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## A Multilevel Analysis for Latin America

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# Competition and Distance to the Technological Frontier as Determinants of Innovation: A Multilevel Analysis for Latin America

E. Tacsir,* M. Pereira,† F. Favata,‡ and J. Leone§

Abstract*

Using a multilevel analysis and the new Harmonized Latin American Innovation Surveys Database (or LAIS database) augmented with indicators from the U.S. Census Bureau's Survey of Business Owners (SBO) and the World Bank's World Integrated Trade Solution (WITS), this paper presents estimates of the effects of import competition and distance to the technological frontier on firm innovation in Latin American countries. Although innovation is recognized as a multilevel phenomenon, with investment decisions not solely affected by the firm characteristics but also by the context in which each firm is embedded, the empirical literature adopting a multilevel design is still nascent and scarce. Using a two-level random slope model allows us to overcome some of the pitfalls of traditional regression models when dealing with the hierarchical structure of data while allowing us to capture the influence of contextual factors. The results suggest that the fostering effect of foreign competition depends on the firm's distance to the technological frontier. The estimates suggest that the lower the foreign competition and the greater the productivity gap, the lower the probability of firms engaging in innovation. In contrast, when a firm operates in a sector that is relatively closer to the technological frontier, firms invest in innovative activities to remain at the top. These results offer a clear and useful guide for designing policies in Latin America regarding innovation among firms. While it is important to promote and stimulate innovation efforts by firms, these factors should not be overlooked as considerations: sectoral characteristics associated with the economies, sectoral openness to foreign competition, and firms' distance to the technological frontier.

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## 1. Introduction

The decision to pursue innovation efforts is not fully explained by microeconomic determinants alone. In addition to the characteristics and capabilities of firms, several meso-economic factors might play a role in firm behavior. This paper focuses on the overlooked role of the context and industry to better understand the conditions under which firms introduce innovations. Sector characteristics provide useful information that has traditionally been underexploited.[1]

Based on a multilevel analysis (i.e., two-level random slope model for binary responses) (Goldstein, 2010; Oshchepkov and Shirokanova, 2022; Srholec, 2011a; Yang and Schmidt, 2021), we examine the effects that context characteristics in which firms operate have on the likelihood of firm innovation. This paper presents novel evidence with two main distinctive features. First, it produces the first research regarding whether the context and sectoral features affect the probability of innovating by means of a multilevel setting in the Latin American context. In particular, the multilevel approach is relevant as it allows us to include a set of dummies and explanatory variables at the sector level and produce more accurate standard errors (SE) than in a typical ordinary least squares (OLS) setting. Second, this paper presents evidence that is comparable across the region by using the Harmonized Latin American Innovation Surveys Database (or LAIS database), a novel dataset that allows us to provide comparable evidence from a larger pool of countries than previously available (Crespi et al, 2022). LAIS is a free-access innovation survey developed by the Inter-American Development Bank (IDB) that provides empirical information for productive sectors in a wide group of countries in the region. The LAIS database includes data on innovation expenditures, sources of information and collaborations for innovation, obstacles to innovation, outputs and effects, protection of innovation results, and general firm characteristics.

This research strategy allows us to include other factors that affect firms' decisions about innovation. Specifically, we considered the impact of sector characteristics—such as import competition (captured by the weighted average for import tariffs) and the

[1] Generally, sectors are only introduced in the empirical analysis as control or fixed effect variables in the cross-section and panel approaches, respectively.

distance to the technological frontier[2]—on innovative behavior and performance at the firm level. The results suggest that the effect of fostering foreign competition depends on the distance that the firm operates from the technological frontier. The estimates suggest that the lower the foreign competition and the greater the productivity gap, the lower the probability of firms engaging in innovation. On the other hand, when firms are relatively closer to the technological frontier, they invest in innovative activities to remain at the top in the sector. These results offer a clear and useful guide for the design of innovation policy in Latin America.

## 2. Relevant Literature

### 2.1 Innovation as a Multilevel Phenomenon: Empirical Challenges

Innovation is a multilevel phenomenon. Investment decisions and performance are not solely affected by a firm's characteristics or capabilities, but also by the context in which each firm operates. Despite acknowledging this phenomenon in the theoretical literature, empirical research that adopts a multilevel design is still nascent and scarce, mostly due to lack of comparable data for different country settings.

