# What effect does the aggregate industrial R&D offshoring have on you? A multilevel study.

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**Abstract**.

The present study argue that R&D offshoring is not just a matter of firm's decision as in previous literature, but also has an important industrial externality component. For a sample of manufacturing and services industries in the period 2005-15, I study the externalities coming from R&D offshorers in a given industry and the heterogeneous effects of enterprises' internal knowledge base characteristics. The evidence points to offshoring externality (OE) presenting an inverted U-shape with respect to the firms' innovative processes. However, firms with higher levels of human capital and/or internal R&D investments obtain higher returns coming from the OE. Overall, it seems that a strategy (R&D offshoring) that is highly beneficial for enterprises individually, might be also optimal for the Spanish economy.

**Keyword:** Industrial externalities; R&D offshoring; multilevel; inter-industry study; panel data.

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## 1. INTRODUCTION

In a globalized world – as it is nowadays – no one can rely exclusively on internal ways of doing and thinking, so that processes such as the external acquisition of knowledge have been proved to be of high relevance for companies as stressed by Un and Rodríguez (2018). The R&D offshoring literature has posited into consideration the relevance of the acquisition of knowledge external to the firm in order to survive, grow, and to approximate to leadership at the firm level (Steinberg et al., 2017; Un and Rodríguez, 2018), as well as at a more aggregated regional level (Castellani and Pieri, 2013). This acquisition of external knowledge can be made by market base transactions through R&D offshoring[2], or by non-market transactions through knowledge spillover.[3] On the one hand, enterprises have noticed the importance of R&D offshoring as an essential step for increasing their innovative activity as highlighted by Murphy and Siedschlag (2015). On the other hand, the literature on knowledge spillover acknowledges the importance of the environment for firms' innovativeness. However, how knowledge spillover complement firms' internal capabilities with respect to innovative activities is an area underperformed in the literature (Audretsch and Belitski, 2020).

In the present study, the aim is to investigate how the externality produced by offshoring firms in a given industry affect not only these firms, but the rest of firms' innovative performance. The literature stresses the importance of knowledge spillovers to recombine and exploit different and/or unconnected ideas. The main advantage is that the knowledge produced by a firm is only partially appropriated by the producer, whereas a fraction of such knowledge spreads to the rest of companies in the same industry. This paper tries to give a step forward in this direction with the main objective of providing evidence on the hypothesis that the industrial context – specifically the Offshoring Externalities (OE) – not only exerts a positive effect on firms' innovation performance but also a negative one, presenting an inverted U-shape pattern with respect to the firms' innovativeness. On top of that, previous literature does not address the

[2] I refer to R&D offshoring as sourcing R&D from an external organization, either within firm or with external partners in a foreign country (Cusmano et al., 2009; Rodgers et al., 2019; Rosenbusch et al., 2019).
[3] Of course, this does not preclude other ways of accessing to external knowledge as for instance, technological collaborations.

heterogeneity within the industry and assume that all firms take the same return from its environment. However, the return coming from the OE may well depend on the firm's internal capacity to build and recombine new ideas. As a matter of fact, despite the technological proximity among firms pertaining to the same industrial environment; differences in the learning processes, in competences, as well as in managerial capabilities, will induce heterogeneity within industries (Malerba, 2002; Phene et al., 2006). Consequently, I believe that the internal capabilities of firms – internal R&D and their level of human capital – as well as their networking strategies with other organizations, may moderate the relationship between the OE and the firm's innovative performance.

A large number of studies have identified R&D offshoring[4] as a mechanism by which firms could not only complement internal sources of knowledge (Añón Higón et al., 2014; Cassiman and Veugelers, 2006; Un and Rodríguez, 2018), but also improve the likelihood as well as the intensity to innovation (Arvanitis et al., 2015; Steinberg et al., 2017; Yamashita and Yamauchi, 2019). Nonetheless, scholars have not considered in the past the relevance of different national contexts to firms' innovation performance. Accessing different knowledge from abroad is very important because it complements the knowledge developed at home with the newest ideas in the international markets (Phene et al., 2006). Therefore, R&D offshoring allows firms to focus on core activities while taking benefit in which other regions/firms have comparative advantage (Rosenbusch et al., 2019; Un and Rodríguez, 2018).

Do the results in the studies surveyed above imply that R&D offshoring only affects offshoring firms? Most studies tend to analyze the impact of R&D offshoring on the offshoring firms. However, R&D offshoring may also affect non-offshoring firms' innovation performance through other channels including but not limited to knowledge spillover. Indeed, the literature acknowledges that the environment affects firms' performance (van Oort et al., 2012), pointing to a high relevance of the institutional context on the relation between R&D offshoring and firms' innovative performance (Rosenbusch et al., 2019), as well as on the location of such R&D offshored (Zhao et al., 2020), thus, focusing only on firm level may generate an incomplete analysis (Backman, 2014). One explanation is the complementarity between internal capabilities of firms and knowledge spillover. On the one hand, knowledge spillover can boost firms' technologies through new and efficient ways of exploiting internal knowledge, generating new combinations of different pieces of unconnected ideas. On the other hand, internal processes of knowledge creation can spread to other firms in a given industry by means of knowledge spillovers, reinforcing and changing internal innovative processes of firms. However, as

[4] Some of the references focuses on external R&D without differencing between the national or international context from where the knowledge is acquired.

suggested by Kotabe (1989)[5], there is a real possibility of underinvestment in R&D at the industry level when too much firms in the industry do R&D offshoring. Furthermore, even much of the literature is focused on multinational enterprises (MNEs) in the manufacturing industry, much less is known about non-manufacturing industries. Indeed, the literature has not provided yet an answer to whether the knowledge spillover coming from the offshoring firms (OE) affects firms in a given industry, and up to what extent industries with higher shares of R&D offshorers may have an effect on its firms' innovative performance including the non-offshoring firms.

To address these limitations, the present study focuses on the influence R&D offshorers have on the innovation performance of all firms in the industry, that is, on the specific externality effect coming from offshoring firms. Due to differences in learning processes, technological regimes, and knowledge bases, international spillovers may occur in different industries through different channels including but not limited to R&D offshoring (Malerba et al., 2013). Indeed, as stressed by Owen-Smith and Powell (2004), these transmission channels will bring non-incremental knowledge to the industry.

The study makes a few contributions. First, I study the influence of industry-level OE on offshoring as well as non-offshoring firms' innovation performance, which as far as the author knows, it is new in the R&D offshoring literature. I argue that an increase in the OE has a positive influence on firms' innovativeness, but only until an intermediate threshold; thereafter, more offshorers may induce negative returns. Second, I investigate whether the return firms take from the OE is also a matter of firms' characteristics. Indeed, previous literature assume that within a given industry, enterprises receive the same effect from their industrial environment. However, this work contributes to filling this gap by studying the benefits and costs of the OE, that may have an important firm level component that moderates the OE effect with respect to firm's innovativeness. Therefore, I study the moderation effect of firms' internal capabilities – internal R&D and their level of human capital – and their networking strategies.

Using the technological innovation panel (PITEC) for Spanish firms in the period 2005–15 as well as a multilevel framework, I find an inverted U-shape relation between the OE and the enterprises' innovative performance. However, I also find this relationship is heterogeneous with respect to firms' internal characteristics, changing the return they obtain from their industrial environment.

## 2. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

[5] Other scholars have also mentioned such a possibility at the firm level (see Kotabe et al., 2007; Un and Rodríguez, 2018).

### 2.1 Firm's R&D offshoring

One of the advantages of the internationalization of the offshoring strategy comes from the fact that firms – thanks to the new information and communication technologies (ICT) – get access to resources owned by foreign enterprises or foreign institutions, as well as gain access to international talent (Youngdahl and Ramaswamy, 2008). Therefore, it is expected that R&D offshoring improves firms' productivity and gives a better access to a well prepared and cheaper labor force (Belderbos et al., 2013; Lewin et al., 2009). These might be some of the reasons why R&D offshoring is an increasing as well as an important strategy for firms seeking to take benefit of the comparative advantage in knowledge of other firms from abroad (Un and Rodríguez, 2018).

Previous studies have identified R&D offshoring as a mechanism by which firms could not only complement internal sources of knowledge (Añón Higón et al., 2014; Cassiman and Veugelers, 2006; Un and Rodríguez, 2018), but also improve the likelihood as well as the intensity to innovation (Arvanitis et al., 2015; Steinberg et al., 2017; Yamashita and Yamauchi, 2019). For instance, Martinez-Noya et al. (2012) stress that the higher the international experience of the manager, the higher the likelihood of success of the offshoring strategy. The latter suggests that the international experience in R&D offshoring allows to detect in a finer way, the specific locations from which it may be more profitable for firms to take advantage of knowledge specificities.

Another relevant advantage is the access to a new and different way of thinking and making, that is, to a different national context. This is very important in the sense of not being trapped by the knowledge developed at home while being in contact with the newest ideas in the international markets. The fact of being in contact with institutions presenting national differences in education and training, in market regulations, in industry specializations, culture and preferences, etc. (Phene et al., 2006) makes that the combination/implementation of such a knowledge may end in new products having higher returns for the enterprise (Tojeiro-Rivero et al., 2019). The latter is more pronounced when technological and cognitive proximities between firms exist due to the improved efficiency in the recombination of knowledge (Cohen and Levinthal, 1990). For instance, Phene et al. (2006) find that in presence of technological proximities, the purchase of technology between two given enterprises generates breakthrough innovations.

Very recently, the literature has noticed the relevance of the environment in which firms operate on the benefits taken from R&D offshoring as well as on the location of such strategy (Zhao et al., 2020). The latter recognizes that not only what happen at the firm level is relevant for the benefit that R&D offshoring might report to the firm, but also the context play a key role. In this sense, Castellani and Lavoratori (2020) point to the relevance of the industrial context on the likelihood of locating firm's R&D abroad, pointing to the heterogeneity among industries.

Furthermore, some scholars evidence that depending on the institutional context, the relation between R&D offshoring and firm's innovation performance might be heterogenous. Hence, the efficiency and effectiveness of the R&D offshoring might depend on the environment in which firms operate (Rosenbusch et al., 2019).

**2.2 The importance of the industrial environment**

The benefits of R&D offshoring might depend not only on the firm specificities, but also on the industrial context (Castellani and Lavoratori, 2020). Nonetheless, based on the analytical and conceptual studies of Sectoral Innovation System (SIS) (Malerba, 2005, 2002), some authors have argued that aspects like the knowledge base, the technological regime, that is, opportunity, appropriability, and cumulativeness, historical and institutional characteristics, as well as the economies of scales or path dependence processes, may be industry specificities (Edquist, 1998, chapter 6).

It is important to notice that because of similar knowledge base, problem-solving techniques, and interpretative schemes of new knowledge, an enterprise placed in one region is in some way expected to be connected with other firms within the same industry but located in other regions or in the same region. Therefore, as stated by Malerba and Adams (2014) "firms within the same industry face the same set of technologies, search within a similar knowledge base, will undertake similar production activities, and will be embedded in the same institutional setting". The result of this is that within a given industry, firms will show similar learning patterns, as well as will present similar behaviors in terms of product generation, while being bounded by similar organizational forms. All this, linked to a standard and easy to codify type of knowledge, that tend to be the case in R&D offshoring, will make geographical proximity less relevant – as in the opposite case of technological collaboration with the need of more tacit knowledge (Teirlinck and Spithoven, 2013).[6] Therefore, other types of proximities, like cognitive and organizational (Boschma, 2005), have a higher relevance here since the ICT allow this type of knowledge to travel easily across geographical borders. Hence, the common knowledge, technological trajectories, and learning processes, may propitiate closeness among the firms pertaining to a given industry.

The literature stresses the importance of knowledge spillovers to recombine and exploit different and/or unconnected ideas. The main advantage is that the knowledge produced by a firm

[6] Studies of the national or regional contexts have the aim of understanding the role of local institutions, government policies, among others, in influencing the innovative performance of firms. However, they do not analyze how the innovation across geographical boundaries are affected by industry characteristics (Malerba and Adams, 2014). Unfortunately, geographical location of firms is not present in the PITEC database.

is only partially appropriated by the producer, whereas a fraction of such knowledge spreads to the rest of companies in the same industry. Thanks to the presence of knowledge spillover, Ornaghi (2006) finds that industrial R&D externalities have a positive role in explaining firm's productivity for Spanish manufacturing enterprises. Indeed, industries with a higher share of R&D intensity performs better not just at the industry level but also at the firm level, being a direct determinant of firm's performance (Short et al., 2006). For instance, Amoroso (2017) studies how firms' collaboration strategies as well as firms' innovative output could be affected by industry heterogeneity for the case of the Netherlands, finding that the industry level of concentration and legal protection, as well as the industry heterogeneity in government R&D funding, are positively associated with firms' collaborations strategies and innovative output.

From the company point of view, it is important to understand how firms' innovative performance take advantage from their industrial context. It is sensible to think that the number of offshorers in a given industry to which the firm belongs to, might be highly beneficial for firms seeking to take advantage of market novelties, since a higher number of firms accessing foreign knowledge might increase the externalities to all firms in the industry.[7] In fact, the relation between internal modes of knowledge generation and knowledge spillovers can be reinforced in different ways. First, knowledge spillovers can boost firms' technologies thanks to the implementation of different and unconnected ideas. Second, it also helps in the creation of new relations of knowledge sharing through more formal ways of knowledge transmissions, like for instance, technological collaborations, knowledge sourcing, or joint ventures, among others. The latter has to do with a more efficient way of identifying the best knowledge partners within the industry, and can be translated into complementarities between the firm's internal knowledge and the one coming through knowledge spillover, generating synergies through new and better relations based on trust, and the improved experience and skills of those firms pertaining to a given industry.

On the other hand, knowledge spillovers can benefit from formal ways of knowledge transmissions, since it would reinforce firms' internal knowledge through a better understanding, adoption, and assimilation of the external knowledge (Audretsch and Belitski, 2020). On top of that, the latter connects with the access to a higher pool of different and novel type of ideas coming from a dissimilar national context possibly ending in more externalities within the industry through the interchange of such a knowledge through the firm's networking strategies. In fact, as stressed by Owen-Smith and Powell (2004), those pipelines might bring to the industry non-incremental knowledge that may be better exchanged later on through knowledge spillovers. Thus, building on previous evidence, firms' innovative performance may depend positively on

[7] See for instance Henderson (2003) for a similar approach proxying industry knowledge externalities.

the pool of general knowledge they have access to in a given industry (Amoroso, 2017; Goya et al., 2016; Ornaghi, 2006).

