INFLUENCE OF INSTITUTIONAL AND GEOGRAPHICAL FACTORS ON THE OPENNESS AND DISPERSION OF KNOWLEDGE-SOURCING PRACTICES

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ABSTRACT

This dissertation consists of three essays examining the influence of contextual factors on the patterns of knowledge-sourcing of firms. I argue that both the institutional framework and the geographical location exert an influence in the way firms search for innovative knowledge outside of their own boundaries and across geographical distances. The first essay explores the influence of location in a peripheral region on the patterns of collaboration for innovation. The second essay focuses on the effect of specific public policies on the characteristics of innovation practices. The third essay studies the changes in the patterns of innovation after a change of ownership produced by the privatization of formerly state-owned companies.

The first essay focuses on the influence of geographical factors (in particular the location in a peripheral economy) on patterns of knowledge sourcing. Using patent data, I examine the dispersion of inventor networks in two countries located in the periphery of Europe. I find that in these settings, the disaggregation of innovation across national borders will depend on a combination of location, multinationality of the firm, knowledge tacitness and organizational capabilities in innovation. In the context of national systems of innovation in peripheral economies, economic actors connected to more innovative locations tend to be part of more geographically dispersed inventor networks. When these economic actors are engaged in tacit knowledge creation, their innovative activities tend to be co-

located, unless the orchestrator of the innovation is a highly innovative company that is able to conduct this type of innovation in a dispersed fashion.

The second essay explores whether publicly-funded schemes for innovation are related to an increase in the "openness" of firms' innovation practices. Using survey data from 5,238 firms in 29 countries, I find that both monetary and non-monetary support policies for innovation are related to an increase in the degree of openness of individual firms. This openness is expressed both in terms of the number of external partners with whom they collaborate and the number of open innovation activities they perform. However, the relationship between the extent of public support and openness seems to be negatively moderated by the existence of previous innovative activity within the firm. Public support has more impact on less innovative firms and less influence when the firm is already innovative, which implies that it is important to target such supports in order to maximize their impact. Additionally, I find that non-monetary support is more critical than financial support in increasing openness. For policy makers facing salient financial constraints, this implies that institutions and government policies can play an important role in fostering open innovation.

The third essay explores the patterns of knowledge sourcing of firms before and after privatization. Privatization of state-owned enterprises generates the adoption of new management practices and changes in the companies' objectives. While the literature has abundantly explored the consequences of privatization over different aspects of firm performance, its effects on innovation have been scarcely explored. While some studies suggest that privatization produces a subsequent reduction in the amount of R&D investment, little else is known about specific changes in the patterns of innovation of privatized firms. I hypothesize that privatized firms are likely to focus on a narrower set of technologies as a response to increased pressure for profitability and short-term results. I also analyze the competing arguments regarding the privatized firms' willingness to engage in collaborations with other firms and to disperse their innovation activities internationally. I used patent data for a sample of privatized firms from multiple countries to assess the validity of these hypotheses.

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CHAPTER 1

THE GEOGRAPHICAL DISPERSION OF INVENTOR NETWORKS IN PERIPHERAL ECONOMIES

1.1 Introduction

What determines the level of connectivity of a peripheral economy to global networks of inventors? Global innovation systems are becoming increasingly complex and involving a wider range of locations. As value chains are disaggregated across borders, countries are increasingly interconnected in global invention networks (Balconi, Breschi, & Lissoni, 2004, Breschi & Lissoni, 2009). Locations outside core OECD countries, attempting to catch-up technologically with core developed economies, try to attract multinational companies to perform innovative activities in their territories and create linkages to these global innovation networks. Connectivity provides an economy with access to a wider variety of world-class pools of knowledge. However, the factors affecting the connectivity of peripheral economies have been overlooked by the literature; this is the main motivation for this paper. I argue that value chain activities involving a high level of tacit knowledge "tend to remain more agglomerated in the parent company" (Cantwell and Santangelo, 1999: 101). These activities will be performed mostly by collocated teams or teams with members in global centers of excellence (Gittelman, 2007) so that the local economy obtains limited connectivity to global innovation networks. I also argue that some leading innovative firms may possess complex organizational capabilities that gives them the ability to orchestrate these such activities in a dispersed manner (Cantwell, 1995, Cantwell & Mudambi, 2011, Tallman & Chacar, 2011).

The connectivity of a location is defined as the particular configuration of its global linkages combined with the specific network structure of these linkages (Lorenzen & Mudambi, 2013). In general, linkages between locations can arise either from organizations or from individuals. In the literature, organization-based linkages have been referred to as “pipelines” (Bathelt, Malmberg, & Maskell, 2004), while those arising from individuals have been referred to as “personal relationships” (Lorenzen & Mudambi, 2013). Further, locations differ in terms of the extent to which their linkages are concentrated in a few central actors. In this paper, I examine empirically one aspect of connectivity in detail: the geographical dispersion of inventor networks across national borders.

Non-core locations have the most to gain from connectivity to global innovation systems (Abramovitz, 1986). In particular, these gains can be best leveraged by economies that have achieved some degree of maturity in terms of local innovative capabilities. “Peripheral economies” form a particularly important class of non-core economies. The concept of a “peripheral” economy fills an intermediate category (Molero, 1995) in the rigid “developed vs. developing/emerging” economies dichotomy. Benito and Narula (2008) provide a definition that characterizes peripheral economies according to detailed criteria like levels of foreign direct investment (FDI), trade in intermediate and manufactured goods and innovation, in order to distinguish them from core OECD economies. Some southern and eastern European countries are good examples (Benito & Narula, 2008, Liagouras, 2010, Narula & Guimón, 2010). This change in global value networks provides opportunities for non-core locations to participate in the high knowledge components of global value chains. Further, since peripheral economies are likely to lag the core in terms of innovation capabilities in almost all sectors, connectivity is likely to have particularly strong effects for them.

I study one particular aspect of the global connectivity of peripheral economies, namely the international dispersion of inventor networks. I use Portugal and Greece as examples of peripheral economies (Benito & Narula, 2008, Narula & Guimón, 2010). Both countries can be considered peripheral to the core region of Europe and are comparable in size, income and the level of development of their innovation systems. Furthermore, their location in the perimeter of the European continent (Portugal in the southwest and Greece in the southeast) and the fact that they do not share borders with the core European economies, create similar challenges in terms of integration with the rest of the continent. I analyze patent data for both countries, encompassing all the patenting activity linked to Portugal and Greece. I include patents from local firms with local inventors, patents from foreign assignees with local Portuguese or Greek inventors, and patents from local Portuguese or Greek firms with inventors located abroad. Therefore, my sample includes firms and inventors located in 44 countries. By understanding how inventor networks work in these peripheral economies, I highlight characteristics that I suggest may be typical of peripheral economies in general.

I find that peripheral economy inventors with collaborators in core economies tend to have more internationally dispersed networks. In addition, I provide some of the first empirical evidence on the Cantwell and Santangelo (2000, 1999) research on the dispersion of innovation activities involving tacit knowledge, in this case extending it to the context of peripheral economies.

The rest of the paper is structured as follows. Next, I review relevant literature. Then, I develop the theoretical bases of my analysis and derive my research hypotheses. Subsequently, data and empirical methods are described. Finally, I discuss the results and the associated implications.

1.2. Literature Review

1.2.1. Peripheral Economies

Periphery is not a new concept. Its roots can be traced to early works on the foundations of capitalism (Wallerstein, 1974) and dependency theory (Prebisch, 1962), which addressed the challenges of economic and technological catch-up for peripheral countries. Much of this early work involved a rather crude definition of the periphery, basing it on the realities of nineteenth century imperialism. By the last decades of the twentieth century, this research had become outmoded and less useful in understanding the nature of global interactions (Cantwell, 1995).

More recently, Molero (1998) defines peripheral economies as an intermediate group that displays less developed productive structures than the core, less internationalization via outward FDI, and with innovation systems marked by medium-low R&D effort and modest levels of patenting. For Benito and Narula (2008), peripheral economies are “not significant destinations for or home to many MNEs; they engage in relatively little trade in intermediate and manufactured goods; they contribute relatively little to innovation and scientific progress; they are weakly linked or accessible physically to the core; they do not play significant decision-making roles within supranational organizations; and they do not share a significant number of formal institutions with core countries” . While displaying these weaknesses, these are relatively affluent economies, with per capita incomes significantly higher than emerging countries, but below the more affluent core economies.

Benito and Narula (2008) specifically emphasize the role of interdependence. For them, the critical difference between core and periphery is the degree of social, political and economic international integration in the world economy. Cross-border activity (like international trade) or vertical cross-border linkages do not necessarily qualify as interdependence; they are merely internationalization. The key to interdependence is reciprocity, which involves ongoing, mutual relationships between economic actors. In this sense, peripheral economies may be connected to the core, but relationships are not mutual, for resources tend to run in one direction. In other words, connectivity doesn't equal interdependence. More unequal relationships weaken integration, leading to peripheral status.

1.2.2. Peripheral regions and knowledge networks

According to Saxenian (2006, p. 3), innovation is the key factor driving the evolution of formerly peripheral economies. One of the ways to foster innovation is to attract and embed MNE R&D activity. Since MNEs form internationally integrated intra-firm networks (Cantwell & Piscitello, 2000, McCann & Mudambi, 2005), more MNE activity is likely to increase the integration of the economy into global networks. However, technologically advanced MNEs are likely to seek locations with significant levels of academic activity (Alcácer & Chung, 2007), with high R&D intensity and a significant magnitude of technical activity (Chung & Alcácer, 2002), all of which is not typical of peripheral economies. In general, these economies are not very attractive locations for MNE R&D activities, because of weak location advantages, relatively under-developed scientific and educational infrastructure, low potential for knowledge spillovers, small market size (Cantwell & Piscitello, 2002, Cantwell & Piscitello, 2005) and low absorptive capacity (Cohen & Levinthal, 1990).

The activity of MNEs in these peripheral economies brings the greatest local benefits when it is associated with “capability/knowledge-augmenting” R&D activities - which seek to tap into local sources of knowledge and resources (Cantwell & Mudambi, 2005). Though “competence-creating” MNE subsidiaries are the most attractive, they usually require locations with a rich resource base (Cantwell & Mudambi, 2000). Peripheral economies tend to attract “competence-exploiting", demand-driven R&D activities due to their disadvantage in technological capabilities vis-à-vis the core (Cantwell & Mudambi, 2000, Narula & Guimón, 2010). In line with this, Ambos and Ambos (2009) explored the location of R&D laboratories and found that out of 25 labs in non-core locations, only 5 had a capability-creating mandate. Competence-exploiting subsidiaries focus on routine replication and local adaptation and are the dominant type in Greece and in Portugal, according to Manolopoulos (2010) and Tavares-Lehmann (2008). In some cases, especially in oligopolistic industries, the main reason to enter the economy is to preempt a competitor or limit its growth prospects (Alcácer, Dezső, & Zhao, 2013). Such subsidiaries are unlikely to spark innovation applicable beyond the local milieu (Cantwell & Mudambi, 2005). Hence, attracting MNEs to peripheral economies may have a limited impact on sparking high quality innovative activity in those economies.

There are, a priori, clear differences in knowledge-sourcing patterns between MNEs and local firms. MNEs are characterized by "multiple embeddedness" (Andersson & Forsgren, 1996, Meyer, Mudambi, & Narula, 2011) in their home country context and in that of their subsidiaries. Simultaneously, MNE subsidiaries are externally embedded in their host milieu and internally embedded within their parent organization network (Andersson & Forsgren, 1996). This multiple embeddedness allows MNEs to integrate diverse knowledge sources and create value through "knowledge arbitrage". Henderson (2003) found that single-plant firms benefit more than multi-unit firms from local information spillovers derived from local concentration of other plants in the same industry. This implies that local and external environments are more important for domestic firms. MNEs can source knowledge from remote units within the organization. Bathelt, Malmberg and Maskell (2004) launched the argument of "local buzz, global pipelines" to discuss the complementarity of tacit knowledge flows confined to the local milieu (the "buzz") and the extra-local exchange of codified knowledge (the "pipelines"). They argue that the availability of both high levels of buzz as well as many pipelines in a certain location provides firms with particular advantages. In peripheral economies, pipelines are basically orchestrated by MNEs. Some factors may drive the creation of thicker pipelines; Alcácer and Zhao (2012) found that the presence of direct competitors in the same location tends to favor the creation of more internal linkages across different subsidiaries and more use of cross-cluster teams. However, pipelines are expensive to build and maintain since the establishment of subsidiaries requires relatively large investments. Furthermore, pipelines to other subsidiaries provide access to networks of inventors that are relatively constrained. A subsidiary 'A' collaborating with another subsidiary ‘B’ may only have access to its local network of inventors and to the local network of subsidiary ‘B’. This is especially true as MNEs are concerned about the protection of their intellectual property, and are likely to refrain from open collaboration with external parties whose loyalty may be unknown (Mariotti, Piscitello, & Elia, 2010, McCann & Mudambi, 2005).

Specialized knowledge not only flows through pipelines. It also circulates through personal networks. Some authors talk about “epistemic communities”, or networks of specialized individuals spanning different organizations. Firms are excluded from important knowledge-sharing if they don’t belong to these knowledge networks (Lissoni, 2001). Lorenzen and Mudambi (2013) refer to these networks as “person-based linkages”, which tend to be serendipitous in origin, to distinguish them from pipelines, which are “organization-based linkages” and are usually strategic in origin. Incorporating a social network view, they argue that the impact of global linkages on the catch-up ability of clusters in emerging regions depends on those linkages’ network structure. Other authors have written about “geographical proximity” and “organized proximity” (Torre & Rallet, 2005); as knowledge circulates through networks, firms do not necessarily require permanent co-location (geographical proximity) for interactive learning to occur. The existence of knowledge networks across regions or countries (organized proximity) allows firms to search non-locally for knowledge that is not available in their home territory. Belussi et al. (2010) explored research networks in one of the most innovative regions of Italy and found a high propensity to establish local or national ties rather than transnational linkages to source knowledge. In turn, Boschma and Ter Wal (2007) explored the knowledge network of firms from a cluster located in a peripheral region (southern Italy) and found that firms having knowledge linkages with non-local firms had better innovation performance than those relying only on local relationships. This implies that firms in peripheral regions benefit from searching knowledge beyond the local milieu, even if they are located in a specialized cluster. Asheim and Isaksen (2002) found that external contacts, outside the local milieu, are crucial for the innovation process of SMEs; too much reliance on local knowledge seems harmful for innovative capacity and can lead to a "technology trap" (Giuliani, 2010).

It follows that the innovative activity of domestic firms and other organizations (e.g. universities and research institutions), that do not possess networks of subsidiaries, will rely more on personal networks for establishing collaboration relationships. These networks are "thin" compared to the "thick" pipelines between units of an MNE, but also cheaper and easier to establish and maintain. Knowledge sourcing and collaboration patterns vary depending on regional characteristics. Munificent regions, with high levels of innovation favor local collaboration, given the availability of local knowledge. Conversely, firms in peripheral economies, given their less favorable location, may be compelled to source knowledge from more remote sources by establishing more geographically dispersed networks based on personal relationships.

This complex combination of organizations and individuals sharing knowledge across the geographic spaces creates an array of possible linkages and knowledge sourcing patterns. Gittelman (2007) found that the spatial distribution of these collaborations tends to be strongly bimodal, with a large number of local collaborations and a large number of very long distance collaborations, but few at intermediate distances. The rationale behind this distribution is that, when knowledge is not available locally, there is little to gain from tapping regions at intermediate distances if those regions do not possess that knowledge either. Once organizations need to establish collaborations outside the local milieu, they tend to do it with centers of excellence elsewhere, driven more by the availability of the knowledge than by distance considerations.

Another aspect to take into account when studying the patterns of dispersion of knowledge networks is the tacitness of knowledge. Cantwell and Santangelo (2000, 1999) argue that co-location of inventors tends to be more prevalent in innovation activities that depend upon tacit knowledge. R&D related to the firm's core technologies and in science-based fields also seem to require more face-to-face interaction. These authors argue that activities involving tacit knowledge are geographically dispersed only in certain cases: (1) when the knowledge is locally embedded, unique and specialized or (2) when there are complex organizational networks in place. Point (2) implies that the "international dispersion of activity is led by technology leaders" (Cantwell, 1995: 155), i.e., that only leading firms possess the capabilities to effectively conduct this type of R&D through geographically dispersed teams. I extend the findings of Cantwell and Santangelo (2000, 1999) to the context of peripheral economies.

1.3. Theory and Hypotheses

The first hypothesis focuses on the relationship between the location of inventors and the level of disaggregation of innovation across national borders, specifically the dispersion of inventor networks. Inventors related to any country are either based locally or based in foreign locations but employed by local organizations. I examine each of these two classes of inventors in the following analysis. I first consider the more straightforward case, i.e. foreign-based inventors of local (peripheral economy) organizations. Organizations in peripheral economies (firms, research institutions, universities, etc.) seek knowledge from both local and non-local inventors, but they are likely to source the most complex, capability-driven, explorative knowledge (requiring the highest degree of collaboration) from core regions, given the shallow knowledge bases of peripheral milieus. Hence, the inventors of peripheral economy organizations based in core economies have access to wider innovation networks than those based in other peripheral economies.

Next I consider the case of locally-based inventors in a peripheral economy. As previously discussed, firms from core regions typically search for explorative knowledge either in their home location or in other core regions. They usually go to peripheral regions in search of exploitative, cost-driven knowledge. As the inventors they hire in peripheral economies undertake mainly exploitative work, they are only locally connected or at most, connected to a home economy subsidiary or to headquarters. Therefore, their networks will be more limited than those of inventors residing in core economies.

Drawing on the literature and the arguments discussed above, I state the following hypothesis:

Hypothesis 1: *Among inventors linked to peripheral economies, those located in core innovative economies will be connected to more internationally dispersed inventor networks than those located in peripheral economies.*

As discussed in the literature section, it is widely accepted that different activities within the value chain have different degrees of transferability, depending fundamentally on the extent of codifiability. More codifiable innovative activities can be either outsourced or disaggregated (even across national borders), through geographically dispersed innovation networks. In contrast, more tacit innovative activities, as a general rule, are more likely to be internalized and conducted by collocated teams. This is true in peripheral economies as much as in other contexts. Therefore, the second hypothesis is the following:

Hypothesis 2: *When innovation in peripheral economies involves tacit knowledge activities, the inventor networks will be less internationally dispersed than when knowledge is more codifiable.*

As Cantwell and Santangelo (1999) argue, there are two factors that facilitate the orchestration of tacit-knowledge innovation across dispersed networks. This first is organization-specific capability, typically associated with leading firms in the relevant knowledge space. The second is that the innovation is focused on competencies that are “non-core” for the company (Cantwell & Santangelo, 2000). Calantone and Stanko (2007) found that firms that are experienced in conducting exploratory research tend to outsource innovation activities (of any kind) to a higher degree. I argue that being an experienced innovator and having the capabilities associated with it will be most critical when the innovation is focused on tacit components. In addition, as argued by Cantwell and Santangelo (2000), for the largest and most experienced MNEs, most innovation with tacit components (such as design innovation) that is dispersed is typically not be a core activity . Therefore, there are two reasons to expect that leading innovative companies will show a higher degree of dispersion in tacit innovation, compared to laggard or sporadic innovators. First, they have developed the necessary capabilities through their extensive experience in innovation. Second, innovation with much of the tacit-knowledge components (such as design innovation) that is dispersed is likely to be a non-core component of their activities. Based on these arguments, I arrive at the following hypothesis.

Hypothesis 3: *The relationship between tacit knowledge and the international dispersion of inventor networks will be moderated by the innovation capabilities of the firms, such that leading innovative firms will be able to disperse their tacit knowledge innovation across borders to a higher degree than innovation laggards.*

In summary, I hypothesize that in the context of peripheral economies, the disaggregation of inventor networks across national borders, will depend on the combination of location, knowledge tacitness and organizational capabilities in innovation.