Although most research into innovation focuses on one specific level (i.e., the firm, or micro, level), there is a growing interest in multilevel setting (Fagerberg and Srholec, 2008; Lorenz, 2014; Srholec, 2010, 2011b; Bresciani et al., 2021; Campisi et al., 2022; Molodchik et al., 2021; Petruzzelli and Murgia, 2021, to name a few contributions). The importance of adopting an adequate econometric approach for the study of multilevel phenomena is twofold. First, statistical reasons urge the adoption of multilevel models. As a result of the hierarchical structure of data, when applying a traditional regression model based on a partial least squares method, the assumption of independent observations would be violated (Hox et al., 2017), leading to biased standard errors and inefficient coefficients (Bryk and Raudenbush, 1992) Additionally, multilevel models avoid both ecological fallacy and individual fallacy. The ecological fallacy occurs when assuming that attributes at the higher level (i.e., the level of sector, region, or nation) are directly reflected in the behavior of firms (Robinson, 2009). The individualistic fallacy results by incorrectly imputing behavior of economic actors (e.g., level 1) to sectors (i.e., level 2) (Seligson, 2002). Secondly, there are theoretical reasons to recommend using

[2] The productivity gap is measured as the gap of the sectoral labor productivity in relation to the equivalent in the United States.

multilevel models. While using a set of "fixed-effect" dummy variables has been applied as a solution to control for contextual variables, such as that of a country, this approach is of little help if the research focuses on understanding the effects of contextual conditions themselves. Only multilevel models allow evaluation of the extent to which specific differences between different contexts are accountable for outcomes at the level of the firm. As far as we know, this paper is the first dealing with a multilevel setting in the context of Latin America and the Caribbean (LAC).

To date, the literature exploiting a multilevel approach is limited. Goedhuys and Srholec (2010) used World Bank datasets of about 19,000 firms in 42 countries to estimate a multilevel production function with effects of firms' technological capabilities in the context of national conditions; the results confirm that the effects of the national conditions and the technological capabilities of firms are closely intertwined. Specifically, Goedhuys and Srholec found that the quality of institutional conditions predicts the firm's likelihood of innovating while the tax system, inflation, basic education, and political system were important determinants for innovation outputs. In a similar spirit, Goedhuys and Srholec later (in 2015) pooled microdata from 32 countries and around 15,000 manufacturing firms. Goedhuys and Srholec's 2015 results indicate that the technological infrastructure and the educational system of the national context make a large difference in innovation and most significantly interact with firms' technological capabilities. Based on a sample of firms from 23 developing countries, Lorenz (2014) investigated whether enterprises are more successful in their innovative activities in nations where social capital is more developed. In this case, the multilevel modeling allowed Lorenz to link the micro-level data on the characteristics and innovative performance of enterprises to national-level measures of social capital. The results of Lorenz (2014) include that (i) social capital (defined as networks and patterns of social interaction) increases the likelihood that firms innovate, and (ii) the benefits of research and development (R&D) expenditures and employee training for the firm's innovation performance are moderated by the level of national social capital.

### 2.2 Import Competition, Productivity Gap, and the Effect on Innovation

Over recent decades, several countries in Latin America have embarked on structural reforms that seek to enhance innovation and increase productivity by reducing both trade barriers and restrictions to direct foreign investment. However, the available evidence largely suggests that results have been disappointing for both factors (Álvarez et al., 2019).[3] Along the same line, Lederman et al. (2013) have argued that low levels of innovation activity in Latin America are the result of shortfalls in competitive pressure, especially for industries that are less exposed to international competition and relatively more concentrated. These findings are in line with research that claims that competition ends up fostering innovation and growth (Blundell et al., 1999; Geroski et al., 1997; Nickell, 1996, to name a few studies).

The most recent literature on industrial organization predicts an inverted-U-shaped relationship between innovation and competition (Acemoglu et al., 2006) in which the escape-competition effect tends to dominate for low initial levels of competition, but the Schumpeterian effect tends to overpower for a more competitive environment. Initially, competition may boost the incremental profits from innovation, consequently encouraging R&D investments aimed at "escaping competition." This is particularly the case for industries in which firms face similar production costs (neck-and-neck firms). In these industries, firms innovate to topple production costs "step-by-step" and a laggard firm must first catch up with the technological leader before it can become a leader itself. However, it should be mentioned that, in industries far away from the productive frontier, more competition may lower innovation as the laggard's reward for catching up with the technological leader may fall, thus boosting other strategies to drive the firm forward (e.g., preserving market quotes, public protection). Beyond a certain threshold, more-competitive markets tend to shrink rents that reward successful innovators. Similarly, Amiti and Khandelwal (2013) address the relationship between innovation (by means of quality upgrading) and import competition. For firms already producing very high-quality goods, low tariffs induce them to produce goods of even higher quality, but for those producing very low-quality goods, lower tariffs discourage upgrading quality.