However, even though the entrance in the industry of a dissimilar pool of knowledge thanks to the firms' R&D offshoring may imply a way of taking advantage of foreign knowledge, not only for firms going abroad in search of such a knowledge but also for those firms not having the means for it but taking profit through knowledge spillovers. There might be a real possibility of underinvestment in R&D at the industry level when too many firms in the industry do R&D offshoring. This might have to do with the presence of a fierce degree of competition (see Keller, 2021; Rojec and Knell, 2018; for the case of FDI knowledge spillovers) as it may be the case when the number of rivals within an industry increase, leading to the necessity of increasing the amount of novelties. Consequently, successful strategies done by leading firms – as for instance R&D offshoring – will be soon available to others and those companies with similar capabilities in the horizontal dimension, that is, in the same industry, will start to imitate the success of others (Malmberg and Maskell, 2006).

The latter may lead to the rise of knowledge spillover in a given industry. In such a case, a disincentive to private investment in R&D may arise. This is explained by the fact that enterprises will not be capable of internalizing such knowledge spilling over which will end in the internal innovative processes of rivals, and therefore, in order to reduce such opportunisms, firms might end reducing internal knowledge creation. These effects will be stronger the higher the knowledge spillovers in the industry are as suggested by Audretsch and Belitski (2020) for the case of general knowledge spillover. Therefore, the more an industry relies in knowledge acquisition from abroad in order to bring novel knowledge increasing the knowledge spillover in the industry, ultimately, the less knowledge base and internal capabilities could be developed by the home firms putting in check the whole industry; and therefore, the negative effects of the OE could overcome the positive ones.[8]

Taking the above evidence, I believe that industries presenting a relative increase in the number of R&D offshorers has a positive influence in its firms' innovativeness, but only until an intermediate threshold; thereafter, the deterioration of the industry internal capacity might be determinant for industries with high level of OE inducing negative returns. Therefore, my first hypothesis arises.

[8] The reader must notice that this is different from the hollowing-out concept in Kotabe (1989), since in that case it was stated only for multinationals having a subsidiary abroad, also known as captive offshoring; while the present study not only uses captive offshoring, but also focuses on knowledge acquisition coming from third party organizations abroad (see footnote 1). Therefore, contrary to Kotabe's case, an enterprise may end losing internal capabilities – and therefore the whole industry – since the knowledge may not be generated by a subsidiary abroad and thus, the enterprises' know how is lost.

**Hypothesis (H1)**. *The relation between the number of R&D offshorers in a given industry and its firms' innovative performance follows an inverted U-shape.*

### 2.3 The role of firm's heterogeneity

The latter is open to criticisms, since – as in previous literature – it assumes that all firms in a given industry can take the same effect from their industrial knowledge spillover. However, the return coming from the OE may well depend on the firm's internal capacity to build and recombine new ideas. For instance, elaborating on Malerba and Adams (2014), firms pertaining to the same industrial context will be more alike than firms from different industries, due to among other things, the share of similar technologies, same labor market policies, and the same product life-cycle (van Oort et al., 2012). However, this does not preclude the heterogeneity among enterprises from within industries. Therefore, despite the technological proximity; differences in the learning processes, in competences, as well as in managerial capabilities, will induce heterogeneity within industries (Malerba, 2002; Phene et al., 2006).

The extent to which firms benefit from the OE, may depend on their internal capabilities and their networking strategies to strengthen firms' absorptive capacity. Recently, the literature has posited into consideration possible complementarities between internal modes of knowledge generation and knowledge spillovers (Audretsch and Belitski, 2020). The idea is that when both modes are done simultaneously, this implies a reduction of time to market as well as in costs for enterprises. Another explanation of the reinforcing effect between internal R&D and knowledge spillovers has to do with the fact that it allows in a more efficient way to explore different knowledge in the industry which allow firms to reduce the amount of resources dedicated to searching and mapping as well as on correcting and implementing the external knowledge. This way, firms can focus more efficiently on internal R&D which also reinforce the capacity firms have for the implementation of the external knowledge (Cohen and Levinthal, 1990). Therefore, a company with higher levels of internal R&D could take more advantage of the entire pool of offshored knowledge by the firms in a given industry, that is, from knowledge spillover. Furthermore, the industry keeps building new capabilities, and this is done through learning by doing and training processes which foster the generation of tacit knowledge (Grimpe and Kaiser, 2010).

Firms with more levels of human capital might have an advantage due to a more likely novel recombination of incoming knowledge thanks to their experienced routines and skills (Grimpe and Kaiser, 2010; Martinez-Noya et al., 2012). This is especially true since the knowledge embedded in individuals can be thought as a tacit type of knowledge, which is hard to codify and share, and thus, highly profitable for firms looking for internalizing their knowledge spilling over. Hence, the level of education and training present in the workforce of enterprises might lead to an increase in the capacity of managers and employees to identify certain type of knowledge specificities, acquire information, as well as to implement innovations developed elsewhere as highlighted by Backman (2014).

Therefore, I expect a positive moderation effect coming from the absorptive capacity, since following the previous arguments, higher levels of absorptive capacities of firms, may positively influence the relationship between the OE and firms' innovative performance, as posit in the next hypothesis.

**H2**. *The relation between the number of R&D offshorers in a given industry and its firms' innovative performance will be moderated by the firm's absorptive capacity. Allowing firms increasing their levels of absorptive capacity to obtain higher returns from the OE in those industries presenting higher levels of OE.*

Some scholars have pointed the fact that internal capabilities goes beyond the absorptive capacities characterized by Cohen and Levinthal (1990); for instance, Spithoven and Teirlinck (2015) highlight that on top of internal R&D efforts, networking is key for strengthening firm's internal capabilities. Hence, firms having collaborative and offshoring relations with other institutions will be more open to external knowledge. Therefore, they might be less dependent on their industrial context since they can more easily go abroad and explore new sources of knowledge while acquiring it directly from knowledge suppliers. The latter is linked to the idea that an enterprise that can access directly foreign knowledge through networking strategies, might be less dependent on the pool of a similar knowledge generated in their industries, since it may be redundant.

On the opposite, those firms with lower degrees of openness may be more prone to take advantage of such knowledge spillover generated in their industries. However, lower degrees of networking also imply that firms will present lower capacity to develop novel innovations since as suggested by Chesbrough (2003), they may end trapped in internal ways of doing not able to adopt novel insights developed elsewhere. Consequently, those firms presenting lower networking experience will have lower capacities to get rid of too much R&D offshoring in their industries not because they do not want to, but probably because they cannot manage such amount of information, with higher costs for searching, detecting, and implementing such technologies, and thus, not able to benefit from the highest levels of such externalities efficiently.

Given the above arguments, I expect that technological collaboration and R&D offshoring strategies at the firm level moderate the relationship between the OE and firms' innovative performance. Therefore, the next hypothesis arises.

**H3**. *The relation between the number of R&D offshorers in a given industry and its firms' innovative performance will be moderated by the firm's networking strategies. Allowing firms increasing their levels of networking strategies to obtain higher returns from the OE in those industries presenting higher levels of OE.*

## 3. DATASET AND VARIABLES

### 3.1 Dataset

The dataset I use is the Technological Innovation Panel (PITEC) which is an unbalanced panel tracing the innovation activity of Spanish enterprises from 2003 until 2015. It uses two surveys: the first – Survey on Technological Innovation of Firms – is the Spanish counterpart to the Community Innovation Survey (CIS) from the Eurostat, following the guidelines of the Oslo Manual; the second is the Statistics on R&D Activities. The PITEC database offers direct measures of the innovation output as product and process innovations – instead of relying only on measures of semi-output, such as patents, or on inputs, such as R&D expenditures.

The PITEC is representative of small and medium-size as well as large firms; enterprises with internal R&D expenditures, as well as those with external R&D expenditures without having internal R&D; and finally, those small and medium-size firms without any expenditures on innovation. The stratification of the sample is for all the business industries that are included in the National Classification of Economic Activities (NACE two-digit level) (see Table 1); and the representativeness of the panel is assured thanks to the annual inclusion of firms with similar characteristics to those that disappear from the sample. The response rate is very high due to the fact that it is mandatory for firms, and the territorial covering is the whole Spanish Economy.[9] The PITEC is a survey in which values are self-reported, however, in this kind of survey, where anonymity is a legal concern, there is not a systematic propensity for over- or under-reporting the innovation that is carried out by the enterprise.

My sample covers the period 2005–15,[10] with around 12,000 enterprises. However, after deleting missing values, considering only companies with more than 10 workers, dropping those observations for firms that declare having products innovations while not presenting innovative

[9] More details on the sample, the quality and validation of the information can be obtained from: https://www.ine.es/dynt3/metadatos/es/RespuestaDatos.html?oe=30061

[10] Due to a methodological change, the year 2003 is discarded, some variables do not present data for the year 2004, so that I have decided to discard it too.

expenditures, as well as those outliers with more than 20 percent of market share in a given industry,[11] the final sample is around 8,200 enterprises.

### 3.2 Firm level variables

In the PITEC survey, firms are asked whether they have developed product innovations in the current year or in the previous two years. Using this information, I proxy for the innovative output of enterprises which is my dependent variable (*PI*) equal to one in case the enterprise developed product innovations in the current year or in the previous two years, and zero otherwise (López-Bazo and Motellón, 2018; Naz et al., 2015; Srholec, 2010). Moreover, building on previous evidence, the reason to focus on product instead of process innovations is that the acquisition of knowledge external to the firm through R&D offshoring has a higher impact on product rather than on process innovations (Bertrand and Mol, 2013; Nieto and Rodríguez, 2011). The latter has to do with the type of knowledge required, which for product innovations tends to be more explicit, while for process innovations, organizational closeness among the enterprises is also required (Phene et al., 2006), which is more difficult. Therefore, as the knowledge embedded on R&D offshoring is assumed standard and codified and is less bounded by geographical proximities, it is expected to impact more on product rather than on process innovations.

Firms' R&D *Offshoring* is measured as the expenditures on external acquisition of knowledge from abroad (Steinberg et al., 2017) as percentage of innovative expenditures, including also its squared term (Mihalache et al., 2012).[12] To control for other firm characteristics I use *Collaboration*, which has been observed to have an important role on product innovation (Robin and Schubert, 2013). It captures whether the firm acquires external knowledge through other channels, and it is measured as a dummy variable equal to one if the firm cooperates in the current year or in the previous two years with other organizations and zero otherwise. For accounting for internal capabilities of firms (Cohen and Levinthal, 1990), I use the amount of *internal R&D* as proportion of total sales (Cassiman and Veugelers, 2006; Spithoven and Teirlinck, 2015).[13] However, previous scholars recognize that this is a limited way of accounting for the internal capabilities of enterprises. Therefore, I include also the number of workers with tertiary education

[11] Firms with more than 20 percent of the market share in a given industry represent around 0.05 percent of total observations in the sample. The threshold of 20 percent of the market share was chosen following previous evidence that is also based on the PITEC survey, such as López-García and Montero (2010).
[12] Even though I do not have information about the nature of the offshored knowledge, this allows to control by the amount offshored being a proxy for the value added. This is more informative than other measures used in the literature, as for instance, dummy variables.
[13] In the case of those observations for which internal R&D expenditures are more than two times the volume of sales, I have replaced such values with a maximum value of 2 – representing around 0.5 percent of total observations. Although the selection of a value of 2 is arbitrary, other smaller values did not imply any change in the results. These additional estimates are available upon request.

and/or training in R&D (as proportion of total workforce), *Human capital*. This way, I intend to take into account the effort and productivity in the innovation process, something not accounted by the internal R&D variable alone, as posit by Griffith et al. (2006).

In addition, *Size* is accounting for the number of total workers measured in logs. For controlling by cohort effects, I use the firm's *Age*, which is measured as the current year minus the born year. Additionally, *Foreign* measures the fact that the company belongs to a multinational group of enterprises implying better financial and innovative environments being a dummy variable equal to one in case the firm belongs to a multinational group with more than 50 percent of its capital from abroad and zero otherwise (Belderbos et al., 2013; Srholec, 2010). Finally, the variable *Market* tries to capture the importance of accessing foreign markets with the idea that a firm facing more competition tends to be more innovative and more competitive. This variable is a categorical variable representing *Regional, National, EU, and Rest of the World* firm's markets with *Regional* being the base category.

### 3.3 Industrial variables

The interest of the present study is on the relation between the externality coming from the industrial context, and specifically, the industrial OE and the firms' innovative performance. Therefore, including industry-level variables allows me to capture variations in the product innovation of firms not captured by firm's characteristics. However, the information on offshoring at the industry level is not present in any other industry representative database as for instance, Eurostat or the Spanish National Institute of Statistics (INE). Therefore, since the PITEC is stratified at the industry level, I can aggregate the R&D offshoring at the NACE two digit level (see for a similar approach Amoroso, 2017; Goya et al., 2016; Ornaghi, 2006). Consequently, *OE* measures the percentage of firms doing R&D offshoring in a given industry. With this, I proxy for the number of firms acquiring foreign knowledge at the industry level, which helps me to study if too much offshorers may have an effect on the likelihood of generating new product innovations.

In addition, on top of accounting for industry heterogeneity using industry random effects, as will be commented below, it is highly important to control for other industry characteristics in order to isolate specifically the relation between the two variables of interest, avoiding the bias due to confounding with other context specific characteristics (Manski, 1993). Thus, I control by the industrial average of resources dedicated to external knowledge (*Ind. Ext. expenditures*) by a representative firm in the industry with the aim of controlling by the intensity while isolating the effect of the OE. On top of that, it is important to notice that not all the industries with the highest share of offshorers are those with the highest expenditures in external R&D; which is another reason for controlling for this. Next, I account for the industrial investment on internal R&D (*Ind.*

*Internal R&D*) which is measured as the average industrial share of internal R&D as percentage of total sales in the whole period. This is an important control since everything else equal, industries with higher share of internal R&D expenditures may show a higher propensity to develop more innovations; however, it may also serve as an entry barrier, and thus, reduce the opportunity and incentive to innovate. Besides, higher levels of concentrations may also induce knowledge diffusion since firms can better internalize knowledge externalities (Amoroso, 2017). Therefore, for measuring industry competitiveness, a Simpson/Herfindahl-Hirschman Index (*HHI*) of concentration is used for each industry in a given year using the firm's market share:

$$ms_{tij} = \frac{sales_{tij}}{\sum_{j=1}^{J} sales_{tij}} \qquad \forall t = 1 \dots T$$

$$HHI_{tj} = \sum_{i=1}^{I} \left(ms_{tij}\right)^2 \qquad \forall t = 1 \dots T;\ \forall j = 1 \dots J$$

where *t* is the time, *i* is the firm, and *j* is the industry. Thereafter averaging for the whole period as follow:

$$HHI_j = T^{-1} \sum_{t=1}^{T} HHI_{tj}$$

Finally, as stated by Malerba (2002), I account for the industry level of appropriation which on the one hand is measured as the industry percentage of firms using other ways of proprietary methods as utility models, trademarks, and/or Copyrights (*Appropriation*); and on the other hand, it is measured as the industry percentage of firms patenting (*Patents*).

