati, 1999). Forming new collaborations is a difficult and complex process, involving negotiations on collaboration agreements and the formation of internal structures and procedures to support collaborations (Gulati and Gargiulo, 1999; Tsai, 2000). Alliance formation capabilities can ease this process, as they comprise the routines, procedures and cognitions, such as rules on sharing and protecting knowledge and intellectual property, project consideration rules, clarifications on decision-making authority and attitudes to external knowledge, developed and internalised through collaboration experience, which facilitate the development of collaborative relationships (Antons and Piller, 2015; Beers and Zand, 2014; Gulati, 1999; Katila and Mang, 2003; Mitchell and Singh, 1996). For example, alliance formation capabilities boost firm ability to form collaborative agreements, as firms can draw on the established routines (e.g., negotiation strategies) and procedures (e.g., prior legal frameworks) developed and refined through prior experience to overcome and manage the challenges (Anand and Khanna, 2000; Bianchi and Lejarraga, 2016; Ryall and Sampson, 2009).

Expanding external collaboration depends on firms' identification of attractive and reliable prospective partners, but identifying such partners is difficult, given vast information asymmetries (Badilo and Moreno, 2016; Gulati, 1999; Simonin, 1997). Our second mechanism proposes that collaboration experience magnifies the indirect effect by enhancing the productivity and effectiveness of firm efforts to identify new collaborative partners. First, firms can gain access to information about current and prospective collaborative partners, and their attractiveness and reliability, from their prior collaborative partners (Gulati, 1999). This information through reducing information asymmetries and providing direction to firms search efforts can increase the productivity and effectiveness of firm search, and thus, facilitate the expansion of external collaboration (Gulati, 1995; Powell et al, 1996). Second, firms develop and refine their search routines through their collaboration experience (e.g., drawing lessons from prior search strategies), which enhances their productivity and effectiveness in identifying new collaborative opportunities (Gulati, 1995; Simonin, 1997). Moreover, as search is path-dependent (Levinthal and March, 1993; Teece et al, 1997), firms with collaboration experience are also more likely to search non-locally to identify external collaborative opportunities, compared to firms without experience (Badilo and Moreno, 2016; Beers and Zand, 2014; Belderbos et al, 2012; Rosenkopf and Nerkar, 2001).

Finally, we propose that collaboration experience magnifies the indirect effect by signalling firm quality to prospective partners. Existing research argues collaboration experience can signal firm quality and through this facilitate greater external collaboration by reducing information asymmetries (e.g., Badilo and Moreno, 2016; Gulati, 1995; Jacob et al, 2013; Ozmel et al, 2013). Collaboration experience may signal that firms possesses valuable resources, capabilities and assets that motivated prior partners to form collaborative ties and share knowledge (Gulati and Higgins, 2003; Nicholson et al, 2005; Ozmel et al, 2013; Podolny, 2001). As such, this could motivate prospective partners to collaborate with a firm to gain access to the valuable resources, capabilities and assets. The signal that firms possess valuable resources, capabilities and assets may also send positive signals about the prospects of the collaboration to generate value (Ozmel et al, 2013). As such, this could motivate prospective partners to collaborate with a firm due to the (perceived) greater probability of value generation. Finally, the quality signal could also operate directly through prior partners referring the firm to new partners (Gulati, 1999; Granovetter, 1985), thus, acting as an interorganisational endorsement for otherwise unknown firms that reduces information asymmetries (Ozmel et al, 2013; Stuart et al, 1999). Taken together, collaboration experience provides firms with status signals (Gulati, 1998; Podolny, 2001) that can reduce information asymmetries, helping to attract new partners and easing the partnership formation process (Eisenhardt and Schoonhoven, 1996; Gulati, 1999; Ozmel et al, 2013; Stuart et al, 1999; Stuart, 1998).

Empirically, a rich body of evidence has supported our arguments of collaboration experience boosting firm external collaboration activities. Belderbos et al (2012), Gareete et al (2009), Gulati (1995; 1999), Jacob et al (2013), Katila and Mang (2003), and Mitchell and Singh (1996) show that firms with collaboration experience are more likely to engage in new collaborations in future. Using data on Spain, the context of this study, Badilo and Moreno (2016) also show that firms with collaboration experience are more likely to engage in new future collaborations. Katila and Mang (2003) and Al-Laham et al (2008) show that firms with collaboration experience form collaborations from opportunities more quickly. Pangarkar et al (2017), Stuart (1998), and Tyler and Canner (2016) show that collaboration experience stimulates the expansion of the number of firms' collaborative relationships. Finally, Powell et al (1996) and Beers and Zand (2014) show that collaboration experience stimulates firms to undertake more diverse (i.e. partner types) future collaborative relationships, and similarly, Shukla and Mital (2016) show that collaboration experience and the diversity (i.e. different partner types) of firms' collaboration experience stimulates firms to collaborate with a more diverse set of future partners.

The above discussions suggest that firm collaboration experience is significantly related to their future collaborative activities, with firms with collaboration experience more likely to expand and diversify their future collaborative activities. This stems for collaboration experience developing firm alliance formation capabilities, search capabilities, and signalling their quality, which enhances their ability to expand and diversify their external collaborative activities. As such, we argue that the indirect effect of R&D subsidies on external collaboration breadth will be greater for firms with collaboration experience.

3.0 METHODOLOGY AND DATA

3.1 INSTITUTIONAL CONTEXT OF SPANISH NATIONAL INNOVATION POLICY

In Spain, national public intervention in innovation is implemented through the National R&D Plan. Since 1988, rolling National R&D plans have been created to articulate the objectives of the Spanish Government's Science, Technology and Innovation Strategy and to define the policy instruments utilised by the Spanish Government to achieve the objectives (Ballesteros and Rico, 2001; Busom and Fernandez-Ribas, 2008). Our reference period for the R&D subsidy and outcome variable refers to the years 2010 to 2013 in which the 2008-2011 and 2013-2016 plans were in place (CICYT, 2013). Particularly the 2008-2011 plan is of relevance, as 2010 is the period the R&D subsidies under consideration were awarded (section 3.2). The 2008-2011 plan focused on four main areas: knowledge generation and capability building, promoting collaboration in R&D, sectoral technological development and innovation, and strategic activities (CICYT, 2007). While stimulating collaboration was an important objective, most programmes did not require collaboration as a precondition of receiving support (Busom and Fernandez-Ribas, 2008; CDTI, 2010)[2]. As such, we are interested in the *indirect* impact of R&D subsidies, mainly intended to fund internal R&D activities, on firm external collaboration breadth.

Spain is an attractive context for our questions as levels of collaboration are limited compared to other European Union (EU) partners (CICYT, 2007). Utilising the 2014 Community Innovation Survey (CIS) measures used here to measure collaboration breadth, we observe in Figure 1 that the percentage of Spanish firms declaring to collaborate with five of the six different types of partner is below the EU average (See Eurostat, 2017). For example, while 32.1% of firms declare to be engaged in any type of collaboration, the EU average is 33.1% and top countries report more than 50%. Similar figures are reported for collaboration with each of the partner types, suggesting lower rates of collaboration in Spain.

[INSERT FIGURE 1 HERE]

[2] Some programmes did encourage collaboration, with several national programmes in 2010 (our subsidy year), specifically incentivising firms to engage in additional collaboration. Such firms received an additional 10%-18% of the total project costs for engaging in additional collaboration (CDTI, 2010).