[3] The evidence of the links between innovation and market competition is quite scarce for LAC countries (Zuñiga and Benavente, 2022). However, there are some insights stemming from the studies on the impact of trade liberalization on firms, which tends to apply to only a range of firms (i.e., larger, and more productive firms) and sectors (i.e., those that already faced import competition) (e.g., Amiti and Konings, 2007; Bustos, 2011; Iacavone et al., 2013).

Benavente and Zuñiga (2021) find strong evidence that competition plays a moderating role in the effectiveness of policies to encourage investment in firm innovation. Also, Zuñiga and Benavente (2022) exploit firm-level data from manufacturing firms from Chile and Colombia to evaluate the causal impact of market competition on firms' innovation engagement. By expanding the analytical framework proposed by Aghion et al., (2005), Zuñiga and Benavente (2022) shows that competition increases the propensity for firms to invest in innovation in the two countries. However, this relationship manifests in different ways: in Chilean firms, the relationship is linear, but among Colombian enterprises, an inverted-U shaped relationship prevails. These findings stress the importance of regulations that promote competition and firm innovation.

Overall, the literature received to date yields two important lessons for policy design. First, the characteristics of the market in which firms operate must be considered when designing public policy to support innovation. Second, the interaction with competition policy is key to spurring innovation and technological change.

## 3. Research Questions and the Implications for Innovation Policy

As mentioned earlier, our objective is to contribute to a better understanding of the contextual factors that drive or constrain firms' innovation. In this context, the literature review leads us to propose a set of research questions. We believe that addressing them will provide useful answers for policymakers regarding innovation in Latin America.

- How do the contextual characteristics, including the sector in which firms operate, affect firms' innovative performance?
- How does the foreign competition within a sector affect the probability of innovation? What factors mediate the relationship between competition and innovation?
- What role does the distance to the technological frontier play regarding innovation by firms in Latin America?

To answer these questions, we use an approach similar to what Arias-Ortiz et al. (2014) used when exploiting the World Bank Enterprise Survey database. That is, we expand the information of the LAIS database with information from other sources such as the U.S. Census Bureau's Survey of Business Owners (SBO) and World Bank's World Integrated Trade Solution (WITS).

# 4. Methodology

## 4.1 Data: Augmented LAIS

Our empirical research begins by exploiting the LAIS database, which was developed and released by the IDB. The LAIS database contains data from 10 Latin American countries from 30 national innovation surveys conducted between 2007 and 2017, for nearly 690 variables, and for 119,900 observations at the firm level.[4] The LAIS database includes data on innovation activities, expenditures, sources of information and collaborations for innovation, obstacles to innovation, outputs and effects, protection of innovation results (for example, with patents), and general firm characteristics. Our research involved exploiting the LAIS database and augmenting it by including indicators that allow estimating (i) the distance from the sector's technological frontier, and (ii) import competition within each sector.

Regarding the technological frontier and the productivity gap, as in Arias-Ortiz et al. (2014), we assume that the most productive firms in the United States are in fact the technological frontier for each sector. That is, we consider the frontier for each sector to be equivalent to the 95th percentile of the ratio of total revenues over full-time employees in the sector as classified in two-digit level classifications in the United States (see Annex 1). There are two different sources to construct such an indicator: the Survey of Business Owners (SBO) and the Annual Business Survey (ABS). The SBO was carried out by the U.S. Census Bureau every five years until 2012, when it was discontinued. The SBO survey captured the number of companies (employers and non-employers), the sales and income for each firm, and the annual payroll and wage bill. The ABS is carried out jointly in the United States by the Census Bureau and the National Center for Science and Engineering Statistics. The ABS came to replace the SBO (among other surveys, including the R&D survey), and for this reason, it has been carried out since 2017 on an annual basis. The ABS provides information on economic and demographic characteristics of businesses and information on business owners by gender, ethnicity,

[4] The LAIS database contains firm-level data over the period 2004–2016, from Argentina, Chile, Colombia, Dominican Republic, Ecuador, El Salvador, Panama, Paraguay, Peru, and Uruguay. All these surveys cover the manufacturing sector and selected services in some countries. See Crespi et al (2022) for more details on the construction and characteristics of the dataset.

race, and military veteran status. In addition, the survey measures R&D activities, innovation results, and technological characteristics of firms.