In addition, I introduce time and technological industry dummy variables for accounting for the technological level of the industries, as well as one year lagged explanatory variables for lessening simultaneity problems.[14]

It is important to highlight that all industrial variables do not vary at lower levels if analyzing inter-industry differences using the multilevel methodology as it is the aim of the present study. Therefore, I averaged for the industry the ones having a yearly variation (Short et al., 2006). Otherwise, you may end analyzing an average of the within- and between-industry with an erroneous effect without an economic interpretation (Bell and Jones, 2015).

[14] Especially at the firm level, since the industry classification is high enough to guarantee no reverse causality, and thus, it is unlikely that a single firm can affect the whole industry environment (see the robustness section for a robustness check using two lags of the explanatory variables).

# 4. METHODOLOGY, EMPIRICAL STRATEGY, AND SPECIFICATION

## 4.1 Methodology

Even though hierarchical models have been used for some time now in other economic fields such as health economics and education economics, it is quite recent that researchers have realized of its importance for accounting for context's differences to analyze industry/regional effects (Corrado and Fingleton, 2012). With this, I expect to consider the hierarchical structure of the dataset for the effect of those industry characteristics affecting/moderating the measure of innovative performance of the firm. There are some theoretical and empirical reasons that drive me to consider the use of the multilevel model, also known as hierarchical or mixed models.

First, the hierarchical structure of the data is not taken into consideration if using an OLS estimation assuming independence of units, since the correlation among those observations pertaining to a given firm (different years), as well as those firms pertaining to a given industry due to the presence of common factors, is left out.[15] This is highly important since the standard errors would be artificially lower ending with a more likely false positive – type error I – in the coefficients (Snijders and Bosker, 2012). Second, the multilevel approach allows to model variances instead of means, which helps to identify the role of firm and industry characteristics separately on the firm's innovative performance using random intercepts for both levels.

Third, in order to guarantee causal estimations as in the Fixed effects approach, I follow Mundlak (1978); this way I estimate the same within – causal – effects as in the Fixed effects case. Due to the fact of possible correlation between the fixed part of the model and the random part of the model, this correction is highly important, otherwise leading to inconsistent estimations (Rabe-Hesketh and Skrondal, 2012). Moreover, the Fixed effect estimation only looks for within variability which in the present study is the lowest (see Tables A1-A2 in the appendix A), reason why the Hausman test adds no information. On the one hand, the Mundlak correction permits the model to give within effects, and on the other hand, the use of higher-level variables – not varying for lower level units – invalidate the results of the Hausman test since it does not account for the effect of time and firm invariant population parameters. In fact, running a Wald Test on the means of firm level variables is equivalent to the Hausman test (Rabe-Hesketh and Skrondal, 2012). On top of that, the traditional approach – Fixed effects – excludes the industry variation controlling for it using industry dummies (Bell and Jones, 2015). Instead, the aim here is to explain such variation.

[15] Notice that this might be solved with cluster robust errors. However, the latter does not allow to study the heterogeneity among groups but to control for it, possibly leading to a misspecified model. On top of that, it is less efficient and requires homogenous clusters (which is not the case here) (Snijders and Bosker, 2012).

### 4.2 Empirical strategy

Even though the reader may think that the decision to start an enterprise in a given industry is not random, as there is not any planner that decides in which industry to put a given firm, it is also true that owners of firms do not decide to start a company in a given industry because such an industry is performing better in terms of R&D offshoring. The latter might be related to other reasons; for instance, having previous knowledge/experience in the industry, market, etc. which can be taken as independent of the offshoring performance in a given industry. Therefore, I do not expect a huge selection problem. Unfortunately, random assignments cannot be done, nor to control for self-selection using observed information in the model due to unavailable information on the reason behind the change of industries in the database. However, the multilevel structure helps me to control for unobserved heterogeneity at firm and industry levels, thus, controlling for sorting issues.

Moreover, as the objective of the paper is the study of inter-industrial differences, using leave-out means – leaving the firm $i$ out of the industrial R&D offshoring average – instead of total group averages, is the same in econometric terms when the number of firms in a group is high (Angrist, 2014), as it is the present case. However, the leave-out mean is a measure that vary between and within industries, while the total group averages varies just between industries being more appropriate for the aim of the paper.

### 4.3 Empirical specification

The structure of the data in the present study follows a three-level hierarchy starting with time ($t$ first level) which is nested in firms ($i$ second level) and these are nested in industries ($j$ third level) (Backman, 2014; van Oort et al., 2012). Besides, instead of assuming a representative firm, and therefore that all firms take on average the same profit from R&D offshoring as in previous studies, it is allowed that the effect of such strategy varies from firm to firm. Therefore, not all firms in different industries should take the same profit from R&D offshoring. The latter is done through a random coefficient for R&D offshoring at the firm level which following Stegmueller (2013) posit no problem in the estimation since the number of higher level units is above 30.

To account for this scheme, the multilevel logit model's reduced form is as follows:

$$y_{tij} = \begin{cases} 1 & if\ y^*_{tij} > 0 \\ 0 & if\ y^*_{tij} \leq 0 \end{cases}$$

$$logit\{\Pr(y_{tij} = 1 | x_{tij}, x_{ij}, z_j, \mu_{0ij}, \mu_{0j}, \mu_{1ij})\} = log\left(\frac{y_{tij}}{1 - y_{tij}}\right)$$

$$= \beta_0 + \sum_{m=1}^{M} \beta_{1m} x_{tijm} + \sum_{n=1}^{N} \beta_{2n} x_{ijn} + \sum_{k=1}^{K} \beta_{3k} z_{jk} + \sum_{k}^{K} \sum_{n}^{N} \beta_{4nk} x_{ijn} z_{jk}$$

$$+ \sum_{k}^{K} \sum_{m}^{M} \beta_{5mk} x_{tijm} z_{jk} + \mu_{0ij} + \mu_{0j} + \mu_{1ij} x_{tij}$$

Where $y^*_{tij}$ is a continuous unobserved latent variable (propensity to innovate) that is related to the observed $y_{tij}$, which refers to the outcome variable; $x_{tij}$ represents *M* time-varying firm level variables, $x_{ij}$ are *N* time-invariant firm level variables as for instance means fixed effects (Mundlak)[16] and technological fixed effects, and $z_j$ are the *K* industry variables. Moreover, $\mu_{0ij} \sim N(0, \sigma_{\mu 0}), and\ \mu_{0j} \sim N(0, \sigma_{\mu 0})$ are the random parts of the model accounting by the unobserved heterogeneity at firm and industry level respectively, while $\mu_{1ij} \sim N(0, \sigma_{\mu 1})$ is the random coefficient for the firm's R&D offshoring allowed to vary between different firms with covariance $\sigma_{\mu 01}$.[17] These random effects are assumed independent of each other, of the covariates, across industries, and $\mu_{0ij}\ and\ \mu_{1ij}$ are assumed independent across firms as well.[18]

However, for the ease of the interpretation I will estimate the model using a linear multilevel specification since the parameter can be directly interpreted as marginal effects. This way, since the study aims is not on the prediction but on the parameters itself, this does not posit a problem. However, in the robustness section, a logit model will be estimated for comparison purposes.

## 5. RESULTS

### 5.1 Descriptive analysis

Table 1 shows summary statistics for the industry variables. First thing to notice is that the percentage of firms doing R&D offshoring – OE – within industries varies substantially across industries. Fourteen industries present values above the national average, not presenting the same dynamics through time, that is, having a higher share of firms doing offshoring at the beginning of the period does not guarantee these industries will maintain such a level time along.[19] More

[16] These parameters will not be shown because of space restriction.

[17] The covariance between the two random effects at firm level measures the relation between both, therefore not restricted to be zero.

[18] The random part of the first-level, equivalent to $\varepsilon_{tij}$ is fixed ($\frac{\pi^2}{3}$) since I am estimating a latent class model (see Rabe-Hesketh and Skrondal, 2012).

[19] Because of space restriction, Table 1 only reports average values without time evolution.

impressive is the size of the differences; industries like Pharmaceutical or R&D Services present nearly six and four times more of firms acquiring foreign knowledge than national averages, being this independent of the industry size. With regard to market concentration, it is clear that few industries are highly concentrated even though the Naval Construction industry presents the highest levels of concentration through all the period. Moreover, the Pharmaceutical industry presents the highest industrial level of appropriation, and the Scientific Research and Development industry presents the highest formal appropriation of knowledge, while presenting different trends throughout the period.

[Insert Table 1 around here]

Interesting facts can be extracted from Table 2, which describe patterns of firm characteristics in the sample. Enterprises seeking to obtain foreign knowledge present strong differences with respect to knowledge inputs and output when compared to those not purchasing foreign knowledge. When differentiating with regard to this, it is clear that these offshorer enterprises dedicate around 21 percent of their innovative expenditures to purchase R&D abroad. Also, they devote three times more internal resources to R&D, and they export beyond Europe around 65 percent more than non-offshoring firms. In addition, they present around three times more a workforce with tertiary education dedicated to R&D. Finally, on average they are more innovative presenting almost the double of product innovations. Therefore, it is sensible to think that offshoring firms are in a better position in terms of knowledge inputs/output with respect to other innovative firms not developing an offshoring strategy.

[Insert Table 2 around here]

**5.2 Empirical results**

Table 3 contains different specifications for studying the influence of the OE on the innovative performance of firms. The first specification is the empty model, and only includes the intercept with the objective of determining how relevant firm and industry levels on the firms' product innovations are. For this, the model divides the random part into three and calculates the variance related with firms' as well as with industries' characteristics. Column 1 shows the relevance of using mixed models, thus, since part of the variability of product innovation is due to the statistically significant influence of the industrial context, it is necessary to account for that. Therefore, the model accounts for the similarity between the observations coming from the same firm as well as for the similarity between firms pertaining to the same industry, as shown by the ICC at the bottom of column 1. Similar to previous studies, and even though both are relevant, the model shows firms characteristics being more important than industrial ones for the innovative process (Backman, 2014; van Oort et al., 2012).[20]

The second specification (column 2) includes only firm level variables showing that when accounting by firm characteristics, the industrial context still matters,[21] even though the decrease of the between-industry variance suggests that the distribution of some of the firm variables varies across industries as illustrated by Figure A1 in the online Appendix A. With regard to the fixed part of the model, it is clear that on average, offshoring is an important strategy for increasing the probability of product innovations; even though, as in previous literature, it presents negative returns (Mihalache et al., 2012). Looking at the random coefficient variance, we see that it is statistically significant, showing evidence of an important variability in the effectiveness of offshoring across enterprises. The estimated covariance suggests that offshoring is more effective in firms where product innovation rates are below average having above average effects of acquiring foreign knowledge.

In addition, the rest of controls at the firm level present the expected sign; for instance, collaborating with other institutions is beneficial for engaging in product innovations. With regard to the size, the larger the firm is, the most prone to develop a product innovation. Enterprises with export activities to the EU, but especially to the rest of the world present a higher likelihood of innovating. Moreover, increasing the amount of R&D workers with tertiary education is highly convenient for the enterprise as stressed by Backman (2014) for the case of firms' productivity. Besides, belonging to an international group of firms, as well as the internal R&D, or the firm's age, do not contribute to increasing the likelihood of product innovations.

Lastly, technological, time, and means fixed effects are jointly significant respectively. This guarantees that the firm level characteristics are not correlated with the firm random effects, which would lead to unbiased parameters. Finally, the industry variance is reduced in specifications 3-4 with respect to specifications 1 and 2, meaning that the industry characteristics included in the model are catching up a great part of the industrial variability.

[Insert Table 3 around here]

To start analyzing the first hypothesis, the model includes the percentage of firms doing offshoring in a given industry and its quadratic term (column 3). First thing to notice is that both are statistically significant, being positive in the linear part of the term, and presenting a negative

[20] See online appendix B for the calculation of the Variance Partition Coefficient (VPC) in case of a logit estimation. For the case of the linear models the term $(\frac{\pi^2}{3})$ should be substituted by $\varepsilon_{tij}$.

[21] Showing a statistically significant industry variance as shown by the LR test as well as an economic significance, since the industry standard deviation is more important than the effect of the collaboration parameter pointing to significant economic differences across industries.

quadratic shape, pointing to a decrease or even negative return for industries presenting higher number of offshorers.

In column 4, the model also controls for other industry characteristics. For instance, the average internal R&D expenditure as percentage of sales in an industry presents a counterintuitive result, being negative and statistically significant, suggesting that it may be acting as an entry barrier to those firms willing to innovate in the industry. Besides, firms working in industries with higher usages of informally methods for appropriating knowledge, are the ones taking the most advantage from its context, while the level of concentration, formal ways of appropriations, and the Ind. Ext. expenditures, do not seem to benefit product innovation engagement. Therefore, all else equal, and in light of the specification in column 3, firms in industries with low-to-intermediate levels of offshorers are benefiting more from knowledge spillovers than similar firms established in industries with high number of offshorers. To illustrate this, Figure 1 presents the marginal effects as well as the predictions for the continuum of values. The left-hand side of Figure 1 presents the average marginal effects, that is, the derivative, in which all else equal, OE has a positive but decreasing effect, thereafter, showing negative returns. As a result, while certain industries take profit from low-to-intermediate levels of offshorers, those with high levels incur in negative returns. Looking at the right-hand side of Figure 1 (predictive margins), the probability of obtaining a new product increases with the number of offshorers in a given industry. The latter reach its maximum at 6.5 percent, from which it starts to show a negative tendency for higher values of OE, showing an inverted U-shape, and thus, confirming hypothesis 1.

[Insert Figure 1 around here]

For disentangling the extent to which firms benefit differently from the OE from the industry to which they belong to, and for the ease of interpretation, in light of Figure 1, I present Figures 2 and 3 for validate hypotheses 2 and 3. These figures plot the marginal effects as well as the predicted probabilities (colored lines) for all the values of the moderators (firm level internal R&D and Human Capital) and the focal variable (OE).