1.4. The empirical context: Portugal and Greece

I chose two typical European peripheral countries as the empirical setting to illustrate the processes underlying innovation networks in peripheral economies: Portugal and Greece. Both countries can be considered textbook cases of European peripheral economies, as they display all characteristics usually attributed to such economies. These include the structure of production, the degree of internationalization and international openness, foreign subsidiary roles, linkages among actors, innovation-related indicators, connectivity with the core, and organizational/institutional characteristics (Benito &

Narula, 2008, Molero, 1998, Molero, 1995). Compared to core European Union (EU) economies, their economies are marked by a low degree of internationalization, low relevance of high tech sectors and a low weight of high tech exports. Their patent production represents only a minimal fraction of the European patenting activity (Roberts & Thomson, 2003). They also show a predominance of SMEs and micro-enterprises with low productivity and often offering non-tradable services (Simões & Godinho, 2011), and a scarcity of indigenous MNEs, a relatively low supply of technology and (in the case of Greece) a risk-averse national culture (Souitaris, 2001). Particularly in Greece, there is also a significant number of under-educated or under-qualified people in senior positions in numerous companies, which poses additional challenges to fostering an innovative culture (Souitaris, 2002). At a more general level, both countries have practically the same population of 10.8 million (CIA, 2013) and similar income levels: the GDP per capita (PPP) of Greece is US$24,300 and that of Portugal is US$23,000 (CIA, 2013). They also have comparable sizes and have the disadvantage of being located in the extremes of Europe, relatively far from the core economic and innovative regions in the continent.

As expected in peripheral economies, linkages among actors in these countries are modest. In Portugal, the low degree of autonomy of foreign subsidiaries limits linkages with the Portuguese science, technology and innovation (STI) system (Tavares-Lehmann, 2008). Foreign-owned subsidiaries in Portugal also tend to source less locally than their domestic counterparts, since few local suppliers can fulfill the standards they require, in quantity and quality, though this is changing (Tavares-Lehmann, 2008). In Greece, there is also little engagement and interaction between the STI programs designed by the government and the innovative firms in the private sector, particularly MNEs (Collins & Pontikakis, 2006). Another problem in Greece is the uneven regional distribution of both big companies and R&D, with the bulk of activity concentrated in Southern Greece relatively little activity in other regions such as Thessaloniki (György & Vincze, 1992).

Literature on patenting activities is more abundant for Portugal than for Greece. Most studies about Portugal (Godinho, 2009, Godinho, Simões, Pereira, Mendonça, & Sousa, 2004, Godinho, Simões, Pereira, & Rebelo, 2008) show that the country is well below the OECD average in terms of patent indicators. Yet, there has been an acceleration in patent applications since 2000 (Godinho, 2009). The recent increase in international patenting is mainly driven by the business sector. Subsidiaries of foreign MNEs and born-globals have been particularly active in filing patents internationally, notably in the United States Patents and Trademark Office (USPTO) (Godinho, Simões, Pereira, & Rebelo, 2008). For high tech firms, most of which are SME startups, patenting in the USPTO is a matter of reputation and "signaling" to potential partners and clients. MNE subsidiaries tend to centralize patenting processes, including patent applications, at headquarters or at a central R&D base. In Greece, there has been a number of programs (EPET I and II, STRIDE Hellas) aimed at increasing the scientific and innovative production of the country. In spite of steady increases in overall production of patents and publications since the 1980s, the country is still a clear innovation laggard in the context of the European Union (Collins & Pontikakis, 2006).

1.5. Data and Methodology

1.5.1. Data

Patent co-inventorship has been used to explore collaboration patterns of inventors (Ejermo & Karlsson, 2006). However, patent data have certain limitations (Archibugi, 1992, Pavitt, 1988), such as lack of consistent quality across national patent systems and uneven approval rates in different countries; for that reason it is recommended that datasets contain patents registered in one single patent institution (Archibugi & Coco, 2005). Another limitation is that patents are poor indicators of innovation output for sectors where most innovations go unpatented (Hu, 2012). The propensity to patent in a foreign system depends on many factors, but the most valuable inventions tend to be patented in the most important patent systems, particularly in the USPTO (Archibugi & Coco, 2005).

The empirical analysis is based on patenting activity involving Portuguese and Greek assignees and inventors. I constructed a population dataset of patents obtained from the USPTO. While the USPTO does not represent the entire innovation output of foreign countries, it tends to contain a valuable portion knowledge generated in a country. Another advantage of USPTO is the predominance of patents granted to firms (the focus of this study), whereas national patent systems, particularly in developing countries, show high incidence of patents granted to individuals (Da Motta e Albuquerque, 2000, Penrose, 1973). In this study, the use of USPTO data, instead of European Patent Office (EPO), is justified for several reasons.

First, I want to include the interactions of firms based in foreign countries with local inventors based in the focal peripheral economy. This particular case (for instance, a firm that conducts innovation in the U.S. but uses a Portuguese inventor) is not likely to be captured in the Portuguese patent system, since the firm is more likely to patent in its home country and in USPTO rather than in Portugal. Second, the European Patent Office (EPO) treats design innovation separately (i.e., there are no design patents), which makes it impossible to use my proxy for tacit knowledge innovation. Third, EPO provides information not only on patents granted, but also includes on the listings applications not yet granted, applications withdrawn, applications deemed to be rejected or withdrawn, among others, for a total of 12 different status. This creates a number of problems, for instance it doesn't allow us to estimate the number of patents a firm possesses, since a search by assignee yields a number of references that are not actual patents (they are applications, patents rejected, etc.). Fourth, the EPO search engine mixes search fields (for instance, company name and street name), which results in unreliable results. And fifth, in Europe it is possible to apply for a patent in the local office of the country (instead of EPO), so many applications are done only in two or three countries and not in EPO; but if these patents are valuable enough, are also likely to be submitted to USPTO. I did, however, conduct an empirical analysis with EPO data. The results are incomplete, since I are missing several variables (Design, MNE, Leader), but the coefficients are consistent with my theory. Based on partial results, I believe that EPO data would be consistent with the results obtained using USPTO patents, such that the USPTO displays a realistic picture of the invention activity in these peripheral economies.

It is important to emphasize that, while the setting of this study is Portugal and Greece, the sample captures the entirety of these countries' innovation systems, which comprises a set of assignees and inventors located in 44 countries. It includes every firm in the world that patents using a Portuguese or Greek inventor and every inventor in the world that works for a Portugal or Greece-based firm. Obviously, such interactions are better captured by USPTO rather than by local patent data.

I collected all USPTO patents associated with the Portuguese and Greek innovation systems in batches. First I collected all the patents that listed at least one assignee based in Portugal. The second batch contained all patents granted where at least one of the inventors was based in Portugal, regardless of the location of the assignee (Portugal- or foreign-based). Then I eliminated duplicate observations (patents included in both batches because they had both assignee and inventors based in Portugal) and also dropped patents assigned to individuals, in order to focus on the patenting activity of companies. I arrived to a first subset of 503 unique patents corresponding to the Portuguese national system of innovation. I repeated the same steps for Greece, constructing a second subset with 864 unique patents corresponding to the Greek national system of innovation. I "pooled" both subsets into one dataset, which I used for the main empirical models. I distinguished the country-subsets by using a dummy variable (GREE_NSI) for the patents that are linked to Greece. The final dataset (after dropping a duplicate patent) contains 1,366 unique patents.

1.5.2. Dependent variable

- *International dispersion of the network of inventors* (*INV_DISP*): I constructed the dependent variable in two steps. First I computed the Herfindahl index of inventor concentration at the country level. For instance, if a patent was authored by four inventors, of which three are located in country A and one is located in country B, the associated Herfindahl index *'H'* is equal to: $0.75^2 + 0.25^2 = 0.625$. If all inventors are located in one country, the Herfindahl index is equal to 1. Since I am interested in the dispersion rather than the concentration of inventor networks are, and I want the coefficient to be positive on the dispersion of inventors, the second step was to construct the dependent variable *'Y'* by transforming Herfindahl index '*H'*, such that:

$$Y = 1 - H$$

As a result, the dependent variable is censored, with a minimum value of 0 (when all inventors are concentrated in one country), and an upper limit asymptotically approaching 1 as the inventors are more dispersed across countries.

1.5.3. Independent variables

- *Inventor-country GDP per capita (IC_GDP*): I use GDP as a proxy for the type of country where inventors are located (i.e. core, peripheral, emerging). This indicator is longitudinal and corresponds to the year each patent was filed. In patents with inventors in more than one country, the weighted average is used (weighing each country score based on the share of inventors from each country in the inventor group).
- *Firm innovative leadership (LEADER*): *LEADER* is a dummy variable for firms in the upper quartile of the sample in terms of their patent pool. I operationalized 'patent pool' as the natural logarithm of the number of USPTO patents issued to each company.
- *Tacit Knowledge activity (DESIGN)*: is operationalized by a dummy variable for any "design patent" in my dataset. According to the USPTO description, a "design

patent” protects “the way an article looks”, in contrast to a “utility patent”, which protects “the way an article is used and works”. In practical terms, a design patent has a “D” before the number. In the literature, design knowledge has been described as the combination of both explicit components and tacit ones, also dubbed "know-x" (Wong and Radcliffe, 2000). The "know-x" component is the ability to select the right piece of information and to use it in the right way, at a right time and place, to carry out a design. In the same vein, other authors (Arora et al., 2001; Leonardi and Bailey, 2008; Yoo et al., 2006) have described different aspects of design as having a significant tacit component. All of this is consistent with the arguments that (1) design contains tacit elements and (2) design usually requires co-location or proximity of inventors.

1.5.4. Interactions terms and control variables

- *Tacit knowledge activities by innovation leaders (LEAD_X_DES)*: this interaction term is the multiplication of *LEADER* and *DESIGN* and reflects the effect of doing innovation in design if the assignee is an innovation “leader”, compared to the effect of doing design by any other assignee who is a “laggard”.
- *Multinational company (MNE)*: I searched for information on every patent assignee; I considered MNE any firm which had operations in more than one country (not counting sales exports). Universities or research organization with only local operations were not considered MNEs. As my data goes back to 1975, it contains a number of defunct firms or assignees that left no trace on the internet. In these cases, I adopted an inclusive criterion, considering the assignee as ‘MNE’ if at least one inventor in the patent was located in a country different than that of the assignee.

- *Geographical dispersion of assignees (ASSI_DISP)*: the international dispersion of assignees calculated in the same way I calculated the dispersion of inventors.
- *Number of inventors (NUM_INV)*: number of inventors participating in the patent.
- *Other organizations (OTHER_ORG): dummy variable for organizations that are not business firms (for example universities, research institutions, etc.)*

I also incorporated technology controls. I used each patent class and classify it into a taxonomy based on HALL et al. (2001), which organizes utility patent classes into six major categories. Those six categories are 1) Chemical, 2) Computers and Communications, 3) Drugs & Medical, 4) Electrical & Electronic, 5) Mechanical and 6) Others. Design constitutes a seventh category of patents. In addition, I also controlled for whether the patent is part of the Portugal or Greece subsets and used year fixed effects.

1.5.5. Estimation

Table 1 presents the summary statistics for the sample. The dependent variable is bounded, with a minimum value of 0 when all the inventors are in the same country, and a maximum observed value of 0.800. Of the patents in the data set, 694 (50.8 %) only have one inventor-country, which means there was no international collaboration involved. The other 49.2 % of the patents involved networks of collaboration between inventors in different countries. There is a large dispersion of innovative capabilities among the sample firms, as measured by their patent pool. The median firm in the sample holds approximately 40 patents. In terms of correlations (Table 2), “International dispersion of the network of inventors” is positively correlated with GDP per capita, implying that in core countries, inventors have access to more extended innovation networks.

I employ a multiple regression approach to test my hypotheses. As described previously, the dependent variable is double censored; the most appropriate technique for this type of dependent variable is a Tobit regression (Greene, 2000: 905-926). Tobit models have been used in many studies with similarly censored dependent variables (Jeong & Weiner, 2012, Laursen & Salter, 2006, Mudambi & Helper, 1998, Ragozzino & Reuer, 2011).

Multicollinearity diagnostic checks were performed by running each model with an OLS regression and calculating variance inflation factors (VIFs). All the estimates showed values of less than 3, well below the commonly accepted threshold of 10 for VIF values (Chatterjee & Price, 1991) . Finally, I acknowledge that there may be other factors not included in my model that affect both location and inventor dispersion. For this reason I do not take the coefficients as indicators of causality but rather as indicators of associations between constructs.

1.5.6. Results

I ran three regression models to test my hypotheses (see Table 3). All models use censored Tobit analysis and the dependent variable is the dispersion of inventors across countries (measured for each focal patent).

Model 1 is the base model and Model 2 is the full model containing the interaction term Tacit knowledge activities by innovation leaders (LEAD_X_DES). Model 3 is similar to Model 2 but only includes patents linked to Greece. As predicted by Hypotheses 1, higher GDP per capita is associated with more international dispersion of inventors. This implies that inventors located in core economies have access to richer networks of innovation. This finding is consistent with the theoretical framework.

Hypothesis 2 focuses on tacit knowledge activities operationalized by design patents. I predict that design patents will be usually authored by co-located teams, due to the high component of tacit knowledge they contain. In other words, the geographical dispersion of teams involved in design patents will be less than for utility patents. The coefficients for DESIGN are negative in all models and significant in the full model 2. This is consistent with H2.

Finally, Hypothesis 3 predicts that innovation leaders are more capable to integrate tacit knowledge innovation across geographic space. Therefore, when innovation in design is carried out by leading firms, the geographical dispersion of inventor teams will be higher than for other organizations. The interaction coefficient LEAD_X_DES is positive and significant in both model 2 and 3, consistent with H3.

In terms of controls, MNE shows positive and significant coefficients. This is consistent with the notion that MNEs will have access to networks in multiple countries, which local firms will not be able to match. The geographical dispersion of assignees (ASSI_DISP) is positive and significant. This is intuitive; if a patent is coauthored by assignees dispersed in different countries, the inventors are also likely to be geographically dispersed. The coefficient for number of inventors (NUM_INV) is also positive and significant. This is not surprising either; the larger the group of inventors participating in the patent, the larger the chance that one or more of them is located in a different country. The coefficient for other organizations (OTHER_ORG) is also positive and significant. This is consistent with the notion that person-based linkages (the type favored by research institutions or universities) are easier to establish than organization-based linkages (the type favored by business firms). Finally, the coefficient for the Greek national system of innovation (GREE_NSI) is not significant, meaning that Greek innovators and their Portuguese counterparts do not show significantly different levels of dispersion.

To test the robustness of the data, I analyze data from other patent sources (EPO) and from other peripheral economies (Czech Republic, Slovakia and Slovenia). The data is not fully comparable, since some variables were missing. However, results (not reported here) seem consistent with the first hypothesis, that inventors in core economies are connected to more internationally dispersed inventor networks.

1.6. Concluding remarks and implications

The traditional development economics literature distinguishes between developed and developing countries (Meier & Rauch, 2005). Later literature identifies some of the old developing country group that experienced rapid catch up along a number of dimensions as ‘emerging economies’ (Awate, Larsen, & Mudambi, 2012, Cuervo-Cazurra, 2012). But, with few exceptions, the growing diversity within the developed country group has not received much attention (Benito & Narula, 2008, Narula & Guimón, 2010). This paper focuses on the sub-group of developed countries that have been labeled ‘peripheral’ due to their relatively lower connectivity with the global economic system, as compared to the ‘core’ developed countries.

I use the comprehensive population data set of U.S. patents issued to Portuguese and Greek assignees (organizations) and inventors (individuals) to analyze the dispersion of inventor networks across national borders in these peripheral economies. Most studies of innovation systems are either couched at the level of organizations or at the level of individual inventors. I build on prior work on inventor networks (Balconi, Breschi, & Lissoni, 2004, Fleming & Marx, 2006, Zucker & Darby, 1996) and disentangle three factors that are associated with the dispersion of those networks: the location of the inventors, the type of knowledge, and the capabilities of the firm.

The first part analyzes the association between location of inventors and the international dispersion of inventor networks. My findings are consistent with the theory that inventors located in core innovative countries have access to more internationally dispersed inventor networks. Thus, interaction with them will provide the economic actors based in peripheral economies with the potential benefits derived from this dispersion. In contrast, too much reliance on local knowledge sources may be harmful for innovative capacity and can lead to a "technology trap" (Giuliani, 2010).

The second part explores how the tacitness of the knowledge involved in the innovation process hinders dispersion. Consistent with theory, I find that design patents are associated with less dispersed inventor networks. This relationship, however, is moderated by the capabilities of the firms conducting the innovation. Highly innovative firms develop capabilities that allow them to conduct this type of innovation in a more dispersed manner. These findings are consistent with the second and third hypotheses. To the best of my knowledge, this is the first empirical testing of the theoretical work of

Cantwell and Santangelo (2000, 1999) about the factors affecting the dispersion of tacit knowledge creation.

I believe this work has two types of implications. For academics, it opens the way to the exploration of a potentially very interesting area of inquiry: the characteristics of innovation in peripheral economies and the differences between the creation of tacit and codified knowledge in those contexts. Further work will be needed to disentangle the complex realities of these economies, but I think this a first step in that direction. For policy makers, I provide some important distinctions about the factors that may affect connectivity in peripheral economies. For economies that are striving to catch up with the core, understanding these drivers may prove to be a very valuable tool.

Concerning policy, the way to diminish the disadvantages of peripherality is to increase connectivity – by promoting the presence of locally based (domestic and foreign-owned) actors in international innovation and supply networks. Such connectivity to global value chains is a key aspect of high levels of local value creation (Humphrey & Schmitz, 2002, Mudambi, 2008). In this context, my findings highlight the crucial role of the individual level of analysis (networks of inventors). Such connectivity requires a strengthening of "system linkages" (Heitor & Bravo, 2010) and "systemic density" (Godinho & Simões, 2013). Given that linkages and networks need time to develop, consistency and predictability of policies is a key factor.

Table 1.1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
International dispersion of inventor networks (INV_DISP)	1366	0.225	0.240	0	0.800
Inventor-country GDP per capita (IC_GDP)	1366	22211	10263.9	2028	50371
Firm innovative leadership (LEADER)	1366	0.250	0.433	0	1
Multinational company (MNE)	1366	0.684	0.465	0	1
Design (DESIGN)	1366	0.138	0.345	0	1
Geographical dispersion of assignees (ASSI_DISP)	1366	0.011	0.074	0	1
Number of inventors (NUM_INV)	1366	2.856	1.882	1	13
Non-business organization (OTHER_ORG)	1366	0.147	0.354	0	1
Design by innovation leaders (LEAD_X_DES)	1366	0.008	0.089	0	1
Greek national system of innovation (GREE_NSI)	1366	0.633	0.482	0	1

Table 1.2: Pearson Correlation Coefficients

		1	2	3	4	5	6	7	8
1	International dispersion of inventor networks (INV_DIS	1.000							
2	Inventor-country GDP per capita (IC_GDP)	0.378	1.000						
3	Firm innovative leadership (LEADER)	0.283	0.188	1.000					
4	Multinational company (MNE)	0.087	0.087	0.155	1.000				
5	Design (DESIGN)	-0.260	-0.154	-0.180	0.066	1.000			
6	Geographical dispersion of assignees (ASSI_DISP)	0.103	0.073	0.111	-0.041	-0.061	1.000		
7	Number of inventors (NUM_INV)	0.418	0.378	0.241	0.045	0.242	0.143	1.000	
8	Non-business organization (OTHER_ORG)	0.204	0.017	0.027	-0.565	0.168	0.110	0.151	1.000

Table 1.3: Tobit Regression Analysis

DV: International dispersion of inventor networks (INV_DISP)	Model 1		Model 2		Model 3	
Inventor-country GDP per capita (IC_GDP)	0.0004	***	0.0000	***	0.0000	***
	(0.000)		(0.000)		(0.000)	
Firm innovative leadership (LEADER)	0.0890	***	0.0685	**	0.0439	†
	(0.021)		(0.021)		(0.023)	
Multinational company (MNE)	0.2317	***	0.2258	***	0.1070	**
	(0.029)		(0.029)		(0.033)	
Design (DESIGN)	-0.0387		-0.1090	*	-0.0667	
	(0.046)		(0.049)		(0.063)	
Geographical dispersion of assignees (ASSI_DISP)	-0.1287		-0.1124		-0.1609	
	(0.106)		(0.105)		(0.129)	
Number of inventors (NUM_INV)	0.0353	***	0.0341	***	0.0123	*
	(0.005)		(0.005)		(0.006)	
Non-business organization (OTHER_ORG)	0.3168	***	0.3109	***	0.2003	***
	(0.034)		(0.033)		(0.037)	
Design by innovation leaders (LEAD_X_DES)			0.4160	***	0.4424	***
			(0.092)		(0.114)	
Greek national system of innovation (GREE_NSI)	-0.0229		-0.0243			
	(0.020)		0.020			
Technology controls	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Constant	-0.4798	***	-0.4723		-0.3633	**
	(0.116)		(0.115)		(0.110)	
Observations	1,355		1,355		854	
Prob>chi2	0.000		0.000		0.000	
Pseudo R2	0.620		0.631		0.742	

† p <0.10; * p < 0.05; ** p < 0.01; *** p < 0.001

CHAPTER 2

PUBLIC SUPPORT FOR INNOVATION AND THE OPENNESS OF FIRMS' INNOVATION ACTIVITIES

2.1. Introduction

There is no theoretical or empirical work that, to the best of my knowledge, connects public policies and open innovation practices. Governments strive to stimulate innovation for the benefits it produces, both to the innovators and to society as a whole (Arrow 1962; Nelson 1959). At the same time, firms pursue innovation as a way of achieving competitive advantage, and that innovation increasingly requires collaborative activities with external partners (firms, research institutions, universities, customers, suppliers, experts such as consultants, or even the general public via "crowdsourcing" mechanisms). These "open innovation" activities can increase firm innovation performance but may also require a significant commitment of resources (Laursen & Salter 2006). While substantial support is dedicated to foster innovative efforts, the relationship between these public policies and the engagement of firms in open innovation is uncharted.