As became evident during our research, the LAIS database concentrates on information for different time periods. Hence, we determined that the frontier to use would have to satisfy (at least) the criterion of being covered by most of the surveys to be exploited for LAC countries. After studying both the SBO and ABS bases, we concluded that the SBO was the most appropriate to construct the sector productivity frontier indicator because its last publication corresponds to 2012, a point in time that was equidistant from the start and finish of the LAIS coverage period (2007–2017). Based on the SBO, we constructed a data series for the sector productivity frontier for each of the considered sectors every year in the period of 2007–2017. Our first step was to construct a frontier base year. To do so, we considered the ratio between the revenue and number of employees reported in the SBO for the year 2012 as the proxy for productivity. After constructing this base, we extrapolated the base in five-year periods immediately before and after 2012 (2007–2011 and 2013–2017, respectively). To achieve this, we made use of the variations in the sector productivity index reported by the U.S. Bureau of Labor Statistics (BLS).[5] In addition, we constructed a correspondence table between both bases by considering a four-digit sectoral breakdown (when possible). Finally, we calculated for each sector of economic activity, the 95th percentile of the distribution of the ratio of sales per employee.[6] As previously noted, this variable is used as our proxy for the sectoral productivity frontier. The final step to augment the LAIS database with the productivity frontiers required an additional effort to adapt the different classifications used. While the LAIS database uses the International Standard Industrial Classification (ISIC), the SBO uses the North American Industry Classification System (NAICS). To correlate the classification systems, we used sectoral concordance tables such as those published by the U.S. Bureau of Census.[7]

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[5] Labor productivity growth is constructed as a difference between output growth and the growth in the hours worked. The series can be consulted at the web site of the U.S. Bureau of Labor Statistics, Office of Productivity and Technology (OPT). See https://www.bls.gov/lpc/data.htm.

[6] In this case, productivity is measured as sales per worker because the data used here does not allow for calculating the total factor productivity (TFP) at the firm level.

[7] See the web site for the North American Industry Classification System (NAICS), https://www.census.gov/naics/?68967.

After determining the technological frontier for each of the different sectors, we were then able to compare for each firm in the LAC dataset. To do so, we generated the firm's productivity gap, which is a relative measure of the firm's productivity compared with the frontier. This measure is defined as the ratio of the firm's sales per worker compared with the sales per worker of a U.S. firm in the sector located at the productivity frontier.

Tables A1 and A2, in the Annex, presents in detail the correspondence of the sectors in the LAIS database to the ISIC codes, with the ISIC revision 3 and ISIC revision 4 presented separately.[8] Finally, for each firm in the LAIS database, a variable capturing the relative distance to the frontier was constructed. This variable was our proxy for the productivity gap for each firm.

For import competition, we measured using import tariffs with data from the World Bank's World Integrated Trade Solution (WITS) database for each country in our sample at the six-digit level, which is the most disaggregated and comparable level.[9] (Data are classified using the Harmonized System (HS) of trade, and the results were presented at the product level for 21 product groups.) Tariffs are a good proxy for import competition as many studies have shown that lowering tariffs leads to pro-competitive pressures in the liberalizing country by reducing markups and inducing a reallocation of resources to more productive firms (Amiti and Khandelwal, 2013). The weighted mean applied tariff (or AHS Weighted Average) is the average of effectively applied rates weighted by the product import shares corresponding to the rest of the world. Tariff line data were matched to the ISIC revision 3 and 4 codes to expand the LAIS dataset. To do that, we employed traditional concordance tables available from the WITS site.

Finally, there are two important clarifications: only in four cases (tobacco, paper, printing, and sewage) was it not possible to obtain a particular weighted tariff. In these cases, the average tariff for the entire manufacturing industry was imputed at the country level and the year level. In the cases where the information presented temporal gaps, the closest tariff in time was imputed.

[8] Depending on the observation year, LAIS uses the classifications known as ISIC 3-rev or ISIC 4-rev.
[9] The World Bank World Integrated Trade Solution (WITS) web site is available at https://wits.worldbank.org/.

## 4.2 Identification Strategy

We applied a random intercept model with group-level explanatory variables for binary responses (also called a multilevel model for binary variables), which is particularly appropriate for research designs when databases are organized at more than one level. In this case, data exhibit a two-level structure: the units of analysis are firms (the lower level of analysis), which are nested within sectors (the higher level). This model differs from a standard regression model in that the intercept is given a probability model and therefore contains more than one error term (i.e., one for each sector). A multilevel approach has several advantages when compared to OLS. Nonetheless, it should be noted that multilevel modeling does not solve some econometric challenges while it amplifies others. Concerning the clustering of errors, multilevel analysis is more vulnerable to a small cluster size. As well, there is a similar trouble regarding omitted variables, which is usually tackled with a quasi-experimental approach (instrumental variables, for instance), which is not incorporated in the multilevel framework. However, with a multilevel approach, a simultaneity issue persists due to the non-independence among explanatory variables and the error term.