Starting by Figure 2 and using the information present in Table 3 (column 5), there are differences in the firms' internal R&D in a given industry with high levels of externalities, showing statistically significant parameters. Therefore, a firm increasing its internal R&D will be in a better position to take advantage from its industrial context. Consequently, enterprises in industries with low-to-intermediate levels of OE that increase their internal R&D, do show lower returns even though it is more advantageous for firms increasing their levels of internal R&D to be located in industries with high levels of OE, showing higher marginal effects as well as higher predicted probabilities of product innovations. With regard to the firms' level of human capital (column 6), it influences the return of OE to product innovation engagement, showing a positive and statistically significant effect as can be seen from Table 3, being the interpretation of Figure 3 similar to that of Figure 2. Therefore, H2 is supported for those enterprises increasing the internal R&D expenditures as well as their level of education and training present in their workforce. In other words, firms with more R&D resources and/or level of human capital are in a better position to take advantage of high knowledge spillover through OE in their industries.

[Insert Figures 2 and 3 around here]

Next, looking at columns 7 and 8, enterprises engaged in networking strategies with other organizations through R&D offshoring and technological collaborations are not taking any advantage from their environment in those industries with the highest knowledge spillovers. Therefore, they are not in a better position than if not collaborating or with lower expenditures in R&D offshoring when their context relies too much on R&D offshoring for being a product innovator, and thus, H3 is not supported.

Finally, it is clear that the R&D offshoring done by the offshoring firms not only affect these firms (firm level offshoring) as studied in previous literature and confirmed by the results, but also, to non-offshoring firms (see the coefficients for OE and OE squared – without being interacted – in column 7). Therefore, showing evidence that R&D offshoring goes beyond the focal firm in a given industry, and thus, the knowledge spreads to other organizations. The latter might be taken as a difference in the benefit both types of firms take from their context.[22]

### 5.3 Robustness

To gain deeper insights about the inverted U-shape of the OE, I next perform several analyses (Haans et al., 2016).[23] First thing to notice is that the turning point is well located within the data range (Figure 1). Second, I check that the slope at both, high and low levels of the OE, has the hypothesized sign and significance. Thus, confirming that both are positive (negative) for the low (high) levels and statistically significant as can be seen in table A4 (column 1) in the online appendix. Third, in order to check that the functional form in H1 is quadratic, I re-estimate the model with a cubic term, as well as converting the OE into 10 dummy variables (deciles) taking the first one as the reference category. With the latter, I let the OE to freely take its shape instead of imposing it. I find in column 2, that the cubic pattern does not hold, not improving the fit of the model. However, when the OE is splitted into 10 dummy variables (column 3), the pattern is close to a quadratic one, increasing until it reaches a point from which it starts to fall down, being

[22] In fact, a supplemental analysis confirms the latter. For this, I re-estimate the model only for offshoring firms and compare with the same model only for non-offshoring firms. The results (no shown in the paper because of space restrictions) show that while the parameter for OE is not significant for offshoring firms (same conclusion as in specification in column 7), it is highly significant with a higher magnitude for non-offshoring firms.

[23] Due to space restrictions, the following analyses are presented in an online appendix.

most of them statistically significant. Another check for the quadratic shape of the OE is to see if the model might be driven by the presence of outliers. For this, I re-estimate the model censoring the data winsorizing it as can be seen in column 4.[24] The results show that the model remains the same, and thus, confirm the hypothesized inverted U-shape in H1.

An important concern is whether the results are biased due to the possibility of firms deciding to change from one industry to another within the period of analysis generating a possible self-selection of firms. In addition, it posits another problem which is the non-hierarchy of firms nested within an industry not accounting for the importance of previous industries' characteristics in the firm's likelihood of becoming a product innovator. I investigate this, re-estimating the model only for those firms not changing industries through all the period, which implies discarding around 16.5 percent of firms from the sample. Table A5 in the online appendix evidences that sorting issues within the analyzed period are not influencing the results, since even though a slight loss of significance probably because of a smaller sample size, the conclusions are unchanged. On top of that, looking at the average born year of firms (around 28 years) for those not changing between industries, sorting can be assumed as an exogenous decision since on average it was taken three decades ago, and thus, not expected to influence today's industry characteristics effects.

Another concern relates to the time lapse between the outcome and the explanatory variables. Since the outcome variable includes a three-years period, while some of the explanatory variables – specifically the firm-level quantitative ones – refers to the current year of the period, it may be the case that the time lag used does not properly capture the effects of knowledge inputs. For studying this, I re-estimate the model and instead of using one-year lag, I use two-years lags for the explanatory variables. The evidence presented in Table A6 points to most of the same conclusions as those in Table 3, even though the second term of the cross-product with the firm's internal R&D is probably lost because of the smaller sample size.

The extent to which firms benefit from R&D offshoring, may also depend on their scale. I would expect knowledge spillovers to differ depending on whether a big company (LEs), or a small company (SMEs) is offshoring R&D activity. Tables A7 and A8 in the online appendix account for this for SMEs and LEs respectively. Starting by Table A7, SMEs are affected by their industrial context. However, when comparing with respect to Table A8, LEs depend more on their industry environment – around a 15.44 percent more – for being a product innovator as can be seen from the ICC as well as from the variance of the industry. Moreover, for the case of the OE, LEs benefit the most from this industrial spillover. In this case, both, SMEs and LEs are positively

[24] I also re-estimate the model discarding the top/bottom 5 percent of the distribution obtaining similar results (even though the positive part of the curve loses its significance which might be due to the smaller sample size); results upon request.

affected until they reach a point from which a higher number of offshorers start to decrease the probability of becoming a product innovator, same as the results in table 3. However, for LEs, the parameter seems to be higher, and thus, pointing to possibly higher benefits from this knowledge spillover. Other differences are worth to be mentioned, for instance, the R&D offshoring at firm-level is only profitable for LEs, being not just statistically significant but even economically more advantageous; being the opposite for SME which it seems they cannot profit from this strategy.

Since the interest of the present study relies on the parameter and not on the predictions of the model, I use a linear model for the ease of the interpretation since it gives directly the marginal effects. However, it is true that the linear model can give results in which the predicted probability may be outside the range 0-1, and thus, I also estimate the logit model in table A9 in the online appendix. It shows the odd ratios, which can be interpreted as the ratio of the probability of success over the probability of fail with respect to the different values of the covariates, being positive (if the coefficient is greater than one) or negative (if lower than one). The results are qualitatively pretty much the same as those presented in Table 3.

Finally, in order to shed more light on the role played by the technological collaboration on the relation between the OE and the firm's innovativeness (H3), I differentiate between the type of agent – public/private – and the geography – national/international – of such strategy.[25] The type of knowledge that can be transmitted in the two cases is quite different (Haus-Reve et al., 2019). The results point to none of these modes of collaborations taking any advantage from the OE.

## 6. DISCUSSION AND CONCLUSIONS

This paper contributes to the literature of R&D offshoring and knowledge spillover analyzing the influence R&D offshoring externalities have on the innovative performance of firms. Most studies (if not all) tend to analyze R&D offshoring on the offshoring firms. Nevertheless, the problem is that the industry also affect firms' performance (van Oort et al., 2012), pointing to the fact that the institutional context play a key role on the relation between R&D offshoring and firms' innovative performance (Rosenbusch et al., 2019), as well as on the location of such R&D offshored (Zhao et al., 2020). Therefore, focusing only on firm level may generate an incomplete analysis. The main idea is that offshoring strategy is not only profitable for the firm implementing it, but also for the rest of firms in the industry. The latter connects with the access to a higher pool of different and novel type of ideas coming from dissimilar national contexts ending in more

[25] I thank an anonymous referee for this suggestion. Because of space restrictions this result is not shown in the paper (these additional estimates are available upon request).

externalities within the industry. Such knowledge spillover may lead to higher industry as well as firm's performance.

The study controls for firm and industrial heterogeneity using a multilevel approach including characteristics at both levels. The evidence provided for Spanish firms from 2005–15 indicates that firm's R&D offshoring is key for enrolling in product innovation, while also indicates that it varies substantially across firms. An important feature of the paper is that firms' characteristics are the most important ones for innovativeness, a result also found in recent literature (Backman, 2014). However, propensity to innovate is also positively affected by the number of offshorers in the industry. Hence, confirming the relevance that the pool of knowledge coming from a different national context has for firms' innovative processes through knowledge spillovers. On top of that, an increase in innovative performance trough R&D offshoring due to the relevance of this strategy at the firm level, may cause other firms to mimic such strategy increasing the competitiveness in the industry. If knowledge spillovers are high, then, firms will start to reduce R&D investments in order to reduce/internalize their knowledge spilling over as suggested by the recent literature (Audretsch and Belitski, 2020). Therefore, the investment in R&D at the industry level when too many firms do R&D offshoring might reduce the likelihood of becoming a product innovator, and thus, it is detrimental to the industry as it is confirmed by the results.

The second contribution of the study is the empirical support for the heterogeneity present among firms pertaining to the same industry. Despite the technological proximity among firms within the same industrial environment; differences in the learning processes, in competences, as well as in managerial capabilities, will induce heterogeneity within industries (Malerba, 2002; Phene et al., 2006). Consequently, the internal capabilities of firms moderate the relationship between the OE and the firm's innovative performance. Those enterprises increasing their internal capacity through investments in internal R&D as well as in a more skilled workforce, are the ones benefiting the most from their industrial context, even presenting positive returns coming from industries with the highest knowledge spillovers. On the opposite, I did not find evidence of enterprises enrolling in external collaborations and/or increasing their resources to R&D offshoring taking any advantage from their industrial knowledge spillover, specifically, from the OE. A possible explanation would be that firms with networking relations with other institutions, and thus, more open to external knowledge, might be less dependent on their industrial context since they can acquire it directly from knowledge suppliers. The latter is linked to the idea that an enterprise that can access directly foreign knowledge through networking strategies, might be less dependent on the pool of a similar knowledge generated in their industries, since it may be redundant.

This study provides new insights into the effects that R&D offshoring has on a firm's innovation performance by arguing that a relative increase in the number of R&D offshorers within an industry has a positive influence in firms' innovativeness, but only until an intermediate threshold; thereafter, higher levels of offshorers induce negative returns. The reason has to do with the fact that the number of offshorers in a given industry to which the firm belongs to, might be highly beneficial for firms seeking to take advantage of market novelties, since a higher number of firms accessing foreign knowledge might increase the externalities to all firms in the industry (Owen-Smith and Powell, 2004). Yet, too much of this industry externality generates negative returns.

As previously highlighted, an increase in innovative performance trough R&D offshoring due to the relevance of this strategy at the firm level, may cause other firms to mimic such strategy increasing the competitiveness in the industry. This may cause that enterprises' abilities to create such a knowledge be undermined, damaging the innovative capacity of firms in the industry as pointed by Un and Rodríguez (2018). Thus, this might be another reason for which the scope for the industrial R&D could be damaged if too many firms do R&D offshoring within an industry reducing the likelihood of becoming a product innovator. As a matter of fact, the literature has noticed recently the relevance of the environment in which firms operate on the benefits taken from R&D offshoring as well as on the location of such strategy (Zhao et al., 2020). The latter recognizes that not only what happen at the firm level is relevant for the benefit that R&D offshoring might report to the firm, but also the industrial context play a key role (Castellani and Lavoratori, 2020; Rosenbusch et al., 2019). This paper aligns in this recent literature that assesses the role of the institutional context to firms' innovative performance and tries to give a step forward in this direction with the main objective of providing evidence on the hypothesis that the industrial context – specifically the Offshoring Externalities (OE) – not only exerts a positive effect on firms' innovation performance but also a negative one, presenting an inverted U-shape pattern with respect to the firms' innovativeness.

The results in this study suggest important implications for enterprises. Organizations should be aware that R&D offshoring not only affect firm's innovativeness, but also, it has an aggregate effect on other firms through the knowledge spilling over. This stresses that R&D offshoring is not only a matter of a firm's decision as in the previous literature, but also, it has an important aggregated industrial component. Two important ideas to bear in mind are: (i) Knowledge coming from abroad through R&D offshoring positively affect not only the offshoring firms, but also the rest of firms in the industry – especially the non-offshoring firms. (ii) Those firms reinforcing their levels of internal capacity, will take more advantage of the OE in those industries with the highest level of offshorers. Therefore, those firms working in an industry presenting high level of

OE, and thus, receiving a negative return from its context, might increase the return if they increase their internal capacity – specifically their levels of human capital.

The evidence provided in this study suggests that some industries are beyond the optimal percentage of offshoring firms. This contrasts with the firm-level over-offshoring case, since, if the firm notices negative effects from R&D offshoring, it might reconfigure the offshoring extent. However, at the industry level, this is far from easy to do[26], since other firms might want to mimic a strategy that is beneficial to other firms. Nevertheless, as previously said, enterprises that receive a negative return from their industrial level of OE can still manage how to benefit from this situation. Following the results of the article, they can increase their internal levels of R&D and/or human capital to counteract and even reverse this situation. This way, companies present tools with which to deal with the return they receive from the industry. On top of that, on average, manufacturing and services industries have around 4.9 percent of firms doing offshoring (see Table 1), while the results reported show around 6.5 percent as the optimal value for the Spanish Economy (see Figure 1) – with only a few industries going beyond this point (see Table 1). Therefore, it seems that a strategy that is highly beneficial for enterprises individually might be also optimal for the whole economy since still there is space for accessing foreign knowledge trough R&D offshoring.

These results have some policy implications; on the one hand, the government might want to increase the innovativeness of firms through a better access to foreign technologies promoting for example, transfer agencies. In particular, policy makers might also see these results as an indication for encouraging firms to strengthen their internal innovative capacity, through internal R&D investments, and especially, increasing their levels of human capital through training processes and hiring personnel with tertiary education. On the other hand, externalities coming from offshoring firms, even though positive, seem to deter firms' innovativeness at high levels of knowledge spillovers. This leads to a lower social optimal level coming from foreign R&D acquisitions than the private return coming from firm-level R&D offshoring in such industries with the highest externalities levels. Two possible interventions may be at hand. (i) For those industries with the highest shares of offshorers, government should encourage firms not just to look abroad but also within the national context for purchasing new technologies. This way, the risk of losing internal capacities of industries might be minimized. (ii) Since most of the industries are below the optimal level of R&D offshorers, it seems that they still have space to increase the foreign acquisition of technologies through R&D offshoring, and thus, should also be encouraged by governmental institutions for those industries in the positive part of the curve.

[26] I thank an anonymous referee for pointing this important issue.