As innovation policy is multi-level, Spanish firms may also receive support from regional and European programmes. We focus solely on national programmes however, as in regional and European programmes, collaboration is often a precondition of receiving support. This may cause an endogeneity problem, thus following Busom and Fernandez-Ribas (2008) we exclude such programmes. For national programmes, collaboration is not a precondition of receiving support for most programmes (Busom and Fernandez-Ribas, 2008; CDTI, 2010). For example, in 2010, of all the projects awarded R&D subsidies by the Centre for Development of Industrial Technology (CDTI), which is the body predominantly responsible for distributing national support in Spain, approximately 90% did not require collaboration as a precondition (CDTI, 2010). In addition, given we are interested in the impact of R&D subsidies on the *breadth* (number of partner types) of collaboration, and not whether firms engage in collaboration, this precondition does not necessarily induce endogeneity in our case.

3.2 DATA

The data for this study comes from the PITEC. The Spanish National Statistical Institute (INE), in association with the Spanish Science and Technology Foundation (FECYT) and the Foundation for Technological Innovation (COTEC), collects these data. As with the CIS, PITEC applies the methodological guidelines defined by the Organization for Economic Cooperation and Development's (OECD) Oslo Manual (OECD, 2005). Questionnaires are sent to the CEOs of organizations and the response rate across the survey period is approximately 92% (Escribano et al, 2009)[3]. Thus, the PITEC offers highly representative data for Spanish organizations. The important advantage of this data for our research is the fact a representative sample of manufacturing and service firms are observed repeatedly over a long period, making the data very suitable for examining the influence of collaboration experience, a construct typically measured over 6 to 9 year periods, while allowing for appropriate staging of variables that avoid simultaneity problems. Equally, detailed information on innovation characteristics is captured in the PITEC, thus, offering a rich dataset from which to examine our key research questions.

The structure and timing of the data are as follows. First, we use cross-sectional data from the PITEC for the period 2007-2013 in the evaluation of the effects of R&D subsidies on

3 This high response is due to firms being legally obliged to answer surveys from Spanish National Institute of Statistics (INE).

collaboration breadth. Specifically, 2010 is the treatment period in which we consider whether firms receive R&D subsidies, 2011 to 2013 is the outcome period, where we observe the impact of R&D subsidies on external collaboration, and 2007-2009 is the pre-treatment period, where we measure the control variables used in our matching procedure (See section 3.3.1). Second, to examine the role of collaboration experience in magnifying the impact of R&D subsidies on external collaboration breadth, we complement the above with data from 2002-2010 on firm collaboration experience, in line with traditional measurement periods for collaboration experience (Heimeriks & Duysters, 2007; Kavusan et al, 2016). Despite the panel structure of the PITEC, our empirical design exploits cross-sectional data in each stage of the research, along with combined information about collaboration experience for the period 2002-2010. The use of the panel explicitly is prevented by the long-time period needed to test our arguments. As commented above, to holistically capture collaboration experience, we require nine years of data.

The panel of companies available in the PITEC is unbalanced during the period 2002-2010. Companies may stop providing information for several reasons, such as mergers, closure, and liquidation. To preserve representativeness, new companies have been incorporated into the survey since 2004. The share of companies that drop out the survey was 1.54% in 2004, 1.95% in 2007 and 1.88% in 2010. These figures reveal a low rate of panel mortality for the period under consideration. Compared to dropout observations, companies staying in the panel during the period 2004-2010 are, on average, larger, invest more in basic and applied research, and obtain a better innovative performance. These facts are consistent with other studies using longitudinal data that survivor companies tend to perform better in terms of R&D and innovation outcomes (Leiponen, 2005). Given the small shares of dropouts in the panel however, we do not believe there is an attrition problem in our case. As longitudinal data is important to measure collaboration experience, we also examine whether non-responses to the variables used to measure collaboration experience creates biases in our estimations. The analysis conducted in this regard does not reveal any bias in the estimations (See section 4 for more details).

After the elimination of missing values, our final sample contains 5,371 observations, of which 933 received an R&D subsidy from the National Spanish Government in the treatment period. 2,353 firms had engaged in external collaboration during the outcome period, with

18.53% of firms collaborating with at least 2 partner types, 5.77% with at least 4 partner types, and 2.22% with all 6 partner types.

3.3 EMPIRICAL APPROACH

3.3.1 Average impact of R&D subsidies on external collaboration

In the first stage of our analysis, we estimate the average impact of R&D subsidies on firm external collaboration breadth. We follow prior studies by using a matching approach to estimate this relationship (Busom and Fernandez-Ribas, 2008). This permits identification of the *average effect* while controlling for the selection bias inherent in R&D subsidy programmes; treated firms self-select into programmes and policymakers select which firms to fund. Matching generates the *average effect* by comparing the external collaboration outcome (Y1) when a firm receives a R&D subsidy (S=1), to the counterfactual external collaboration outcome (Y0) the same firm would have experienced if they had not received a R&D subsidy. However, as the counterfactual outcome is not directly observable (i.e. firms cannot be in both states simultaneously), matching generates the counterfactual outcome by identifying non-treated twin firms, which are equivalent in terms of their exogenous characteristics to the treated firm (Caliendo and Kopeinig, 2008). Invoking the conditional independence assumption (Rubin, 1977) means twin firms can be considered valid proxies for the counterfactual external collaboration outcome of treated firms. To satisfy this assumption however, it is necessary to identify equivalent firms on all important characteristics influencing selection into R&D subsidies (Caliendo and Kopeinig, 2008). The wealth of information in our dataset satisfies this assumption. Several variations of matching exist, with the type of matching influencing the construction of the control group (Caliendo and Kopeinig, 2008). We follow the literature standard by employing propensity score nearest neighbour matching (PSM) (Czarnitzki and Lopes-Bento, 2013; Hottenrott and Lopes-Bento, 2014). PSM matches each treated firm with their closest control firms based upon a propensity score[4]. The propensity score represents firms' probability of receiving a R&D subsidy. To ensure quality matches, we impose a 0.01 caliper restriction to PSM, ensuring only twin firms are matched (Caliendo and Kopeinig, 2008).

4 Most treated firms are matched to two control firms to construct the counterfactual outcome.

3.3.2 Differential impact of R&D subsidies & the role of collaboration experience

In the second stage of our analysis, we turn our attention to the *differential impact* of R&D subsidies and the role of collaboration experience in magnifying the impact of R&D subsidies on external collaboration. To examine this relationship, we first identify the individual level impact of R&D subsidies on external collaboration for each treated firm, which will act as our dependent variable in this second stage. To identify the individual effect, we employ the approach deployed by Czarnitzki and Licht (2006), Hottenrott and Lopes-Bento (2014) and Beck et al (2016), which is as follows:

$$\alpha_i^{TT} = Y_i - \hat{Y}_i^c \tag{1}$$

α_i^{TT} represents the individual effect. This is defined as the difference between the external collaboration of a treated firm i (Y_i), and the counterfactual level of external collaboration the treated firm i would have had in the absence of R&D subsidies ($\hat{Y}_i^c$). For example, if a treated firm had an external collaboration score of 5 and their counterfactual level would have been 4, the individual effect would be 1. Examining the distribution of α_i^{TT} permits insight into the *extent of differential effects* generated by R&D subsidies on external collaboration breadth. Using α_i^{TT} as the dependent variable in a regression model, we can estimate whether collaboration experience magnifies the impact of R&D subsidies on external collaboration. Specifically, we estimate this relationship as being determined per the following OLS regression model:

$$\alpha_i^{TT} = \beta_0 + \beta_1 CollabExperience_i + W'\pi + \varepsilon \tag{2}$$

Where $CollabExperience$ represents collaboration experience, W is a matrix of control variables, β and π are the parameters to be estimated and ε is the random error term[5].