We propose the set of equation 1 and equation 2 to evaluate, all else being equal, the effect of firms' innovation and sectoral characteristics. Additionally, a random effect at the sectoral level was incorporated to capture variations in the probability of innovation bringing about or giving rise to differences between sectors. Formally:

$$Innovations_{ij}^{*} = \beta_{0j} + \beta_1 FirmsInnov_{ij} + \lambda' CV_{ij} + \varepsilon_{ij} \quad (1)$$

$$\beta_{0j} = \beta_{00} + \beta_1 FirmsInnov_{ij} + \alpha_1 Contextual_j + u_j \quad (2)$$

In the mixed or combined form, this model reads as follows:

$$Innovations_{ij}^{*} = \beta_0 + \beta_1 FirmsInnov_{ij} + \alpha_1 Contextual_j + \lambda' CV_{ij} + u_j + \varepsilon_{ij} \quad (3)$$

where *i* indexes firms and *j* indexes the sector. The dependent variable $Innovations_{i,j}^{*}$ is a binary variable that takes the value of 1 if the firm has introduced a technological (or non-technological) innovation. The right side of equation 3 consists of $FirmsInnov_{i,j}$, a vector that includes variables at the firm level associated with their innovative capabilities; $Contextual_j$ is a vector of contextual variables at the sectoral level; and finally

$CV_{i,j}$ represents the set of control variables. In this model, we have two residuals, (i) a group random effect, $u_j \sim N(0, \sigma_u^2)$, and (ii) an individual random effect, $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$. Both residuals are assumed independent of each other and of the covariates. Given the random effect $u_j$, the outcome $Innovations_{ij}^{*}|u_j$ follows an ordinary linear model with intercept $\beta_0 + u_j$, hence the name "random intercept." While $\beta_0$ is the overall intercept in the linear relationship between the probability of innovating and the independent variables, the intercept for a given sector $j$ is $\beta_0 + u_j$, which will be higher or lower than the overall intercept depending on whether $+u_j$ is greater or less than zero.[10]

The set of indicators related to firms' capabilities to innovate[11] expressed as $FirmsInnov_{i,j}$) includes: (i) the firms' innovative profile, (ii) the existence of an R&D department, (iii) the share of professional employees in the labor force, and (iv) cooperation to innovate (for R&D, training, product testing, among others) with competitors, suppliers, clients, universities, and R&D laboratories. The set of indicators that capture the sectoral characteristics that affect innovation (expressed as $Contextual_j$) is composed of (i) the distance to the technological frontier (i.e., the productivity gap), (ii) the average import tariff of each country and sector with respect to the rest of the world, and (iii) the interaction between the productivity gap and the average import duty. Finally, the set of indicators linked to the control variables (expressed as $CV_{i,j}$) includes: (i) size stratum, (ii) country and year fixed effect, (iii) the firm's export profile, and (iv) the firm's labor productivity level. To estimate equation 1, we employ a mixed-effects model for binary or binomial responses.[12]

A final clarification regarding methodology relates to the endogeneity of foreign competition. As mentioned by Álvarez et al. (2019), this problem arises mainly from three sources. First, there may be causality in the opposite direction—that is, more innovation may affect competition in the industry. For example, a firm could be less affected by competition if it innovates with products or processes to make itself more efficient and

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[10] Note that this specification is equivalent to the traditional panel data random effects model. Only the intercept varies at the sector level. Hence only the intercept is considered a random coefficient. In other words, the vector of contextual variables is restricted to have a common effect on all sectors. As will be indicated in section 7, Conclusions, relaxing this restriction and estimating a model that allows for random variation of intercept and slope across sectors may be explored in another paper.
[11] A detailed presentation of the variables used in this study is discussed in section 5, Data and Descriptive Statistics.
[12] To read a further description of the statistical model used to estimate the parameters, see StataCorp., 2023, and the information available at: https://www.stata.com/manuals/memeprobit.pdf.

competitive; and the opposite may also be true. Second, several works have documented that self-reported measures of obstacles to innovation, such as a lack of competition, are endogenous (Álvarez and Crespi, 2015; Mohnen et al., 2008; Savignac, 2008). One reason is that, for instance, a firm that does not invest in innovation (in the form of R&D, for example) might justify this decision by reporting greater obstacles to doing so. Furthermore, in relation to the first reason, a firm that invests relatively more might perceive smaller obstacles. Third, errors might be made in measuring foreign competition, which leads to attenuation bias in estimators.