The research conducted in this study is limited in several respects, but mainly by the lack of geographical information of firms. In the study, it is argued that other types of proximities may be at work, since the type of knowledge accessed through R&D offshoring is more of a standard nature and easy to codify diminishing the geographical proximity relevance. However, having the location of the firm might enrich the research. Another important limitation is the fact of not having access in the survey to the industry from which firms purchase the knowledge in order to incorporate into the study Marshalian/Jacobian type of externalities. In this case, it is sensible to think that depending on the industry from which knowledge is acquired, inter- or intra-industry externalities will differ. The conducted research assumes that the knowledge accessed abroad can be automatically transferred back to the home country. Unfortunately, the PITEC database does not allow to control for the nature of the offshored knowledge.[27] However, I believe that this can be controlled for on the one hand, using the industries random effects, and on the other hand, through the expenditures in R&D offshoring at the firm level as it is done in the paper. Finally, as pointed by one of the referees, an interesting line for a future research would be to explore the mechanisms through which the offshoring firms affect the non-offshoring firms.

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Table 1. Descriptive analysis of industry-level variables

| Industries | OE | Ind. Ext. expenditures | Ind. Internal R&D | HHI | Appropriation | Patent |
|---|---|---|---|---|---|---|
| **High tech manufacture** | | | | | | |
| Pharmaceutical products (21) | 27.07 | 627,702.4 | 7.38 | 0.029 | 36.87 | 31.06 |
| Computer, electronic and optical products (26) | 6.03 | 16,786.5 | 12.18 | 0.037 | 22.90 | 15.56 |
| **Medium tech** | | | | | | |
| Chemicals products (20) | 6.75 | 43,137.66 | 3.28 | 0.015 | 26.02 | 12.15 |
| Rubber and plastic products (22) | 7.24 | 46,631.13 | 1.73 | 0.033 | 19.08 | 14.81 |
| Other non-metallic mineral products (23) | 4.20 | 19,457 | 1.66 | 0.018 | 20.60 | 8.45 |
| Metallurgy (24) | 7.52 | 57,827.13 | 0.76 | 0.033 | 8.66 | 9.51 |
| Metal products, excepts machinery and equipment (25) | 2.45 | 4,235.76 | 1.98 | 0.014 | 16.36 | 12.86 |
| Electrical machinery and material (27) | 7.63 | 38,929.11 | 3.53 | 0.040 | 26.36 | 22.09 |
| Other machinery and equipment n.e.c. (28) | 3.33 | 21,362.46 | 3.43 | 0.014 | 19.80 | 19.37 |
| Motor vehicles (29) | 13.54 | 567,345.7 | 1.93 | 0.067 | 12.30 | 14.77 |
| Naval construction (301) | 4.77 | 98,717.28 | 9.92 | 0.158 | 14.98 | 6.56 |
| Aircraft and spacecraft (303) | 15.49 | 1,615,770 | 12.61 | 0.117 | 9.41 | 18.84 |
| Other transport equipment (30) | 13.86 | 324,714.5 | 2.94 | 0.118 | 16.65 | 21.26 |
| Repair and installation of machinery and equipment (33) | 0.68 | 326 | 2.74 | 0.040 | 9.35 | 8.58 |
| **Low tech** | | | | | | |
| Food, beverages, and tobacco products (10-12) | 3.12 | 24,274.55 | 1.39 | 0.009 | 25.86 | 6.44 |
| Textile (13) | 4.93 | 12,277.98 | 2.01 | 0.019 | 16.28 | 8.08 |
| Wearing apparel (14) | 2.56 | 4,237.49 | 2.20 | 0.089 | 22.49 | 4.11 |
| Leather and related products (15) | 0.96 | 745.98 | 1.55 | 0.069 | 14.18 | 5.60 |
| Wood and cork (16) | 0.87 | 4,951.11 | 0.87 | 0.075 | 12.28 | 5.62 |
| Cardboard and Paper (17) | 5.79 | 25,670.75 | 0.50 | 0.043 | 14.56 | 7.88 |
| Graphic arts and reproduction (18) | 1.10 | 1,104.13 | 1.53 | 0.056 | 12.15 | 7.02 |
| Furniture (31) | 1.22 | 1,027.01 | 1.24 | 0.030 | 26.82 | 14.81 |
| Other manufacturing (32) | 6.60 | 13,205.78 | 6.05 | 0.046 | 32.51 | 22.95 |
| **Knowledge intensive sectors KIS** | | | | | | |
| Telecommunications (61) | 5.54 | 984,176.7 | 10.01 | 0.149 | 27.16 | 9.63 |
| Computer programming, consultancy and related activities (62) | 2.24 | 4,734.10 | 16.67 | 0.059 | 22.01 | 6.60 |
| Information and communications (58-63) | 2.27 | 6,534.51 | 8.88 | 0.053 | 29.23 | 3.79 |
| Financial and insurance activities (64-66) | 2.02 | 5,998.36 | 0.83 | 0.036 | 19.46 | 2.35 |
| Scientific research and development (72) | 16.10 | 348,462 | 94.96 | 0.045 | 27.89 | 39.58 |
| Other activities (69-71, 73-75) | 2.48 | 45,824.24 | 13.47 | 0.023 | 15.14 | 8.83 |
| Education (85 excluding 854) | 0.76 | 433.67 | 7.76 | 0.075 | 20.57 | 1.49 |
| Health activities and social services (86-88) | 0.23 | 201.61 | 4.10 | 0.037 | 10.18 | 3.55 |
| Arts, entertainment and recreation | 0.61 | 129.45 | 1.46 | 0.090 | 12.72 | 1.36 |
| **Non-knowledge intensive sectors NKIS** | | | | | | |
| Wholesale trade (45-47) | 1.52 | 10,177.19 | 1.10 | 0.025 | 16.67 | 4.78 |
| Transport (49-53) | 0.96 | 2,189.21 | 0.45 | 0.038 | 7.25 | 2.50 |
| Accommodation and food service activities (55-56) | 0.21 | 65.17 | 0.06 | 0.022 | 7.78 | 0.58 |
| Real estate activities (68) | 1.00 | 1,344.68 | 3.66 | 0.076 | 11.68 | 2.75 |
| Administrative and support services activities (77-82) | 0.45 | 1,660.12 | 1.53 | 0.023 | 6.73 | 1.79 |
| Other services (95-96) | 2.58 | 15,423.67 | 11.82 | 0.036 | 16.41 | 2.87 |
| National averages | 4.91 | 131,520.9 | 6.84 | 0.051 | 18.09 | 10.29 |

OE, Appropriation, and Patent are the percentage of firms developing the characteristic in a given industry. Internal R&D is the average industrial share of Internal R&D over the industrial sales (in percentage), Ind. Ext. expenditures is the average amount of euros dedicated to R&D offshoring by a representative firm in a given industry; and HHI is the concentration index defined in section 3.3. In parenthesis is the CNAE09 industry code. Source: Eurostat and PITEC (see page 19 for the industrial classification): http://www.ine.es/en/daco/daco43/metoite2013_en.pdf

Table 2. Descriptive analysis of firm-level variables

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **Non-Offshoring Firms** | | | | **Offshoring Firms** | | | |
| VARIABLES | Mean | Sd | Min | Max | Mean | Sd | Min | Max |
| **Innovative Performance** | | | | | | | | |
| Product innovation (dummy) | 0.482 | 0.500 | 0 | 1 | 0.801 | 0.399 | 0 | 1 |
| **Controls** | | | | | | | | |
| Offshoring | | | | | 0.215 | 0.294 | 0 | 1 |
| Collaboration (dummy) | 0.359 | 0.480 | 0 | 1 | 0.649 | 0.477 | 0 | 1 |
| Internal R&D | 0.050 | 0.201 | 0 | 2 | 0.167 | 0.406 | 0 | 2 |
| Human Capital | 0.031 | 0.089 | 0 | 1 | 0.088 | 0.150 | 0 | 1 |
| Size | 361.0 | 1,649 | 10 | 41,509 | 410.9 | 1,027 | 10 | 21,905 |
| Age | 27.19 | 21.19 | 0 | 551 | 30.79 | 21.89 | 0 | 170 |
| Foreign (dummy) | 0.109 | 0.312 | 0 | 1 | 0.291 | 0.454 | 0 | 1 |
| Regional Market (dummy) | 0.949 | 0.218 | 0 | 1 | 0.928 | 0.258 | 0 | 1 |
| National Market (dummy) | 0 .259 | 0 .438 | 0 | 1 | 0.069 | 0.254 | 0 | 1 |
| EU Market (dummy) | 0.163 | 0.369 | 0 | 1 | 0.121 | 0.326 | 0 | 1 |
| Rest of the World Market (dummy) | 0.480 | 0.499 | 0 | 1 | 0.794 | 0.404 | 0 | 1 |

Table 3. Effect of OE on firms' product innovation (PI)

| VARIABLES | (1)<br>PI | (2)<br>PI | (3)<br>PI | (4)<br>PI | (5)<br>PI | (6)<br>PI | (7)<br>PI | (8)<br>PI |
|---|---|---|---|---|---|---|---|---|
| Offshoring | | 0.203** | 0.203** | 0.203** | 0.202** | 0.199** | 0.262*** | 0.204** |
| | | (0.093) | (0.093) | (0.093) | (0.094) | (0.095) | (0.070) | (0.094) |
| Offshoring$^2$ | | -0.327*** | -0.327*** | -0.327*** | -0.325*** | -0.322*** | -0.321*** | -0.327*** |
| | | (0.116) | (0.116) | (0.116) | (0.116) | (0.117) | (0.116) | (0.116) |
| Collaboration (dummy) | | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.049** |
| | | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.020) |
| Human Capital | | 0.124*** | 0.124*** | 0.125*** | 0.123*** | 0.345*** | 0.125*** | 0.125*** |
| | | (0.047) | (0.047) | (0.046) | (0.047) | (0.050) | (0.046) | (0.046) |
| Internal R&D | | 0.008 | 0.009 | 0.008 | 0.037 | 0.007 | 0.008 | 0.009 |
| | | (0.011) | (0.011) | (0.011) | (0.026) | (0.011) | (0.011) | (0.011) |
| Size (log) | | 0.038*** | 0.038*** | 0.038*** | 0.038*** | 0.038*** | 0.038*** | 0.038*** |
| | | (0.011) | (0.011) | (0.011) | (0.010) | (0.011) | (0.010) | (0.011) |
| National market | | 0.003 | 0.003 | 0.004 | 0.004 | 0.003 | 0.004 | 0.004 |
| | | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) |
| EU market | | 0.035* | 0.035* | 0.035* | 0.035* | 0.034* | 0.035* | 0.035* |
| | | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| Rest of the World market | | 0.049** | 0.049** | 0.049** | 0.049** | 0.048** | 0.049** | 0.049** |
| | | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) |
| Foreign (dummy) | | -0.011 | -0.011 | -0.011 | -0.011 | -0.011 | -0.012 | -0.011 |
| | | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Age (log) | | 0.004 | 0.004 | 0.004 | 0.003 | 0.003 | 0.004 | 0.004 |
| | | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| OE | | | 0.022*** | 0.011** | 0.012** | 0.013** | 0.012** | 0.011** |
| | | | (0.007) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) |
| OE $^2$ | | | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ind. Ext. expenditure | | | | -0.000 | -0.000 | 0.000 | -0.000 | -0.000 |
| | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ind. Internal R&D | | | | -0.003*** | -0.003*** | -0.002*** | -0.003*** | -0.003*** |
| | | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| HHI | | | | 0.483 | 0.484 | 0.496 | 0.487 | 0.486 |
| | | | | (0.331) | (0.330) | (0.331) | (0.331) | (0.330) |
| Appropriation | | | | 0.007*** | 0.007*** | 0.006*** | 0.007*** | 0.007*** |
| | | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Patent | | | | 0.004 | 0.004 | 0.004* | 0.004 | 0.004 |
| | | | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Internal R&D* OE | | | | | -0.011** | | | |
| | | | | | (0.005) | | | |
| Internal R&D*OE$^2$ | | | | | 0.001*** | | | |
| | | | | | (0.000) | | | |
| Human Capital* OE | | | | | | -0.075*** | | |
| | | | | | | (0.012) | | |
| Human Capital* OE $^2$ | | | | | | 0.003*** | | |
| | | | | | | (0.001) | | |
| Offshoring* OE | | | | | | | -0.014 | |
| | | | | | | | (0.014) | |
| Offshoring* OE $^2$ | | | | | | | 0.000 | |
| | | | | | | | (0.000) | |
| Collaboration (dummy)* OE | | | | | | | | -0.000 |
| | | | | | | | | (0.005) |
| Collaboration (dummy)* OE $^2$ | | | | | | | | 0.000 |
| | | | | | | | | (0.000) |
| Technological dummy variables | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.646*** | 0.448*** | 0.391*** | 0.374*** | 0.372*** | 0.367*** | 0.373*** | 0.375*** |
| | (0.019) | (0.039) | (0.043) | (0.050) | (0.050) | (0.050) | (0.050) | (0.051) |
| Observations | 47,493 | 47,493 | 47,493 | 47,493 | 47,493 | 47,493 | 47,493 | 47,493 |
| Number of Industries | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| Variance (industry) | 0.0122 | 0.0079 | 0.0058 | 0.0010 | 0.0009 | 0.0009 | 0.0010 | 0.0010 |
| Variance (firm) | 0.0939 | 0.0877 | 0.0877 | 0.0876 | 0.0876 | 0.0874 | 0.0876 | 0.0876 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variance (Offshoring) | | 0.117 | 0.117 | 0.116 | 0.116 | 0.116 | 0.117 | 0.116 |
| Covariance (random intercept-coefficient) | | -0.0427 | -0.0425 | -0.0430 | -0.0428 | -0.0430 | -0.0432 | -0.0431 |
| ICC Industry | 0.0560 | 0.0389 | 0.0291 | 0.0051 | 0.0050 | 0.0047 | 0.0051 | 0.0051 |
| ICC Firm | 0.487 | 0.470 | 0.464 | 0.451 | 0.451 | 0.450 | 0.451 | 0.451 |
| LR test Firm random intercept | 14689*** | 13883*** | 13729*** | 13184*** | 13180*** | 13138*** | 13180*** | 13157*** |
| LR test Industry random intercept | 548.9*** | 334*** | 269.4*** | 48.64*** | 47.69*** | 43.60*** | 48.78*** | 48.78*** |
| Wald Test Mean values | | 212.9*** | 226.5*** | 274.4*** | 275.8*** | 284.4*** | 274.1*** | 274.8*** |
| Wald Test Time dummies | | 653.6*** | 653.7*** | 653.6*** | 653.3*** | 651.3*** | 653.2*** | 652.8*** |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012. pp. 88-89). ICC is conditional on zero values of random-effects covariates.

