HUMAN RESOURCE MANAGEMENT PRACTICES AND INNOVATION AMONG COLOMBIAN FIRMS

INTRODUCTION

Influenced by the seminal work in Schumpeter (1942), innovation has been identified as one of the most important factors building and sustaining a firm's competitive advantage (Kogut and Zander, 1992; Teece, 1996). At the same time, innovation can be conceptualized as a human resource management (HRM)-related outcome, mirroring the HRM- performance linkage (Seeck and Diehl, 2017). Indeed, it has been argued for quite some time now that factors internal to the firm may foster or hamper innovation (Van de Ven, 1986). However, most firms in emerging economies in general and in Latin America in particular still devote few resources to innovation in comparison with firms in advanced economies, and pay even fewer attention to the impact human resources practices may have on innovation, compromising even further their competitive positions.

In this paper we take a closer look at the way firms organize internal human resources for innovation, specifically we consider one human resource practice: how talent from different departments working in isolation or combined contribute to innovation. This we do by analyzing firm-level survey data from Colombia, which include information on firms' innovation performance as well as on the type of human resources involved with innovation. In particular, we will be interested in whether there is any evidence of workers in the R&D department being complementary in innovation with workers in any other department of the firm. We will test whether firms that combine for innovation purposes workers in R&D departments with workers in any other department within the firm are more likely to introduce new products and processes, introduce more product innovations, obtain a higher percentage of sales from innovative products and a higher return from innovative expenditures than firms that choose not to combine these two types of workers. The results obtained so far fail to find support for the existence of complementarity relationship between these two groups, suggesting that surveyed firms are not able to capture potential incremental effects from the combination of innovation resources.

As pointed out above, many firms in developing countries lag behind in terms of in- novation. In the specific case of Colombia, indicators of firm innovation suggest a modest performance. In the period 2011-2012 the same survey used for this research reported 73.6% of non-innovative firms (Arias-Pérez et al., 2015). For the period 2015-2016 that percentage has not decreased, on the contrary it has slightly increased: 73.7%. These poor indicators suggest that diverse sources of innovation activities must be tackled. In this sense, the richness of the DANE's (Departamento Administrativo Nacional de Estadística) database allows us to make an effective contribution. The empirical approach is a test of the existence of complementarities (Milgrom and Roberts, 1990), closely following contributions such as Cassiman and Veugelers (2006) or Cassiman and Valentini (2016) between employees in the following two broad areas within the firm: R&D departments and non-R&D ones. While most relevant research up to date (Arora and Gambardella, 1994; Cassiman and Veugelers, 2006) finds that innovative firms benefit from complementing internal with external R&D, this study explores whether complementarity exists within firms. This is a novel question that may be studied given the features of the database that we are analyzing.

The organizational perspective of innovation has been mostly analyzed by focusing on the interfirm organization of R&D activities. However, intrafirm organization of R&D activities has received relatively less attention, one of the reasons being lack of adequate data. As an exception, Argyres and Silverman (2004) study whether a more or less centralized R&D structure has any effect on the type of innovation, specifically the breadth of potential applicability of the innovation. A centralized R&D implies a capabilities' broadening search, whereas a decentralized R&D structure implies a capabilities' deepening search. This contribution suggests the existence of a relationship between the way firms organize its resources and its propensity to innovate as well as the type of innovations the firm pursues. For instance, divisional and geographic dispersion of research efforts may condition the type of research undertaken by the firm. Or the way firms com- bine personnel from different departments within the firm in innovation teams may affect innovativeness.

What the business community knows is that several contextual factors have to be taken into account when deepen on factors that hinder or enhance the innovative performance by firms. In addition to organization (Haneda and Ito, 2018), other circumstances such as stakeholder orientation (Flammer and Kacperczyk, 2016), the business cycle (Garicano and Steinwender, 2016; Armand and Mendi, 2018), institutionalism (Hollingsworth, 2000), or the incentive structure (Manso, 2011; Ederer and Manso, 2013) may also impact innovation. Hence, it makes sense to assume that contextual factors restrict the options/opportunities to take innovations outside the boundaries of the firm (e.g. open innovations). While this holds true, since this study focuses only at firm-level outputs, those contextual factors will be discussed tangentially, and in so far as they help the discussion of the findings.

The internal organization of innovation is a discussion that falls into a wide range of fields of knowledge. In the theoretical discussion, success or failure of innovation goals is entailed in people, team (departments) and at the organizational level (Lin and Sanders, 2017). On the other hand, the approach in Milgrom and Roberts (1990) has been developed on the basis of firms' organizational design, namely ‘complementarity view’ (or ‘supermodularity view’) of technological development. In this approach, the adoption of new technologies is the result of a process of organizational change where firms seek to optimize their organizational and technological practices. In this order of thoughts, looking into the possible complementarity between talent from the R&D department and those non-R&D for innovation rather than looking at the inter-firm complementarity of innovation activities or the contextual factors, may give valuable and applicable insights of ways to foster innovation.