5 As OLS regression requires the assumption of homoscedasticity for valid statistical inference, we tested for the presence of heteroscedasticity. The Breusch-Pegan/Cook-Weisberg test indicates the existence of heteroscedasticity. Therefore, we conducted OLS estimations using Huber-White standard errors. We replace the variance of the OLS estimator based on homoscedasticity by the heteroscedasticity robust standard errors defined by $(XX')^{-1}X\Sigma(XX')^{-1}$.Where X is the matrix of covariates and Σ is the diagonal matrix containing the error term, σ_i^2, which varies across observations. Σ is estimated empirically from the residuals of the OLS regression models under consideration. This procedure provides more accurate standard errors, thus making statistical inference more trustworthy (Greene, 2003).

3.4 DEPENDENT VARIABLES

Our analysis is separated into two parts. In the first part (matching analysis), the dependent variable refers to external collaboration breadth. We follow Laursen and Salter (2006) and Love et al (2014) to create this variable by summing binary values – where the value of 1 indicates collaboration – for 6 partner types (i.e. other companies in the firm's business group, customers, suppliers, competitors, universities, other organizations). This variable has a maximum score of 6 and a Cronbach's alpha of 0.7880, indicating a satisfactory degree of internal consistency. In the second part (magnifying effect of collaboration experience) of our analysis, the dependent variable is α_i^{TT} (individual impact of R&D subsidies on external collaboration). This variable ranges in value from -6 to 6, with positive levels indicating R&D subsidies induced additional external collaboration, and negative values indicating firms reduced their external collaboration when receiving R&D subsidies. We also run the models using the logarithm of this indicator as the dependent variable.

3.5 MAIN EXPLANATORY VARIABLES

In the first part, the receipt of R&D subsidies is the main explanatory variable. As in prior studies (Busom and Fernandez-Ribas, 2008; Czarnitzki and Lopes-Bento, 2013), we define the R&D subsidy variable as a binary indicator equal to 1 if firms received a R&D subsidy from Spanish national programs, and zero otherwise. In the second part, our main explanatory variable is collaboration experience. Following prior research, we assume prior R&D collaboration is a valid proxy for collaboration experience (Love et al, 2014; Sampson, 2005). The PITEC includes information on whether firms engaged in R&D collaboration with six partner types measured for three-year periods. If the firm collaborated with each partner type, this is coded as 1 and 0 otherwise within each three-year period. We use a nine-year measure to ensure we obtain a comprehensive understanding of the collaboration experience possessed. To create our main measure of collaboration experience, we sum three variables; first, the number of partner types firms had collaborated with in the period 2002-2004, second, the number of partner types firms had collaborated with in the period 2005-2007, and third, the number of partner types firms had collaborated with in the period 2008-2010. This creates a variable ranging from 0 (no collaboration if any period) to 18 (collaboration with all partner types in all periods).

3.6 CONTROL VARIABLES

We further control for a range of variables (Table 1). We first include FIRM SIZE and FIRM AGE variables to control for possible scale and age effects. Next, we account for prior experience of receiving R&D subsidies, where PRIOR R&D SUBSIDIES equals one if the firm received a R&D subsidy in the three years preceding the treatment period. Prior experience in receiving subsidies may enhance ability to produce successful applications and policymakers may use prior receipt as a quality indicator when allocating R&D subsidies. We also include two dichotomous variables, BUSINESS AFFILIATION and FOREIGN CAPITAL, to account for the fact that governments prefer to support domestic firms (Gonzalez and Pazo, 2008). Next, we account for the level of collaboration at the industry level (COLLABORATION INDUSTRY), as policymakers may prefer to fund firms with greater networks, given the increased potential for knowledge spillovers (Hottenrott and Lopes-Bento, 2014). Prior innovation activities may play a key role in making firms eligible for R&D subsidies, and in increasing their odds of receiving R&D subsidies (Gelabert et al, 2009). Thus, we account for this using INNOVATOR, which equals one if firms reported product or process innovations in the three years preceding treatment and PATENT APPLICATIONS, which represents the number of patent applications in the prior three years. Since exporting is another factor that may influence the likelihood of receiving R&D subsidies, we include the dummy variable EXPORT, which awards the value of one if company exported outside the EU. Governments may prefer to support exporting firms because such firms are pushed to be more competitive and thus more innovative. Finally, we account for sources of unobserved heterogeneity across industries classifying following the OECD taxonomy at the two-digit level (OECD, 2005). The second stage additionally employs R&D ACTIVE, a dummy equal to one if the firm invests continuously in R&D activities and RESEARCH INTENSITY, capturing the proportion of R&D expenditure devoted to research activities. These reflect the well-established role of absorptive capacity in influencing external collaboration (Cohen and Levinthal, 1990) and research intensity in increasing firm incentive to form collaborative partnerships to exploit the outcomes of their research activities (Rothaermel and Deeds, 2006).

[INSERT TABLE 1 HERE]

4.0 RESULTS

Table 2 shows the descriptive statistics for our variables in both stages of the analysis and Table 3 presents the descriptive statistics utilised in the matching procedure spilt by firms

R&D subsidy status (i.e. treated and control firms). As can be seen in Table 3 significant differences exist between the control and treated groups on all characteristics. For example, on average, treated firms appear to be younger, more likely to have received subsidies previously, and have applied for more patents. In terms of external collaboration, we can see treated firms collaborate with significantly more partner types than control firms. At this stage however, given the potential presence of selection bias, it is not possible to know how much of this additional external collaboration is due to R&D subsidies, and how much is due to the selection effect.

[INSERT TABLE 2 HERE]
[INSERT TABLE 3 HERE]

As noted earlier for our matching procedure to control for the selection effect, we first run a probit model to obtain the predicted probability for each firm of receiving a R&D subsidy (i.e. propensity score). As shown in Table 4, prior subsidies, patenting, collaboration[6], exporting and firm size drive selection into R&D subsidies. Contrarily, foreign capital reduces the likelihood of selection into R&D subsidies. These findings broadly align with existing findings on the determinants of selection into R&D subsidies (Czarnitzki and Lopes-Bento, 2013; Hottenrott and Lopes-Bento, 2014).

[INSERT TABLE 4 HERE]

Based on the propensity score, we now match firms. The characteristics and external collaboration for the matched treated and control firms are shown in Table 5. As can be seen, all statistically significant pre-matching (Table 3) differences between the treated and control groups have been removed post-matching. Equally, comparing the (pseudo) R-squared of the model pre- (0.265) and post- (0.004) matching indicates conditioning on these characteristics no longer predicts receipt of R&D subsidies[7]. These tests indicate the matching was successful, with the control group now a valid counterfactual for the treated group. Any remaining differences in external collaboration can now be attributed to R&D subsidies. The results show R&D subsidies, on average, generate an increase in external collaboration breadth from 1.408 partner types to 2.310 partner types, an increase of 0.902 partner types, or

6 We also run the analysis with the collaboration variable measured at the firm level and the results remain meaningful unchanged.

7 Results available from the authors upon request.

64.06%. Thus, our results suggest R&D subsidies, on average, indirectly generate economically significant increases in external collaboration breadth. To account for potential selection bias on unobservable characteristics, we test the robustness of this result using an instrumental variable approach. Discussion of the validity of our instrumental variables and the results of this regression are shown in detail in Appendix 1. Briefly, the results confirm our matching results that R&D subsidies, on average, stimulate significant increases in external collaboration.