Figure 1. Average marginal effects and Predictive margins of OE on product innovation

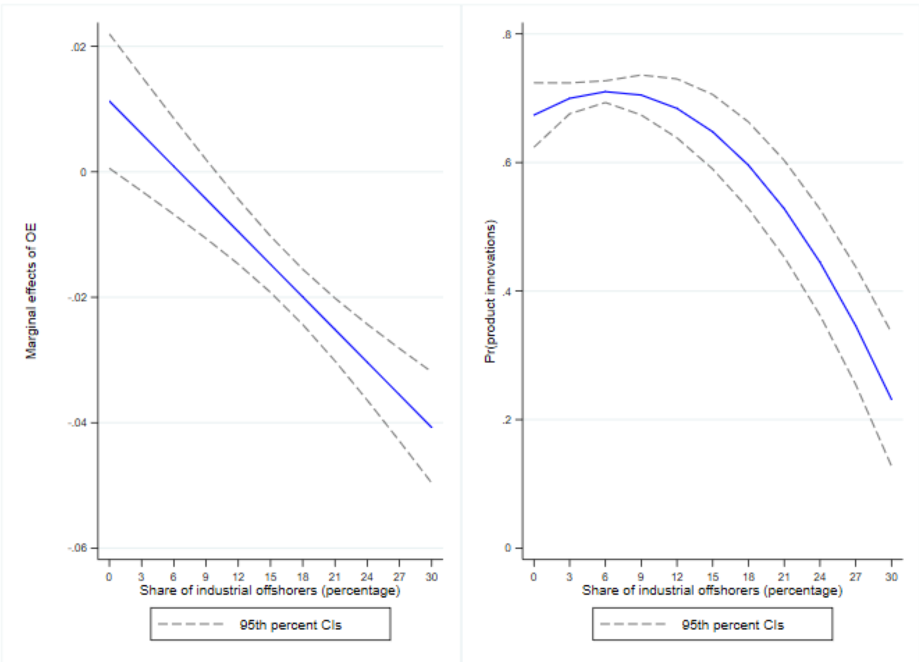
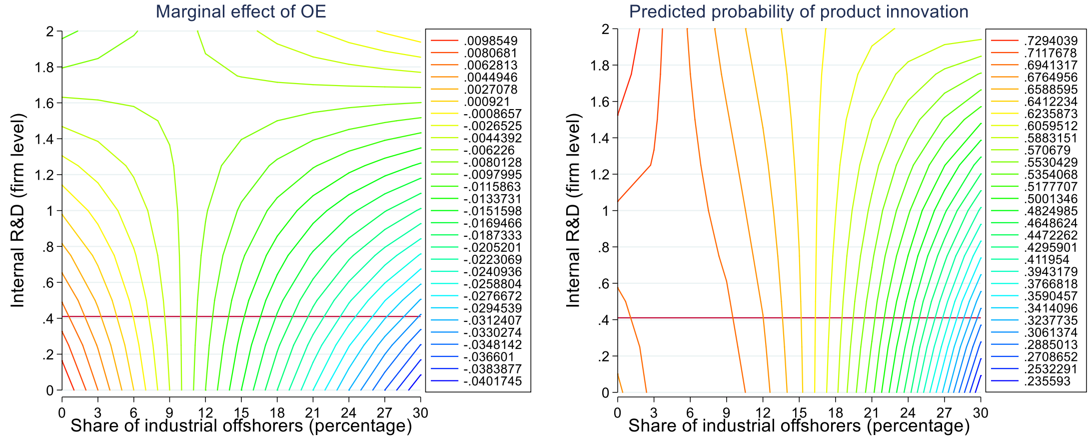
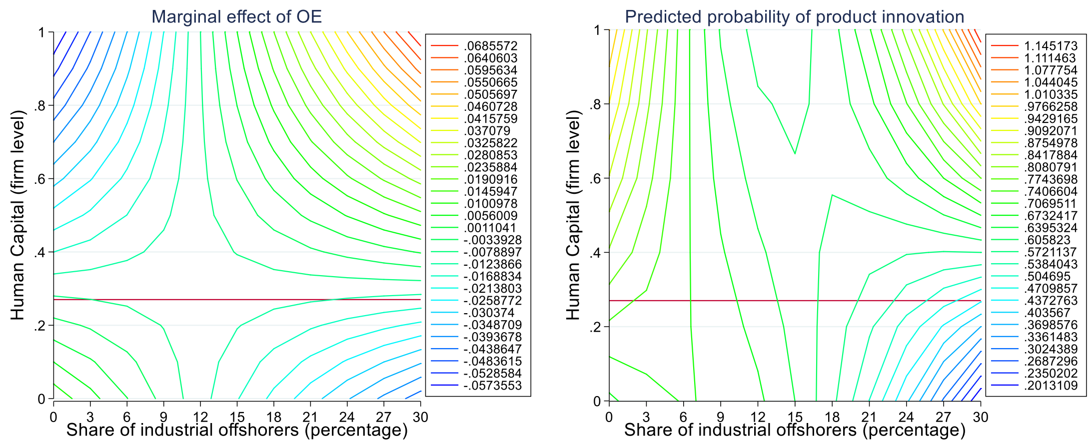


Figure 2. Average marginal effects and Predictive margins of OE on product innovation by firm's Internal R&D




Note: The horizontal red line is the 95% percentil level of Internal R&D

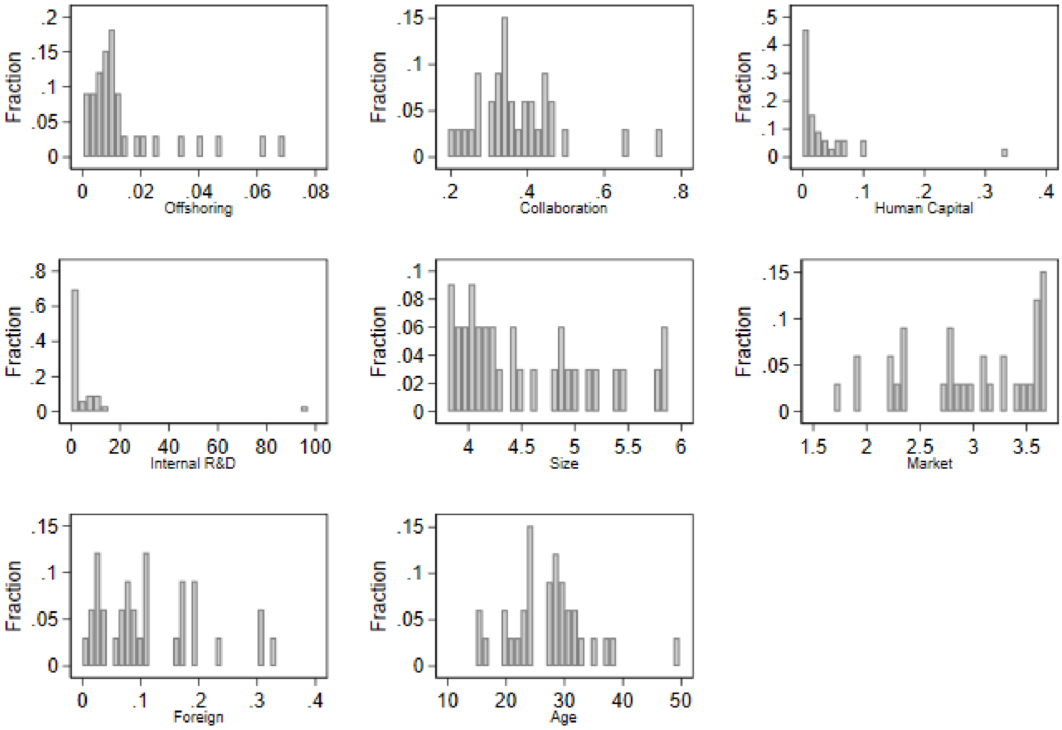
Figure 3. Average marginal effects and Predictive margins of OE on product innovation by firm's Human Capital




Note: The horizontal red line is the 95% percentil level of Human Capital

# APPENDIX A. ADDITIONAL INFORMATION

Figure A1. Distribution of firm-level variables across industries




Note: Calculated as the avergage firm-level characteristics for each sector

Table A1. Descriptive statistics for industry-level variables

| Variable | | Mean | Std. Dev. | Min | Max | Observations | |
|---|---|---|---|---|---|---|---|
| OE | Overall | 0.049 | 0.058 | 0 | 0.321 | N | 456 |
| | Between | | 0.056 | 0.002 | 0.271 | n | 38 |
| | Within | | 0.015 | -0.041 | 0.102 | T | 12 |
| Ind. Ext. expenditures* | Overall | 130 | 396.26 | 0 | 3,692.53 | N | 456 |
| | Between | | 310.83 | 0.059 | 1,456.92 | n | 38 |
| | Within | | 250.47 | -1,317.41 | 2,777.37 | T | 12 |
| Ind. Internal R&D | Overall | 0.068 | 0.153 | 0.0001 | 1.011 | N | 456 |
| | Between | | 0.153 | 0.0003 | 0.949 | n | 38 |
| | Within | | 0.022 | -0.027 | 0.209 | T | 12 |
| HHI | Overall | 0.051 | 0.040 | 0.0001 | 0.176 | N | 456 |
| | Between | | 0.036 | 0.009 | 0.157 | n | 38 |
| | Within | | 0.018 | -0.055 | 0.119 | T | 12 |
| Appropriation | Overall | 0.182 | 0.091 | 0 | 0.484 | N | 456 |
| | Between | | 0.075 | 0.067 | 0.368 | n | 38 |
| | Within | | 0.052 | 0.034 | 0.339 | T | 12 |
| Patent | overall | 0.102 | 0.091 | 0 | 0.441 | N | 456 |
| | between | | 0.086 | 0.006 | 0.399 | n | 38 |
| | within | | 0.032 | -0.018 | 0.279 | T | 12 |

*Because of space restrictions Ind. Ext. expenditures is measured in thousands of euros.

## Table A2. Descriptive statistics for the firm-level variables

| Variable | | Mean | Std. Dev. | Min | Max | Observations | |
|---|---|---|---|---|---|---|---|
| PI (dummy) | Overall | 0.496 | 0.499 | 0 | 1 | N | 97,751 |
| | Between | | 0.392 | 0 | 1 | n | 10,841 |
| | Within | | 0.324 | -0.420 | 1.412 | T-bar | 9.01 |
| Offshoring | Overall | 0.016 | 0.098 | 0 | 1 | N | 59,705 |
| | Between | | 0.077 | 0 | 1 | n | 9,236 |
| | Within | | 0.061 | -0.862 | 0.930 | T-bar | 6.46 |
| Collaboration (dummy) | Overall | 0.377 | 0.484 | 0 | 1 | N | 72,156 |
| | Between | | 0.361 | 0 | 1 | n | 9,421 |
| | Within | | 0.331 | -0.539 | 1.294 | T-bar | 7.65 |
| Internal R&D | Overall | 0.055 | 0.215 | 0 | 2 | N | 97,751 |
| | Between | | 0.210 | 0 | 2 | n | 10,841 |
| | Within | | 0.097 | -1.607 | 1.886 | T-bar | 9.01 |
| Human Capital | Overall | 0.033 | 0.093 | 0 | 1 | N | 89,340 |
| | Between | | 0.087 | 0 | 1 | n | 10,578 |
| | Within | | 0.043 | -0.730 | 0.873 | T-bar | 8.44 |
| Size | Overall | 4.495 | 1.459 | 2.302 | 10.633 | N | 97,751 |
| | Between | | 1.449 | 2.302 | 10.585 | n | 10,841 |
| | Within | | 0.306 | -0.200 | 8.982 | T-bar | 9.01 |
| Foreign (dummy) | Overall | 0.117 | 0.321 | 0 | 1 | N | 97,751 |
| | Between | | 0.280 | 0 | 1 | n | 10,841 |
| | Within | | 0.134 | -0.799 | 1.033 | T-bar | 9.01 |
| Age (log) | Overall | 3.131 | 0.662 | 0 | 551 | N | 93,718 |
| | Between | | 0.658 | 0 | 546 | n | 9,505 |
| | Within | | 0.194 | 1.377 | 3.987 | T-bar | 9.85 |
| Markets (categorical) | Overall | 3.056 | 1.056 | 0 | 4 | N | 97,751 |
| | Between | | 0.976 | 0 | 4 | n | 10,841 |
| | Within | | 0.441 | 0.306 | 5.806 | T-bar | 9.01 |

## Table A3. Correlation matrix

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Offshoring | 1 | | | | | | | | | | | | | |
| (2) Collaboration | 0.03 | 1 | | | | | | | | | | | | |
| (3) Human Capital | -0.02 | 0.16 | 1 | | | | | | | | | | | |
| (4) Internal R&D | -0.02 | 0.14 | 0.65 | 1 | | | | | | | | | | |
| (5) Size (log) | 0.09 | 0.13 | -0.24 | -0.18 | 1 | | | | | | | | | |
| (6) Markets | 0.07 | 0.04 | -0.06 | -0.11 | 0.06 | 1 | | | | | | | | |
| (7) Foreign | 0.19 | 0.04 | -0.08 | -0.08 | 0.28 | 0.13 | 1 | | | | | | | |
| (8) Age (log) | 0.04 | 0.01 | -0.23 | -0.23 | 0.31 | 0.19 | 0.10 | 1 | | | | | | |
| (9) OE | 0.10 | 0.09 | 0.20 | 0.25 | 0.03 | 0.18 | 0.13 | 0.02 | 1 | | | | | |
| (10) Ind. Ext expenditures | 0.09 | 0.10 | 0.15 | 0.18 | 0.11 | 0.07 | 0.11 | -0.03 | 0.76 | 1 | | | | |
| (11) Ind. Internal R&D | -0.01 | 0.15 | 0.55 | 0.68 | -0.13 | -0.11 | -0.08 | -0.22 | 0.40 | 0.29 | 1 | | | |
| (12) HHI | 0.03 | 0.06 | 0.14 | 0.14 | 0.06 | -0.10 | 0.02 | -0.12 | 0.17 | 0.46 | 0.19 | 1 | | |
| (13) Appropriation | -0.002 | 0.03 | 0.18 | 0.16 | -0.14 | 0.17 | 0.01 | -0.003 | 0.45 | 0.15 | 0.26 | -0.08 | 1 | |
| (14) Patent | 0.05 | 0.08 | 0.31 | 0.40 | -0.13 | 0.21 | 0.04 | -0.05 | 0.75 | 0.47 | 0.62 | 0.004 | 0.49 | 1 |