One of the motivations of this paper is to understand how schemes to support innovation at the macro level, whether be direct monetary support (e.g. subsidies for innovation, financing for new projects, tax breaks for R&D) or non-monetary support (e.g. information, facilitation of collaboration), can affect firms' innovation policies. At the macro level, governments design schemes to foster innovation in general. At the micro level, firms pursue innovation in order to gain a competitive advantage; those who engage in open innovation activities can improve their innovative performance, but also need to commit resources to build and manage these collaborative relationships. It follows that, if public support plays a role in supplying part of those resources, firms can potentially undertake more open innovation, which in turn can increase their aggregated innovation production, benefiting themselves and society as a whole. There is a clear connection between these macro and micro levels of analysis, but in spite of its topical relevance for both managers and governments, prior research has paid limited attention to this potentially relevant area of inquiry. Hence, the motivation for this paper is to take a first, exploratory step, towards understanding the relationship between different types of public support schemes for innovation and the actual practice of open innovation at the firm level.

My research makes at least three significant contributions. First, it focuses on the overlooked relationship between public policies to stimulate innovation in general, and the degree of openness of individual firms performing the innovation activities. Second, it disentangles the differential effects of monetary and non-monetary support schemes, providing important distinctions for policy makers. And third, it focuses on many potential sources of innovation, covering most of the potential partners for innovative collaboration and most types of activities that can be called “open innovation”.

The rest of the paper is structured as follows. The following sections review the relevant literature and the theoretical bases of my analysis. Then I describe the data utilized and the empirical methods. Finally, I discuss the results, some practical implications and potential lines of future research.

2.2. Literature review

2.2.1. Open innovation

Firms increasingly understand internal ideas or knowledge are insufficient to sustain their innovative efforts and remain competitive (Chesbrough 2006; Dahlander & Gann 2010; Van de Vrande et al. 2009). The romantic idea of the inventor-entrepreneur working in solitude to bring a new product to life is a faint image of a distant past. A significant body of literature recognizes that innovation is increasingly not only a team effort, but also one that requires tapping into external sources to complement the internal innovation efforts. For instance, Von Hippel (1988) observed that innovation users and suppliers of innovation-related components were sometimes more important as functional sources of innovation than product manufacturers themselves. Firms search for knowledge outside of their own boundaries in a variety of ways, such as acquiring licenses, outsourcing R&D, recruiting specialized knowledge workers or directly acquiring other firms (Arora & Gambardella 1990; Cockburn & Henderson 1998; Granstrand et al. 1992). Even the largest companies cannot rely only on their internal generation of knowledge (Rigby & Zook 2002). Katila and Ahuja (2002) distinguished two dimensions of external search: ‘scope’ is the variety of knowledge obtained and 'depth' is the frequency of use of the knowledge obtained. It was Chesbrough (2003), however, who popularized the concept of “open innovation” to describe how firms reach out outside their boundaries to harness new ideas and knowledge. Chesbrough defined open innovation as a purposive exchange of inflows and outflows of knowledge between a firm and external parties, in order to accelerate internal innovation. The open innovation perspective gained acceptance because it provides a useful concept to understand the practices in which firms engage in order to increase their permeability to external knowledge.

The effects of openness on innovative performance were empirically examined for the first time on a large-scale dataset by Laursen and Salter (2006). These authors used concepts equivalent to those of Katila and Ahuja ('search scope' and 'search depth'), dubbing them 'openness breadth' and 'openness depth'. Breadth referred to the number of external sources sought in the search of new knowledge, while depth referred to how deeply the firm was able to draw from each of those external sources. These authors found that the relationships between both breadth and depth, and innovative performance had inverted-U shape relationships: openness increases innovative performance up to a certain point and becomes detrimental afterwards. One reason is that excessive openness produces loss of control and core competences (Djankov & Murrell 2002). Another reason is the "attention allocation" problem (Koput 1997; Laursen & Salter 2006; Ocasio 1997). As managers' attention is a scarce resource, they need to focus their efforts on a limited number of issues to excel in their performance. Considering that searching externally and engaging in collaborations with other parties demands attention and resources, too much external exploration may be as negative as too little of it.

2.2.2. The determinants of openness

Firms engage in open innovation to varying extents. My work explores how this openness is related to the different types of government support firms receive. This particular angle has been mostly overlooked by the literature. Other factors affecting openness are, however, known. One of determinants of openness is firm size; in fact, until recently, most studies in open innovation focused on large firms, usually multinationals (Di Benedetto 2010; Van de Vrande et al. 2009). Scholars have argued that larger enterprises may better prepared to engage in open innovation because they have the scale and resources necessary to manage a larger array of innovation activities (Van de Vrande et al. 2009). Another important reason why larger firms may be able to manage more open innovation is their level of absorptive capacity (Cohen & Levinthal 1990). Literature points to a positive relationship between size of the firm and the level of in-house R&D (Arbussà & Coenders 2007; Veugelers 1997); if external and internal R&D are complementary, the presence of absorptive capacity in large firms, generated by their internal R&D activities, can increase their ability to absorb external knowledge and benefit from it. Van de Vrande and others (2009) were among the first authors to look into open innovation practices among SMEs. They surveyed 605 small and medium-sized companies and found that the medium-sized companies were more heavily involved in open innovation than small ones, reinforcing the idea that size influences the practice of open innovation activities. Classen et al. (2012) explored the effects of different factors such as ownership (family vs. non-family), size and firm age on openness. They found that family firms were more 'closed' than nonfamily firms and that size was again positively related to the openness breadth, while age had no significant effect. Schroll and Mild (2011) also found that size was positively correlated with open innovation adoption and, in their study, high-tech industries were more likely to adopt open innovation practices than low-tech ones. Keupp and Gassmann (2009) also found that size was correlated with open innovation breadth but age of the firm was not. Although it could be argued that, if open innovation can create "virtual scale", smaller firms may have more to gain from it, the empirical evidence strongly suggests that size is one of the main internal determinants of openness. Technological complexity also seems to play a role, which is to be expected, because high-tech sectors will be more innovative in general (Acs & Audretsch 1988; Sarkar et al. 2006; Zahra 1996), offering more opportunities for open innovation practices.

Firms can also manage the degree of openness to protect themselves from potential knowledge losses and imitation by rivals. Liebeskind (1996) argues that firms can use their embedded institutional capabilities to protect unique resources and capabilities, through mechanisms such as disaggregation of information. Firms can also limit the scope of R&D alliances to prevent unintended leakages of technology (Oxley & Sampson 2004). Building strong internal linkages and interdependences across subsidiaries also helps firms maintain tighter control over local innovation, in particular when they operate in clusters where direct competitors are located (Alcácer & Zhao 2012). In the same vein, Giarratana and Mariani (2014) found that firms in clusters where risk of imitation is high tend to reduce external knowledge sourcing. Other external factors (such as the institutional, economic and cultural context) may also influence the degree of openness firms are willing to undertake. For instance, local knowledge availability is associated with broader and deeper external knowledge sourcing (Garriga et al. 2013). Literature about the effect of contextual factors on open innovation is, however, still very limited.

One critical clarification when discussing the concept of openness is to distinguish its definition in the open innovation literature from the use of the term in the literature about open source software development. In the open innovation literature, openness refers to the search for knowledge outside the firm's boundaries. Firms are open to source from and collaborate with external partners, but that does not mean they are open to reveal knowledge to the public. Openness is simply the empirical operationalization of the underlying open innovation phenomenon. On the other hand, in the open source literature, openness refers to the willingness to reveal code and/or make their developments open to the public (Fosfuri et al. 2008; Henkel 2006). In fact, Henkel investigates "if and under what conditions openness leads to informal development collaboration, i.e., open innovation", explicitly distinguishing between both. Openness is, in this view, the opposite of protection of intellectual property (Henkel 2009). In sum, a firm that practices open innovation has openness to collaborate with one or more external partners, but may be closed to disclosing knowledge to the rest of the world.

2.2.3. Public support for innovation

Since innovation activity is assumed to have positive external effects, governments commit substantial resources to support knowledge creation with the aim of fostering innovation (Arrow 1962; Nelson 1959). This new knowledge is produced not only in universities and research institutions, but also in firms' R&D labs. Therefore, part of the public support for innovation goes to the business sector. Firms usually launch innovation projects that are expected to be profitable; thus, there may be projects that would have positive benefits to society but have no certainty of covering the costs, and therefore are not pursued. If these projects are not carried out, the quantity of innovations remains below the socially desirable level (Arrow 1962; Nelson 1959). There are many reasons why governments intervene in the domain of private R&D; the majority revolve around market failure arguments, such as imperfect appropriability of the benefits of private investments in R&D due to opportunities for free ride (Martin & Scott 2000).

Another example of market failure is the difficulty of smaller firms to finance R&D in the presence of information asymmetries; as intangibles and high-risk projects, such as R&D, tend to be financed with internal funds rather than debt or new equity, SMEs are more constrained than large firms due to their shallower pockets (Baghana & Mohnen 2009). In sum, all of this leads to underinvestment in R&D, such that the level of R&D expenditure is suboptimal. By supporting innovation activities, the government bears part of the risk for early stage technologies; public funding reduces the price for private investors, and thus it is expected to increase the overall innovation output (Lokshin & Mohnen 2012).

My focus is on the effects of direct support measures and not indirect institutional aspects such as the level of intellectual property protection, the existence of a technology transaction market or the overall rule of law. These mechanisms play a role as well; intellectual property protection, for instance, may be relevant for firms as long as opening up the innovation process increases the risks of revealing internal resources and secrets to the external environment (Dahlander & Gann 2010). A market for technological transactions, such as technology transfers, technology-equity share exchange and technology intermediation, also facilitates innovative activity. Although in my models I control for the degree of IP protection and the overall innovative intensity at the country level, those general institutional aspects are not the central focus of this research; instead, I direct my attention to support schemes that benefit firms directly.

Despite the substantial body of literature about the relationships between public policies and private innovation, there has been limited exploration of the relationship between open innovation and support schemes for innovation. Nations, however, are increasingly attentive to policies that can stimulate collaboration for innovation and open innovation practices. In China, for instance, the 2009 “Notice of Taxation on Issuing the State Industrial Technology Policies” emphasizes the pursuit of “extensive efforts in international cooperation and exchange and reinforcing technological introduction, absorption and re-innovation, together with fiscal and tax policies to support external sourcing” (Fu & Xiong 2011). Another example of public policy fostering open-innovation related activities is the American program called EPSCoR (Experimental Program to Stimulate Competitive Research) with the support of the National Science Foundation; a number of states participating in EPSCor are already providing support for many elements of the open innovation paradigm (Mayer 2010). But in spite of the increasing attention of researchers to open and collaborative innovation, the role of public policy in stimulating open innovation remains unexplored (De Jong et al. 2008). This paper seeks to examine this research gap by assessing the relationships between public policies and the degree to which firms engage in open innovation practices.

Direct, publicly-funded, support schemes for innovation at the firm level can be monetary (e.g. financing for projects, subsidies, grants, tax breaks, infrastructure building) or non-monetary (e.g. providing information, facilitating networking and coordinating collaboration). They can also be classified into inputs for private innovation processes (i.e. supply side), and instruments influencing innovation outputs, such as public procurement (i.e. demand side) (Aschhoff & Sofka 2009). Different instruments have different effects; tax incentives, for instance, have been argued to be more neutral than direct grants and subsidies, since they “give business more freedom to determine the projects” (Baghana & Mohnen 2009) and provide more stable conditions, because they are not subject to annual budgetary debates (Cappelen et al. 2010). Support schemes that rely on providing funding or any other tangible input for private innovation processes operate on the supply side. However, public schemes can also operate on the demand side, for example with public-procurement programs which secure an outlet for domestic innovations. Aschhoff and Sofka (2009) classify policy instruments for innovation in four categories: public procurement, regulation (both demand side), universities and research institutions, and public R&D subsidies (both supply side). According to these authors, other mechanisms have different risks and benefits. Subsidies bring the benefit of cost reduction and the risk of crowding-out. Public procurement has as a positive effect a reduction of the market risk; on the flip side, it has the risk of creating idiosyncratic demand. Regulation also reduces market risk, but can create “egalitarianism”.

Monetary public support and openness.

There are multiple mechanisms through which publicly-funded schemes can increase the availability of resources for firms. In turn, if conducting open innovation demands significant resources from firms, these public schemes that alleviate the overall cost of innovation may make open innovation initiatives more feasible for those firms that receive support. For instance, the most complex innovative projects usually require large investments; therefore it makes sense for firms to partner and collaborate in complex projects to attain economies of scale and avoid duplication of efforts (Hagedoorn 1993). If monetary support for innovation, through grants or subsidies, reduces the cost of undertaking complex projects, firms will engage more often in these types of projects, which due to their complexity, will often require the practice of some form of open innovation. Thus, there should be a relationship between the availability of support schemes for innovation and the openness of firms.

Open innovation entails maintaining ongoing external linkages in order to acquire and exchange innovative knowledge. This requires two fundamental factors: internal resources at the firm (Hoffmann & Schlosser 2001; Laursen & Salter 2006; Mohr & Spekman 1994; Van de Vrande et al. 2009) and external conditions that allow the establishment of collaborative relationships between the parties (Bathelt et al. 2004; Cantner & Graf 2006; Hagedoorn & Wang 2012; Lorenzen & Mudambi 2013; Teece 1986). Public support can play a direct or indirect role in increasing the availability of both factors. Some examples through which public funding can support open innovation initiatives are the Maryland Industrial Partnerships Program, which provides matching grants for university-industry research partnerships, tax credits to encourage investments and pools of firms, and pension funds invested in venture capital funds to provide capital to innovation investors (Mayer 2010). In sum, publicly-funded support schemes for innovation provide supply-side resources, in the form of monetary contributions which may potentially enhance the ability of firms to undertake higher levels of openness, both in terms of the number of activities they will perform and the number of partners with whom they will collaborate. Firms with more diversified activities may collaborate with different types of partners and, on the other hand, firms with more innovation partners will tend to perform more varied open innovation activities. Based on these arguments I can expect monetary public support for innovation to be positively related to firms' openness, both in terms of the number of open innovation activities they will perform and the number of external partners with whom they will collaborate.

Non-monetary support for innovation and openness

Even when projects are potentially profitable and the financial resources are available, there must be both a proper institutional environment and a set of conditions that enable collaboration between different parties. Open innovation requires the establishment of often complex networks of relationships between private companies and other organizations such as universities and research institutions. However, there are information barriers that must be overcome, relationships that must be established, social networks to manage and contracting problems to solve (Hoffmann & Schlosser 2001; Lee et al. 2010; Mohr & Spekman 1994; Van de Vrande et al. 2009). Non-monetary support can foster this by providing institutions to facilitate collaboration (Porter 2005; Porter & Emmons 2003; Porter & School 1998). For example, if collaboration between enterprises requires similar competences (de Jong et al. 2010), governments can facilitate the catch-up of laggard firms by providing training, mentoring and coaching entrepreneurs (Mayer 2010). If newly-innovative firms face obstacles to find partners and bring their ideas to the marketplace, governments can help by assisting with patent applications, facilitating the access to engineering or marketing knowledge, and providing venues and organizing events to facilitate networking and the creation of linkages between prospective partners (Mayer 2010). Governments can act as brokers or matchmakers (de Jong et al. 2010), bringing together different players within the innovation system, or have a role building efficient technology transaction markets (Fu & Xiong 2011). This guidance may be vital to connect laggard firms with potential partners capable of transferring the know-how or technology necessary to carry out certain projects. In sum, non-monetary support schemes can also foster open innovation practices and improve the conditions for collaboration. Based on these arguments, I expect non-monetary support, in its different forms, to be related to more firm openness, by facilitating the creation of partnerships and collaborative linkages between organizations, and therefore increasing also the number of open innovation activities of firms.

The crowding-out problem

Allocation of funding to innovation-support schemes is a challenge; public support can either induce or substitute private investment in R&D. If firms use available support they don’t need, public funds may then be “crowding out” private investments. The meaning of the term "crowding out" in my work is equivalent to "investment displacement", i.e. firms substituting their own investments with public money without actually increasing the overall research activity. This use of the term is common in the literature on public support for R&D (Aerts & Schmidt 2008; Aschhoff & Sofka 2009; David et al. 2000) and should not to be confused with the traditional meaning of the term in the finance literature.

Literature on public support policies has extensively examined the net effect of support policies on private R&D investment. Aerts & Schmidt (2008) and Almus and Czarnitzki (2003) found that funded firms in Belgium and Germany were significantly more R&D active than non funded firms; no evidence of crowding-out was found. However, a significant number of studies found mixed results (David & Hall 2000; García-Quevedo 2004; Hall & Van Reenen 2000; Klette et al. 2000). This suggests that there is little consensus as to the effectiveness of subsidies and research programs. All studies highlight the importance of the moderating variables. For instance, crowding out may be less likely when appropriability mechanisms are weak (Gelabert et al. 2009) or when the subsidized project can lower the cost of non-subsidized R&D for the firm (Lach 2002). Takalo et al.(2013) theorize that the net effect may depend on firm-specific or even project-specific factors. Busom (2000), David (2000) and Almus and Czanitski (2003) identify the challenge of measuring the actual effects of R&D on innovation, due to potential endogeneity and selection bias problems. Specifically, their concern is that innovative firms are more likely to apply for innovation subsidies in the first place, and therefore a positive relationship between public support and private innovative activity may not be indicative. Governments may also bias their supports toward less risky projects to avoid being perceived as wasting taxpayers' money (Lach 2002).

I consider the crowding-out problem in the context of this study. I have argued that resources provided by public support can lower the cost of innovation for firms, enabling higher levels of open innovation. It follows that, when crowding out is present, the total investment in innovation will be largely unchanged public support, and therefore a shift from closed to open innovation strategies is unlikely to occur. I further argue that crowding-out may be more likely to occur in highly innovative firms, which possess sufficient resources for innovation without public support policies. On the other hand, less innovative firms may need support to build their innovative capacity and therefore may be less likely to be subject to crowding-out. As long as there is any level of crowding-out, the relationship between public support and openness should be negatively moderated by the current level of innovative activity of firms.