[INSERT TABLE 5 HERE]

Next, we examine the *extent* of differential collaboration impacts generated by R&D subsidies. Figure 2 depicts the distribution of the individual level impact of R&D subsidies on external collaboration breadth for each treated firm in our matching analysis. As can be seen, the effect is vastly heterogeneous across firms, supporting the existence of differential impacts. Moreover, while R&D subsidies generate a positive impact on average, this effect is concentrated in only 56% of treated firms who experience an increase in external collaboration. Equally, despite the average positive effect, 12.92% of firms experience no impact and 30.40% of firms a negative impact. That is, for approximately a third of treated firms, their external collaboration did not increase when receiving R&D subsidies, but rather decreased. To further explore the differential impacts, Table 6 presents them across firm size and age categories (Beck et al, 2016), given evidence suggests such characteristics may influence the impacts of R&D subsidies and firm external collaboration activities (Hottenrott and Lopes-Bento, 2014; Roper et al, 2017)[8]. While the distribution of these effects does not follow a clear pattern by firm age, negative and null effects seems to be more concentrated in smaller firms; approximately half of the firms experiencing these results are small. Positive effects, in contrast, seem to be more equally distributed by size and age.

[INSERT FIGURE 2 HERE]
[INSERT TABLE 6 HERE]

We now use the individual level impact of R&D subsidies on external collaboration breadth as our dependent variable in an OLS regression model, to examine the theorised effect of

8 We thank an anonymous reviewer for this suggestion.

collaboration experience. Two main models are estimated to test the relationship, which are shown in table 7. In model 1, we include the log value of collaboration experience a firm possesses. From this estimation, we see collaboration experience has a positive and statistically significant effect on the external collaboration impact firms obtain from R&D subsidies. In model 1, a one percent increase in collaboration experience translates into an increase of 0.011 in additional external collaboration from R&D subsidies. In model 2, the count of collaboration experience is examined to relax the logarithmic assumption, with the results again showing a significantly positive collaboration experience effect. In model 2, a one partner increase in collaboration experience translates into 0.205 additional external collaboration from R&D subsidies. As such, the results show support for our argument that the indirect effect of R&D subsidies on external collaboration breadth is greater for firms with collaboration experience.

[INSERT TABLE 7 HERE]

As the organisational learning literature has highlighted the importance of the *extent* and *age* of (collaboration) experience in different contexts and for different outcomes (Baum and Ingram, 1998; Clarysse et al, 2009; Love et al, 2014; Sampson, 2005), we undertake a post-hoc analysis to examine whether the *extent* and *age* of collaboration experience matters for the indirect effect of R&D subsidies on external collaboration breadth. In model 3, we include a dichotomous variable indicating whether firms had any collaboration experience and in model 4 we include several dichotomous variables indicating the extent of collaboration experience. This enables us to granularly examine how the effect of collaboration experience may vary according to the *extent* of experience. Model 3 shows the existence of prior collaboration experience increases the external collaboration impact of R&D subsidies by 1.430 partner types, compared to firms with no collaboration experience; an economically significant impact. Model 4 shows the *extent* of experience appears to matter more than the existence however, with collaboration experience with 1-4 partner types, 5-8 partner types and 9 plus partner types, increasing the external collaboration impact of R&D subsidies by 0.65, 1.48 and 2.36 partner types, respectively. We check the robustness of this insight in model 5 by developing a piecewise approach, where experience > 0 equals one when a firm has collaboration experience with at least one partner type, experience >4 equals one when at least five, and experience >8 equals one when at least nine. As can be seen the coefficients are all significant and increase in magnitude as the extent of collaboration experience increases, in line with model 4. As such, the external collaboration impact of collaboration experience grows with the *extent* of collaboration experience firms possess, with no decreasing returns to collaboration experience evident[9].

Next, we estimate three models (models 6-8) to examine the influence of the *age* of collaboration experience, which are shown in table 8. Model 6 contains three count variables each representing the extent of collaboration experience within one of the three time waves used to build our main collaboration experience measure; 2002-2004, 2005-2007 and 2008-2010. As can be seen only collaboration experience in 2008-2010, that is the most recent experience, has a statistically significant effect. This effect is also economically significant, with a one unit increase in collaboration experience in 2008-2010 translating into 0.554 more external collaboration breadth from R&D subsidies. In models 7 and 8, we interact the two older periods of experience (2002-2004 and 2005-2007) with the most recent period (2008-2010), to consider whether older experience enables firms to better leverage their recent collaboration experience. In model 7, the 2002-2004 and 2008-2010 interaction is not significant. In model 8, the 2005-2007 and 2008-2010 interaction is statistically significant at a weak level, with a small positive coefficient. Experience in 2008-2010 alone remains statistically and economically significant in both models however. Thus, the results suggest that more recent experience matters most and the value of collaboration experience decays overtime.

[INSERT TABLE 8 HERE]

Given the long-time period used to measure collaboration experience (9 years), some non-response in these variables is expected. In the second stage, the sample includes 898 companies, resulting from the matching procedure described above. Out of these companies, 697 companies reported valid information about R&D collaboration in the three waves under consideration in the study (i.e. 2002-2004, 2005-2007 and 2008-2010), 182 companies did not report information on collaboration in the period 2002-2004, while one company failed to report information in 2005-2007. Finally, 10 companies have missing values for collaboration variables in all periods. To see if non-responses introduce any bias, we apply multiple

9 We also tested for the presence of decreasing returns to collaboration experience using the squared term of the count of collaboration experience. This is insignificant in the models, further supporting the notion that no decreasing returns are evident (Results available from authors upon request).

imputation analysis to estimate the previously described models[10]. No meaningful differences are observed in the results after the imputation, as such, we consider our results on collaboration experience are robust to this issue (results available upon request).

With respect to the control variables, R&D subsidy experience has a significant and negative impact, potentially suggesting some evidence that the impact firms experience from R&D subsidies are sensitive to prior R&D subsidy experience (Clarysse et al, 2009). The results also suggest R&D active firms and firms with higher research intensities experience greater external collaboration impacts from R&D subsidies, aligning with the understanding of absorptive capacity and research intensity supporting external collaboration (Cohen and Levinthal, 1990; Rothaermel and Deeds, 2006).

5.0 DISCUSSION

By analysing Spanish manufacturing and service firms, this paper advances understanding of the indirect behavioural additionality impacts of R&D subsidies. Our results uncover that R&D subsidies, on average, indirectly stimulate economically significant increases in external collaboration breadth, when compared to the counterfactual of not receiving a R&D subsidy. Further analysis illustrates this indirect impact of R&D subsidies on external collaboration is subject to differential gains, with the impact concentrated in only a subset of treated firms, while the remainder experience no impact, or a negative effect. Our results further reveal that the external collaboration impact is concentrated in firms with prior collaboration experience, and that more extensive and recent collaboration experience magnifies the impact.