The ability to create and generate complementarities in between different and diverse departments in a firm, moreover, in between those that are not engage on innovative activities with those that are responsible for innovations is overlapped with the Dynamic Capability (DC) framework. Knowledge deployment and acquisition are embedded in people, thus not only organizational culture is required but also individual capabilities. If complementarities occur in between different departments of a firm and, this complementarity improve gains for the firm (market share, sales, etc.), complementarity becomes a competitive advantage by nature (Teece et al., 1997). Capabilities in the Teece et al. (1997) framework emphasize the key role of strategic management in appropriately adapting, integrating, and reconfiguring internal and external organizational skills.

In unpredictable markets, where the competitive landscape is shifting, the dynamic capabilities for the reconfiguration of internal and external competencies to address rapidly changing environments become the source of sustained competitive advantage. For in- stance, in low technological environments innovation process can be explained in the form of practical ways by ‘learning-by-doing, by-using, and by interacting’, where on-the- job problem solving occurs and people interact and share experiences (Trott and Simms, 2017).

From the perspective in this paper, one way of managing intra-firm innovation would require attention to the internal talent allocated to the different organizational departments: a specific human resource practice that prevents isolation of talent and the development of knowledge “silos”. Teams can bring together “knowledge that hitherto existed separately” (p. 248), potentially resulting in non-trivial process advancement or novel products as indicated by Laursen and Foss (2003). For example, new innovations projects in a R&D department from Marketing and Sales department should be a common way of doing innovation of new products or refreshed products. The same is expected, for instance, from production departments.

At the individual level and focusing on talent, “successful innovators are those that are able to overcome the departmental barriers and synthesize their expertise” (Lin and Sanders, 2017). It is not surprising then that team work has been related to better use of local knowledge leading to improvements in processes and some minor product improvement (Perdomo-Ortiz et al., 2009; Fay et al., 2015). Specifically, Perdomo-Ortiz et al. (2009) found a direct relationship and a positive effect of teamwork and technological innovation. Knowledge and information sharing impact on innovation has been highlighted previously (MacCurtain et al., 2010), thus since working together favors the sharing and creation of knowledge, when members of different departments join efforts to accomplish similar goals the innovation environment is enhanced. In this line, Love and Roper (2009) find a positive impact of the implementation of cross-functional teams, although the impact substantially varies between the two countries studied, Germany and the UK.

Something alike seems to be working out for HACEB, the biggest Colombian producer of house appliances. They have an innovation and digital transformation (I+DT) department that reports directly to the C-suite. The main objective of the I+DT department is to "decentralize innovation". To do so, they have a group of innovation leaders that rotate through every process of the firm gathering ideas and teaching methodologies for innovation. In this sense, HACEB promotes a risk-taking culture, in which every employee is motivated to work in innovation activities and to behave in an innovative manner. Actually, the I+DT department is not responsible for leading innovation processes, but to enhance them in the whole organization.

The remainder of the paper is organized as follows. Section 2 presents the data used in the current paper. Section 3 presents the empirical analysis, whose results are discussed in Section 4. Finally, Section 5 presents some concluding comments.

DATA

The data that we use in this paper is firm-level data extracted from three waves of EDIT (Encuesta de Desarrollo e Innovación Tecnológica), the innovation survey conducted by DANE, the Colombian Statistical Office. DANE periodically implements an innovation survey in Colombia, following the recommendations in the Oslo Manual, and using a questionnaire similar to that used in the Community Innovation Survey, which is implemented across different EU countries, as well as in a growing number of non-EU countries.

The three waves used in the paper collect information on innovation practices in the 2011-12, 2013-14 and 2015-16 periods, respectively, and the use of three waves will allow us to lag strategy and performance variables, so as to reduce potential biases arising from simultaneity between the strategies and the outcomes. In particular, the performance variables will be constructed using observations from the survey that covers the 2015-16 period, whereas the independent variables of interest, including the strategy variables, will be constructed using data drawn from the 2013-14 survey. Furthermore, we will include in our specifications a measure of the labor productivity and initial innovation activities of the firm from the 2011-12 survey, so as to avoid simultaneity with the choice of strategy. DANE classifies firms into five categories, according to their innovation activities in the survey period. Innovative firms are those that introduced either a new or a significantly improved product or service, or a new process, organizational form, or marketing method. Within innovative firms, strict innovators are those firms that introduced a product that is new to the international market, and the rest of the innovative firms are innovators in a broad sense, comprising technological innovators (product and/or process innovators) and organizational and marketing innovators. Potential innovators are firms that had either ongoing but not completed innovation, or abandoned innovation. Firms with innovation prospects are those that do not qualify as innovators or potential innovators, but that declare that they plan to innovate in the near future. Finally, non-innovators are firms without any actual, ongoing, abandoned or planned innovative activities. In this paper, however, we will follow the bulk of the literature on R&D and innovation and consider a firm to be innovative in a technological sense, that is, if it introduces a new or significantly product or process, has some ongoing innovation activities, or has some abandoned innovation activities in the reference period.