2.3. Data and methods

2.3.1. Data source

The data used for this paper comes from the Flash Eurobarometer #215, a.k.a. Innobarometer 2007 (European Commission 2007), a survey conducted in October 2007 by the The Gallup Organization, at the request of the European Commission. The study covers 29 European countries and surveys firms with least 20 employees. The target sample of companies was 200 per country, except for small countries (Cyprus, Malta and Luxembourg), where the sample was 70 firms and for non-EU countries (Switzerland and Norway), where sample was 100. Eligible respondents were top managers with strategic decision-making responsibilities (typically, general managers, financial managers or owners). Companies were selected randomly within each country, with only two conditions: ensuring representation of companies in each size category (20-49, 50-249, 250-499 and 500+ employees) and selecting companies within a targeted list of activities. The activities selected by the European Commission to be included in this survey were: Information technology, Medical devices, Production technology, Communications equipment, Biopharmaceuticals, Automotive, Analytical Industry, Construction Equipment, Metal Manufacturing, Lighting and electrical Equipment, Aerospace Vehicles, Defense, Plastics, Construction Materials, Entertainment, Transportation and Logistics, Furniture, Processed Food, Business services, Aerospace Engines, Chemical Products, Heavy machinery, Power Generation and transmission, Building Fixtures, Equipment, Services, Hospitality and tourism, Publishing and Printing, Textiles, Financial services, Oil and gas products and services, Apparel, Distribution services, Fishing and fishing products, Heavy construction services, Footwear, Jewelry and precious metals, Sporting and children Goods, and Leather. For simplification purposes, in the questionnaire, firms were asked to classify themselves into 8 broader industry categories: ICT and Communication equipment, Software, Aeronautics and Space, Biotechnologies (agricultural, health, industrial), Pharmaceuticals, Medical devices and instruments, Entertainment, and Others (all the rest). In terms of the way interviews were conducted, Gallup interviewed 5,238 enterprises across Europe, between October 15 and 23, 2007, using fixed-line telephone methodology (European Commission 2007).

There has been several papers published using data from this or previous versions of Innobarometer, although none of them focused on this specific angle. Some of the topics explored using these surveys have included the impact of the 2008 economic crisis on innovation (Archibugi & Filippetti 2011; Filippetti & Archibugi 2011), the patterns of innovation in service industries (Tether 2005), innovation at the state level (Daugeliene & Juocepyte 2012), the relationship between innovation and internationalization patterns (Filippetti et al. 2011) and the role of design as a source of innovation (Filippetti 2011).

2.3.2. Dependent Variables

Openness: two variables were constructed to measure the degree of openness of the firms, one for the number of *total open innovation activities* performed by the firm *(oi_a)* and the other for the number of *total open innovation partners* with whom the firm collaborates for innovation *(oi_p).*

- *Total open innovation activities (oi_a)* was constructed following Laursen and Salter (2006) as the sum of 7 binary items (hence, its value will range from 0 to 7), counting the positive responses for all 7 types of possible open innovation activities surveyed. The 7 items included in the scale are: "Contracting out R&D to other companies, consultants, universities, or research institutes" (*oi_a1*); "Customizing or modifying products that were originally developed by other companies, organizations or individuals" (*oi_a2*); "Developing entirely new products in collaboration with other companies, consultants, universities, etc." (*oi_a3*); "Customizing or modifying processes originally developed by other companies, organizations or individuals" (*oi_a4*); "Developing entirely new processes or significantly improving existing ones in collaboration with other companies, consultants, universities, etc." (*oi_a5*); "Customizing or modifying organizational methods originally developed by other companies, organizations or individuals" (*oi_a6*); and "Developing new or significantly improved organizational methods in collaboration with other companies, consultants, universities, etc." (*oi_a7*).

- *Total open innovation partners (oi_p)* is a sum of 4 dummies, hence ranging in value from 0 to 4. The binary items included in the construct are the 4 types of external partners with whom the firm can potentially collaborate for innovation: "The original (external) developer or supplier of any product or process being currently modified or customized at the focal firm" (*oi_p1*)"; "Other companies that use similar products or processes" (*oi_p2*); "The firm's customers for these products or processes" (*oi_p3*); and "Experts such as consultants, universities, etc." (*oi_p4*).

I conducted several controls to ensure the validity of my dependent variables. First, in terms of content validity, my dependent variables are conceptually similar to the way openness is measured in other open innovation papers. Laursen and Salter (2006), for instance, measure "Open innovation breadth" as a scale of 16 binary items which represent 16 possible sources where the firm can access knowledge. This is basically the same way I constructed the *total open innovation partners* (*oi_p)* variable (except I captured fewer items). In a similar fashion, Classen et al. (2012) use the dependent variable "Search breadth", which is also a scale of binary items (6 items in this case), representing 6 potential types of open innovation partners (customers, suppliers, competitors, universities, public agencies and other organizations). Van de Vrande et al. (2009) constructed their variables asking respondent about their engagement in 8 potential open innovation activities, similar to the ones included in my *total open innovation activities* (*oi_a*) variable.

Second, both scales were tested for consistency (reliability) using Cronbach's Alpha. *Total open innovation activities* (*oi_a*) displayed an Alpha of 0.737 and *total open innovation partners* (*oi_p*) displayed an Alpha of 0.660. The first one is above and the second one is only slightly below the commonly accepted value of 0.7 (Echambadi et al., 2006; Tavakol and Dennick, 2011), indicating a good level of reliability that the items included in the scales are measuring the same underlying concepts.

Third, I controlled for unidimensionality of my scales. When constructing indicators, it is necessary to distinguish whether they are reflective or formative indicators (Echambadi et al., 2006). Reflective indicators allow to capture some measurable dimension of an underlying factor, without causing changes in that latent variable. On the other hand, formative indicators are measures that produce changes in the underlying construct (Diamantopoulos and Winklhofer, 2001; Echambadi et al., 2006). Based on this definition, my dependent variables can be considered formative. For instance, if a firm engages in more types of open innovation activities (like the ones captured in my variable), it is by definition increasing its level of openness; in other words, the measure is at the same time producing the construct. Although widely used, conventional procedures such as factor analysis are not appropriate for formative indicators (Diamantopoulos and Winklhofer, 2001). Therefore, other procedures must be used, such as tetrachoric and polychoric correlation (Ekström, 2011; Hattie, 1985; Uebersax, 2006; Woods, 2002). The tetrachoric correlation coefficient calculates the relationship between two dichotomous variables assumed to have an underlying bivariate normal distribution (Ledesma et al., 2011; Pearson, 1900) and the polychoric correlation is used for ordinal variables and multi-item scales (Ekström, 2011). For unidimensionality purposes, the set of coefficients were correlated "item-to-scale", i.e. correlating the responses to a particular question with the responses to all of the other questions on that scale. For *total open innovation activities* (*oi_activ*), the polychoric correlation matrix displayed item-to-scale correlations between 0.346 and 0.497. For *total open innovation partners* (*oi_p*), the correlations varied from 0.792 and 0.896. In both scales the correlations were significantly above the 0.3 rule of thumb to include an item in a scale (Webmoor, 2007).

Finally, following prior studies (Anderson et al., 2012) I set the missing data points to a zero value for the binary items included in *oi_activ* and *oi_p.*

2.3.3. Independent Variables

Two variables were constructed to measure public support for innovation; one for *total monetary support* (*mon_sup*) and another for *total non-monetary support* (*nonm_sup*).

- *Total monetary support (mon_sup)* is a scale from 0 to 6 counting the positive responses for all 6 types of monetary support surveyed by the questionnaire: "Direct support to finance R&D-based innovation projects" (*sup_1*); "Direct support to finance innovation projects with no R&D involved" (*sup_2*); "Subsidies for buildings or other infrastructure for innovation activities" (*sup_3*); "Subsidies for acquiring machinery, equipment or software" (*sup_4*); "Tax breaks for R&D expenditures" (*sup_5*); and "Tax breaks for innovation expenditures other than R&D" (*sup_6*).
- *Total non-monetary support (nonm_sup)* is a scale from 0 to 4 counting the positive responses for all 4 types of non-monetary support surveyed by the questionnaire: "Attending or participating in trade fairs or trade missions" (*supp_7*); "Facilitation of networking with universities and other research institutions" (*supp_8*); "Facilitation of networking with companies" (*supp_9*); and "Provision of information on market needs, market conditions, new regulations, etc." (*supp_10*).

For the two independent variables I conducted reliability and unidimensionality controls similar to the ones I performed for the dependent variables. In terms of reliability, *mon_sup* displayed a Cronbach's Alpha of 0.705 and *nonm_sup* displayed an Alpha of 0.771. These two variables can be considered formative indicators, as defined previously. They are formative because they affect the underlying construct (e.g. if a company answers "yes" to receiving public subsidies automatically this is affecting the latent variable, which is the level of support). Therefore, I also estimated polychoric correlations to assess unidimensionality. The *mon_sup* scale displayed polychoric correlations between 0.837 and 0.891, while *nonm_sup* varied between 0.911 and 0.944. Overall, both variables showed high levels of reliability and unidimensionality. Finally, for both *mon_sup* and *nonm_sup* I coded to a zero value any missing responses in the binary items included on the scales (see, for instance, Anderson et al, 2012).

Additionally, to conduct robustness checks, I created three independent variables (*supp_12, supp_34* and *supp_56)* which are simply the items that compose the variable *mon_sup*, grouped by type (see Table 5):

- *Tax breaks (*supp_56*)* is simply the sum of the two binary items that represent tax breaks (*supp_5* and *supp_6*).
- *Direct support to finance projects (*supp_12*)* is the sum of the two binary items that represent direct support (*supp_1* and *supp_2*).
- *Subsidies (supp_34)* is the sum of the two binary items that represent direct support (*supp_3* and *supp_4*).

2.3.4. Control Variables and Interactions

The current level of innovation in the firm, was operationalized with two different variables, one measuring the presence of internal innovation activities in the previous two years *(innov)* and the second measuring the annual expenditures in innovation *(inn_exp)*:

- *Internal innovation activities (innov78)* is the sum of two binary variables indicating if a) "The firm conducted in-house R&D in the last two years", and b) "The firm applied for one or more patents in the last two years". Thus, *innov* will have values between 0 and 2.
- *Innovation expenditures (inn_exp)* is a categorical variable which measures the total amount spent on innovation activities by the firm. Values can range from 1 to 5, corresponding to annual expenditures in innovation of less than €100k, €100k-500k,

€500k-1M, €1M-5M, and more than €5M. However, when using this variable I lose almost 2,000 observations due to missing data, so I ran models with both variables (*innov* and *inn_exp*) in order to check the robustness of my results.

- *Internal search scope (intsearch)* is a scale from 0 to 5 counting how many different areas in the company are active sources of innovative ideas. The areas are (1) Production engineers or technicians, (2) Marketing department, (3) Design staff, (4) Management, and (5) Research department. Therefore, it displays values between 0 and 5. This variable is of interest because practicing cross-functional integration (Love and Roper, 2009) and sourcing knowledge across departments and division may help firms develop capabilities that are valuable to orchestrate open innovation practices.

- *Multinationality (mne)* is a binary variable with value 1 if the firm indicated to have operations in other countries (not counting sales or after- sales support), and 0 otherwise.

- *Size (size)* is calculated as the natural log of the number of employees (in the country where the firm was surveyed).

- *Startup (startup)* is a binary variable with a value 1 if the firm established after January 1st, 2000, and 0 otherwise.

- *Support was crucial (crucial):* is binary variable with a value of 1 if the firm responded positively to the question "Was the support from publicly funded schemes crucial to any of your company's innovation projects, such that the innovation would not have been developed or introduced without the support?". A negative response implies that the firm has received support but this support is not critical for the company; this could be an indicator of potential crowding-out.

- *Country IP protection (ipri_ipr)* is the country level of intellectual property protection, reported by the International Property Rights Index, 2012 Report (Tiwari, 2012).
- *Country R&D intensity (ctr_rdint)* is the percentage of total private and public R&D expenditures over the country GDP (European Commission, 2011). The rationale to include this control variable is that countries that invest more in R&D could potentially provide more opportunities for open innovation than countries with low R&D intensity.
- *GDP per capita* (*ln_gdppc*): Natural log of GDP per capita. This variable is included to control for the fact that richer countries can potentially have more dynamic business sectors than relatively poorer countries, providing more opportunities for collaboration.
- *Industry controls:* I controlled for industry, using the 8 broader industry categories provided in the survey: ICT and Communication equipment, Software, Aeronautics and Space, Biotechnologies (agricultural, health, industrial), Pharmaceuticals, Medical devices and instruments, Entertainment, and "Others".

2.3.5. Descriptive Statistics

Table 1 summarizes the variables used in my empirical analysis. The variable *oi_a* shows a mean of 1.572, which means that the average firm conducts between 1 and 2 activities that can be considered open innovation. The range of values goes from 0 (no open innovation activies) to 7 (the firm conducts all the possible open innovation activities). *oi_p* displays a mean of 1.188 (the average firm has more than one external partners with whom it collaborates). The mean for *mon_sup* is 0.499 and the mean for *nonm_sup* is 0.634, which means that firms receive on average one type of monetary support and one type of non-monetary support. The mean for *intsearch* is 1.876; i.e. firms tend to source innovative ideas from more than one internal department. The mean size is 376 employees per company; small and medium size firm are a majority in my sample. Finally, the average value of *startup* is 0.165, which means that the majority of firms are at least more than 7 years old.

Table 2 displays the correlations between the main variables (industry controls are not included). It is clear from the table that there are no major concerns about correlations among the basic variables. One of the few correlations above 0.5 is between *oi_p* and *oi_a*; this is expected, since more open innovation partnerhips will increase the opportunities for open innovation activities, and vice versa. The rest of correlations amongst the main variables are very low. A few of the correlations among control variables are high; however even in these cases, the correlations with the main variables of my study are very low and statistically insignificant. There is a slight chance that the correlation amongst these control variables could muddy attribution of the marginal effects. Therefore I ran the base regression model dropping these potentially problematic variables (*ctr_rdint* and *ipri_ipr*) and found that the estimates are extremely stable.

2.3.6. Statistical methods

I used a multiple regression approach. As described earlier, the dependent variables *Total open innovation activities (oi_a)* and *Total open innovation partners (oi_p)* are nonnegative count variables. The appropriate methods for this type of variables are either the Poisson or the negative binomial regression. Negative binomial is a variation of Poisson incorporating individual unobserved effects into the conditional mean (Hausman et al., 1984; Yanadori and Cui, 2013) and has been suggested as an alternative when there are signs of overdispersion (i.e. the conditional variance is larger than the mean) and therefore the Poisson assumptions are violated (Berk and MacDonald, 2008; Cameron and Trivedi, 1990). Coefficients in a Poisson or a negative binomial model represent percentage changes in the expected count of the dependent variables for each unit change in the independent variables (Ceccagnoli and Jiang, 2012). I analyzed the data and found only minor signs of overdispersion, with the variance being slightly larger than the mean only at certain values of the covariates. I therefore ran all models using Poisson but used negative binomial as a robustness test (results not reported). The sign and significance of the coefficients obtained with negative binomial were similar to those obtained with Poisson. The fact that both models produced comparable results provides confidence about the robustness of the results.

I performed multicollinearity tests by using variance inflation factors (VIFs) over OLS runs of the models. The highest value was only 5.02 (for one of the control variables). The independent variables and the main predictors (*mon_sup* and *nonm_sup*) displayed values of less than 2, , which is well below the suggested cutoff threshold of 10 (Chatterjee and Price, 1991).

2.4. Results

Models 1 to 7 use number of *Total open innovation activities* (*oi_a*) as dependent variable. Model 1 is the base model, using *innov_78* to measure internal innovation activities. Model 2 is similar to model 1 but adds interaction terms between *monetary support* and *internal innovation activities* and *non-monetary support* and *internal innovation activities*. Models 3 and 4 are similar to models 1 and 2 but replacing the innovation variable for *spending in innovation* (*inn_exp*). Models 5, 6 and 7 are similar to base model 1, but adding interactions between *crucial* and *internal innovation activities* (model 5), *crucial* and *size* (model 6) and *crucial* and *mne* (model 7).

Models 8 to 14 use number of *Total open innovation partners* (*oi_p*) as dependent variable. Model 8 is the base model, using *innov_78* to measure internal innovation activities. Model 9 is similar to model 7 but adds interaction terms between *monetary support* and *internal innovation activities* and *non-monetary support* and *internal innovation activities*. Models 10 and 11 are similar to models 7 and 8 but replacing the innovation variable for *spending in innovation* (*inn_exp*). Models 12, 13 and 14 are similar to base model 7, but adding interactions between *crucial* and *internal innovation activities* (model 12), *crucial* and *size* (model 13) and *crucial* and *mne* (model 14).

The coefficient for *Total monetary support* (*mon_sup*) is positive in all models from 1 to 7, although only significant in two of them (models 2 and 3). These results are weak but suggest that monetary support for innovation may be related to a higher level of openness in terms of the number of open innovation activities in which the firm is involved. In terms of the effect on *open innovation partners* (models 8 to 15), the results for *mon_sup* are mixed, with same coefficients being negative and significant (models 8, 12 and 14) and others being positive but not significant. Overall, results for monetary support are inconclusive and more evidence would be needed to reach a conclusion.

On the other hand, the coefficients for *Total non-monetary support* (*nonm_sup*) are positive and significant in all fourteen regression models (only one of them at the 10% level). This is strongly consistent with the theory that monetary support for innovation may be related to more openness, both for activities and partners. The fact that *non-monetary support (mon_sup)* produces more consistent and significant results than *monetary support (nonm_sup)* implies that public support for innovation may not need to be financial in order to enable more open innovation. On the contrary, according to my results, non-monetary support seems to have a stronger relationship with openness than monetary support. In other words, having the right public policies and institutions may be more effective in enabling open innovation than providing firms with financial incentives for innovation.

In order to analyze whether the relationship between public support for innovation and the openness of firms is moderated by the innovativeness of the firms, I used interaction terms. Interaction term *monetary support X internal innovati*on activities *(ms_x_in78)* is negative in both models 2 and 9, and significant in the latter. Interaction term *non-monetary support X internal innovation activities (nm_x_inn)* is negative and significant in both models 2 and 9. The coefficient *ms_x_exp* is negative but not significant significant in models 2, 10 and 12, and negative but not significant in model 4. The coefficients *ms_x_exp* and *nm_x_exp* are all negative but only the latter is significant in model 11, which can potentially be attributed to the decrease in sample size due to missing data (the sample is reduced by nearly 2,000 observations in models 3, 4, 10 and 11). The coefficient for *crucial X internal innovation activities (cru_x_in78)* is negative and significant in both models 5 and 12 and *crucial X size (cru_x_size)* is negative and significant in model 13 (i.e. for open innovation partners). I did not mean-center the interaction terms (as is done in many studies) because this practice is not useful to curb possible collinearity effects (Echambadi and Hess, 2007). Overall, the interaction terms between support and open innovation suggests that public-support schemes have less effect on openness when the companies are innovative. This finding is consistent with the potential occurrence of crowding out. Innovative companies may not need public support but still receive it; therefore, they are unlikely to alter their innovation practices, including their engagement in open innovation, when they obtain support. Size may be also a factor determining possible crowding-out, but only for partners and not for activities.

The variable *Total open innovation activities (oi_a)* is a positive and significant predictor of *Total open innovation partners (oi_p)* and vice versa. This is expected since dealing with more innovation partners may generate a broader array of open innovation activities, and at the same time companies that try more open innovation activities may build ties with more external collaborators. Other interesting conclusions can be drawn from the empirical results. *Internal innovation activities* and *Innovation expenditures* are related to a larger number of open innovation activities, but not so clearly to a larger number of partners. This implies that firms that innovate more internally also tend to have more open innovation activities, but not necessarily more external partners. This may be due in part to the fact that the firms that have the most powerful incentive to build ties with external partners are those that have an internal weakness as innovators; they may be the ones that seek external collaborations to compensate for their shallow knowledge foundation. The coefficient for *Internal search scope (intsearch)* is positive and significant in all models, indicating that firms that search broadly for internal knowledge tend to be more open as well. This suggests that some of the capabilities needed to search internally across different areas of the company to manage cross-functional integration (Love and Roper, 2009), are also enablers of open innovation. As expected, firm *size* is a positive determinant of openness, but only for activities and not for partners. However, multinationals (*mne*) seem to be more likely to work with external partners, but not necessarily to undertake more open innovation activities. Newer firms (*startup*) appear to be more open in terms of partnerships than older firms; this may be explained by the need new firms have to search externally for partners that can provide the knowledge they haven't been able to generate internally yet. It's interesting to note that these results with respect to firm's age differ from the results of some prior studies (Classen et al., 2012; Keupp and Gassmann, 2009).