Table A4. Testing the quadratic shape of OE

| VARIABLES | (1)<br>PI | (2)<br>PI | (3)<br>PI | (4)<br>PI |
|---|---|---|---|---|
| Offshoring | 0.203** | 0.203** | 0.200** | 0.200** |
| | (0.093) | (0.093) | (0.093) | (0.093) |
| Offshoring$^2$ | -0.327*** | -0.327*** | -0.323*** | -0.323*** |
| | (0.116) | (0.116) | (0.116) | (0.116) |
| Other firm-level controls | Yes | Yes | Yes | Yes |
| OE (2nd decile) | | | 0.094*** | |
| | | | (0.035) | |
| OE (3th decile) | | | 0.098*** | |
| | | | (0.036) | |
| OE (4th decile) | | | 0.133*** | |
| | | | (0.050) | |
| OE (5th decile) | | | 0.054 | |
| | | | (0.037) | |
| OE (6th decile) | | | 0.135** | |
| | | | (0.056) | |
| OE (7th decile) | | | 0.177*** | |
| | | | (0.054) | |
| OE (8th decile) | | | 0.181*** | |
| | | | (0.050) | |
| OE (9th decile) | | | 0.108** | |
| | | | (0.048) | |
| OE (10th decile) | | | 0.077 | |
| | | | (0.072) | |
| OE | 0.011** | 0.013 | | 0.062*** |
| | (0.005) | (0.010) | | (0.020) |
| OE $^2$ | -0.001*** | -0.001 | | -0.007*** |
| | (0.000) | (0.001) | | (0.002) |
| OE $^3$ | | 0.000 | | |
| | | (0.000) | | |
| Other industry controls | Yes | Yes | Yes | Yes |
| Technological dummy variables | Yes | Yes | Yes | Yes |
| Constant | 0.374*** | 0.370*** | 0.251*** | 0.250*** |
| | (0.050) | (0.056) | (0.084) | (0.091) |
| Observations | 47,493 | 47,493 | 47,493 | 47,493 |
| Number of Industries | 38 | 38 | 38 | 38 |
| Variance (industry) | 0.00100 | 0.000996 | 0.00102 | 0.00151 |
| Variance (firm) | 0.0876 | 0.0876 | 0.0877 | 0.0877 |
| Variance (Offshoring) | 0.116 | 0.116 | 0.117 | 0.117 |
| Covariance (random intercept-coefficient) | -0.0430 | -0.0429 | -0.0427 | -0.0430 |
| ICC Industry | 0.00510 | 0.00507 | 0.00520 | 0.00765 |
| ICC Firm | 0.451 | 0.451 | 0.451 | 0.453 |
| LR test Firm random intercept | 13184*** | 13184*** | 13193*** | 13294*** |
| LR test Industry random intercept | 48.64*** | 47.76*** | 22.91*** | 56.46*** |
| Wald Test Mean values | 274.4*** | 269*** | 219.9*** | 225.9*** |
| Wald Test Time dummies | 653.6*** | 653.6*** | 654.4*** | 654.1*** |
| H0: $\beta_{OE} + \beta_{OE^2} * OE(low) = 0$ | 0.0109** | | | |
| H0: $\beta_{OE} + \beta_{OE^2} * OE(high) = 0$ | -0.0357*** | | | |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012. pp. 88-89). ICC is conditional on zero values of random-effects covariates. In column 4, I changed the outliers in OE by the highest value (not being an outlier) in the distribution. Other firm-level controls include collaboration, human capital, internal R&D, size, markets, foreign, age. Other industry controls include ind. ext. expenditures, ind. internal R&D, HHI, appropriation, patent.

Table A5. Excluding firms moving across industries

| VARIABLES | (1) PI | (2) PI | (3) PI | (4) PI | (5) PI | (6) PI | (7) PI | (8) PI |
|---|---|---|---|---|---|---|---|---|
| Offshoring | | 0.203** | 0.202** | 0.203** | 0.201** | 0.200** | 0.279*** | 0.203** |
| | | (0.101) | (0.101) | (0.101) | (0.101) | (0.102) | (0.080) | (0.100) |
| Offshoring$^2$ | | -0.361*** | -0.360*** | -0.360*** | -0.358*** | -0.356*** | -0.354*** | -0.360*** |
| | | (0.126) | (0.126) | (0.126) | (0.127) | (0.127) | (0.126) | (0.125) |
| Collaboration (dummy) | | 0.052*** | 0.052*** | 0.052*** | 0.052*** | 0.052*** | 0.052*** | 0.047** |
| | | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.022) |
| Human Capital | | 0.153*** | 0.153*** | 0.154*** | 0.146*** | 0.311*** | 0.154*** | 0.154*** |
| | | (0.038) | (0.038) | (0.038) | (0.041) | (0.090) | (0.038) | (0.038) |
| Internal R&D | | 0.028 | 0.029 | 0.028 | 0.087*** | 0.027 | 0.028 | 0.029 |
| | | (0.018) | (0.018) | (0.018) | (0.030) | (0.019) | (0.019) | (0.018) |
| Other firm-level controls | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| OE | | | 0.022*** | 0.010 | 0.010* | 0.011* | 0.011* | 0.010 |
| | | | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| OE $^2$ | | | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Internal R&D*OE | | | | | -0.013** | | | |
| | | | | | (0.005) | | | |
| Internal R&D* OE $^2$ | | | | | 0.001* | | | |
| | | | | | (0.000) | | | |
| Human Capital* OE | | | | | | -0.047*** | | |
| | | | | | | (0.018) | | |
| Human Capital* OE $^2$ | | | | | | 0.002** | | |
| | | | | | | (0.001) | | |
| Offshoring* OE | | | | | | | -0.018 | |
| | | | | | | | (0.017) | |
| Offshoring* OE $^2$ | | | | | | | 0.001 | |
| | | | | | | | (0.001) | |
| Collaboration (dummy)* OE | | | | | | | | 0.001 |
| | | | | | | | | (0.005) |
| Collaboration (dummy)* OE $^2$ | | | | | | | | 0.000 |
| | | | | | | | | (0.000) |
| Other industry controls | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Technological dummy variables | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.645*** | 0.455*** | 0.396*** | 0.376*** | 0.369*** | 0.370*** | 0.375*** | 0.378*** |
| | (0.020) | (0.036) | (0.042) | (0.049) | (0.049) | (0.049) | (0.049) | (0.051) |
| Observations | 38,418 | 38,418 | 38,418 | 38,418 | 38,418 | 38,418 | 38,418 | 38,418 |
| Number of Industries | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| Variance (industry) | 0.0129 | 0.00861 | 0.00662 | 0.00116 | 0.00112 | 0.00110 | 0.00116 | 0.00116 |
| Variance (firm) | 0.0948 | 0.0888 | 0.0888 | 0.0887 | 0.0887 | 0.0886 | 0.0887 | 0.0886 |
| Variance (Offshoring) | | 0.122 | 0.122 | 0.122 | 0.122 | 0.122 | 0.123 | 0.122 |
| Covariance (random intercept-coefficient) | | -0.0458 | -0.0457 | -0.0462 | -0.0460 | -0.0463 | -0.0471 | -0.0463 |
| ICC Industry | 0.0589 | 0.0420 | 0.0326 | 0.00586 | 0.00567 | 0.00557 | 0.00590 | 0.00588 |
| ICC Firm | 0.492 | 0.475 | 0.470 | 0.455 | 0.455 | 0.455 | 0.455 | 0.455 |
| LR test Firm random intercept | 12146*** | 11449*** | 11325*** | 10800*** | 10794*** | 10769*** | 10798*** | 10772*** |
| LR test Industry random intercept | 483.2*** | 291.2*** | 238.2*** | 44.51*** | 42.49*** | 41.49*** | 44.74*** | 44.68*** |
| Wald Test Mean values | | 157.2*** | 168.5*** | 202.8*** | 203.4*** | 205.8*** | 202.5*** | 202.8*** |
| Wald Test Time dummies | | 454*** | 453.9*** | 453.5*** | 453*** | 452.1*** | 453.3*** | 453.2*** |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012. pp. 88-89). ICC is conditional on zero values of random-effects covariates. Other firm-level controls include collaboration, human capital, internal R&D, size, markets, foreign, age. Other industry controls include ind. ext. expenditures, ind. internal R&D, HHI, appropriation, patent.

Table A6. Two lags of explanatory variables

| VARIABLES | (1) PI | (2) PI | (3) PI | (4) PI | (5) PI | (6) PI | (7) PI | (8) PI |
|---|---|---|---|---|---|---|---|---|
| Offshoring | | 0.099 | 0.099 | 0.100 | 0.098 | 0.096 | 0.048 | 0.100 |
| | | (0.090) | (0.090) | (0.090) | (0.091) | (0.092) | (0.083) | (0.090) |
| $Offshoring^2$ | | -0.205** | -0.205** | -0.205** | -0.204** | -0.201* | -0.204* | -0.206** |
| | | (0.102) | (0.102) | (0.102) | (0.103) | (0.104) | (0.106) | (0.102) |
| Collaboration (dummy) | | 0.027*** | 0.027*** | 0.027*** | 0.026*** | 0.026*** | 0.027*** | 0.021 |
| | | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.017) |
| Human Capital | | 0.088** | 0.088** | 0.089** | 0.082** | 0.279*** | 0.089** | 0.089** |
| | | (0.035) | (0.035) | (0.035) | (0.036) | (0.052) | (0.035) | (0.035) |
| Internal R&D | | -0.010 | -0.010 | -0.010 | 0.035 | -0.012 | -0.010 | -0.010 |
| | | (0.018) | (0.018) | (0.018) | (0.029) | (0.018) | (0.018) | (0.018) |
| Other firm-level controls | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| OE | | | 0.022*** | 0.014** | 0.014** | 0.015*** | 0.014** | 0.014** |
| | | | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| $OE^2$ | | | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Internal R&D* OE | | | | | -0.010** | | | |
| | | | | | (0.005) | | | |
| Internal R&D* $OE^2$ | | | | | 0.000 | | | |
| | | | | | (0.000) | | | |
| Human Capital* OE | | | | | | -0.056*** | | |
| | | | | | | (0.012) | | |
| Human Capital* $OE^2$ | | | | | | 0.002*** | | |
| | | | | | | (0.001) | | |
| Offshoring* OE | | | | | | | 0.010 | |
| | | | | | | | (0.017) | |
| Offshoring* $OE^2$ | | | | | | | -0.000 | |
| | | | | | | | (0.001) | |
| Collaboration (dummy)* OE | | | | | | | | 0.001 |
| | | | | | | | | (0.005) |
| Collaboration (dummy)* $OE^2$ | | | | | | | | 0.000 |
| | | | | | | | | (0.000) |
| Other industry controls | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Technological dummy variables | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.619*** | 0.353*** | 0.298*** | 0.278*** | 0.272*** | 0.269*** | 0.278*** | 0.280*** |
| | (0.019) | (0.038) | (0.042) | (0.050) | (0.050) | (0.050) | (0.050) | (0.051) |
| Observations | 42,779 | 42,779 | 42,779 | 42,779 | 42,779 | 42,779 | 42,779 | 42,779 |
| Number of Industries | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| Variance (industry) | 0.0123 | 0.00771 | 0.00580 | 0.00111 | 0.00108 | 0.00103 | 0.00111 | 0.00111 |
| Variance (firm) | 0.0992 | 0.0920 | 0.0920 | 0.0919 | 0.0919 | 0.0917 | 0.0919 | 0.0918 |
| Variance (Offshoring) | | 0.0777 | 0.0777 | 0.0780 | 0.0779 | 0.0773 | 0.0761 | 0.0778 |
| Covariance (random intercept-coefficient) | | -0.0233 | -0.0233 | -0.0239 | -0.0240 | -0.0238 | -0.0237 | -0.0239 |
| ICC Industry | 0.0547 | 0.0369 | 0.0280 | 0.00549 | 0.00534 | 0.00510 | 0.00547 | 0.00550 |
| ICC Firm | 0.494 | 0.477 | 0.472 | 0.460 | 0.460 | 0.459 | 0.460 | 0.460 |
| LR test Firm random intercept | 13171*** | 12536*** | 12405*** | 11926*** | 11923*** | 11887*** | 11919*** | 11910*** |
| LR test Industry random intercept | 519.5*** | 310.3*** | 250.7*** | 51.03*** | 48.86*** | 46.16*** | 50.82*** | 51.16*** |
| Wald Test Mean values | | 360.8*** | 374*** | 422*** | 423.2*** | 429.4*** | 422.3*** | 421.2*** |
| Wald Test Time dummies | | 668.4*** | 668.4*** | 668.1*** | 668.6*** | 666.3*** | 668.2*** | 667.3*** |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012. pp. 88-89). ICC is conditional on zero values of random-effects covariates. Other firm-level controls include collaboration, human capital, internal R&D, size, markets, foreign, age. Other industry controls include ind. ext. expenditures, ind. internal R&D, HHI, appropriation, patent.