Table 1 contains definitions of the main variables used in the present study, distinguishing between dependent, independent, and control variables. As a performance (de- pendent) variables we will consider the firm’s status as a technological innovation, INNOVATIVE, as well as indicator variables of the introduction of product and process innovations, PRODINNOV and PROCINNOV, respectively. This way, INNOVATIVE, PRODINNOV and PROCINNOV measure the extensive margin of innovation. The intensive margin of innovation is measured by NEWPROD, that is, the number of new products that the firm introduces in the 2015-16 period.

The two continuous dependent variables used in the econometric analysis are SALESIN-NOVATIVE, the ratio of sales from new or significantly improved products introduced by the firm during the 2015-16 period to sales in 2016. This is a commonly used measure of innovation performance, see for instance Cassiman and Veugelers (2006) or Cassiman and Valentini (2016). Finally, INSALESEXPEN is the ratio of sales from new or significantly improved products introduced by the firm during the 2015-16 period to the average innovation expenditures in the 2013-14 period, and measures the productivity of innovation expenditures. However, a limitation of both variables –common to all studies that rely on this type of survey data- is the fact that a product is classified as innovative from the perspective of the firm. In particular, a firm may classify as innovative a product that is an imitation of an existing product. Unfortunately, we do not have enough information to discriminate between sales from true innovations and sales from imitative products. Another problem associated with the use of this measure of innovation performance is the fact that process innovations are automatically excluded from this criterion.

The test for complementarity that is used, for instance, in Cassiman and Veugelers (2006) or Mohnen and Roller (2005) classifies firms into four different mutually-exclusive categories, and then tests whether there is a significant difference between the sum of two of the coefficients (joint adoption of strategies plus adoption of neither) and the sum of the other two (adoption of single strategies). In our case, the independent variables of interest are RDONLY, OTHERONLY, BOTH, and NEITHER, which are four mutually-exclusive dummy variables that indicate whether the firm uses employees in the R&D department and/or any other departments for innovation purposes. In the econometric specifications we will use the lagged (observations from the 2013-14 survey) value of these variables, to avoid reverse causality from performance to strategy choice. Intuitively, what we are verifying is whether past innovation strategies are affecting current performance.

The estimated models also include a number of control variables. Firm size has been found to be positively associated with the propensity to innovate, and it has been proxied for by the logarithm of the number of employees in 2014, LNEMPLOYEES. In the firm's choice to introduce new products and/or processes, some obstacles are found to be relevant. In particular, IMITATION, INTERNALRESOURCES, and PERSONNEL variables control for the firm's perception of the importance of different obstacles for innovation and these are taken from the 2015-16 survey. These variables have been normalized to be between zero an one, with higher values indicating greater importance of a particular obstacle.

The fact that we can use several waves of the survey implies that we can proxy and control for unobserved characteristics of the firm. Specifically, LABORPRODUCT is the logarithm of sales per employee, taken from the 2011-12 survey, so as to avoid simultaneity with the choice of strategies, which are observed in the 2013-14 survey. Data on the number of employees involved in innovation activities is for the year 2014. While not fully exploiting the panel characteristics of the dataset, the inclusion of these lagged variables is intended to control for unobserved, time-invariant, firm characteristics. Actually, Zoghi et al. (2010) discusses the issue of reverse causality, meaning that the implementation of a particular innovation may be driving human resource practices. The inclusion of these controls tries to mitigate the problem of endogeneity caused by reverse causality.

The database contains data for 7,099 firms that are observed in all three waves, thus giving us information spanning from 2011 to 2016. Out of these, 3,907 are never technologically innovative, meaning that they never introduce any new products, any new processes, or had some ongoing or abandoned innovation during the 2011-16 time span. In contrast, 401 firms are technologically innovative in all three waves, and the remaining 2,791 firms are technologically innovative in at least one of the waves. This suggests the existence of a low degree of persistence of innovation activities among firms in Colombia. Table 2 presents summary statistics of the subsample of firms that report on human resource strategies in the 2013-14 wave. All firms that are classified as non-innovative in a broad sense (technological and/or organizational and marketing) do not report the number of employees devoted to innovation activities. Only these firms report on the importance of different obstacles to innovation. In the table, we split the sample into two subsamples. The first subsample includes observations for the two broad industry categories whose contribution to GDP is highest. Divisions 19 to 30 in the CIUU-4 industry classification, which is the one used by DANE, are included in this category. These industries include oil, chemical, pharmaceutical, rubber and plastics, metal, machinery and equipment, automobile, other transportation. The second group (column 2 of Table 2) includes the rest of the industries. The sample size is 2,020 firms, out of which 997 are in industries 4 and 5, and the remaining 1,023 are in the rest of the industries.