Finally, the role of contextual factors shows some interesting results. The coefficient for IP protection (*ipri_ipr*) is either negative or non-significant, meaning that policies that ensure high protection of intellectual property rights do not necessarily encourage more openness. This is counterintuitive, since one of the risks of being open is to lose secrets and knowledge to potential competitors; therefore, logically more protection of IP rights should encourage greater knowledge sharing. A possible explanation is that in these more mature institutional environments, firms have greater absorptive capacity and hence greater ability to absorb competitors' knowledge, so firms in general may be more protective. It has been documented that, in weak institutional environments, firms may conduct significant innovation and still protect themselves from the loss of knowledge through alternative mechanisms (Zhao, 2006). In terms of national levels of innovation, *R&D intensity (ctr_rdint)* is positive and significant; this is expected, because a context of high-innovation activity will provide more opportunities for collaboration.

2.5. Robustness checks

In order to test the robustness of my findings and make new distinctions, I conducted a sub-sample analysis. In Table 5, I compare non-innovative vs. innovative firms. Non-innovative firms are those that score 0 for the variable *innov*. For this analysis, I disaggregated the variable *mon_sup* in three subcomponents: *tax breaks (supp_56)*, *direct support to finance projects (supp_12)* and *subsidies (supp_34)*. I listed this components in this order, from more universally available (tax breaks are available to all firms, in general) to more specific (subsidies tend to require specific activities by the firm). The results obtained with this analysis are particularly interesting. Among the monetary types of support, only subsidies are positive and significant predictors of openness; but this is only for partners and for non-innovative firms. The fact that subsidies are more impactful than tax breaks or support to finance innovation projects suggests that the more specific the mechanism, the more effective it is. *Non-monetary support (nonm_sup)* is highly significant for non-innovative firms and only significant for innovative firms on the open innovation partners model (but not for activities). Overall, the data on both *subsidies* and *non-monetary support* suggest that support schemes may potentially stimulate openness in non-innovative firms, rather than in firms that had prior innovative activity. I believe these results are consistent with the argument that a certain level of crowding out may occur if support for innovation is provided to firms that are already innovative.

In Table 6, I compared small vs. medium and large firms; the cutoff between the two sub-samples was 100 employees. In Table 7, I compared peripheral vs. core European countries, based on GDP per capita; the cutoff between the two groups was

$25,000. The rationale for this separation is that there may be unobserved heterogeneity among countries in terms of the innovative activities of firms, so it may be useful to analyze whether the original findings hold both in richer, more innovative countries, as well as in poorer, less innovative countries. *Total monetary support* shows positive and significant coefficients for the dependent variable *open innovation partners* in both small and medium-big firms. The coefficients for *total monetary support* are also positive but not significant for *Open innovation activities*. For the peripheral vs. core country analysis (Table 7), monetary support is positive and significant in all models except for for *open innovation activities* in peripheral countries; *non-monetary support* is consistently positive and significant across all models. Overall, these results are consistent with the our base models, although with some distinctions. Results for *non-monetary support* are consistently stronger than results for *monetary support. Monetary support* seems to have a stronger influence for partners than for activities. Interactions terms are negative and significant in the majority of models, which is also consistent with the possibility of potential crowding out. Overall, the sub-sample analysis is consistent with the general findings and provides confidence about the robustness and stability of the results.

2.6. Limitations

Using a survey instrument designed and conducted by someone else is challenging. Responses have to be taken at face value, because there is no way to control for their accuracy. In particular, there may be concerns with questions related to past events or those where the respondent is requested to answer in detail about all the firm's collaboration relationships. It is impossible to assess whether respondents had sufficient knowledge to respond accurately. However, respondents were top managers of the firms, and it's plausible to assume that top managers have a big-picture view of the activities of the firms and are sufficiently aware of the main relationships and corporate activities. A second limitation is that, although firms are supposed to have been selected randomly within each interest group/country, there's no way to control whether there was any systematic selection bias. However, the fact that the survey has been conducted by Gallup, a global specialist in surveys, provides a level of reassurance in terms of the quality of the overall process of data collection and the experience of the interviewers. Gallup has been conducting the Eurobarometer survey series since 2001. Third, given the cross-sectional nature of the data set, it is important to bear in mind that coefficients should be understood and indications of relationships rather than causality. Another potential issue when evaluating the effect of a treatment, such as a public policy, is the "selection based on unobservables" (Cappelen et al., 2012), in this case the possibility that firms obtaining public support are the firms that are open innovators in the first place. One possible approach to deal with this problem is propensity score matching; PSM, however, presents several disadvantages, such as accounting only for observable covariates. I believe self-selection is not a significant problem in my analysis because many of the support measures I include in my model (such as tax incentives for innovative activities) are either universally available for all firms or not available at all; firms don't need to apply and be selected for those types of support. Additionally I included in my model as many controls as possible, both at the country level and at the firm level, in order to account for other sources of unobserved heterogeneity. I also conducted sub-sample analyses to assess whether my results hold when slicing the dataset based on different criteria. All of this provides confidence about the results, which are very stable and robust to different empirical designs.

2.7. Conclusions

This paper sheds light on the previously uncharted relationship between publicly-funded schemes to support innovation and the openness of firms' innovation activities. The theoretical contribution is to combine these two streams of research that have been historically separate and explore empirically for the first time, on a large scale dataset, the effects of public support on openness. I find that some public schemes to support for innovation are related to higher levels of engagement in open innovation. I also find that the impact of public support seems to diminish in firms that are already innovative. This suggests the possibility of crowding-out, or substitution of private investment with public funding, but further empirical work on this emerging central issue is necessary. Another contribution is disentangling the effects of monetary and non-monetary support schemes; I find that non-monetary support seems to exert a stronger influence on openness than monetary support. The implication is that institutions matter, even more than financial help. For policy makers, this could be considered good news. In times of financial constraints, they can potentially foster open innovation by establishing appropriate policies and institutions, instead of exclusively spending taxpayers' money to fund schemes to stimulate innovation. This conclusion also suggests the need for a more microscopic assessment of the public policies and programs that foster this openness behavior. It also warrants a more fine grained simultaneous review of the corporate processes that respond to these inducements. Academic studies of the nexus of these two will yield the most insightful public policy and firm diagnoses and prescriptions.

To attain validity of the statistical conclusions in an empirical study, it is important to rule out rival hypotheses; mathematical relationships between the variables are simply not enough. It is important to reduce the possibility of endogeneity and selection bias, since the positive correlation between public support and openness could partially reflect the fact that open firms apply for subsidies more than other firms. I believe the subsample analysis sheds light on this and helps us make important distinctions. The data suggests that support is received by both innovative and non-innovative firms, but only exerts strong influence on the openness of non-innovative firms. This is consistent with my theory and provides confidence about the value of the results.

The potential implications for both managers and policy makers are relevant and significant. Billions of dollars are spent every year in supporting innovation activities, but accountability and assessment of the actual impact of those monies is less than ideal. If open innovation practices increase the firm's innovative performance, a crucial relationship is whether public support for innovation actually increases the openness of firms. Furthermore, in times of tight national budgets, I unearth the effects of both monetary and non-monetary support; results show that non-monetary support also plays an important role in increasing open innovation and therefore policy makers may have some room for creativity when trying to foster innovation with scarce resources. I have suggested future research to unpack the public policy issues and firm internal mechanisms that determine whether public support increases open innovation or is used to substitute private investment. In summary, I believe this exploratory study provides useful insights with relevant implications for academics, company managers and politicians and raises substantial issues for future study.

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Table 2.1: List of variables and descriptive statistics

Variable	Description	Mean	S.D.	Min.	Max.
Open Innovation Activities:					
oi_a1	Contracting-out R&D to other firms, consultants or research institutes	5238	0.235	0.424	0	1
oi_a2	Customizing or modify products developed by others	5238	0.233	0.423	0	1
oi_a3	Developing new products in collaboration with other firms, consultants or	5238	0.252	0.434	0	1
oi_a4	Customizing or modify processes developed by others	5238	0.254	0.435	0	1
oi_a5	Developing entirely new processes or significantly improving existing ones	5238	0.250	0.433	0	1
oi_a6	Customizing or modifying organizational methods originally developed by	5238	0.169	0.374	0	1
oi_a7	Developing new or significantly improved organizational methods in collal	5238	0.181	0.385	0	1
oi_a	**Total open innovation activities: Σ (*oi_act1:oi_act7*)**	**5238**	**1.572**	**1.824**	**0**	**7**
Open Innovation Partners:					
oi_p1	Partnering or collaborating with the original developer/supplier of the pro	5238	0.354	0.478	0	1
oi_p2	Partnering with other companies that use similar products/processes	5238	0.253	0.435	0	1
oi_p3	Partnering with the firm's customer for these products/processes	5238	0.295	0.456	0	1
oi_p4	Partnering with experts such as consultants, universities, etc.	5238	0.287	0.452	0	1
oi_p	**Total open innovation partners: Σ (*oi_p1:oi_p4*)**	**5238**	**1.188**	**1.337**	**0**	**4**
Monetary support for innovation:					
sup_1	Direct support to finance R&D based projects	5238	0.104	0.305	0	1
sup_2	Direct support to finance innovation projects with no R&D involved	5238	0.077	0.266	0	1
sup_3	Subsidies for buildings or other infrastructure for innovation activities	5238	0.079	0.270	0	1
sup_4	Subsidies for acquiring machinery, equipment or software	5238	0.126	0.331	0	1
sup_5	Tax breaks for R&D expenditures	5238	0.068	0.251	0	1
sup_6	Tax breaks for innovation expenditures other than R&D	5238	0.046	0.210	0	1
mon_sup	**Total monetary support: Σ (*supp_1:supp_6*)**	**5238**	**0.499**	**1.041**	**0**	**6**
Non monetary support for innovation:					
sup_7	Participation in trade fairs or trade missions	5238	0.193	0.395	0	1
sup_8	Networking with universities and other research institutions	5238	0.109	0.312	0	1
sup_9	Networking with firms	5238	0.155	0.362	0	1
sup_10	Information on market needs, market conditions, new regulations, etc.	5238	0.177	0.381	0	1
nonm_sup	**Total non-monetary support: Σ (*supp_7:supp10*)**	**5238**	**0.634**	**1.124**	**0**	**4**
dummy_ms	Dummy- Monetary support	5238	0.255	0.436	0	1
dummy_nms	Dummy- Non-monetary support	5238	0.300	0.458	0	1
dummy_sup	Dummy- Any type of support	5238	0.393	0.488	0	1
intsearch	Internal search scope	5238	1.876	1.508	0	5
innov78	Internal innovation activities	5238	0.535	0.675	0	2
inn_exp	Spending in innovation	3282	1.696	1.034	1	5
mne	Multinational	5212	0.503	0.500	0	1
size	Natural log of number of employees	5169	4.560	1.285	2.996	11.513
startup	Firm was started after 1/1/2000	5225	0.165	0.372	0	1
ipri_ipr	Country IP protection score	5238	7.072	1.087	4.800	8.600
ctr_rdint	Total private and public R&D expenditures/GDP	5238	1.578	0.931	0.460	3.750
ln_gdppc	Natural log of number of GDP per capita	5238	10.225	0.356	9.495	10.932
crucial	Support was crucial	5238	0.105	0.307	0	1

Table 2.2: Correlations

	Variable	Description	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	*oi_a*	Total open innovation activities	1.000													
2	*oi_p*	Total open innovation partners	0.621	1.000												
3	*mon_sup*	Total monetary support	0.237	0.188	1.000											
4	*nonm_sup*	Total non-monetary support	0.266	0.250	0.378	1.000										
5	*intsearch*	Internal search scope	0.421	0.325	0.273	0.288	1.000									
6	*innov78*	Internal innovation activities	0.341	0.204	0.261	0.234	0.450	1.000								
7	*inn_exp*	Spending in innovation	0.299	0.180	0.181	0.141	0.313	0.319	1.000							
8	*mne*	Multinationality	0.128	0.121	0.036	0.108	0.143	0.212	0.148	1.000						
9	*size*	Natural log of number of employees	0.243	0.160	0.146	0.150	0.223	0.212	0.482	0.156	1.000					
10	*startup*	Firm was started after 1/1/2000	0.005	0.058	-0.013	0.040	-0.098	0.027	-0.062	0.028	-0.039	1.000				
11	*ipri_ipr*	Country IP protection score	0.043	-0.059	0.040	0.021	0.061	0.057	0.196	-0.080	0.047	-0.219	1.000			
12	*ctr_rdint*	Total private and public R&D expenditures/GDP	0.077	0.004	-0.001	0.001	0.047	0.104	0.196	-0.002	0.059	-0.090	0.797	1.000		
13	*ln_gdppc*	Natural log of number of GDP per capita	0.065	-0.026	0.101	0.042	0.079	0.082	0.203	-0.097	0.043	-0.165	0.838	0.713	1.000	
14	*crucial*	Support was crucial	0.143	0.164	0.452	0.267	0.153	0.151	0.092	0.021	0.042	0.000	0.045	0.021	0.059	1.000

Table 2.3: Poisson Regression Models for *Total open innovation activities*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total monetary support (mon_sup)	0.009 (0.011)	0.039* (0.019)	0.025* (0.012)	0.048* (0.023)	0.008 (0.011)	0.009 (0.011)	0.009 (0.011)
Total non-monetary support (nonm_sup)	0.028** (0.010)	0.116*** (0.016)	0.026* (0.011)	0.039† (0.022)	0.028** (0.010)	0.028** (0.010)	0.029** (0.010)
Total open innovation partners (oi_p)	0.383*** (0.009)	0.375*** (0.010)	0.358*** (0.011)	0.357*** (0.011)	0.381*** (0.009)	0.382*** (0.009)	0.383*** (0.009)
Internal search scope (intsearch)	0.164*** (0.010)	0.158*** (0.010)	0.131*** (0.011)	0.130*** (0.011)	0.163*** (0.010)	0.164*** (0.010)	0.165*** (0.010)
Internal innovation activities (innov78)	0.184*** (0.019)	0.296*** (0.024)			0.215*** (0.021)	0.185*** (0.019)	0.184*** (0.019)
Spending in innovation (inn_exp)			0.068*** (0.013)	0.086*** (0.016)			
MNE (mne)	-0.026 (0.025)	-0.023 (0.025)	0.019 (0.027)	0.018 (0.027)	-0.027 (0.025)	-0.026 (0.025)	-0.007 (0.027)
Size (size)	0.049*** (0.008)	0.052*** (0.008)	0.031** (0.011)	0.032** (0.011)	0.050*** (0.008)	0.053*** (0.009)	0.049*** (0.008)
Startup (startup)	0.049 (0.032)	0.051 (0.032)	0.010 (0.036)	0.008 (0.036)	0.048 (0.032)	0.049 (0.032)	0.047 (0.032)
Support was crucial (crucial)	-0.007 (0.035)	-0.028 (0.035)	-0.033 (0.038)	-0.033 (0.038)	0.171** (0.055)	0.122 (0.110)	0.063 (0.051)
Country IP protection (ipri_ipr)	-0.028 (0.023)	-0.027 (0.023)	-0.010 (0.026)	-0.013 (0.026)	-0.024 (0.023)	-0.027 (0.023)	-0.027 (0.023)
Country R&D intensity (ctr_rdint)	0.061** (0.020)	0.061** (0.020)	0.032 (0.023)	0.033 (0.023)	0.060** (0.020)	0.060** (0.020)	0.060** (0.020)
GDP per capita (ln_gdppc)	0.064 (0.061)	0.054 (0.061)	0.080 (0.067)	0.082 (0.067)	0.054 (0.061)	0.062 (0.061)	0.061 (0.061)
Monetary support X Internal innovation activities (ms_x_in78)		-0.018 (0.013)					
Non-monetary support X Internal innovation activities (nm_x_in78)		-0.085*** (0.012)					
Monetary support X Spending in innovation (ms_x_exp)				-0.010 (0.008)			
Non-monetary support X Spending in innovation (nm_x_exp)				-0.006 (0.008)			
Crucial X Internal innovation activities (cru_x_in78)					-0.166*** (0.039)		
Crucial X Size (cru_x_size)						-0.025 (0.021)	
Crucial X MNE (cru_x_mne)							-0.115† (0.061)
Constant	-1.536** (0.534)	-1.509** (0.533)	-1.487* (0.589)	-1.519* (0.588)	-1.478** (0.534)	-1.545** (0.533)	-1.521** (0.533)
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5133	5133	3248	3248	5133	5133	5133
Pseudo R2	0.271	0.274	0.201	0.202	0.271	0.271	0.271

a Estimated coefficients and associated robust standard errors (in parentheses) are reported
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 2.4: Poisson Regression Models for *Total open innovation partners*

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Total monetary support (mon_sup)	-0.023*	0.035†	-0.017	0.003	-0.023*	-0.022†	-0.023*
	(0.012)	(0.020)	(0.012)	(0.023)	(0.012)	(0.012)	(0.012)
Total non-monetary support (nonm_sup)	0.042***	0.114***	0.042***	0.088***	0.042***	0.043***	0.042***
	(0.011)	(0.017)	(0.011)	(0.022)	(0.011)	(0.011)	(0.011)
Total open innovation activities (oi_a)	0.265***	0.261***	0.234***	0.233***	0.263***	0.264***	0.265***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Internal search scope (intsearch)	0.133***	0.125***	0.050***	0.048***	0.131***	0.132***	0.133***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Internal innovation activities (innov78)	-0.052*	0.074**			-0.015	-0.050*	-0.052*
	(0.022)	(0.027)			(0.024)	(0.022)	(0.022)
Spending in innovation (inn_exp)			-0.016	0.018			
			(0.014)	(0.017)			
MNE (mne)	0.059*	0.060*	0.044†	0.042	0.058*	0.058*	0.068*
	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)	(0.026)	(0.029)
Size (size)	-0.008	-0.006	0.003	0.004	-0.008	0.004	-0.008
	(0.009)	(0.009)	(0.011)	(0.011)	(0.009)	(0.010)	(0.009)
Startup (startup)	0.099**	0.101**	0.066†	0.061†	0.100**	0.101**	0.099**
	(0.033)	(0.033)	(0.034)	(0.034)	(0.033)	(0.033)	(0.033)
Support was crucial (crucial)	0.206***	0.177***	0.175***	0.174***	0.385***	0.592***	0.239***
	(0.037)	(0.037)	(0.036)	(0.036)	(0.055)	(0.112)	(0.052)
Country IP protection (ipri_ipr)	-0.122***	-0.120***	-0.110***	-0.113***	-0.118***	-0.120***	-0.122***
	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Country R&D intensity (ctr_rdint)	0.071**	0.072**	0.066**	0.068**	0.070**	0.070**	0.071**
	(0.022)	(0.021)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
GDP per capita (ln_gdppc)	0.071	0.055	0.009	0.008	0.061	0.067	0.070
	(0.067)	(0.067)	(0.068)	(0.068)	(0.068)	(0.067)	(0.067)
Monetary support X Internal innovation activities (ms_x_in78)		-0.044**					
		(0.014)					
Non-monetary support X Internal innovation activities (nm_x_in78)		-0.075***					
		(0.013)					
Monetary support X Spending in innovation (ms_x_exp)				-0.010			
				(0.009)			
Non-monetary support X Spending in innovation (nm_x_exp)				-0.022*			
				(0.009)			
Crucial X Internal innovation activities (cru_x_in78)					-0.183***		
					(0.042)		
Crucial X Size (cru_x_size)						-0.078***	
						(0.021)	
Crucial X MNE (cru_x_mne)							-0.054
							(0.065)
	-0.735	-0.655	0.177	0.147	-0.674	-0.762	-0.729
	(0.593)	(0.593)	(0.605)	(0.603)	(0.594)	(0.593)	(0.593)
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5133	5133	3248	3248	5133	5133	5133
Pseudo R2	0.197	0.201	0.138	0.139	0.198	0.198	0.197

a Estimated coefficients and associated robust standard errors (in parentheses) are reported
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table 2.5: Poisson Regression Sub-sample Analysis, Non-innovative vs. Innovative firms, by type of monetary support