First, we advance understanding beyond the direct impacts of R&D subsidies on R&D expenditure (Czarnitzki and Lopes-Bento, 2013) by providing new insights on the growing body of *indirect* behavioural additionality effects (e.g., Clarysse et al, 2009; Kleer, 2010). Specifically, our results complement and extend previous studies focused on the indirect impact of R&D subsidies on firms' *propensity* to collaborate (e.g., Busom and Fernandez-Ribas, 2008), by demonstrating the important indirect impact on external collaboration *breadth*. This extension is important considering the knowledge firms need to innovate is

10 We imputed values for the experience count variables corresponding to each wave. Thus, multivariate imputation was applied. By assuming that the imputed variables are continuous, we used multivariate normal regression for the imputation by following the methods of Schafer (1997).

increasingly distributed across the innovation value chain (Chesbrough, 2006; Lakhani et al, 2013), and external collaboration breadth is crucial for firms to gain access to this knowledge and enhance their innovation efforts (Beck and Schenker-Wicki, 2014; Laursen and Salter, 2006; Roper et al, 2017). We reveal R&D subsidies stimulate firms to expand their external collaboration breadth by 0.901 partner types, moving from collaboration with 1.408 partner types, to collaboration with 2.310 partner types (on average), thus, empirically illustrating R&D subsidies *indirectly* play an important role in influencing external collaboration breadth. As policymakers face constrained resources (Gupta and Guerguil, 2014; Mazzucato, 2013) and alternative interventions to R&D subsidies (e.g., tax credits), our results contribute to a more comprehensive understanding of the (in)direct impacts of R&D subsidies that can inform policymakers about their role and utility in innovation policy. Moreover, as policymakers become interested in stimulating firm external collaboration (Cano-Kollmann et al, 2016; Chesbrough and Vanhaverbeke, 2011), given the social benefits (Roper et al, 2017), our results show that R&D subsidies, while not directly intended to influence collaboration, could form an important part of a policy mix (Flanagan et al, 2011) to raise firm engagement in external collaboration breadth toward the optimum level (Beck and Schenker-Wicki, 2014; Roper et al, 2017).

Second, we contribute to the literature on R&D subsidies by being the first to explicitly consider both the *average* and *differential* effect of R&D subsidies on external collaboration. This approach extends understanding by providing novel empirical evidence showing while R&D subsidies, on average, induce economically significant increases in external collaboration breadth, the positive impacts are concentrated in only a subgroup of the firms awarded R&D subsidies. The extent of differential gains we identify is consistent with that found by Beck et al (2016) and Hottenrott et al (2015) for R&D expenditure, suggesting for both direct and indirect impacts of R&D subsidies, only a subset of firms are positively impacted. The differential effects also suggest a significant portion of firms awarded R&D subsidies may experience negative treatment effects. Together with Beck et al. (2016) and Hottenrott et al. (2015), we are the first to empirically reveal that solely considering the average effect, as is currently standard in the literature, masks considerable heterogeneity in the impacts of R&D subsidies. As such, we call attention to the need for future studies to explicitly consider both the *average* and *differential* impacts of R&D subsidies to obtain more nuanced insights on the impacts of R&D subsidies for academics, policymakers and organisations alike.

Third, we advance understanding of the characteristics shaping the differential impact of R&D subsidies on external collaborative breadth (Cano-Kollmann et al, 2016) by being the first to illustrate the important role of collaboration experience. Specifically, the results advance previous studies focused on the average impact (Busom and Fernandez-Ribas, 2008) by demonstrating that the important indirect impact of R&D subsidies on external collaboration breadth is significantly greater for supported firms with collaboration experience. As such, we advance a more theoretically nuanced understanding of this relationship by shedding light on the conditions under which R&D subsidies stimulate firm external collaborative breadth. We also advance prior studies which have considered the role of contemporaneous external collaboration in moderating the impacts of R&D subsidies (Beck et al, 2016; Hottenrott and Lopes-Bento, 2014) by demonstrating the importance of considering collaboration *experience*.

Finally, we make two contributions to budding conversations in the strategy literature on the antecedents of external collaboration (e.g., Alexy et al, 2016) and the *nature* of collaboration experience (e.g., Sampson, 2005). For the former, extant work has largely focused on internal factors (e.g., size, managerial cognitions) as important antecedents of external collaboration breadth, with less attention to external factors (Cano-Kollmann et al, 2016; Garriga et al, 2013). Our results complement and extend the growing focus on external factors by demonstrating that government R&D subsidies influence external collaboration breadth (Chapman and Yacoub, 2016). For the latter, existing research has largely focused on the implications of the *extent* and *age* of collaboration experience for innovation outcomes (e.g., Sampson, 2005; Love et al, 2014). In this paper, we considered the implications for firm external collaboration activities (see also Gulati (1999), showing that the *extent* of collaboration experience matters more than the existence, and that *recent* collaboration experience is more beneficial.

For policymakers, our results suggest that R&D subsidies, while not directly intended to influence external collaboration, could form an important part of an innovation policy mix (Flanagan et al, 2011) targeted toward raising firm external collaboration breadth toward the optimum level (Roper et al, 2017). Particularly, R&D subsidies could be useful in stimulating external collaboration breadth for firms with collaboration experience. Considering the prevalence of and significant resources already devoted to R&D subsidies in most countries innovation policy (Fernandez-Zubieta, 2014; 2015), this could represent a resource effective approach for policymakers in the current context of government austerity (Gupta and Guerguil, 2014; Mazzucato, 2013). More generally, our results extend understanding of the range of important (in) direct behavioural additionality effects R&D subsidies have upon organisations, thus, strengthening the rationale for continued intervention. For managers, our results suggest in addition to R&D subsidies aiding their firm in funding new R&D projects (e.g., Czarnitzki and Lopes-Bento, 2013), R&D subsidies can also indirectly help firms, particularly those with collaboration experience, to expand their external collaborative breadth.

More research is needed to explore and clarify some of the insights raised in this paper. First, while our data provides insight into the indirect impact on external collaboration breadth, it does not allow us to explore whether (and how) R&D subsidies influence the nature (e.g. intensity of interaction, quality of interaction) of external collaborative relationships. The nature of collaboration relationships may be important in predicting their value for innovation; hence, this could offer a fruitful avenue for future research. Second, despite our substantial efforts in addressing the endogeneity problem (e.g., matching procedure, instrumental variables), we recognise that our data does not provide enough information to exclude the very small number of national programmes requiring collaboration as a precondition. Given this is significantly less problematic as we are interested in the *breadth* of collaboration, we believe our results are meaningfully robust to this issue. Still, we believe further research on R&D subsidies should strive for more granular subsidy information to disentangle the effects of specific programmes and their pre-conditions on organisations. This will make for a more nuanced and relevant understanding for policymakers, firms and academics alike. Finally, our analysis suggests around a third of firms experience a negative treatment effect from R&D subsidies. To date the literature has focused exclusively on positive outcomes from R&D subsidies, except for a few studies which theoretically suggest the potential for negative effects (Georghiou and Clarysse, 2006). A fruitful avenue for future studies could hence, be untangling these potential negative treatment effects, we and others (Beck et al, 2016; Hottenrott et al, 2015) have identified.

6.0 CONCLUSION

In this paper, we examined how R&D subsidies *indirectly* influence firm external collaboration breadth. After controlling for the inherent selection bias utilising a matching procedure, our results show that R&D subsidies stimulate firms to expand their external collaboration breadth by approximately one partner type on average. Moreover, by explicitly considering differential effects we find that the impact of R&D subsidies on external collaboration breadth is concentrated in only approximately half of supported firms. Finally, we show that collaboration experience significantly magnifies the indirect effect of R&D subsidies on external collaboration breadth, with more extensive and recent experience having the largest effect. Overall, the results provide new insights for academics, policymakers and managers regarding the indirect behavioural additionality impacts of R&D subsidies.