Approximately 50% of the firms in the sample are technologically innovative in the 2015-16 wave, with slightly over one quarter of them introducing product and process innovations. The percentage of product innovators is slightly higher among firms in industries 4 and 5 than in the rest of the industries, and the opposite occurs with process innovations. Firms in the two industry groups are similar in terms of size, and firms in industries 4 and 5 appear to be slightly more productive than the rest of the firms. Regarding innovation strategies, about 20% of the firms declare not to engage workers in any department in innovation activities. The recourse to R&D workers seems to be slightly more frequent among firms in industries 4 and 5, but most often, approximately two thirds of the times, only workers in departments other than R&D are engaged in innovation activi- ties. This suggests that the presence of formal R&D departments is a relatively infrequent phenomenon among firms in our sample. Finally, regarding the importance of obstacles to innovation, there does not seem to be an important difference in the perception of the relevance of different obstacles to innovation between firms in the two groups.

An inspection of Table 3 reveals that a relatively low proportion of firms that were innovative in a broad sense in 2013-14 had employees in the R&D department involved in innovation activities in the 2013-14 period. Indeed, 1,591 out of 2,020 firms reported that employees in departments other than the R&D department were involved in innovation activities. Among departments, production is the most often represented department in innovation teams, followed by general management. Notice that our criterion for classification into a given category is that at least one employee from a certain department be involved in innovation activities. We leave the analysis using higher threshold values of the minimum number of employees for future work.

EMPIRICAL ANALYSIS

In this section, we present estimated coefficients of the models that estimate the effect of the chosen innovation strategies, namely the lagged values of RDONLY, OTHERONLY, BOTH, and NEITHER, on the propensity to innovate, on the proportion of sales from innovative products, and on the productivity of R&D expenditures. The proportion of sales from innovative products is SALESINNOVATIVE, whereas INSALESEXPEN is the ratio of volume of sales from innovative products to current innovation expenditures. The empirical analysis is based on Cassiman and Veugelers (2006) and Cassiman and Valentini (2016). We test for the existence of complementarities in innovation strategies. In this case, the two strategies that firms may choose are the involvement of employees in the internal R&D department and in any other department of the firm in innovation activities. Given that we focus on two strategies, there are four possible combinations. The complementarity test verifies whether that the function that relates the behavior of a certain performance variable as a function of the two strategies is supermodular. Intuitively, the function is supermodular if a strategy is adopted when the other strategy is in place has a higher impact on the value of the function than in the case when the other strategy is not present. This will boil down to a Chi-squared or an F test, depending on the specific econometric specification.

First, we consider the extensive margin of innovation, that is whether or not the firm engages in innovation in 2013-14, and the results are reported in Table4. As dependent variables, we consider the indicator variables of the firm being innovative (columns 1, 2 and 3), of introducing at least one product innovation (column 4), and introducing at least one process innovation (column 5). The independent variables are observed with a lag, that is in 2013-14, so as to avoid simultaneity with the dependent variable and mitigate reverse causality. The results from the complementarity tests are reported at the bottom of each column. Reported are marginal effects of the different regressors. In the first column, we estimate a linear probability model where the dependent variable is INNOVATIVE. In this case, the coefficients may be directly interpreted as marginal effects, in the sense of in- creasing the probability of being innovative relative to the excluded category, NEITHER, whose effect is picked up by the constant. The coefficients of all three strategies are positive an significant, and that on the lagged value of BOTH appears to be slightly greater than that on the lag of RDONLY. The complementarity test boils down to a test of the coefficient on BOTH being larger than the sum of those on RDONLY and OTHERONLY. However, in this case, the value of the F statistic is 2.29, which is not statistically significant at the 10% level. In the second column, we do the same exercise but in this case, the estimation method used is a Probit. Reported in Table 4 are estimated marginal effects, which are very similar to those estimated using a linear probability model. In this case, the value of the Chi-squared statistic also fails to reject the null of no complementarity be- tween personnel in R&D and personnel in any other department regarding the propensity to innovate.

The third column of Table 4 takes into consideration firms' decisions to engage work- ers of different departments in innovation activities, a decision that takes place in the 2013-14 period. More precisely, we report estimated marginal effects of the variables, estimated using a Probit model with sample selection. The selection equation refers to the decision to combine workers in 2013-14, and is determined by a firm's industry, as well as by its labor productivity and whether it introduced a new product and/or process in 2011-12. The regression equation contains the same set of regressors as in the previous columns. Comparing the estimated coefficients with those in the previous two columns, we observe that they remain positive and statistically significant, although they some- what decrease in size. The complementarity test fails to reject the null hypothesis of no complementarity.