Dependent variable:	Total open innovation activities			Total open innovation partners	
	Non-innovative firms	Innovative firms		Non-innovative firms	Innovative firms
Direct support to finance project (sup_12)	-0.002 (0.063)	0.014 (0.030)		-0.041 (0.070)	0.027 (0.031)
Subsidies (sup_34)	-0.021 (0.044)	0.021 (0.029)		0.161*** (0.045)	0.036 (0.032)
Tax breaks (sup_56)	0.034 (0.068)	0.049 (0.035)		-0.066 (0.077)	-0.045 (0.038)
Total non-monetary support (nonm_sup)	0.077*** (0.020)	0.014 (0.014)		0.069** (0.022)	0.035* (0.014)
Total open innovation partners (oi_p)	0.465*** (0.017)	0.339*** (0.013)			
Total open innovation activities (oi_a)				0.331*** (0.013)	0.226*** (0.008)
Internal search scope (intsearch)	0.269*** (0.019)	0.086*** (0.013)		0.235*** (0.019)	0.045** (0.015)
MNE (mne)	-0.045 (0.045)	-0.016 (0.034)		0.069 (0.045)	0.072* (0.035)
Size (size)	0.058*** (0.017)	0.058*** (0.011)		-0.002 (0.018)	-0.011 (0.012)
Startup (startup)	0.110† (0.061)	-0.007 (0.046)		0.065 (0.061)	0.089* (0.044)
Country IP protection (ipri_ipr)	-0.048 (0.043)	0.032 (0.033)		-0.103* (0.041)	-0.120*** (0.032)
Country R&D intensity (ctr_rdint)	0.063† (0.039)	0.049† (0.028)		0.085* (0.039)	0.080** (0.030)
GDP per capita (ln_gdppc)	0.090 (0.108)	-0.094 (0.090)		0.056 (0.115)	0.014 (0.100)
Constant	-2.126* (0.936)	0.231 (0.790)		-1.139 (1.003)	0.230 (0.894)
Industry controls	Yes	Yes		Yes	Yes
Observations	2908	1693		2908	1693
Pseudo R2	0.265	0.167		0.218	0.133

Table 2.6: Poisson Regression Sub-sample Analysis, Small vs. Medium & Big Firms

Dependent variable:	Total open innovation activities		Total open innovation partners	
	Small firms	Medium and big firms	Small firms	Medium and big firms
Total monetary support (mon_sup)	0.022 (0.028)	0.038 (0.024)	0.072* (0.029)	0.057* (0.026)
Total non-monetary support (nonm_sup)	0.092*** (0.023)	0.125*** (0.022)	0.144*** (0.025)	0.080*** (0.023)
Total open innovation partners (oi_p)	0.424*** (0.014)	0.326*** (0.013)		
Total open innovation activities (oi_a)			0.280*** (0.010)	0.237*** (0.009)
Internal search scope (intsearch)	0.183*** (0.014)	0.137*** (0.013)	0.135*** (0.016)	0.110*** (0.015)
Internal innovation activities (innov78)	0.288*** (0.036)	0.279*** (0.032)	0.101* (0.040)	0.041 (0.036)
MNE (mne)	0.016 (0.035)	-0.061† (0.034)	0.081* (0.036)	0.035 (0.037)
Size (size)	0.084* (0.042)	0.047*** (0.013)	0.008 (0.040)	0.010 (0.015)
Startup (startup)	0.044 (0.045)	0.064 (0.044)	0.093* (0.045)	0.116* (0.047)
Country IP protection (ipri_ipr)	-0.040 (0.035)	-0.026 (0.030)	-0.142*** (0.032)	-0.101** (0.033)
Country R&D intensity (ctr_rdint)	0.088** (0.031)	0.053* (0.026)	0.086** (0.030)	0.072* (0.030)
GDP per capita (ln_gdppc)	0.042 (0.090)	0.071 (0.082)	0.036 (0.097)	0.053 (0.094)
Monetary support X Internal innovation activities (ms_x_in78)	-0.013 (0.022)	-0.012 (0.016)	-0.067** (0.024)	-0.037* (0.018)
Non-monetary support X Internal innovation activities (nm_x_in78)	-0.092*** (0.022)	-0.079*** (0.015)	-0.081** (0.024)	-0.053** (0.017)
Constant	-1.633* (0.808)	-1.453* (0.709)	-0.485 (0.872)	-0.707 (0.828)
Industry controls	Yes	Yes	Yes	Yes
Observations	3044	2089	3044	2089
Pseudo R2	0.278	0.242	0.209	0.177

Table 2.7: Poisson Regression Sub-sample Analysis, Peripheral vs. Core Countries

Dependent variable:	Total open innovation activities			Total open innovation partners	
	Peripheral countries	Core countries		Peripheral countries	Core countries
Total monetary support (mon_sup)	0.017 (0.037)	0.046* (0.021)		0.073* (0.036)	0.059** (0.022)
Total non-monetary support (nonm_sup)	0.123*** (0.032)	0.123*** (0.018)		0.121*** (0.029)	0.115*** (0.021)
Total open innovation partners (oi_p)	0.402*** (0.016)	0.358*** (0.012)			
Total open innovation activities (oi_a)				0.259*** (0.011)	0.259*** (0.008)
Internal search scope (intsearch)	0.177*** (0.017)	0.150*** (0.012)		0.121*** (0.018)	0.131*** (0.014)
Internal innovation activities (innov78)	0.306*** (0.040)	0.296*** (0.030)		0.162*** (0.044)	0.027 (0.035)
MNE (mne)	-0.033 (0.042)	-0.009 (0.031)		0.090* (0.041)	0.042 (0.034)
Size (size)	0.054*** (0.016)	0.050*** (0.010)		-0.028† (0.017)	0.001 (0.011)
Startup (startup)	0.052 (0.052)	0.062 (0.042)		0.123* (0.053)	0.047 (0.047)
Country IP protection (ipri_ipr)	0.023 (0.046)	-0.099** (0.031)		-0.119** (0.044)	-0.127*** (0.035)
Country R&D intensity (ctr_rdint)	-0.003 (0.069)	0.101*** (0.023)		-0.091 (0.069)	0.093*** (0.025)
GDP per capita (ln_gdppc)	0.177 (0.171)	0.436** (0.135)		0.227 (0.183)	0.161 (0.170)
Monetary support X Internal innovation activities (ms_x_in78)	-0.011 (0.027)	-0.021 (0.014)		-0.064* (0.026)	-0.040* (0.017)
Non-monetary support X Internal innovation activities (nm_x_in78)	-0.107*** (0.029)	-0.078*** (0.014)		-0.083** (0.027)	-0.070*** (0.016)
Constant	-3.060* (1.504)	-5.026*** (1.272)		-2.168 (1.626)	-1.762 (1.602)
Industry controls	Yes	Yes		Yes	Yes
Observations	2046	3087		2046	3087
Pseudo R2	0.286	0.267		0.206	0.198

CHAPTER 3

THE EFFECT OF PRIVATIZATION ON THE CHARACTERISTICS OF INNOVATION

3.1. Introduction

Privatization, defined as the “deliberate sale by a government of state-owned enterprises (SOEs) or assets to private economic agents” (Megginson & Netter, 2001, page 321) has been abundantly studied in literature, following the worldwide spread of the phenomenon in the 1980s and 1990s. Thousands of SOEs around the world were privatized during this period. Scholars have discussed the theoretical arguments for privatization as well as its practical consequences (D'souza and Megginson, 1999; Djankov and Murrell, 2002; Estrin et al., 2009; Megginson and Netter, 2001; Megginson et al., 1994). Despite the abundance of work on the topic, certain important angles have been neglected; in particular, how privatization affects the characteristics of innovation and knowledge-sourcing of the organizations. This is the focus of this paper.

The importance of exploring the innovation angle is that it may be an overlooked driver of the differential in performance between privatized firms and state-owned enterprises. Privatized firms have been found, in general (though not universally), to be more efficient and perform better than SOEs (Boubakri and Cosset, 1998; D'souza and Megginson, 1999; Megginson et al., 1994). So far, several arguments have been used to explain this increase in performance. Some revolve around ownership structure; concentration of ownership in private firms provides stronger incentives for monitoring than the dispersed ownership of SOEs (Alchian, 1977; Pedersen and Thomsen, 2003). Another school of thought proposes that SOEs have less incentives to be efficient because they enjoy “soft budget constraints” (Berglof and Roland, 1998; Frydman et al., 2000; Lange, 1936). This refers to the fact that SOEs endure little financial pressure and rarely face the risk of bankruptcy, because the government is usually willing to bail them out in case of mismanagement. Other drivers of differences in performance are that SOEs often engage in hiring practices based on political affiliation rather than professional qualification (Krueger, 1990) and they can be used to pursue political goals rather than profitable business opportunities (Shleifer and Vishny, 1986). Although these arguments shed light on some of the drivers of performance, innovation has been mostly neglected as a likely source of competitive advantage in privatized firms.

I argue that newly privatized firms are likely to change their innovation patterns. Based on different factors, private firms may patent more or less than SOEs, but they are very likely to patent differently. In particular, pressure for short-term results is likely to affect the technology focus, forcing firms to invest their resources in the technologies with the highest potential for commercial success. While SOEs may pursue the generation of new knowledge for the broad national interest (Munari, 2002), private firms prioritize the creation of value for shareholders. To the best of my knowledge, this is the first paper to explore empirically the change of technological focus that occurs in privatized firms.

At the same time, privatized firms are less subject to political constraints, which will allow them to be more open to search for innovative knowledge wherever this is available, rather than be limited to source knowledge locally for political reasons. The practical consequence of this openness would be that privatized firms may engage more in collaboration with other organizations and disperse their innovation networks more internationally.

The contribution of this work is to shed light on the underexplored area of innovation in privatized firms, and particularly to disentangle the effects of privatization on different aspects of the innovation activities, such as the technological focus, the engagement in collaborative projects with other firms and the geographical dispersion of the knowledge sourcing. The paper is structured as follows: in the next section, I review the theoretical arguments and propose our hypotheses; next, I describe the data, variables and methods; I present the results and finally I discuss my conclusions.

3.2. Theory and Hypotheses

The first hypothesis focuses on the technological specialization of the innovation activities of privatized firms. There are different theories about what is the most critical difference between SOEs and private firms. According to the property rights hypothesis (Alchian, 1977), concentration of ownership, typical of the private sector, allows for higher specialization and creates incentives for more competent management. With public ownership, on the other hand, there is a lower correlation between the costs borne by individual decision-makers and the actual costs of the decision they make. Another school of thought proposes that the main source of inefficiency for SOEs are their 'soft budget constraints' (Berglof and Roland, 1998; Frydman et al., 2000). Soft budget constraints refer to the fact that, while in private firms managers are disciplined by force, having to meet certain financial goals and being scrutinized by shareholders and analysts, in SOEs there's no risk of bankruptcy, since the state is usually there to subsidize or bail out failing companies; this lack of financial constraints makes managers of SOEs less efficient than their private counterparts. In any case, privatization produces profound organizational changes that can be considered paradigm-changing (Ahuja et al., 2013) in terms of innovation.

Some authors have found that state ownership is negatively related to corporate risk taking (Boubakri et al., 2013). It follows that privatized firms should engage in innovation more intensely. However, empirical evidence is not necessarily consistent with this argument. Some argue that privatization tends to reduce R&D spending as a consequence of increased pressure for short-term profitability (Jamasb and Pollitt, 2008). This reduction does not necessarily affect the number of patents; in fact, in some cases privatized firms cut in R&D investments while increasing the number of patents and their quality (Munari and Sobrero, 2003).

Regardless of the overall level of spending in R&D, it seems reasonable to expect privatized firms to realign their innovation objectives toward the accomplishment of business goals rather than the broader national interest (Munari, 2002). This implies the abandonment of unpromising projects and technologies (György and Vincze, 1992), in order to give priority to the most promising ones. If value creation for shareholders is key, applied projects will be privileged, reducing or eliminating basic research and long-term projects. Based on these arguments, I propose the first hypothesis:

Hypothesis 1: *Privatization will increase technological specialization*

The second hypothesis focuses on the degree of collaboration with other firms for innovative purposes. Firms that are more open collaborate with external partners and to open their innovative practices to incorporate external ideas, increase their innovation performance (Laursen and Salter, 2006). If privatization produces a restructuring of R&D activities and a change of goals, it is also very likely to affect their openness and willingness to collaborate with other organizations. There are, however, two competing views on the effect privatization can potentially exert on collaboration, which I will call H2a and H2b.

The first view is that SOEs, for political reasons, may be likely to favor autarchy and conduct more R&D activities in-house. If privatized firms tend to reduce their R&D spending while pushing for quicker results, they will try to leverage collaborative relationships in order to benefit from the pools of knowledge possessed by other organizations. Therefore, following this rationale, I hypothesize that:

Hypothesis 2a: *Privatization will increase the likelihood of collaborating with other organizations for innovation activities*

The second view is that privatized firms, for a number of reasons, may be less open to collaborate with others. One reason is that private firms are subject to more competition; this may hinder their willingness to open up to a collaboration with potential rivals and risk the leakage of vital information. There is also evidence from certain countries that SOEs get actively involved in collaborations with private partners, which would demonstrate that SOEs are at least as open to collaborate as private firms, if not more. Chinese SOEs, for instance, regularly collaborate with external partners for innovative projects. In the U.S., for instance, NASA frequently engages in collaboration with private firms like Lockheed Martin. Following this view, an argument can be made that private firms will focus more on internal innovation which will allow them to protect their IP, while SOEs are willing to pursue complex long term projects with external partners. Therefore, I hypothesize that:

Hypothesis 2b: *Privatization will reduce the likelihood of collaborating with other organizations for innovation activities*

The third hypothesis focuses on the geographical dispersion of knowledge sourcing. In other words, I focus on whether private firms will absorb knowledge from sources (e.g. inventors) located around the world, while SOEs will be more local. Again, there are two possible points of view on this aspect. The first view (H3a) is that SOEs are subject to political constraints and the pursuit of political goals (Shleifer and Vishny, 1986); therefore, for political reasons, they will often privilege knowledge developed nationally. This prevents them from developing organization-based linkages (Lorenzen and Mudambi, 2013) or “pipelines” (Bathelt et al., 2004) to source knowledge from remote locations. Private firms, on the other hand, do not have these constraints. Often, they belong to multinational conglomerates, which allows them to benefit from “multiple embeddedness” (Meyer et al., 2011) and to benefit from both local knowledge and from knowledge pools in geographically distant locations. By being at the same time more open and having a larger geographical footprint, privatized firms will enjoy more opportunities to engage in collaborative projects with other organizations and to source knowledge from locations outside of national borders. These arguments lead to the the following hypothesis:

Hypothesis 3a: *Privatization will increase the geographical dispersion of knowledge sourcing*

There is, however, a competing argument, which I call H3b. This competing argument is that SOEs are increasingly operating as multinational enterprises, just like private MNEs, accounting for a high percentage of the cross-border M&A activity. Therefore, privatization will not necessarily alter their geographical footprint. Following this rationale, I posit that:

Hypothesis 3b: *Privatization will not increase the geographical dispersion of knowledge sourcing*

3.3. Sample and Variables

3.3.1. Sample

The data used comes from three main sources: the SDC and Worldscope databases, and the United States Trademark and Patent Office (USPTO). As a first step, I downloaded a list of all privatization deals available in the SDC (10,978 companies). The second step was to search which of these companies had financial information available in the Worldscope database; this reduced the list to 485 companies. In order to operationalize the innovation variables, I used patent data obtained from USPTO. I searched the 485 companies for which I had financial information in USPTO; of those companies, 109 had patents granted by USPTO until July 2013. The aggregated pool of patents for those 109 firms was more than 21,000. In order to establish "before and after" comparisons, I only kept the firms that had filed patents both before and after the privatization date. The final sample contains 63 privatized companies with 19,126 patents.

3.3.2. Dependent Variables

The variables *diversif_1* (used to test Hypothesis 1) and *diversif_2* (for robustness) are operationalized as the count of technology categories *(diversif_1)* and subcategories *(diversif_2)* on each focal patent. I reclassified the USPTO patent classes listed on each patent into a simpler taxonomy based on Hall, Jaffe & Trajtenberg (2001), which organizes USPTO utility patent classes into 6 major categories, which contain 36 subcategories. These categories and subcategories are the ones counted for our variable. In practical terms, a patent containing more categories/subcategories will have a broader technological focus and be less specialized.

The variable *collab_1* (for Hypothesis 2) is operationalized as the number of assignees (i.e. companies who own the patent) on each focal patent. A patent with more than one assignee means the project was carried out in collaboration with at least one other organization. The maximum number of assignees in a patent from our dataset is 4. For robustness, I also measured collaboration within the organization *(collab_2)* with the number of inventors listed in a focal patent. *collab_2* ranges from 1 to 22.

The variable geographical dispersion of knowledge sourcing, used in Hypothesis 3, was operationalized in two different ways. The first *(dispersion_1)* was constructing an index of geographical dispersion of the inventor network. The index was constructed in two steps, first by computing the Herfindahl index of inventor concentration at the country level. That Herfindahl index "H" is equal to 1 when all inventors are concentrated in one country. Since I want to measure the dispersion rather than the concentration of inventor networks, I constructed a variable 'Y' by transforming Herfindahl index 'H', such that: Y = 1 – H. As a result, the variable is censored, ranging from a minimum value of 0 (when all inventors are concentrated in one country), and an upper limit asymptotically approaching 1 as the inventors are more dispersed across countries. To control for the robustness of the results, I operationalized this variable in a second way *(dispersion_2)*, as the number of countries where inventors in the focal patent are located. The maximum number of inventor-countries in a focal patent is 6.

3.3.3. Independent Variables

In order to measure the effects of privatization I created two independent variables. The first one (*after_pri*) is a dummy with a value of 1 if the patent was filed before or the same the day of the privatization, and 0 if it was filed afterwards. The second one (*d_file_priv*) counts the number of days between the patent application and the privatization date. This variable will assume negative values for patent applications that took place before the privatization. This is a relatively less blunt instrument than the first variable, since the effects of privatization do not manifest immediately, but rather take time, due to inertia, residual inefficiency and resistance to change (Munari and Oriani, 2005).

3.3.4. Control Variables

To isolate the impact of privatization on innovation activities, I use several control variables. I collect firm- and country-level data. For firm-level variables, I measure firm size with the logarithm of total assets *(size)*. Larger firms are likely to spend a larger amount of resources in innovation activities. I include the level of economic development as a country-level variable. I measure economic development with the natural logarithm of the GDP per capita at the time the patent was filed *(log_gdp_pc)* according to World Bank data.

Other variables were constructed, but the number of missing observations (especially for patents prior to 1990) diminished the usefulness of these variables. For that reason, I only used them for robustness testing, which produced results mostly consistent with the ones published here.

One of these variables was *leverage.* As discussed in Chava et al. (2013), firms can also finance their innovation activities from bank loans; therefore, I computed *leverage* as the ratio of total debt to total assets. Growth opportunities were also taken into account, using *capex* as a proxy. *Capex* was operationalized as the sum of the investment in property, plant, and equipment as percentage of total sales. The research and development expenses *(r_d)* scaled by total assets were also considered. The amount of missing observations for these variables, however, biased the results and hence I dropped them for the main models.

3.4. Descriptive Statistics, Methods and Results

In order to compare the change in innovation patterns before vs. after privatization, I analyzed it in two ways. The first one is a direct comparison between all the patents filed before the privatization date vs. the patents filed after. There are at least two potential issues with this approach. The first one is that patent filings are the result of a relatively long previous R&D process, which may take years to complete. This means that patents filed some time after the privatization date may be reflecting innovation efforts that took place before the privatization. The second issue is that firms that are to be privatized sometimes change their management practices before the privatization. This is because government may make a deliberate effort to restructure the company to make it more attractive to potential buyers (Dewenter and Malatesta, 2001). This means that patents filed a short time before or after the privatization may potentially be misleading indicators. For this reason I created two windows of three years each one, one starting from five years (1825 days) before privatization and ending two years (730 days) before it; this is indicated as "Years -5, -4, -3". For comparison, I created a similar window after the privatization (Years 3, 4, 5) dubbed "Years 3, 4, 5", which starts 730 days after the privatization date and finishes 1825 (5 years) after it. This eliminates the potential issues with patents filed near the privatization date and provides with two comparable windows of equal length, but obviously reduces the sample size.