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Table 1: Definition and timing of measurement of the variables

Variables	Stage of Analysis	Description
Dependent variables		
External Collaboration	1	Number of partner type links a company formed during the post-treatment period of 2011-2013.
Individual Impact (α_i^{TT})	2	Individual Firm Level Impact of R&D Subsidies on External Collaboration
Independent variables		
R&D Subsidies	1	Dummy Equal to 1 if Firm Received National R&D Subsidies in 2010
Experience (in log values & count)	2	Count variable indicating the number of partner type links a company has formed between 2002-2010
Control Variables		
Cooperation Industry	1	Proportion of companies with R&D cooperation links measured at two-digit NACE level in the pretreatment period of 2007-2009
Patent Applications (in log values)	1	Number of patent applications during the pretreatment period of 2007-2009
Innovator	1	Binary variable equal to one if the firm reported product or process innovations during the pretreatment period of 2007-2009
Foreign Capital	1	Binary variable equal to 1 if a firm has a capital structure with more than 50% of foreign capital in the pretreatment period of 2007-2009
Exports	1	Binary variable equal to 1 if the firm reported exports to countries outside the European Union (EU) in the pretreatment period of 2007-2009.
Business Affiliation	1-2	Binary variable equal to 1 if the firm belongs to a business group in the pretreatment period of 2007-2009.
Firm Age	1-2	Number of years since the company foundation.
Firm Size	1-2	Binary variable equal to 1 if the company has more than 200 employees, 0 otherwise, during the period 2007-2009 at the first stage and the period 2008-2010 in the second stage.
Industry	1-2	5 binary variables based on OECD categories; high-technology industry, medium-high technology industry, medium-low technology industry, low-technology industry, knowledge intensive business services, and non-knowledge intensive business services. Equal to one if the firm belongs to group and zero otherwise. Corresponds to the period 2007-2009 at the first stage and the period 2008-2010 in the second stage.
Prior R&D Subsidies	1-2	Binary variable equal to 1 if the firm obtained R&D subsidies during the period 2007-2009 in the first stage and the period 2008-2010 in the second stage.
Research Intensity (in log values)	2	Proportion of internal R&D a firm devoted to basic and applied research during the period 2008-2010.
R&D Active	2	Binary variable equal to one if a firm has stated it makes a continuous effort in R&D during the period 2008-2010.

Table 2: Descriptive statistics

Variable	**Mean**	**SD**	**Min.**	**Max.**
Dependent variables (2011-2013)				
External collaboration	1.08	1.60	0	6
Individual effect $\left(\alpha_i^{TT}\right)$	0.90	2.12	-6	6
Independent variable				
R&D subsidies (2010)	0.10	0.30	0	1
Experience count (2002-2010)	2.95	3.77	0	18
Control variables in the first stage (2007-2009)				
Cooperation Industry	0.27	0.11	0.03	1
Patent Application	0.49	5.15	0	278
Innovator	0.69	0.46	0	1
Foreign Capital	0.12	0.32	0	1
Exports	0.40	0.49	0	1
Business Affiliation	0.40	0.49	0	1
Firm Age	25.22	19.95	0	545
Firm Size	0.25	0.44	0	1
Prior R&D Subsidies (2007-2009)	0.29	0.46	0	1
High-Tech Industry	0.03	0.17	0	1
Medium-High Tech Industry	0.17	0.37	0	1
Medium-Low Tech Industry	0.14	0.35	0	1
Low-Tech Industry	0.15	0.36	0	1
Knowledge Intensive Business Services	0.28	0.45	0	1
Non-Knowledge Intensive Business Services	0.15	0.36	0	1
Other Industries	0.08	0.26	0	1
Control variables in the second stage (2008-2010)				
Business Affiliation	0.41	0.49	0	1
Firm Age	26.22	19.95	0	546
Firm Size	0.25	0.43	0	1
Prior R&D Subsidies (2007-2009)	0.29	0.46	0	1
Research Intensity	19.52	34.93	0	100
R&D Active	0.35	0.48	0	1
High-Tech Industry	0.03	0.16	0	1
Medium-High Tech Industry	0.17	0.37	0	1
Medium-Low Tech Industry	0.14	0.34	0	1
Low-Tech Industry	0.15	0.36	0	1
Knowledge Intensive Business Services	0.28	0.45	0	1
Non-Knowledge Intensive Business Services	0.15	0.36	0	1
Other Industries	0.07	0.26	0	1

Table 3: Descriptive Statistics for Treated and Control Firms Separately

Variables	Treated Firms	Control Firms	Difference	P-value
	(N=933)	(N=4,438)		
Control variables				
Prior R&D Subsidies	0.904	0.351	0.553	***
Cooperation (Industry)	0.356	0.277	0.079	***
Patent Applications (log)	0.443	0.146	0.297	***
Innovator	0.919	0.841	0.077	***
Foreign Capital	0.074	0.147	-0.073	***
Business Affiliation	0.504	0.451	0.053	***
Exports	0.550	0.502	0.048	**
Firm Age (log)	2.988	3.132	-0.144	***
Firm Age Square (log)	9.433	10.234	-0.801	***
Firm Size	0.303	0.268	0.036	**
High-Technology Industry	0.054	0.029	0.025	***
Medium-High Technology Industry	0.155	0.222	-0.067	***
Medium-Low Technology Industry	0.098	0.147	-0.050	***
Low-Technology Industry	0.104	0.160	-0.056	***
Knowledge-Intensive Business Sector	0.433	0.246	0.188	***
Non-Knowledge-Intensive Business Sector	0.049	0.114	-0.065	***
Outcome variable				
External Collaboration	2.361	0.823	1.538	***

*** (**, *) indicate a significance level of 1% (5%, 10%). The second stage variables presented in Table 2 are excluded in this comparison as only treated firms are included in the second stage.

Table 4: Probit Results for the Probability to Receive R&D Subsidies

Variables	**Coef.**	**Std. Err.**
Prior Subsidies	1.354***	0.056
Cooperation Industry	1.559***	0.223
Patent Applications (log)	0.218***	0.037
Innovator	0.101	0.081
Foreign Capital	-0.336***	0.085
Business Affiliation	0.165***	0.055
Exports	0.109**	0.054
Firm Age (log)	-0.097	0.229
Firm Age Square (log)	0.012	0.036
Firm Size	0.144**	0.061
High-Technology Industry	-0.020	0.135
Medium-High Technology Industry	-0.373***	0.095
Medium-Low Technology Industry	-0.251**	0.104
Low-Technology Industry	-0.191	0.103
Knowledge-Intensive Business Sector	0.137	0.088
Non-Knowledge-Intensive Business Sector	-0.169	0.123
Constant	-2.277***	0.385
No of observations	5,371	
Log-likelihood	-1810.8315	
Pseudo R-square	0.2652	

*** (**, *) indicate a significance level of 1% (5%, 10%)

Table 5: Matching Results

Variables	Treated Firms	Control Firms	Difference	P-value
	(N=898)	(N=1,869)		
Control variables				
Prior R&D Subsidies	0.901	0.894	0.007	
Cooperation Industry	0.347	0.354	-0.006	
Patent Applications (log)	0.376	0.413	-0.037	
Innovator	0.919	0.921	-0.003	
Foreign Capital	0.076	0.083	-0.007	
Business Affiliation	0.502	0.526	-0.023	
Exports	0.547	0.552	-0.005	
Firm Age (log)	2.994	2.980	0.014	
Firm Age Square (log)	9.465	9.382	0.083	
Firm Size	0.294	0.282	0.012	
High-Technology Industry	0.056	0.042	0.013	
Medium-High Technology Industry	0.159	0.177	-0.018	
Medium-Low Technology Industry	0.100	0.105	-0.005	
Low-Technology Industry	0.107	0.116	-0.009	
Knowledge-Intensive Business Sector	0.420	0.408	0.012	
Non-Knowledge-Intensive Business Sector	0.050	0.042	0.008	
Outcome variable				
External Collaboration	2.310	1.408	0.901	***

*** (**, *) indicate a significance level of 1% (5%, 10%)

Table 6. Average Treatment Effect on Cooperation Breadth by Size and Age. N= 898

	Percentage of firms	Firm Size			Firm age in years			
	N=898	**S=1-49**	**M= 50-249**	**L=250-max**	**<15**	**16-30**	**31-75**	**76-max**
$\alpha^{tt}<0$	30.40	50,18	35,53	14,29	32,60	37,36	26,01	4,03
$\alpha^{tt}=0$	12.91	43.97	34.48	21.55	26.72	47.42	22.41	3.45
$\alpha^{tt}>0$	56.68	33.60	35.76	30.65	26.92	38.51	30.06	4.52
$\alpha^{tt}>3$	14.81	21.80	39.10	39.10	26.32	37.59	30.83	5.26
$\alpha^{tt}<-3$	1.78	50.00	31.25	18.75	43.75	37.50	12.50	6.25

Note: Values of α^{tt} are comprised in the interval of -6 to 6.