Finally, columns 4 and 5 of Table 4 report estimated marginal effects, also using a Probit model with sample selection, where the dependent variables are the indicators of introduction of new products (column 4) and new processes (column 5). In the case of product innovations, the size of the estimated marginal effect of RDONLY slightly increases relative to the third column, whereas that of BOTH decreases. This makes the Chi-squared statistic to be significant at the 10% level. Note that the sum of the coefficients of RDONLY and OTHERONLY exceeds the size of the coefficient on BOTH. This means that, if anything, the test suggests the existence of a substitutability relation between employees in R&D and employees in any other department of the firm.

Moving our analysis towards the intensive margin of innovation, Table 5 presents estimated coefficients of models where the dependent variable is the number of new products that the firm has declared to introduce in the 2015-16 survey. As independent variables, we use the same ones as in the previous table. The estimation methods used are OLS in column 1, a Heckman selection model in the second column and a Tobit model in the third column, taking into consideration the fact that some of the observations of the dependent variable take value zero. In the first column, where the estimation method is OLS, we have used observations for firms with product innovations. The estimated coefficients are not statistically significant, and the complementarity test fails to reject the null of no com- plementarity. In the second column, the selection equation refers to the firm's decision to use human resources for innovation in the 2013-14 period, as in the third column of Table 4, using the same independent variables to determine selection, and the regression equation being the number of innovative products in 2015-16. In this case, the coefficients on RDONLY and on BOTH are positive and statistically significant at least at the 10% level, but not that on OTHERONLY. The value of the Chi-squared statistic is low and the null of no complementarity is not rejected.

Finally, the third column of the table reports estimated marginal effects from a Tobit model where the dependent variable is the number of innovative products. In this case, since the set of regressors is the same as in column 2 and therefore includes the importance of obstacles variables, only firms that were innovative in a broad sense in 2013-14 are included in the sample. In this case, the estimated marginal effects are positive and statistically significant at the 1% level. Furthermore, the value of the F-statistic is significant at the 5% level. However, we can easily observe that the sum of the marginal effects of RDONLY and OTHERONLY exceeds that of BOTH, suggesting again the existence of a relationship of substitutability between R&D workers and workers in other department of the firm.

We now turn our attention towards the SALESINNOVATIVE variable, that is the pro- portion of sales from new products, as a performance measure. In the first column of Table 6, we have estimated by OLS a model that includes three of the four innovation strategy variables as independent variables, excluding NEITHER, whose effect will be picked up by the constant term. The estimated coefficients of the independent variables of interest, which may be interpreted as marginal effects, are all positive and statistically significant, at least at the 10% level. Looking at the complementarity test, the value of the F-statistic is not statistically significant. A similar conclusion is obtained in the second column, where the estimation method is GLM, justified by the fact that the dependent variable is a proportion, thus taking values between zero and one, not excluding the boundaries. In the third column we estimate a Heckman model with the same selection equation as in the previous table, and the complementarity test fails to reject the null of no complementarity. Finally, in the case of a Tobit model being used, the test suggests the existence of substitutability.

We now turn our attention to the productivity of innovation expenditures. Table 7 reports estimated marginal effects of different models where the dependent variable is in all cases INSALESEXPEN, that is the ratio of sales from new products in 2015-16 to innovation expenditures in 2013-14. In the first column the estimation method is OLS, and in the second and third columns, we have reported marginal effects from a Heckman and Tobit models, respectively. In all cases, the value of the complementarity test is significant at the 10% level, but note that the value of the marginal effect of RDONLY is greater than that of BOTH. Again, consistent with the results in the previous tables, these results suggest that, for the case of product innovations, the relationship is one of substitutability rather than complementarity.

Finally, Table 8 presents estimation results splitting the sample into different industries. Specifically, columns 1 and 2 use observations from the two manufacturing industry groups whose contribution to Colombian GDP is highest. These include divisions 19 to 30 in the industry classification used by DANE (CIIU-4): oil, chemical, pharmaceutical, rubber and plastics, metal, machinery and equipment, automobile, other transportation. In columns 3 and 4 observations from firms in all other industries are included. The dependent variable is SALESINNOVATIVE, that is, sales of innovative products as a percentage of total sales. We report estimated marginal effects using two alternative methods: Heck- man (columns 1 and 3) and Tobit (columns 2 and 4). The most significant effects appear in the last column. In fact, the F-statistic is significant at the 5% level, again, suggesting a substitutability relationship. The F-statistic in the case of column 2 is not statistically significant, suggesting that the results in the previous tables are driven by industries not in groups 4 and 5.