Tables 1 to 4 show a general overview of the data by firm. Table 1 displays the patenting activity (number of patents) filed before and after privatization. The average number of patents filed any time before privatization is 126.3, while the average number of patents filed any time after privatization is 177.3. These number aren't very indicative, since both periods may not be directly comparable (e.g. we don't know the date where the companies were created or started patenting and there is a truncation on the right side as well due to the date when the data were collected). The three-year windows are more directly comparable and they show a slight increase in the number of patents filed (35.8 in years -5, -4 and -3 vs. 38.5 in years 3, 4 and 5). The figures show, however, high variability, with some firms sharply increasing their patenting activity and others decreasing it.

Table 2 shows data on technological *diversification*, measured by the number of technology categories contained on each patent. Consistent with H1, the data shows a drop after privatization, both considering the entire activity or the three-year windows. Table 3 shows data on *collaboration*, measured by the number of assignees listed on each patent. The numbers show a slight decrease after privatization, which is not consistent with H2. Table 4 displays data on *dispersion*, which shows and increase after privatization, consistent with H4.

Table 5 shows the descriptive statistics. The mean number of technology categories per patent (*diversif_1*) is 1.26 and the maximum is 5. The mean number of assignees per patent (*collab_1*) is 1.19 and the maximum is 4. In terms of correlations, Table 6 shows a few interesting facts. The variable *diversif_1* is negatively correlated with both *after_pri* and *d_file_pri*, indicating more technological specialization after privatization, which is consistent with H1. *Collab_1* is positively correlated with both *after_pri* and *d_file_pri*, consistent with H2. *Dispersion_1* is positively correlated with *after_pri* (consistent with H3) but negatively correlated with *d_file_pri* (which would contradict H4). Finally, *size* is positively correlated with both *after_pri* and *d_file_pri*, indicating that firms tend to become larger after privatization.

Tables 7 to 9 show the results of the multiple regression analysis. The dependent variables have different characteristics and therefore require different types of regressions. The variables *diversif_1* and *collab_1* are positive count variables. The best method for such a variable is the Poisson regression (Hausman et al., 1984; Yanadori and Cui, 2013; Cameron and Trivedi, 1990). *Dispersion_1* is a double censored variable with values between 0 and 1. The technique for this type of dependent variable is a Tobit regression (Greene, 2000: 905-926), which has been used in studies with similarly censored dependent variables (Jeong and Weiner, 2012; Laursen and Salter, 2006; Mudambi and Helper, 1998; Ragozzino and Reuer, 2011). Given the fact that, on average, each firm has more than one hundred patents, I also tested the robustness of the results by clustering the standard errors by firm.

Table 7 shows the results for *diversif_1*. Models 1 and 2 use the *after_pri* dummy variable as dependent variable, but Model 1 contains the entire patent pool for each firm, while Model 2 only contains two three-year windows starting two years before and after the privatization date. This increases the validity of the comparison but reduces the sample size significantly. Model 3 uses the variable *d_file_priv*, which counts the days between the patent filing and the privatization. Models 1, 2 and 3 were estimated with robust standard errors. Models 4, 5 and 6 are identical to models 1, 2 and 3 except for the fact that the standard errors are clustered by firm. The coefficient for *after_pri* is always negative. It is highly significant in model 1 but marginally significant (10% level) in models 2, 5 and 6. The coefficient for *d_file_priv* is negative and highly significant in models 3 and 6. This variable may be more indicative than the dummy *after_pri*, for it captures the cumulative change that takes place in the firm as time passes. Models 4, 5, 6 show coefficients of similar sign and magnitude as models 1, 2, 3 but with less significance, which is expected. Overall, these results are consistent with H1.

Table 8 shows the results for *collab_1*. Models 7 and 8 use the *after_pri* dummy variable as dependent variable, but Model 7 contains the entire patent pool for each firm, while Model 8 only contains two three-year windows starting two years before and after the privatization date. Model 9 uses the variable *d_file_priv*, which counts the days between the patent filing and the privatization. As in the previous table models 7, 8 and 9 were estimated with robust standard errors and models 10, 11 and 12 are identical but with the standard errors clustered by firm. The variable *after_pri* produces inconclusive results; the coefficient is positive in models 7 and 10 (consistent with H2a) and negative in models 8 and 11 (consistent with H2b). The models with clustered standard errors are not significant. The coefficient for *d_file_priv*, however, is positive and significant in both models 9 and 12, which is consistent with H2a. As previously discussed, this variable is more nuanced than the dummy *after_pri*, and the coefficients for it seem to be indicating that over time, privatized firms tend to collaborate more than state owned firms, as predicted. Overall, results seem to provide more support for H2a than H2b, but more evidence would be needed to reach a conclusion.

Table 9 provides the results for *dispersion_1*. Models 13 and 14 use the *after_pri* dummy variable as dependent variable, but Model 13 contains the entire patent pool for each firm, while Model 14 only contains two three-year windows starting two years before and after the privatization date. Model 15 uses the variable *d_file_priv*. As in the previous table, models 16, 17 and 18 repeat the analysis but with the standard errors clustered by firm. *After_pri* is positive and significant in all models, consistent with H3a. *D_file_priv* is, however, negative in all models (although only significant at the 10% level in model 18), which would be more consistent with H3b. The coefficients seem to indicate that, while privatized firms tend to search knowledge across more countries, consistent with H3a, this pattern does not grow over time. Overall, these mixed results suggest the need for more inquiry into this specific aspect.

In all models, I used two control variables, one at the firm level (*size*) and the other at the country level (*log_gdp_pc*). The use of other control variables (*leverage, capex, r_d*) was tested for robustness purposes but did not yield significantly different results. One of the issues is the sharp drop in sample size when using more control variables, due to missing data. For this reason I only kept the most important firm control, size, because is likely to be highly related to the level of innovative activity. After controlling for collinearity using variance inflation factors, I found that several country dummies were highly collinear. For this reason, I dropped country-dummy controls and opted for GDP per capita instead.

Overall, I found strong support for H1 but mixed results for H2 and H3. This suggest that there are, as hypothesized, competing effects at play in H2 and H3. Thus, depending on the sample we use, we may see results supporting either H2a or H2b, H3a or H3b. I also acknowledge that results may be affected by the significant amount of missing data at the firm level. The sample size could potentially be increased by exploring two avenues. One is by looking at the innovative activity of the rest of the firms in the 10,000+ list of privatizations downloaded from SDC. The problem is that, while we may find patent data for these firms, we lack any financial information. The second avenue is to try to reconstruct financial data from the firms with significant amount of missing data; while this is potentially feasible, it would be a very time-consuming process. In either case, increasing the sample size may provide a clearer picture and this the next step in further developing this study.

3.5. Discussion and Conclusions

This work contributes to both the innovation and the privatization literatures, by exploring a new angle to explain the performance of privatized firms. My results show that privatized firms change their technology scope to focus their innovation efforts on a narrower set of technologies. The evidence, however, is not so clear in terms of the willingness to collaborate with other organizations and to source knowledge from more geographically dispersed networks. The change in technological focus, to prioritize applied projects with quicker payout, may help explain why privatized firms can sustain their innovation output while curtailing their R&D expenses (Munari and Sobrero, 2003). However, it is clear that more fine-grained evidence will be needed in order to reach robust conclusions.

A discussion would not be complete without acknowledging the limitations of this work. First, the final sample of firms I analyzed only represents less than one percent of all the firms that have been privatized in the last few decades. Increasing the sample size would be an obvious priority, but firm performance data is difficult to collect from two groups of firms. The first one is firms in emerging countries; the second one is firms that have been privatized before 1990, since performance data older than 20-25 years is difficult to obtain. A second but important limitation is the difficulty to compare firms over long periods of time, considering the overwhelming number of mergers, acquisitions, spinoffs and changes in structure that most of these firms tend to suffer over time.

Future research should try to address some of the aspects this work is not covering. One potentially important aspect is to determine the relationship between the type of owners acquiring the privatized firm and the changes that occur. Different type of owners (foreign vs. domestic, MNE vs. local firm, privately owned firm vs. state-owned enterprise based in a foreign country, etc.) can potentially drive different types of changes in the innovation activities of the privatized entities. Another aspect that remains to be analyzed is the tradeoff between diversification along different dimensions (geographical, technological) in order to find the optimum tradeoff under different circumstances. A third question derived from my research is to explore the changes in the underlying innovation activities during and after a privatization process. It is important to acknowledge that my research is only capturing the patenting activity, which is the external output of those innovation activities, without exploring the processes behind this output. While my research looks at the visible output of those activities (i.e. the patents obtained), a qualitative analysis focusing on the internal mechanisms driving this output could produce valuable insights.

This research sheds light on the important but previously unexplored aspect of the innovation activities of privatized firms. Privatization literature is abundant and broad but, surprisingly, almost no attention has been paid to the critical issue of innovative activities. I hope this work provides some initial insights, paving the way for future work trying to understand the differences in performance between SOEs and private firms.

Table 3.1: Patenting activity by firm, before and after privatization

Firm	Country	Priv. Date	Total before privatization	Years -5, -4, -3	Years 3, 4, 5	Total after privatization
Alcatel Alsthom CGE	France	10/8/1991	1	0	23	140
Alstom SA	France	6/26/2006	992	435	210	426
AMRAD Corp Ltd	Australia	11/23/1993	14	6	12	34
Autostrade SpA	Italy	10/31/1999	7	3	1	3
British Airways PLC	United Kingo	1/27/1987	1	0	1	17
British Gas	United Kingo	12/8/1986	136	40	45	172
British Telecommunications P	United Kingo	12/6/1991	401	176	210	1072
Carbone Lorraine SA	France	6/30/1995	42	16	2	15
Central Japan Railway Co	Japan	8/25/1997	3	2	6	41
CEPSA	Spain	7/17/1996	3	1	0	3
China Petrochemical Dvlp Cor	Taiwan	6/28/1991	2	1	0	27
China Steel Corp(Taiwan)	Taiwan	6/28/1992	13	8	0	16
Chunghwa Telecom Co Ltd	Taiwan	12/17/2002	6	2	5	21
Dassault Systemes SA	France	9/5/2003	32	22	25	57
Deutsche Post AG	Germany	11/19/2000	3	0	17	31
Distrigaz SA	Belgium	5/6/1994	4	0	0	0
DSM NV	Netherlands	3/26/1996	2	0	7	17
EADS	France	12/27/2007	8	4	0	6
East Japan Railway Co	Japan	8/2/1999	3	1	1	3
Egis Gyogyszergyar(Hungary)	Hungary	6/21/1994	53	22	5	38
Enel SpA	Italy	10/22/2004	30	5	5	8
ENI SpA	Italy	10/25/1996	27	10	45	173
Finmeccanica SpA	Italy	6/5/2000	48	22	0	5
France Telecom SA	France	11/26/1998	467	194	176	636
Japan Petroleum Exploration (	Japan	12/10/2003	2	0	4	12
Jiangsu Hengrui Medicine Co	China	12/31/2003	1	0	3	5
JT	Japan	6/11/2004	20	7	11	22
Kemira Oyj	Finland	11/15/1994	58	10	18	139
KEPCO	South Korea	12/29/1989	7	0	0	4
Krka dd Novo mesto	Slovenia	9/15/1995	8	1	0	15
Kumho Tire Co Inc	South Korea	2/17/2005	11	1	15	25
Lafarge SA	France	10/31/1996	53	6	17	103
Mitsui Mining Co Ltd	Japan	3/29/2005	448	105	61	137
Montefibre SpA(Enichem SpA	Italy	7/12/1996	18	1	0	3
National Power PLC	United Kingo	3/6/1995	10	3	4	10
Neste Oil Corporation	Finland	11/17/1995	145	39	7	57
Ningbo United Group Co Ltd	China	4/14/2010	127	26	15	56
NTT	Japan	4/1/1985	505	167	180	4325
OMV AG	Austria	8/1/1994	9	1	3	10
OMX AB	Sweden	2/27/2008	23	11	1	3
Qantas Airways Ltd	Australia	3/10/1993	4	0	3	3
QinetiQ Group PLC	United Kingo	2/28/2003	219	65	61	206
Rautaruukki Oyj	Finland	11/17/1993	10	5	1	7
Renault SA	France	3/11/1994	500	26	18	388
Rhone-Poulenc SA	France	1/22/1993	2229	496	601	1094
Richter Gedeon Vegyeszeti Gy	Hungary	9/22/1994	309	40	6	60
Saipem SpA	Italy	8/20/1996	30	3	5	71
Salzgitter AG(West Germany)	Germany	12/29/1989	37	4	0	16
Sasol Ltd	South Africa	6/28/1996	16	3	47	170
Snecma SA	France	5/11/2005	450	156	317	583
SSAB(Sweden)	Sweden	7/30/1992	6	1	1	15
Studsvik AB	Sweden	5/4/2001	26	1	1	7
Swiss Telecom PTT	Swiss	10/3/1998	4	0	40	125
Tele Norte Leste (Telebras)	Brazil	7/29/1998	6	1	0	1
Telefonica de Espana SA	Spain	8/9/1994	15	12	29	36
Telenor ASA	Norway	3/29/2004	14	3	3	9
Telia AB	Sweden	6/13/2000	69	39	1	13
Telstra Corp Ltd	Australia	11/17/1997	20	12	14	21
Tessenderlo Chemie NV	Belgium	5/30/1996	7	2	2	25
ThyssenKrupp AG	Germany	5/19/2003	69	9	118	265
Total SA	France	8/5/1993	80	20	20	156
Usiminas	Brazil	10/24/1991	1	0	0	1
VEBA AG	Germany	3/24/1994	90	7	5	13
Mean			**126.3**	**35.8**	**38.5**	**177.3**

Table 3.2: Diversification by firm, before and after privatization

Firm	Country	Priv. Date	Total before privatization	Years -5, -4, -3	Years 3, 4, 5	Total after privatization
Alcatel Alsthom CGE	France	10/8/1991	3.00000	N/A	1.26087	1.32140
Alstom SA	France	6/26/2006	1.30141	1.30805	1.25238	1.23709
AMRAD Corp Ltd	Australia	11/23/1993	1.42857	1.66667	1.66667	1.61765
Autostrade SpA	Italy	10/31/1999	1.00000	1.00000	1.00000	1.00000
British Airways PLC	United Kingd	1/27/1987	1.00000	N/A	1.00000	1.23529
British Gas	United Kingd	12/8/1986	1.41176	1.37500	1.31111	1.38953
British Telecommunications P	United Kingd	12/6/1991	1.33666	1.31818	1.23810	1.19030
Carbone Lorraine SA	France	6/30/1995	1.73810	1.56250	1.00000	1.33333
Central Japan Railway Co	Japan	8/25/1997	1.00000	1.00000	1.16667	1.26829
CEPSA	Spain	7/17/1996	1.00000	1.00000	N/A	1.00000
China Petrochemical Dvlp Cor	Taiwan	6/28/1991	1.00000	1.00000	N/A	1.03704
China Steel Corp(Taiwan)	Taiwan	6/28/1992	1.15385	1.12500	N/A	1.37500
Chunghwa Telecom Co Ltd	Taiwan	12/17/2002	1.16667	1.50000	1.40000	1.28571
Dassault Systemes SA	France	9/5/2003	1.03125	1.04545	1.12000	1.08772
Deutsche Post AG	Germany	11/19/2000	1.00000	N/A	1.35294	1.35484
Distrigaz SA	Belgium	5/6/1994	1.25000	N/A	N/A	N/A
DSM NV	Netherlands	3/26/1996	2.00000	N/A	1.14286	1.35294
EADS	France	12/27/2007	1.62500	1.75000	N/A	1.33333
East Japan Railway Co	Japan	8/2/1999	1.00000	1.00000	2.00000	1.33333
Egis Gyogyszergyar(Hungary)	Hungary	6/21/1994	1.54717	1.50000	1.60000	1.42105
Enel SpA	Italy	10/22/2004	1.36667	1.20000	1.40000	1.25000
ENI SpA	Italy	10/25/1996	1.18519	1.20000	1.13333	1.16185
Finmeccanica SpA	Italy	6/5/2000	1.12500	1.09091	N/A	1.40000
France Telecom SA	France	11/26/1998	1.26767	1.26804	1.17614	1.13050
Japan Petroleum Exploration (	Japan	12/10/2003	1.50000	N/A	1.00000	1.16667
Jiangsu Hengrui Medicine Co	China	12/31/2003	2.00000	N/A	1.66667	1.60000
JT	Japan	6/11/2004	1.20000	1.28571	1.18182	1.09091
Kemira Oyj	Finland	11/15/1994	1.17241	1.20000	1.16667	1.17266
KEPCO	South Korea	12/29/1989	1.14286	N/A	N/A	1.25000
Krka dd Novo mesto	Slovenia	9/15/1995	1.12500	1.00000	N/A	1.20000
Kumho Tire Co Inc	South Korea	2/17/2005	11.00000	1.00000	1.00000	1.04000
Lafarge SA	France	10/31/1996	1.22642	1.33333	1.17647	1.27184
Mitsui Mining Co Ltd	Japan	3/29/2005	1.47098	1.55238	1.31148	1.28467
Montefibre SpA(Enichem SpA	Italy	7/12/1996	1.22222	1.00000	N/A	1.66667
National Power PLC	United Kingd	3/6/1995	1.40000	1.66667	1.50000	1.40000
Neste Oil Corporation	Finland	11/17/1995	1.23448	1.23077	1.14286	1.08772
Ningbo United Group Co Ltd	China	4/14/2010	1.05512	1.03846	1.00000	1.01786
NTT	Japan	4/1/1985	1.33267	1.25150	1.40556	1.14405
OMV AG	Austria	8/1/1994	1.33333	1.00000	1.00000	1.20000
OMX AB	Sweden	2/27/2008	1.00000	1.00000	1.00000	1.00000
Qantas Airways Ltd	Australia	3/10/1993	1.33333	N/A	1.00000	1.00000
QinetiQ Group PLC	United Kingd	2/28/2003	1.27854	1.21538	1.26230	1.25728
Rautaruukki Oyj	Finland	11/17/1993	1.10000	1.20000	1.00000	1.42857
Renault SA	France	3/11/1994	1.35200	1.26923	1.38889	1.29124
Rhone-Poulenc SA	France	1/22/1993	1.30821	1.32661	1.33444	1.35649
Richter Gedeon Vegyeszeti Gy	Hungary	9/22/1994	1.54045	1.60000	1.50000	1.43333
Saipem SpA	Italy	8/20/1996	1.46667	2.00000	1.00000	1.19718
Salzgitter AG(West Germany)	Germany	12/29/1989	1.13514	1.00000	N/A	1.06250
Sasol Ltd	South Africa	6/28/1996	1.25000	1.00000	1.19149	1.11765
Snecma SA	France	5/11/2005	1.40444	1.36538	1.38801	1.37050
SSAB(Sweden)	Sweden	7/30/1992	1.16667	1.00000	1.00000	1.06667
Studsvik AB	Sweden	5/4/2001	1.50000	2.00000	1.00000	1.28571
Swiss Telecom PTT	Swiss	10/3/1998	1.25000	N/A	1.30000	1.16000
Tele Norte Leste (Telebras)	Brazil	7/29/1998	1.00000	1.00000	N/A	2.00000
Telefonica de Espana SA	Spain	8/9/1994	1.06667	1.00000	1.03448	1.08333
Telenor ASA	Norway	3/29/2004	1.28571	1.00000	1.00000	1.11111
Telia AB	Sweden	6/13/2000	1.05797	1.00000	1.00000	1.00000
Telstra Corp Ltd	Australia	11/17/1997	1.50000	1.50000	1.28571	1.19048
Tessenderlo Chemie NV	Belgium	5/30/1996	1.71429	1.50000	1.00000	1.04000
ThyssenKrupp AG	Germany	5/19/2003	1.13043	1.22222	1.19492	1.13208
Total SA	France	8/5/1993	1.16250	1.20000	1.05000	1.16026
Usiminas	Brazil	10/24/1991	1.00000	N/A	N/A	1.00000
VEBA AG	Germany	3/24/1994	1.17778	1.28571	1.00000	1.00000
Mean			**1.45288**	**1.25295**	**1.20986**	**1.23312**