## 5. Data and Descriptive Statistics

As noted in Section 4, the dataset used for this paper arises from expanding the Harmonized Latin American Innovation Surveys Database (or LAIS database) with indicators from the U.S. Census Bureau's Survey of Business Owners (SBO) and the World Bank's World Integrated Trade Solution (WITS). Table 1 shows the countries and observations, and Table 2 shows a detailed description of the variables constructed. Two important clarifications should be made. First, although the LAIS dataset presents information for 10 countries, we have grouped some countries to maintain a homogeneous analysis: Ecuador and Paraguay were combined into one group (representing 11 percent of observations), while Panama, El Salvador, and the Dominican Republic were combined into another group (representing 1 percent of observations), as shown in Table 1. This consolidation results in seven distinct country categories. This decision is based on the fact that a limitation of multilevel models emerges in contexts where the number of second-level observations is limited (Oshchepkov and Shirokanova, 2022).

Table 1. Country Observations

| Country | Observations. | Frequency | Cumulative frequency |
|---|---|---|---|
| Ecuador and Paraguay | 3,633 | 11% | 11% |
| Panama, Salvador and Dominican Republic | 474 | 1% | 12% |
| Argentina | 2,138 | 6% | 19% |
| Chile | 1,909 | 6% | 25% |
| Colombia | 21,302 | 65% | 89% |
| Peru | 2,079 | 6% | 95% |
| Uruguay | 1,489 | 5% | 100% |
| Total | 33,024 | 100% | |

*Source:* Authors' elaboration based on LAIS.

Table 2. Variable Description

| Variable | Description |
|---|---|
| | **Dependent variables** |
| TPP_inno_broad | Binary variable that indicates **whether the firm achieves a technological innovation (or TPP innovation, including both product and process innovation) in** a broad sense (new to the firm, country, or world) |
| TPP_inno_narrow | Binary variable that indicates whether the firm achieves a TPP innovation in a narrow sense (new to the country or world) |
| NonTech_inno | Binary variable that indicates whether the firm achieves a non-technological innovation |
| | **Covariates at the firm level** |
| RD_department | Binary variable that indicates whether the firm has an R&D department |
| inno_public_program | Binary variable that indicates whether the firm accesses public programs to support innovation |
| Share_prof | Ratio between the number of professional employees and the total workforce |
| Innovative_firm | Binary variable indicating whether the firm has made expenditures for innovation activities |
| Link_Competitors_Clients | Binary variable that indicates whether the firm has established links with competitors, customers, and suppliers |
| Link_Univ_RDLabs | Binary variable that indicates whether the firm has established links with universities and R&D laboratories |
| Export_status | Binary variable that indicates whether the firm declared sales to external markets |
| Labor_productivity | Ratio of sales per employee |
| Size | Set of binary variables indicating the size of the firm—whether the firm is classified as micro (0 to 10 employees), small (11 to 40 employees), medium (41 to 100 employees), or large (101 employees or more) |
| | **Covariates at the sector level** |
| Prod_Gap | Distance between sector labor productivity and U.S. labor productivity, measured in US$ million |
| Import_duty | Average import tariff by country, year, and sector |

*Source:* Authors' elaboration based on LAIS.

Second, the LAIS coverage at the sector level differs from country to country, so this study only considers manufacturing sectors. Therefore, the final number of observations is 33,024. Table 1 shows the distribution of observations at the country level. About 65 percent of the database are observations from Colombia. The participation of the rest of the countries in the database is very homogeneous and ranges between 2,000 and 3,000 observations except for relatively smaller countries such a Panama, Salvador, and Uruguay. Each individual country survey provides nationally representative data at the sector level.

Table 3 shows summary statistics for the variables included in the model, with the firm-level variables in the upper panel and the sector-level variables in the lower panel. Thirty percent of the manufacturing firms in the LAIS dataset met the criteria for a technological innovation, at least using the broader definition. If we impose the more-stringent definition of innovation (either new to the market or the world), this figure falls to less than 20 percent of firms. The difference is significant and reflects the limitations of the self-reported innovation indicator. Finally, about 30 percent of the companies reported having achieved non-technological innovation.

Almost 37 percent of the surveyed firms self-report themselves as exporters, and the average firm labor productivity (expressed in the ratio of sales to employees) is close to US$ 105,000 per year. Firm size is defined based on the number of permanent employees. The largest share of surveyed firms is small (43 percent, with 11 to 40 employees), while only 21 percent have a staff above 100 employees. While a relative relevant proportion (30 percent) self-report that they are making innovation efforts, only a very small proportion of firms state that they have access to public funds for innovation, declare that they cooperate with the aim of innovating (especially with competitors and suppliers), and have a dedicated internal R&D department. Similarly, only a tiny proportion have applied for a patent in the recent period. Also, the share of professionals among total employees barely reaches 14 percent. Unfortunately, the dataset does not allow for differentiating the roles and area of the firm for these relatively high-skilled employees. Regarding sector-level variables, the average productivity gap (i.e., the distance to the international technological frontier) is around US$ 97 million and this is widely dispersed among the different sectors. With respect to import competition, the average tariff is 4.78 percent.