DISCUSSION OF THE RESULTS

We have tested the existence of a complementarity relationship between between employees involved in innovation activities in R&D departments and employees involved in innovation activities in any other department of the firm. Complementarities generally occur when two activities reinforce each other in such a way that doing one activity in- creases the value of doing the other Milgrom and Roberts (1990). In this study is search for a specific innovative output, the complementarity effects in between departments of firms in a developing economy.

We have used one extensive-margin (propensity to innovate) and two intensive-margin performance variables, namely sales from innovative products as a percentage of total sales, and productivity of innovation expenditures, measured as sales from innovative products divided by innovation expenditures. The empirical approached adopted is similar to that in Cassiman and Veugelers (2006); Cassiman and Valentini (2016): we have created four exclusive categories and tested for the existence of a different between the sum of the coefficients of joint adoption and no adoption on one hand, and separate adoption on the other. Our results suggest that there is no complementarity relationship overall, and that there may even be a substitutability relationship in the case of product innovations. No complementarity or substitutability is observed in the case of process innovations. The analysis carried out by industry, were he have analyzed the two industry groups that contribute the most to GDP on one hand, and the rest of the industries on the other, go in the same line.

One potential problem with our data is the fact that respondents may be overestimating the involvement of employees not in the R&D department in innovation activities. In fact, most innovative firms declare that employees in departments other than R&D are innovation-active. Indeed, the ”R&D only” category contains only a few observations in our data. A further inquiry into the composition of these cross-department teams is called for. In order to mitigate this problem, we have analyzed the impact of using different thresholds in the definition of the different categories. However, the results are in line with the case of a zero-threshold definition, that is, the fail to present evidence in favor of the existence of complementarities.

As pointed out in the introduction, the institutional setting is a fundamental contextual factor, although data in the database does not allow us to test the effect on innovations. Why? Innovation investments are highly risky investments by nature and, the effect is higher in developing economies where economic, political and social factors are too volatile. For instance, previous work in Costamagna (2015) proves that inflation in developing economies deteriorates innovations investments. Peng et al. (2009) opportunely suggest that taking institutions in background will not cooperate to clarify the strategy research on emerging economies. Facts in institutional frameworks between emerging economies and developed economies should push scholars to take institutional effects as one of the key variable in addition to industry-based and resource-based factors. The fundamental role of institutions is to reduce uncertainty and provide meaning.

CONCLUSIONS

In this paper we have tested the hypothesis of the existence of a complementarity relationship between employees in a firm's internal R&D department and employees in any other department of the firm for innovation activities. In order to accomplish this task, we have made use of Colombian data from DANE's EDIT database, which is an innovation survey that follows the general guidelines of the Community Innovation Survey. The fact that DANE conducts the innovation survey every other year allows us to track the performance of specific firms. While the low number of successive waves does not allow for the full implementation of panel data, we can at least exploit the dynamic structure of the data by introducing lagged values of some of the independent variables, so as to mitigate simultaneity biases. In this study, we have used observations from three waves of the survey, specifically 2011-12, 2013-14 and 2015-16.

The empirical approach used is similar to that in Cassiman and Veugelers (2006) or Cassiman and Valentini (2016). The empirical test is one of supermodularity in the performance variable as a function of the strategy choices. In our study, the four mutually- exclusive categories are using neither employees in the R&D department nor in any other department for innovation, using employees both in R&D and in at least one other department, in R&D only, or in any department except R&D for innovation activities. As performance variables, we have considered both the extensive and the intensive margin of innovation. In all cases, the empirical tests fail to reject the null hypothesis of no complementarity. These results are found to be robust to the use of different threshold values for the classification of firms into each category.

While the results seem to reject the existence of a relationship of complementarity between the two types of employees and even suggest the existence of substitubability in the case of product innovations, we believe further research effort must be exerted to ensure that this is indeed the case. For instance, the results may be driven by some specific industries (although we have analyzed in isolation the industries that contribute the most to GDP in Colombia). On the other hand, the contribution of personnel engaged in innovation may be heterogeneous across departments different than the R&D department. Further research in these lines is clearly called for.