Table 7: The Effect of Collaboration Experience

Variables	Individual External Collaboration Impact of R&D Subsidies (α_i^{TT})				
	Model 1	Model 2	Model 3	Model 4	Model 5
Experience (in log values)	1.064***	–	–	–	–
	(0.092)				
Experience count	–	0.205***	–	–	–
		(0.017)			
Experience > 0 partners (dummy)	–	–	1.430***	–	–
			(0.214)		
Experience 1-4 partners (dummy)	–	–	–	0.652***	–
				(0.228)	
Experience 5-8 partners (dummy)	–	–	–	1.484***	–
				(0.241)	
Experience > 8 partners (dummy)	–	–	–	2.360***	–
				(0.253)	
Experience > 0 (dummy)	–	–	–	–	0.652***
					(0.228)
Experience > 4 (dummy)	–	–	–	–	0.832***
					(0.202)
Experience > 8 (dummy)	–	–	–	–	0.875***
					(0.206)
Prior R&D Subsidies	-0.887***	-0.806***	-0.542*	-0.740***	-0.740***
	(0.266)	(0.254)	(0.281)	(0.257)	(0.257)
Research Intensity (log)	0.071*	0.056	0.126***	0.083*	0.083*
	(0.042)	(0.042)	(0.043)	(0.043)	(0.043)
R&D Active	0.619**	0.648**	0.980***	0.761***	0.761***
	(0.257)	(0.258)	(0.243)	(0.252)	(0.252)
Firm Size	0.366*	0.356*	0.557***	0.433**	0.433**
	(0.198)	(0.197)	(0.208)	(0.201)	(0.201)
Firm Age	-0.064	-0.097	-0.046	-0.059	-0.059
	(0.136)	(0.133)	(0.149)	(0.137)	(0.137)
Business Affiliation	-0.089	-0.191	0.048	-0.090	-0.090
	(0.173)	(0.172)	(0.186)	(0.175)	(0.175)
High-tech Industry	-0.636*	-0.732**	-0.377	-0.567*	-0.567*
	(0.335)	(0.325)	(0.361)	(0.339)	(0.339)
Medium-High-Tech Industry	-0.300	-0.267	-0.264	-0.293	-0.293
	(0.274)	(0.266)	(0.291)	(0.275)	(0.275)
Medium-Low-Tech Industry	-0.006	-0.065	0.066	-0.014	-0.014
	(0.299)	(0.296)	(0.315)	(0.301)	(0.301)
Low-Tech Industry	-0.511	-0.457	-0.564*	-0.513	-0.513
	(0.325)	(0.321)	(0.342)	(0.327)	(0.327)
Knowledge Intensity Service Industry	-0.497**	-0.574**	-0.246	-0.449*	-0.449*
	(0.244)	(0.239)	(0.260)	(0.245)	(0.245)
Knowledge Non-Intensity Service Industry	-0.431	-0.376	-0.344	-0.400	-0.400
	(0.408)	(0.385)	(0.469)	(0.401)	(0.401)
Constant	-0.374	0.272	-0.940	-0.258	-0.258
	(0.585)	(0.567)	(0.631)	(0.593)	(0.593)
Observations	697	697	697	697	697
R-squared	0.2372	0.2369	0.1060	0.1932	0.1932
F statistics	21.87***	20.38***	9.17***	14.45***	14.45***

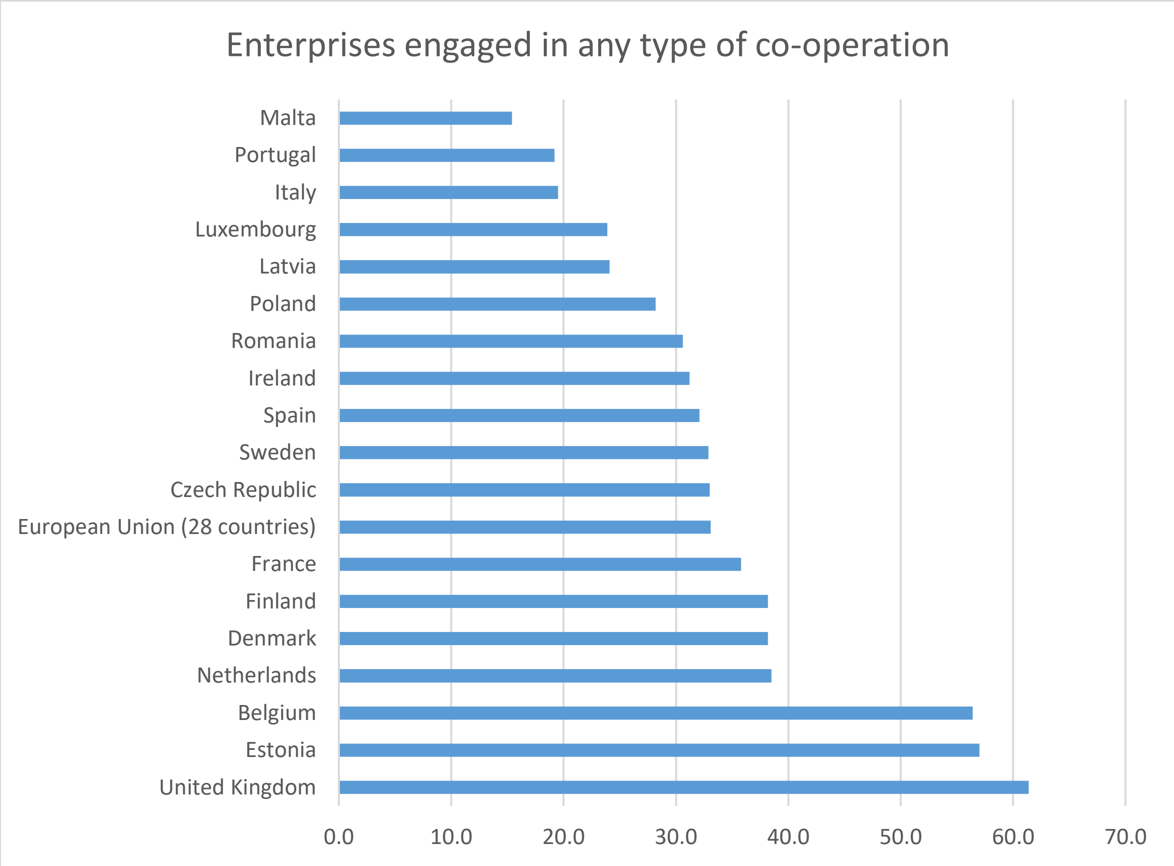
*** (**, *) indicate a significance level of 1% (5%, 10%). Robust standard errors in parenthesis.