Table 3. Summary Statistics

| | *N* | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| **Covariates at the firm level** | | | | | |
| TPP_inno_broad | 33,024 | 0.308 | 0.462 | 0 | 1 |
| TPP_inno_narrow | 33,024 | 0.196 | 0.397 | 0 | 1 |
| Size—Micro | 33,024 | 0.154 | 0.361 | 0 | 1 |
| Size—Small | 33,024 | 0.432 | 0.495 | 0 | 1 |
| Size—Medium | 33,024 | 0.201 | 0.401 | 0 | 1 |
| Size—Large | 33,024 | 0.213 | 0.41 | 0 | 1 |
| Export_status | 33,024 | 0.367 | 0.482 | 0 | 1 |
| Labor_productivity | 33,024 | 105.8 | 921.4 | 0 | 68891 |
| NonTech_inno | 33,024 | 0.296 | 0.456 | 0 | 1 |
| RD_department | 33,024 | 0.0984 | 0.298 | 0 | 1 |
| inno_public_program | 33,024 | 0.0297 | 0.17 | 0 | 1 |
| Share_prof | 33,024 | 14.64 | 14.9 | 0 | 100 |
| Innovative_firm | 33,024 | 0.355 | 0.479 | 0 | 1 |
| Link_Competitors_Clients | 33,024 | 0.18 | 0.38 | 0 | 1 |
| Link_Univ_RDLabs | 33,024 | 0.09 | 0.29 | 0 | 1 |
| **Covariates at the sector level** | | | | | |
| Prod_Gap | 33,024 | 0.97 | 1.45 | -0.42 | 13.98 |
| Import_duty | 33,024 | 4.78 | 3.21 | 0.14 | 20.88 |

*Source:* Authors' elaboration based on LAIS database, U.S. Census Bureau's Survey of Business Owners (SBO), and World Bank's World Integrated Trade Solution (WITS).

*Notes:* (i) All monetary values are expressed in US dollars. (ii) The productivity gap (Prod_Gap) averages around US$ 97 million across sectors. (iii) Labor productivity is approximately US$ 105,000 per employee per year on average. (iv) The average import tariff (Import_duty) is 4.78 percent. (v) For detailed definitions of variables, please refer to Table 2

## 6. Results

Table 4 shows the results for the estimation of equation 1 employing a random intercept model. All parameters were estimated employing a mixed-effect probit regression, and Table 4 reports marginal effects. The first and second column show the different determinants of technological innovation (or TPP innovation, including both product and process innovation). The difference among the columns is related to the scope of the TPP innovation. The first column is broad in scope, considering innovative results for the firm, country, and world; in contrast, the second column presents a narrower and more-demanding definition in that it only considers those innovations that have an inventive step necessary at the country level or world level. The last column shows determinants of non-technological innovation.[13] To organize the results presented in Table 4, we first discuss the role of micro-determinants of innovation, then analyze the incidence of meso-determinants of innovation results, and finally present the sectoral ranking of random effects.

With regard to the micro-determinants of innovation, the first result to highlight corresponds to the impact attributed to the firm's innovative profile. This covariate indicates whether the firm performs innovative activities or not. The evidence suggests a positive and significant impact (+30 percentage points, or p.p., on average) on the probability of obtaining innovation results (both TPP and non-technological). In addition, among firms that perform innovative activities, the presence of a formal R&D department induce an increase in the probability of technological innovation (+4 p.p.). As expected, this covariate does not affect the chances of achieving non-technological innovation. Overall, the result seems trivial, but it characterizes the innovative profile of Latin American firms and its impact on innovative performance. Most firms do not perform innovation activities (65 percent do not, according to the LAIS dataset), but those that do exert these efforts manage to achieve innovation results.[14]

The micro-determinants associated with achieving TPP innovation are different when we break down the variables considered. This is particularly evident when we consider the incidence of both (i) firms accessing programs that support innovation and (ii) cooperation with or links to universities or R&D labs. The results suggest that these variables are not associated with firms achieving introductions of innovations that are novel beyond the firm level—that is, at the country level and world level. This result suggests two complementary explanations. On the one hand, it may reflect that these knowledge institutions are mostly focused on solving problems for which there are globally available solutions, but this knowledge is somehow not yet mastered by the LAC firms, thus LAC universities and research organizations may not be such interesting partners for firms innovating at the world-class level. On the other hand, the result suggests that the most innovative firms have already moved toward internalizing these

[13] These include innovations in logistics, commercialization, marketing, and organization.
[14] It should be mentioned that different contributions have highlighted the high share of firms that self-report as innovators in LAC, in comparison to the evidence provided by innovation surveys in other regions.

capabilities. Similarly, it seems that its effect of public support programs for innovation is relevant only for those firms that are trying to catch up with existing practices and routines, and with a portfolio of products that is known to the market.