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TABLES

Table 1: Variable definitions

Dependent variables	
INNOVATIVE	Dummy variable that takes value 1 if the firm is technologically innovative in 2015-16, zero otherwise.
PRODINNOV	Dummy variable that takes value 1 if the firm introduced new or significantly improved products in 2015-16, zero otherwise.
PROCINNOV	Dummy variable that takes value 1 if the firm introduced new or significantly improved production processes in 2015-16, zero otherwise.
NEWPROD	Number of innovative products introduced in the 2015-16.
SALESINNOVATIVE	Ratio of sales from new or significantly improved products to total sales in 2015-16.
INSALESEXPEN	Ratio of sales from new or significantly improved products in 2015-16 to average innovation expenditures in 2013-14.
Independent variables	
RDONLY	Dummy variable that takes value 1 if only employees in the internal R&D department are involved in innovation activities in 2014, 0 otherwise.
OTHERONLY	Dummy variable that takes value 1 if only employees in departments other than the internal R&D department are involved in innovation activities in 2014, 0 otherwise.
BOTH	Dummy variable that takes value 1 if both employees in the internal R&D department and in any other department are involved in innovation activities in 2014, 0 otherwise.
NEITHER	Dummy variable that takes value 1 if no employees are involved in innovation activities in 2014, 0 otherwise.
Control variables	
LNEMPLOYEES	Logarithm of the number of employees in 2014.
LABORPRODUCT	Logarithm of sales per employee in 2012.
INITIALINNOV	Dummy variable that takes value 1 if the firm is technologically innovative in 2011-12, zero otherwise.
IMITATION	Importance of potential imitation as a factor hampering innovation, in a 0-1 range.
INTERNALRESOURCES	Importance of lack of internal resources as a factor hampering innovation, in a 0-1 range.
PERSONNEL	Importance of lack of qualified personnel as a factor hampering innovation, in a 0-1 range.

Table 2: Summary Statistics, subsample of industry groups 4 and 5 and rest of industries

	Industries 4 and 5 2	Rest of industries 3	All firms Total
INNOVATIVE	0.52	0.46	0.49
	(0.50)	(0.50)	(0.50)
PRODINNOV	0.33	0.22	0.27
	(0.47)	(0.42)	(0.45)
PROCINNOV	0.25	0.29	0.27
	(0.43)	(0.45)	(0.45)
SALESINNOVATIVE	0.04	0.02	0.03
	(0.10)	(0.08)	(0.09)
LNEMPLOYEES	4.28	4.33	4.31
	(1.29)	(1.44)	(1.37)
LNLABORPROD_LAG2	11.69	11.50	11.59
	(1.02)	(0.98)	(1.00)
RDONLY_LAG	0.03	0.02	0.02
	(0.16)	(0.12)	(0.14)
OTHERONLY_LAG	0.62	0.68	0.65
	(0.49)	(0.47)	(0.48)
BOTH_LAG	0.17	0.11	0.14
	(0.38)	(0.31)	(0.34)
NEITHER_LAG	0.18	0.20	0.19
	(0.39)	(0.40)	(0.39)
IMITATION	0.47	0.45	0.46
	(0.44)	(0.44)	(0.44)
INTERNALRESOURCES	0.53	0.51	0.52
	(0.43)	(0.43)	(0.43)
PERSONNEL	0.48	0.44	0.46
	(0.47)	(0.47)	(0.47)

Table 3: Number of firms in each category, 2013-14 survey

		Other personnel No	Other personnel Yes	Total
R&D personnel	No	387	1,313	1,700
	Yes	42	278	320
	Total	429	1,591	2,020

Table 4: Extensive margin: Propensity to innovate

	(1) Innovative	(2) Innovative	(3) Innovative	(4) Product	(5) Process
RDONLY LAG	0.299***	0.291***	0.224***	0.264***	0.148*
	(0.078)	(0.079)	(0.081)	(0.076)	(0.083)
OTHERONLY LAG	0.158***	0.155***	0.097***	0.104***	0.108***
	(0.027)	(0.027)	(0.032)	(0.036)	(0.039)
BOTH LAG	0.344***	0.350***	0.292***	0.219***	0.236***
	(0.042)	(0.042)	(0.045)	(0.046)	(0.049)
LNEMPLOYEES	0.062***	0.060***	0.050***	0.069***	0.041***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
EXPINTEN LAG	0.015	0.013	0.006	-0.019	-0.114
	(0.068)	(0.066)	(0.072)	(0.074)	(0.079)
IMITATION	0.040	0.040	0.056**	0.080***	0.006
	(0.025)	(0.025)	(0.025)	(0.026)	(0.028)
INTERNALRESOURCES	0.021	0.021	0.018	0.019	0.009
	(0.027)	(0.026)	(0.026)	(0.028)	(0.029)
PERSONNEL	0.010	0.009	0.008	-0.033	0.025
	(0.025)	(0.024)	(0.024)	(0.026)	(0.027)
Number of obs.	2020	2020	2020	2020	2020
Complement. test	1.84	1.25	.11	3.42	.05
p-value	.17	.26	.74	.06	.82

Industry dummies included in the set of control variables.
Robust standard errors in parenthesis below estimated coefficients.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Extensive margin: Number of product innovations