Table 3.3: Collaboration by firm, before and after privatization

Firm	Country	Priv. Date	Total before privatization	Years -5, -4, -3	Years 3, 4, 5	Total after privatization
Alcatel Alsthom CGE	France	10/8/1991	1.00000	N/A	1.00000	1.01429
Alstom SA	France	6/26/2006	1.01210	1.01149	1.00952	1.00939
AMRAD Corp Ltd	Australia	11/23/1993	1.00000	1.00000	1.00000	1.00000
Autostrade SpA	Italy	10/31/1999	1.14286	1.33333	1.00000	1.00000
British Airways PLC	United King	1/27/1987	0.00000	N/A	1.00000	0.00000
British Gas	United King	12/8/1986	1.03676	1.05000	1.04444	1.04651
British Telecommunications P	United King	12/6/1991	1.01746	1.00000	1.02857	1.00746
Carbone Lorraine SA	France	6/30/1995	1.11905	1.06250	1.00000	1.06667
Central Japan Railway Co	Japan	8/25/1997	1.33333	1.00000	2.00000	1.58537
CEPSA	Spain	7/17/1996	1.00000	1.00000	N/A	1.00000
China Petrochemical Dvlp Co	Taiwan	6/28/1991	1.00000	1.00000	N/A	1.14815
China Steel Corp(Taiwan)	Taiwan	6/28/1992	1.23077	1.37500	N/A	1.00000
Chunghwa Telecom Co Ltd	Taiwan	12/17/2002	1.00000	1.00000	1.00000	1.00000
Dassault Systemes SA	France	9/5/2003	1.00000	1.00000	1.00000	1.00000
Deutsche Post AG	Germany	11/19/2000	1.00000	N/A	1.00000	1.00000
Distrigaz SA	Belgium	5/6/1994	2.00000	N/A	N/A	N/A
DSM NV	Netherlands	3/26/1996	1.00000	N/A	1.00000	1.05882
EADS	France	12/27/2007	1.25000	1.50000	N/A	1.00000
East Japan Railway Co	Japan	8/2/1999	3.00000	2.00000	1.00000	2.00000
Egis Gyogyszergyar(Hungary)	Hungary	6/21/1994	1.01887	1.00000	1.00000	1.00000
Enel SpA	Italy	10/22/2004	1.10000	1.00000	1.00000	1.00000
ENI SpA	Italy	10/25/1996	1.00000	1.00000	1.84444	1.83815
Finmeccanica SpA	Italy	6/5/2000	1.06250	1.09091	N/A	1.00000
France Telecom SA	France	11/26/1998	1.13704	1.16495	1.10227	1.08805
Japan Petroleum Exploration (	Japan	12/10/2003	3.00000	N/A	2.25000	2.75000
Jiangsu Hengrui Medicine Co	China	12/31/2003	2.00000	N/A	1.66667	1.60000
JT	Japan	6/11/2004	1.20000	1.14286	1.00000	1.00000
Kemira Oyj	Finland	11/15/1994	1.10345	1.10000	1.05556	1.07194
KEPCO	South Korea	12/29/1989	1.00000	N/A	N/A	1.00000
Krka dd Novo mesto	Slovenia	9/15/1995	1.00000	1.00000	N/A	1.00000
Kumho Tire Co Inc	South Korea	2/17/2005	1.00000	1.00000	1.00000	1.00000
Lafarge SA	France	10/31/1996	1.18868	1.33333	1.23529	1.06796
Mitsui Mining Co Ltd	Japan	3/29/2005	1.16071	1.08571	1.11475	1.12409
Montefibre SpA(Enichem SpA	Italy	7/12/1996	1.00000	1.00000	N/A	1.33333
National Power PLC	United King	3/6/1995	1.00000	1.00000	1.00000	1.00000
Neste Oil Corporation	Finland	11/17/1995	1.04138	1.02564	1.00000	1.03509
Ningbo United Group Co Ltd	China	4/14/2010	1.03150	1.03846	1.00000	1.07143
NTT	Japan	4/1/1985	2.32277	3.25150	1.53333	1.45942
OMV AG	Austria	8/1/1994	1.00000	1.00000	1.00000	1.00000
OMX AB	Sweden	2/27/2008	1.00000	1.00000	1.00000	1.00000
Qantas Airways Ltd	Australia	3/10/1993	1.00000	N/A	1.00000	1.00000
QinetiQ Group PLC	United King	2/28/2003	1.00000	1.00000	1.00000	1.00485
Rautaruukki Oyj	Finland	11/17/1993	1.00000	1.00000	1.00000	1.28571
Renault SA	France	3/11/1994	1.23400	1.26923	1.22222	1.22423
Rhone-Poulenc SA	France	1/22/1993	1.00628	1.00403	1.01331	1.01645
Richter Gedeon Vegyeszeti G	Hungary	9/22/1994	1.02265	1.02500	1.00000	1.01667
Saipem SpA	Italy	8/20/1996	1.33333	2.00000	1.00000	1.04225
Salzgitter AG(West Germany)	Germany	12/29/1989	1.02703	1.00000	N/A	1.06250
Sasol Ltd	South Africa	6/28/1996	1.06250	1.00000	1.06383	1.04118
Snecma SA	France	5/11/2005	1.06889	1.06410	1.03470	1.04631
SSAB(Sweden)	Sweden	7/30/1992	1.00000	1.00000	1.00000	1.00000
Studsvik AB	Sweden	5/4/2001	1.03846	1.00000	1.00000	1.00000
Swiss Telecom PTT	Swiss	10/3/1998	1.00000	N/A	1.02500	1.04000
Tele Norte Leste (Telebras)	Brazil	7/29/1998	1.00000	1.00000	N/A	1.00000
Telefonica de Espana SA	Spain	8/9/1994	1.00000	1.00000	1.00000	1.00000
Telenor ASA	Norway	3/29/2004	1.00000	1.00000	1.00000	1.00000
Telia AB	Sweden	6/13/2000	1.04348	1.00000	1.00000	1.07692
Telstra Corp Ltd	Australia	11/17/1997	1.10000	1.08333	1.57143	1.38095
Tessenderlo Chemie NV	Belgium	5/30/1996	1.14286	1.00000	1.00000	1.04000
ThyssenKrupp AG	Germany	5/19/2003	1.11594	1.11111	1.08475	1.10189
Total SA	France	8/5/1993	1.20000	1.40000	1.20000	1.34615
Usiminas	Brazil	10/24/1991	1.00000	N/A	N/A	1.00000
VEBA AG	Germany	3/24/1994	1.06667	1.14286	1.00000	1.15385
Mean			**1.15827**	**1.14741**	**1.11961**	**1.11703**

Table 3.4: Dispersion by firm, before and after privatization

Firm	Country	Priv. Date	Total before privatization	Years -5, -4, -3	Years 3, 4, 5	Total after privatization
Alcatel Alsthom CGE	France	10/8/1991	0.00000	N/A	0.00000	0.02303
Alstom SA	France	6/26/2006	0.13183	0.14028	0.09460	0.10864
AMRAD Corp Ltd	Australia	11/23/1993	0.08730	0.00000	0.06881	0.07664
Autostrade SpA	Italy	10/31/1999	0.00000	0.00000	0.00000	0.00000
British Airways PLC	United Kingo	1/27/1987	0.00000	N/A	0.00000	0.00000
British Gas	United Kingo	12/8/1986	0.00000	0.00000	0.00000	0.01026
British Telecommunications P	United Kingo	12/6/1991	0.00560	0.00253	0.01642	0.03026
Carbone Lorraine SA	France	6/30/1995	0.02918	0.02778	0.00000	0.05467
Central Japan Railway Co	Japan	8/25/1997	0.00000	0.00000	0.00000	0.00000
CEPSA	Spain	7/17/1996	0.00000	0.00000	N/A	0.16667
China Petrochemical Dvlp Co	Taiwan	6/28/1991	0.00000	0.00000	N/A	0.00000
China Steel Corp(Taiwan)	Taiwan	6/28/1992	0.11111	0.18056	N/A	0.00000
Chunghwa Telecom Co Ltd	Taiwan	12/17/2002	0.00000	0.00000	0.00000	0.00000
Dassault Systemes SA	France	9/5/2003	0.00000	0.00000	0.03556	0.02997
Deutsche Post AG	Germany	11/19/2000	0.00000	N/A	0.00000	0.00000
Distrigaz SA	Belgium	5/6/1994	0.37500	N/A	N/A	N/A
DSM NV	Netherlands	3/26/1996	0.00000	N/A	0.11714	0.07438
EADS	France	12/27/2007	0.00000	0.00000	N/A	0.00000
East Japan Railway Co	Japan	8/2/1999	0.00000	0.00000	0.00000	0.00000
Egis Gyogyszergyar(Hungary)	Hungary	6/21/1994	0.00000	0.00000	0.00000	0.00000
Enel SpA	Italy	10/22/2004	0.00000	0.00000	0.00000	0.00000
ENI SpA	Italy	10/25/1996	0.00000	0.00000	0.08907	0.04952
Finmeccanica SpA	Italy	6/5/2000	0.03966	0.05495	N/A	0.00000
France Telecom SA	France	11/26/1998	0.01097	0.00515	0.01307	0.02168
Japan Petroleum Exploration (	Japan	12/10/2003	0.12245	N/A	0.00000	0.00000
Jiangsu Hengrui Medicine Co	China	12/31/2003	0.00000	N/A	0.00000	0.00000
JT	Japan	6/11/2004	0.00000	0.00000	0.00000	0.00000
Kemira Oyj	Finland	11/15/1994	0.01628	0.09444	0.11136	0.09011
KEPCO	South Korea	12/29/1989	0.00000	N/A	N/A	0.00000
Krka dd Novo mesto	Slovenia	9/15/1995	0.00000	0.00000	N/A	0.02500
Kumho Tire Co Inc	South Korea	2/17/2005	0.04545	0.00000	0.00000	0.03875
Lafarge SA	France	10/31/1996	0.01811	0.00000	0.02614	0.08227
Mitsui Mining Co Ltd	Japan	3/29/2005	0.00682	0.00000	0.01184	0.00527
Montefibre SpA(Enichem SpA	Italy	7/12/1996	0.00000	0.00000	N/A	0.00000
National Power PLC	United Kingo	3/6/1995	0.00000	0.00000	0.12500	0.21250
Neste Oil Corporation	Finland	11/17/1995	0.03772	0.04375	0.00000	0.06069
Ningbo United Group Co Ltd	China	4/14/2010	0.00394	0.00000	0.00000	0.00000
NTT	Japan	4/1/1985	0.00000	0.00000	0.00894	0.01350
OMV AG	Austria	8/1/1994	0.00000	0.00000	0.00000	0.00000
OMX AB	Sweden	2/27/2008	0.04652	0.03409	0.00000	0.00000
Qantas Airways Ltd	Australia	3/10/1993	0.00000	N/A	0.46296	0.34722
QinetiQ Group PLC	United Kingo	2/28/2003	0.00778	0.00684	0.00615	0.01139
Rautaruukki Oyj	Finland	11/17/1993	0.00000	0.00000	0.00000	0.00000
Renault SA	France	3/11/1994	0.00567	0.00000	0.02083	0.02593
Rhone-Poulenc SA	France	1/22/1993	0.00556	0.00985	0.05687	0.05669
Richter Gedeon Vegyeszeti Gy	Hungary	9/22/1994	0.00606	0.01466	0.00000	0.01198
Saipem SpA	Italy	8/20/1996	0.04398	0.12500	0.00000	0.05145
Salzgitter AG(West Germany)	Germany	12/29/1989	0.00000	0.00000	N/A	0.00000
Sasol Ltd	South Africa	6/28/1996	0.04514	0.09259	0.07584	0.07343
Snecma SA	France	5/11/2005	0.01575	0.02708	0.00276	0.00637
SSAB(Sweden)	Sweden	7/30/1992	0.00000	0.00000	0.00000	0.00000
Studsvik AB	Sweden	5/4/2001	0.01923	0.00000	0.00000	0.07143
Swiss Telecom PTT	Swiss	10/3/1998	0.00000	N/A	0.00000	0.01489
Tele Norte Leste (Telebras)	Brazil	7/29/1998	0.00000	0.00000	N/A	0.00000
Telefonica de Espana SA	Spain	8/9/1994	0.00000	0.00000	0.00000	0.00000
Telenor ASA	Norway	3/29/2004	0.03571	0.16667	0.00000	0.00000
Telia AB	Sweden	6/13/2000	0.02355	0.00000	0.00000	0.18803
Telstra Corp Ltd	Australia	11/17/1997	0.00900	0.01500	0.03571	0.02381
Tessenderlo Chemie NV	Belgium	5/30/1996	0.18063	0.38222	0.00000	0.05724
ThyssenKrupp AG	Germany	5/19/2003	0.01978	0.00000	0.04935	0.05676
Total SA	France	8/5/1993	0.01094	0.00000	0.09444	0.08233
Usiminas	Brazil	10/24/1991	0.00000	N/A	N/A	0.00000
VEBA AG	Germany	3/24/1994	0.00000	0.00000	0.00000	0.00000
Mean			**0.02408**	**0.02737**	**0.02986**	**0.03633**

Table 3.5: Descriptive statistics

Variable	Description	Observations	Mean	Std. Dev.	Min.	Max.
diversif_1	Number of tech. categories/patent	19,126	1.26106	0.50872	1	5
diversif_2	Number of tech. subcategories/patent	19,126	1.42968	0.67967	1	6
collab_1	Number of tech. assignees/patent	19,126	1.19121	0.60808	1	4
collab_2	Number of tech. inventors/patent	19,126	2.94866	1.98846	1	22
dispersion_1	One minus Herfindahl index	19,126	0.02737	0.10913	0	0.81633
dispersion_2	Number of inventor-countries/patents	19,126	1.06614	0.26914	1	6
size	natural log of assets	13,290	16.97820	1.99142	4.76458	19.71600
leverage	Debt/Assets	13,287	0.30388	0.15177	0	0.84188
capex	Investment in property, plant & equipment	12,885	0.08012	0.05774	0.00407	0.37796
r_d	R&D expenditures/sales	11,742	0.02840	0.04106	0	0.42909
log_gdp_pc	natural log of GDP per capita, target country	14,738	10.22506	0.47857	5.92372	11.33328

Table 3.6: Correlations

	after_pri	*d_file_priv*	*diversif_1*	*collab_1*	*dispersion_1*	*size*	*log_gdp_pc*
after_pri	1						
d_file_priv	0.4949	1					
diversif_1	-0.079	-0.1602	1				
collab_1	0.0555	0.1491	0.0024	1			
dispersion_1	0.0997	-0.0869	0.0255	0.0143	1		
size	0.3734	0.5002	-0.1137	0.0397	0.0136	1	
log_gdp_pc	0.1994	0.3687	-0.0236	0.0726	0.0007	0.3038	1

Table 3.7: Diversification (H1)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	***diversif_1***	***diversif_1***	***diversif_1***	***diversif_1***	***diversif_1***	***diversif_1***
after_pri	-0.04029***	-0.03155†		-0.04029†	-0.03155†	
After privatization dummy	(0.00903)	(0.01610)		(0.02419)	(0.01793)	
d_file_priv			-0.00002***			-0.00002***
Days between filing and privatization			(0.00000)			(0.00000)
size	-0.01909***	-0.00761†	-0.00974***	-0.01909†	-0.00761	-0.00974
Natural log of assets	(0.00186)	(0.00419)	(0.00202)	(0.01073)	(0.00890)	(0.00709)
log_gdp_pc	0.01198†	0.04019**	0.03900***	0.01198	0.04019	0.03900
Natural log of GDP per capita	(0.00664)	(0.01506)	(0.00681)	(0.03765)	(0.02746)	(0.02804)
Constant	0.43440***	-0.01175	0.01078	0.43441	-0.01176	0.01078
	(0.06245)	(0.15483)	(0.06869)	(0.42638)	(0.26672)	(0.30159)
Robust Standard Errors	Yes	Yes	Yes	No	No	No
Standard Errors Clustered by Firm	No	No	No	Yes	Yes	Yes
Sample	All	Years -5,-4,-3,3,4,5	All	All	Years -5,-4,-3,3,4,5	All
Observations	13,244	3,285	13,244	13,244	3,285	13,244

a Estimated coefficients and associated robust standard errors (in parentheses) are reported
*** p < 0.001, ** p < 0.01, * p < 0.05, † p < 0.10

Table 3.8: Collaboration (H2)

	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	***collab_1***	***collab_1***	***collab_1***	***collab_1***	***collab_1***	***collab_1***
after_pri	0.04609***	-0.04088**		0.04609	-0.04088	
After privatization dummy	(0.00858)	(0.01239)		(0.05821)	(0.02527)	
d_file_priv			0.00002***			0.00002***
Days between filing and privatization			(0.00000)			(0.00001)
size	0.00130	0.01128***	0.01217***	0.00130	0.01128	-0.01217
Natural log of assets	(0.00157)	(0.00285)	(0.00174)	(0.01460)	(0.00715)	(0.02018)
log_gdp_pc	0.06625***	-0.0180791†	0.02813***	0.06625	-0.01808	0.02813
Natural log of GDP per capita	(0.00624)	(0.00976)	(0.00535)	(0.05098)	(0.02031)	(0.03143)
Constant	-0.59390***	0.08860	0.00359	-0.59390†	0.08860	0.00359
	(0.05877)	(0.10036)	(0.05206)	(0.31871)	(0.16815)	(0.19523)
Robust Standard Errors	Yes	Yes	Yes	No	No	No
Standard Errors Clustered by Firm	No	No	No	Yes	Yes	Yes
Sample	All	Years -5,-4,-3,3,4,5	All	All	Years -5,-4,-3,3,4,5	All
Observations	13,244	3,285	13,244	13,244	3,285	13,244

a Estimated coefficients and associated robust standard errors (in parentheses) are reported

*** p < 0.001, ** p < 0.01, * p < 0.05, † p < 0.10

Table 3.9: Geographical Dispersion (H3)

	(13)	(14)	(15)	(16)	(17)	(18)
Dependent Variable:	***dispersion_1***	***dispersion_1***	***dispersion_1***	***dispersion_1***	***dispersion_1***	***dispersion_1***
after_pri	0.51570***	0.55032***		0.51571***	0.55032***	
After privatization dummy	(0.04319)	(0.06440)		(0.12484)	(0.13208)	
d_file_priv			-0.00006***			-0.00006†
Days between filing and privatization			(0.00001)			(0.00003)
size	-0.02323***	-0.00412	0.05966***	-0.02323	-0.00412	0.05966
Natural log of assets	(0.00658)	(0.01322)	(0.00888)	(0.02801)	(0.04243)	(0.04232)
log_gdp_pc	-0.04407†	0.03036	0.08134*	-0.04407	0.03036	0.08134
Natural log of GDP per capita	(0.02628)	(0.05110)	(0.03773)	(0.10129)	(0.09775)	(0.17669)
Constant	-0.74410**	-1.63399**	-2.88092***	-0.74410	-1.63399†	-2.88092
	(0.25559)	(0.54742)	(0.40073)	(1.01412)	(0.87293)	(1.83401)
Robust Standard Errors	Yes	Yes	Yes	No	No	No
Standard Errors Clustered by Firm	No	No	No	Yes	Yes	Yes
Sample	All	Years -5,-4,-3,3,4,5	All	All	Years -5,-4,-3,3,4,5	All
Observations	13,244	3,285	13,244	13,244	3,285	13,244

a Estimated coefficients and associated robust standard errors (in parentheses) are reported

*** p < 0.001, ** p < 0.01, * p < 0.05, † p < 0.10

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