Table 8: Magnifying Effect of Collaboration Experience by Experience Age

Variables	Individual External Collaboration Impact of R&D Subsidies (α_i^{TT})		
	Model 6	Model 7	Model 8
Experience 2002-2004 (count)	0.076	0.038	–
	(0.049)	(0.064)	
Experience 2005-2007 (count)	-0.010	–	-0.022
	(0.057)		(0.067)
Experience 2008-2010 (count)	0.554***	0.522***	0.458***
	(0.048)	(0.057)	(0.061)
Experience 2008-2010 x Experience 2002-2004	–	0.013	–
		(0.018)	
Experience 2008-2010 x Experience 2005-2007	–	–	0.031*
			(0.018)
Subsidies Past Three Years	-0.813***	-0.760***	-0.877***
	(0.249)	(0.234)	(0.234)
Research (in log values)	0.042	0.033	0.041
	(0.039)	(0.035)	(0.038)
R&D Performer	0.600**	0.237	0.613**
	(0.262)	(0.215)	(0.258)
Firm Size	0.230	0.204	0.226
	(0.188)	(0.171)	(0.186)
Firm Age	-0.104	-0.001	-0.098
	(0.128)	(0.110)	(0.127)
Business Affiliation	-0.156	-0.172	-0.125
	(0.238)	(0.216)	(0.236)
High-tech Industry	-0.169	-0.192	-0.148
	(0.177)	(0.162)	(0.176)
Medium-High-Tech Industry	-0.551*	-0.602**	-0.531*
	(0.312)	(0.293)	(0.306)
Medium-Low-Tech Industry	-0.110	-0.197	-0.099
	(0.256)	(0.245)	(0.252)
Low-Tech Industry	-0.027	-0.033	-0.013
	(0.277)	(0.254)	(0.276)
Knowledge Intensity Service Industry	-0.448	-0.526*	-0.413
	(0.312)	(0.280)	(0.308)
Knowledge Non-Intensity Service Industry	-0.477**	-0.362*	-0.454**
	(0.233)	(0.215)	(0.228)
Constant	0.121	0.302	0.168
	(0.545)	(0.479)	(0.538)
Observations	697	706	879
R-squared	0.3069	0.3086	0.2795
F statistics	21.82***	22.40***	22.58***

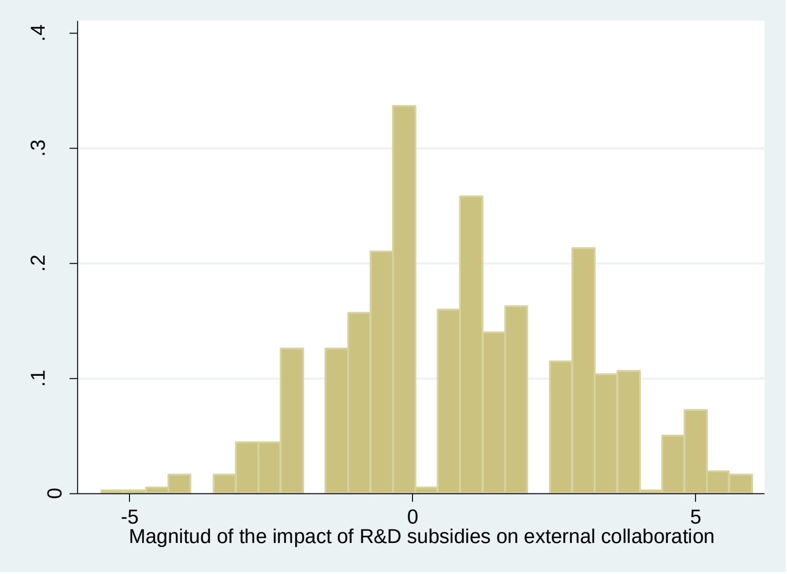
*** (**, *) indicate a significance level of 1% (5%, 10%). Robust standard errors in parenthesis.

Figure 1. Cooperation across European countries based on CIS 2014.



Note: Own elaboration with data from Eurostat Science, Technology and Innovation statistics available at http://ec.europa.eu/eurostat/web/science-technology-innovation/data/database

Figure 2. Differential Effect of R&D Subsidies on External Collaboration



Appendix 1: Instrumental Variable Robustness Check

As matching only controls for selection on observable characteristics, it is important to assess the robustness to the potential presence of selection on unobservable characteristics. We use an instrumental variable approach to test this. Two instruments were employed for R&D subsidy receipt. First, the share of companies receiving a national subsidy at the industry level (IV1). Funding agencies have industry preferences when choosing firms to be supported (Beck et al, 2016). For example, the Spanish government highlights in each national R&D plan which industries to support, based on their importance for the Spanish economy. Hence, firms' industry influences odds of receiving R&D subsidies (Blanes and Busom, 2004). Our expectation is that such government preferences are not correlated to unobserved firm factors. Second, we use the share of females holding a PhD degree in firms' R&D teams (IV2). The rationale for this instrument is recent Spanish R&D plans have been indicating the necessity to improve both the share of females in R&D teams and their level of qualification (CYCIT, 2007, 2013). Thus, we expect public agencies will be more likely to provide support to companies with PhD females in their R&D teams. Our expectation is the share of PhD females is also not correlated to unobserved firm factors. Both instruments fulfil the statistical tests for instrument validity, namely both are highly significant in the first stage, and the Hansen J-test of over-identification is insignificant in the second stage. As shown in Table A1, the results confirm our matching estimation, with R&D subsidies having a significant positive impact on external collaboration.

Table A1: Instrument variable regression analysis

Variables	First-stage	Second-stage
	R&D Subsidies	2SLS on External Collaboration
Share of Female with a PhD Degree (IV1)	0.033***	–
	(0.003)	
Likelihood of Being Subsidized (IV2)	0.633***	–
	(0.088)	
National R&D Subsidies	–	3.083***
		(0.399)
Subsidies Past Three Years	0.242***	0.065
	(0.010)	(0.117)
Cooperation Industry	-0.269***	0.501*
	(0.092)	(0.297)
Patent Applications (in log values)	0.056***	0.067
	(0.010)	(0.060)
Innovator	0.000	0.199***
	(0.011)	(0.054)
Foreign Capital	-0.068***	0.182**
	(0.013)	(0.082)
Business Affiliation	0.035***	0.307***
	(0.011)	(0.053)
Exports	0.016	-0.007
	(0.010)	(0.049)
Firm Age	-0.036	-0.391*
	(0.048)	(0.234)
Firm Age Square	0.005	0.072*
	(0.008)	(0.037)
Firm Size	0.038***	0.331***
	(0.012)	(0.062)
High-Technology Industry	-0.055	-0.330**
	(0.037)	(0.150)
Medium-High Technology Industry	-0.095***	-0.170*
	(0.020)	(0.099)
Medium-Low Technology Industry	-0.062***	-0.099
	(0.022)	(0.102)
Low-Technology Industry	-0.055***	-0.094
	(0.021)	(0.101)
Knowledge-Intensive Business Sector	0.017	-0.196**
	(0.019)	(0.094)
Non-Knowledge-Intensive Business Sector	-0.020	-0.125
	(0.021)	(0.105)
Constant	0.029	0.581
	(0.082)	(0.397)
Observations	5,371	5,371
Uncentered R-squared	0.3813	0.3448
F-test exclusion instruments	$F(2, 5352) = 77.96$***	–
Hansen's J test statistics	–	$\chi^2(1) = 1.008$

*** (**, *) indicate a significance level of 1% (5%, 10%). Robust standard errors in parenthesis.