	(1) OLS	(2) Heckman	(3) Tobit
RDONLY_LAG	0.682	0.963*	4.935***
	(0.923)	(0.535)	(1.183)
OTHERONLY_LAG	-0.232	-0.006	2.091***
	(0.430)	(0.099)	(0.612)
BOTH LAG	0.593	0.794***	4.268***
	(0.576)	(0.255)	(0.764)
LNEMPLOYEES	0.286***	0.156***	1.109***
	(0.100)	(0.033)	(0.167)
EXPINTEN_LAG	-0.752	-0.409	-0.847
	(0.912)	(0.335)	(1.208)
IMITATION	0.409	0.227*	1.130**
	(0.374)	(0.127)	(0.450)
INTERNALRESOURCES	-0.524	-0.118	0.416
	(0.413)	(0.147)	(0.465)
PERSONNEL	0.431	0.049	-0.330
	(0.373)	(0.122)	(0.438)
Number of obs.	550	2020	2020
Complement. test	.02	.08	4.881
p-value	.89	.78	.027

Industry dummies included in the set of control variables.
Robust standard errors in parenthesis below estimated coefficients.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Intensive margin: Sales from innovative products

	(1) OLS	(2) GLM	(3) Heckman	(4) Tobit
RDONLY_LAG	0.044*	0.033	0.037	0.182***
	(0.026)	(0.027)	(0.026)	(0.044)
OTHERONLY_LAG	0.009*	0.008	0.005	0.082***
	(0.005)	(0.011)	(0.006)	(0.021)
BOTH LAG	0.031***	0.019	0.024**	0.148***
	(0.011)	(0.015)	(0.011)	(0.027)
LNEMPLOYEES	0.004**	0.005*	0.004*	0.037***
	(0.002)	(0.003)	(0.002)	(0.006)
EXPINTEN_LAG	0.000	-0.012	-0.001	0.010
	(0.013)	(0.018)	(0.014)	(0.043)
IMITATION	0.008*	0.005	0.011**	0.044***
	(0.005)	(0.007)	(0.005)	(0.016)
INTERNALRESOURCES	0.000	0.001	-0.000	0.011
	(0.005)	(0.009)	(0.005)	(0.017)
PERSONNEL	0.000	0.004	-0.001	-0.014
	(0.005)	(0.006)	(0.005)	(0.016)
Number of obs.	2003	2003	2007	2003
Complement. test	.67	.62	.43	6.221
p-value	.41	.43	.51	.013

Industry dummies included in the set of control variables.
Robust standard errors in parenthesis below estimated coefficients.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Intensive margin: Productivity of innovation expenditures

	(1) OLS	(2) Heckman	(3) Tobit
RDONLY_LAG	1.867***	1.637***	6.009***
	(0.702)	(0.571)	(1.806)
OTHERONLY_LAG	0.379	0.332	2.689**
	(0.264)	(0.295)	(1.167)
BOTH_LAG	0.998***	0.778**	4.561***
	(0.380)	(0.365)	(1.303)
LNEMPLOYEES	0.488***	0.394***	1.636***
	(0.069)	(0.069)	(0.228)
EXPINTEN_LAG	0.183	-0.128	0.840
	(0.568)	(0.508)	(1.611)
IMITATION	0.470**	0.429**	1.817***
	(0.187)	(0.187)	(0.620)
INTERNALRESOURCES	0.025	0.011	0.202
	(0.200)	(0.193)	(0.630)
PERSONNEL	-0.200	-0.236	-0.646
	(0.179)	(0.180)	(0.598)
Number of obs.	1576	2009	1576
Complemt. test	2.958	3.94	4.75
p-value	.086	.05	.03

Industry dummies included in the set of control variables.
Robust standard errors in parenthesis below estimated coefficients.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Intensive margin: Industry-specific regressions

	(1) Heckman	(2) Tobit	(3) Heckman	(4) Tobit
RDONLY_LAG	0.003	0.090	0.096	0.182***
	(0.018)	(0.056)	(0.061)	(0.044)
OTHERONLY_LAG	-0.001	0.038	0.011**	0.082***
	(0.010)	(0.027)	(0.005)	(0.021)
BOTH_LAG	0.021	0.118***	0.027	0.148***
	(0.015)	(0.034)	(0.017)	(0.027)
LNEMPLOYEES	0.007**	0.040***	0.001	0.037***
	(0.003)	(0.008)	(0.003)	(0.006)
EXPINTEN_LAG	-0.031	-0.059	0.030	0.010
	(0.019)	(0.061)	(0.022)	(0.043)
IMITATION	0.010	0.038*	0.011*	0.044***
	(0.007)	(0.022)	(0.006)	(0.016)
INTERNALRESOURCES	-0.006	-0.007	0.006	0.011
	(0.007)	(0.023)	(0.007)	(0.017)
PERSONNEL	0.007	0.021	-0.008	-0.014
	(0.007)	(0.021)	(0.006)	(0.016)
Number of obs.	969	966	1038	2003
Complemt. test	.87	.025	1.63	6.221
p-value	.352	.875	.2	.013

Industry dummies included in the set of control variables.
Robust standard errors in parenthesis below estimated coefficients.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.