Table A7. SMEs

| VARIABLES | (1)<br>PI | (2)<br>PI | (3)<br>PI | (4)<br>PI | (5)<br>PI | (6)<br>PI | (7)<br>PI | (8)<br>PI |
|---|---|---|---|---|---|---|---|---|
| Offshoring | | 0.141 | 0.142 | 0.140 | 0.138 | 0.138 | 0.207** | 0.139 |
| | | (0.103) | (0.103) | (0.103) | (0.103) | (0.105) | (0.102) | (0.104) |
| Offshoring$^2$ | | -0.283** | -0.284** | -0.283** | -0.280** | -0.278** | -0.279** | -0.282** |
| | | (0.114) | (0.114) | (0.114) | (0.115) | (0.117) | (0.111) | (0.115) |
| Collaboration (dummy) | | 0.041*** | 0.041*** | 0.041*** | 0.041*** | 0.041*** | 0.041*** | 0.030 |
| | | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.024) |
| Human Capital | | 0.142*** | 0.142*** | 0.142*** | 0.142*** | 0.348*** | 0.142*** | 0.142*** |
| | | (0.048) | (0.049) | (0.048) | (0.049) | (0.052) | (0.048) | (0.048) |
| Internal R&D | | 0.007 | 0.007 | 0.007 | 0.030 | 0.006 | 0.007 | 0.008 |
| | | (0.010) | (0.010) | (0.010) | (0.024) | (0.011) | (0.010) | (0.010) |
| Other firm-level controls | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| OE | | | 0.024*** | 0.011* | 0.012** | 0.013** | 0.012** | 0.011* |
| | | | (0.008) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| OE $^2$ | | | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Internal R&D* OE | | | | | -0.010** | | | |
| | | | | | (0.004) | | | |
| Internal R&D* OE $^2$ | | | | | 0.001*** | | | |
| | | | | | (0.000) | | | |
| Human Capital* OE | | | | | | -0.073*** | | |
| | | | | | | (0.014) | | |
| Human Capital* OE $^2$ | | | | | | 0.003*** | | |
| | | | | | | (0.001) | | |
| Offshoring* OE | | | | | | | -0.017 | |
| | | | | | | | (0.021) | |
| Offshoring* OE $^2$ | | | | | | | 0.000 | |
| | | | | | | | (0.001) | |
| Collaboration (dummy)* OE | | | | | | | | 0.002 |
| | | | | | | | | (0.006) |
| Collaboration (dummy)* OE $^2$ | | | | | | | | 0.000 |
| | | | | | | | | (0.000) |
| Other industry controls | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Technological dummy variables | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.632*** | 0.391*** | 0.333*** | 0.322*** | 0.320*** | 0.316*** | 0.322*** | 0.326*** |
| | (0.021) | (0.040) | (0.046) | (0.052) | (0.052) | (0.052) | (0.052) | (0.053) |
| Observations | 34,673 | 34,673 | 34,673 | 34,673 | 34,673 | 34,673 | 34,673 | 34,673 |
| Number of Industries | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| Variance (industry) | 0.0136 | 0.00844 | 0.00605 | 0.00156 | 0.00155 | 0.00144 | 0.00156 | 0.00157 |
| Variance (firm) | 0.0928 | 0.0884 | 0.0884 | 0.0883 | 0.0883 | 0.0882 | 0.0883 | 0.0883 |
| Variance (Offshoring) | | 0.115 | 0.115 | 0.115 | 0.115 | 0.116 | 0.117 | 0.116 |
| Covariance (random intercept-coefficient) | | -0.0358 | -0.0358 | -0.0361 | -0.0359 | -0.0359 | -0.0371 | -0.0368 |
| ICC Industry | 0.0619 | 0.0411 | 0.0298 | 0.00785 | 0.00782 | 0.00728 | 0.00785 | 0.00793 |
| ICC Firm | 0.485 | 0.471 | 0.465 | 0.453 | 0.453 | 0.452 | 0.453 | 0.453 |
| LR test Firm random intercept | 10192*** | 9866*** | 9752*** | 9408*** | 9406*** | 9376*** | 9405*** | 9382*** |
| LR test Industry random intercept | 352.5*** | 239.7*** | 193*** | 47.21*** | 46.68*** | 42.90*** | 47.16*** | 47.54*** |
| Wald Test Mean values | | 115.6*** | 129.7*** | 157.5*** | 158.7*** | 166*** | 157.3*** | 157.1*** |
| Wald Test Time dummies | | 593*** | 593.1*** | 592.9*** | 592.7*** | 590.2*** | 592.7*** | 591.6*** |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012. pp. 88-89). ICC is conditional on zero values of random-effects covariates. Other firm-level controls include collaboration, human capital, internal R&D, size, markets, foreign, age. Other industry controls include ind. ext. expenditures, ind. internal R&D, HHI, appropriation, patent.

Table A8. LEs

| VARIABLES | (1)<br>PI | (2)<br>PI | (3)<br>PI | (4)<br>PI | (5)<br>PI | (6)<br>PI | (7)<br>PI | (8)<br>PI |
|---|---|---|---|---|---|---|---|---|
| Offshoring | | 0.301** | 0.299** | 0.305** | 0.303** | 0.300** | 0.423*** | 0.308*** |
| | | (0.122) | (0.123) | (0.122) | (0.123) | (0.121) | (0.127) | (0.120) |
| Offshoring$^2$ | | -0.390** | -0.388** | -0.392** | -0.390** | -0.387** | -0.391** | -0.395** |
| | | (0.157) | (0.159) | (0.157) | (0.158) | (0.157) | (0.162) | (0.154) |
| Collaboration (dummy) | | 0.074*** | 0.074*** | 0.075*** | 0.074*** | 0.074*** | 0.074*** | 0.078*** |
| | | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.024) |
| Human Capital | | -0.033 | -0.034 | -0.035 | -0.038 | 0.306 | -0.035 | -0.034 |
| | | (0.089) | (0.089) | (0.088) | (0.093) | (0.307) | (0.089) | (0.088) |
| Internal R&D | | 0.017 | 0.018 | 0.016 | 0.051 | 0.011 | 0.017 | 0.017 |
| | | (0.044) | (0.044) | (0.044) | (0.130) | (0.045) | (0.044) | (0.044) |
| Other firm-level controls | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| OE | | | 0.025*** | 0.018** | 0.017** | 0.019** | 0.019** | 0.019** |
| | | | (0.006) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| OE$^2$ | | | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Internal R&D* OE | | | | | 0.009 | | | |
| | | | | | (0.036) | | | |
| Internal R&D* OE$^2$ | | | | | -0.001 | | | |
| | | | | | (0.002) | | | |
| Human Capital* OE | | | | | | -0.069* | | |
| | | | | | | (0.038) | | |
| Human Capital* OE$^2$ | | | | | | 0.002** | | |
| | | | | | | (0.001) | | |
| Offshoring* OE | | | | | | | -0.024* | |
| | | | | | | | (0.015) | |
| Offshoring* OE$^2$ | | | | | | | 0.001 | |
| | | | | | | | (0.000) | |
| Collaboration (dummy)* OE | | | | | | | | -0.002 |
| | | | | | | | | (0.007) |
| Collaboration (dummy)* OE$^2$ | | | | | | | | 0.000 |
| | | | | | | | | (0.000) |
| Other industry controls | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Technological dummy variables | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.674*** | 0.426*** | 0.364*** | 0.334*** | 0.328*** | 0.326*** | 0.331*** | 0.333*** |
| | (0.024) | (0.060) | (0.058) | (0.083) | (0.083) | (0.083) | (0.082) | (0.083) |
| Observations | 11,832 | 11,832 | 11,832 | 11,832 | 11,832 | 11,832 | 11,832 | 11,832 |
| Number of Industries | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| Variance (industry) | 0.0157 | 0.00655 | 0.00420 | 0.000539 | 0.000529 | 0.000522 | 0.000553 | 0.000539 |
| Variance (firm) | 0.0973 | 0.0859 | 0.0859 | 0.0853 | 0.0853 | 0.0852 | 0.0853 | 0.0853 |
| Variance (Offshoring) | | 0.132 | 0.132 | 0.130 | 0.130 | 0.131 | 0.130 | 0.130 |
| Covariance (random intercept-coefficient) | | -0.0470 | -0.0461 | -0.0471 | -0.0471 | -0.0473 | -0.0477 | -0.0469 |
| ICC Industry | 0.0725 | 0.0339 | 0.0220 | 0.00289 | 0.00284 | 0.00280 | 0.00296 | 0.00289 |
| ICC Firm | 0.521 | 0.479 | 0.472 | 0.460 | 0.460 | 0.460 | 0.460 | 0.460 |
| LR test Firm random intercept | 4124*** | 3491*** | 3435*** | 3232*** | 3226*** | 3225*** | 3231*** | 3230*** |
| LR test Industry random intercept | 214.8*** | 67.36*** | 43.11*** | 1.965* | 1.917* | 1.889* | 2.044* | 1.967* |
| Wald Test Mean values | | 104.7*** | 121.6*** | 139.6*** | 139.6*** | 140.1*** | 139.9*** | 139.4*** |
| Wald Test Time dummies | | 97.37*** | 97*** | 96.24*** | 96.36*** | 96.50*** | 95.95*** | 96.17*** |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012. pp. 88-89). ICC is conditional on zero values of random-effects covariates. Other firm-level controls include collaboration, human capital, internal R&D, size, markets, foreign, age. Other industry controls include ind. ext. expenditures, ind. internal R&D, HHI, appropriation, patent.

Table A9. Logit estimation

| VARIABLES | (1) PI | (2) PI | (3) PI | (4) PI | (5) PI |
|---|---|---|---|---|---|
| Offshoring | 8.113* | 8.089* | 7.596* | 12.228** | 8.084* |
| | (8.791) | (8.807) | (8.271) | (12.216) | (8.736) |
| Offshoring$^2$ | 0.054** | 0.055** | 0.058** | 0.054** | 0.055** |
| | (0.070) | (0.071) | (0.075) | (0.074) | (0.071) |
| Collaboration (dummy) | 1.590*** | 1.590*** | 1.589*** | 1.590*** | 1.437** |
| | (0.119) | (0.118) | (0.117) | (0.119) | (0.211) |
| Human Capital | 3.420** | 3.326** | 27.573*** | 3.419** | 3.436** |
| | (1.701) | (1.690) | (16.133) | (1.700) | (1.694) |
| Internal R&D | 1.065 | 1.507 | 1.048 | 1.065 | 1.069 |
| | (0.126) | (0.458) | (0.127) | (0.126) | (0.125) |
| Other firm-level controls | Yes | Yes | Yes | Yes | Yes |
| OE | 1.086* | 1.090* | 1.103** | 1.086* | 1.080 |
| | (0.053) | (0.053) | (0.053) | (0.053) | (0.054) |
| OE $^2$ | 0.992*** | 0.992*** | 0.991*** | 0.992*** | 0.992*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Internal R&D* OE | | 0.879* | | | |
| | | (0.061) | | | |
| Internal R&D* OE $^2$ | | 1.006* | | | |
| | | (0.003) | | | |
| Human Capital* OE | | | 0.497*** | | |
| | | | (0.068) | | |
| Human Capital* OE $^2$ | | | 1.030*** | | |
| | | | (0.006) | | |
| Offshoring* OE | | | | 0.925 | |
| | | | | (0.133) | |
| Offshoring* OE $^2$ | | | | 1.002 | |
| | | | | (0.005) | |
| Collaboration (dummy)* OE | | | | | 1.024 |
| | | | | | (0.041) |
| Collaboration (dummy)* OE $^2$ | | | | | 1.000 |
| | | | | | (0.001) |
| Other industry controls | Yes | Yes | Yes | Yes | Yes |
| Technological dummy variables | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.118*** | 0.116*** | 0.110*** | 0.117*** | 0.122*** |
| | (0.065) | (0.064) | (0.062) | (0.065) | (0.068) |
| Observations | 47,493 | 47,493 | 47,493 | 47,493 | 47,493 |
| Number of Industries | 38 | 38 | 38 | 38 | 38 |
| Variance (industry) | 0.0771 | 0.0763 | 0.0717 | 0.0773 | 0.0772 |
| Variance (firm) | 6.024 | 6.025 | 6.016 | 6.026 | 6.013 |
| Variance (Offshoring) | 10.50 | 10.56 | 10.18 | 10.27 | 10.60 |
| Covariance (random intercept-coefficient) | -1.310 | -1.289 | -1.381 | -1.328 | -1.302 |
| ICC Industry | 0.00821 | 0.00813 | 0.00765 | 0.00823 | 0.00823 |
| ICC Firm | 0.650 | 0.650 | 0.649 | 0.650 | 0.649 |
| LR test Firm random intercept | 10521*** | 10521*** | 10479*** | 10518*** | 10493*** |
| LR test Industry random intercept | 45.72*** | 44.77*** | 41.37*** | 45.75*** | 45.83*** |
| Wald Test Mean values | 1.982 | 1.911 | 1.954 | 1.979 | 1.971 |
| Wald Test Time dummies | 628.8 | 629.1 | 627 | 628.6 | 627.5 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Odd ratios. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012. pp. 88-89). ICC is conditional on zero values of random-effects covariates. Other firm-level controls include collaboration, human capital, internal R&D, size, markets, foreign, age. Other industry controls include ind. ext. expenditures, ind. internal R&D, HHI, appropriation, patent.

## APPENDIX B. VARIANCE PARTITION COEFFICIENT (VPC)

It measures the proportion of the total residual variance in the propensity to develop a product innovation due to differences between groups going from zero (meaning no group differences) to one (no within-group differences). In the present case, it should be noted that the unconditional VPC and Intra-class Correlation (ICC) coincide for the highest level (industry), while they do not coincide for lower levels. However, when conditional on characteristics, the inclusion of offshoring in the random part of the model imply differences in the calculation of both.[28]

$$VPC_{firm} = \frac{\sigma^2_{\mu 0ij}}{\sigma^2_{\mu 0j} + \sigma^2_{\mu 0ij} + (\frac{\pi^2}{3})}$$

$$VPC_{ind.} = \frac{\sigma^2_{\mu 0j}}{\sigma^2_{\mu 0j} + \sigma^2_{\mu 0ij} + (\frac{\pi^2}{3})}$$

$$VPC_{firm} = \frac{\sigma^2_{\mu 0ij} + 2 * offshoring * \sigma_{\mu 01ij} + \sigma^2_{\mu 1ij} * offshoring^2}{\sigma^2_{\mu 0j} + \left[\sigma^2_{\mu 0ij} + 2 * offshoring * \sigma_{\mu 01ij} + \sigma^2_{\mu 1ij} * offshoring^2\right] + (\frac{\pi^2}{3})}$$

$$VPC_{ind.} = \frac{\sigma^2_{\mu 0j}}{\sigma^2_{\mu 0j} + \left[\sigma^2_{\mu 0ij} + 2 * offshoring * \sigma_{\mu 01ij} + \sigma^2_{\mu 1ij} * offshoring^2\right] + (\frac{\pi^2}{3})}$$

Making use of the notation introduced in section 4.3, the first two VPC correspond to those of column 1 of Table 3, and thus, are the unconditional ones. These will divide the proportion of the total residual variance in the propensity to develop a product innovation due to differences between industries on the one hand, and between enterprises on the other. Consequently, replacing the values in Table 3 (column 1) in those formulas, firm-level variation (around 40 percent) in the proportion of product innovations is higher than the industrial one (around 7 percent) and thus, more important. The last two VPC correspond to those of the firm and industry levels (columns 3-4 of Table 3). In any case, it should be noted that irrespective of conditional/unconditional VPC, the firm-level variation is more important than the industrial one.

[28] Unconditional VPC is based on the observed response, while the conditional VPC is based on the residual, and thus, it measures the proportion of outcome variation unexplained by the variables in the model.