Regarding the presence of professionals in the workforce, this has a heterogeneous impact on innovation performance. Two results that emerge from the descriptive statistics are worth mentioning: (i) around 15 percent of the companies do not have professional human **resources, and (ii) among those firms that include professionals, the proportion of the employees who** are professionals is small (16 percent). In this context, the evidence suggests that having professionals in the firm workforce positively affects the probability of obtaining product or process innovation results with a degree of novelty at a national or global level. In contrast, if we adopt a broader definition of innovation (being new for that firm is enough), this positive correlation disappears. Finally, the presence of a higher share of professionals in the workforce is positively associated with non-technological innovation.

It is worth emphasizing that a random intercept model is a model in which intercepts are allowed to vary across sectors, and in this study, we assume that the intercept varies at the sector level. Therefore, the impact of meso-determinants on the probability of achieving innovation results is exerted through the intercept.

Regarding the sectoral characteristics that affect the probability of firms innovating, we first conduct an analysis of both import competition and the productivity gap.[15] Following Acemoglu et al. (2006), the expected effect of competition on innovation may depend on the distance of each industry to the international technological frontier. The estimated beta for coefficient capturing the interaction between the average import tariff and the productivity gap yields a negative value, which suggests that import tariffs have a significant impact on the probability of TPP innovation, but whether import tariffs have a positive or negative effect depends on how far away the sector is from the technological frontier. These results support distance-to-frontier models developed by Aghion et al. (2009), which provide a clear understanding

[15] Prior evidence for the LAC region indicates that, as individual effects, firm size, proximity to the technology frontier, and exporting orientation in developing country firms are often positively associated with firms' propensity to innovate (Crespi and Zuñiga, 2012; Crespi et al, 2014.)

of these findings. That is, if a firm belongs to a sector that is close to the world frontier,[16] it is in the firm's interest to invest in innovation to stay in that top position. In these sectors, the lower level of tariffs together with smaller distance to the frontier induce firms to innovate to compete globally (i.e., either via exports and/or with imports in their home market). However, if a firm belongs to a sector that is a long way from the frontier, the firm realizes that, even if it invests in costly innovation, it is still quite unlikely to catch up to the firms already at the frontier. Said differently, in sectors far away from the technological frontier, import tariffs act as a deterrent to foreign competition, limiting the incentive for firms to innovate to catch up with technological leaders. Additionally, estimated results suggest that the interaction between the sectoral productivity gap and import competition has no influence on the probability of obtaining non-technological innovation results.[17]

[16] As in this paper, in Aghion et al (2009), the distance to the frontier is measured on the industry level relative to the U. S. labor productivity levels.

[17] As a robustness test, we use another indicator associated with the level of competition in a sector. We take the Herfindahl-Hirschman index (HHI) as a proxy for concentration in a given market. The main findings are not altered since the estimates indicate that the interaction between the productivity gap and the HHI negatively impacts the probability of firms achieving innovations. The results can be found in Annex 2.

Table 4. Probability to Innovate: Micro- and Meso- Determinants

| | TPP_inno_broad | TPP_inno_narrow | NonTech_inno |
|---|---|---|---|
| **Firm-level covariates** | | | |
| Innovative firm | 0.284** | 0.303** | 0.324** |
| | (0.003) | (0.004) | (0.003) |
| R&D department | 0.046** | 0.020** | 0.003 |
| | (0.004) | (0.004) | (0.005) |
| Cooperation with competitors, clients, suppliers | 0.052** | 0.043** | 0.029** |
| | (0.004) | (0.004) | (0.004) |
| Cooperation with universities and R&D laboratories | 0.013** | 0.003 | 0.025** |
| | (0.005) | (0.005) | (0.005) |
| Access to public funding to innovation | 0.020** | -0.007 | 0.024** |
| | (0.007) | (0.007) | (0.007) |
| Share of professional | 0.008 | 0.014* | 0.015** |
| | (0.005) | (0.007) | (0.006) |
| **Sector-level covariates** | | | |
| Productivity gap (US$ millions) | 0.002 | 0.009** | -0.002 |
| | (0.002) | (0.003) | (0.002) |
| Import duty | -0.001 | -0.002+ | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| Productivity gap * Import duty | -0.001+ | -0.004** | -0.000 |
| | (0.001) | (0.001) | (0.001) |
| Observations | 33,024 | 33,024 | 33,024 |
| Number of firms | 1376 | 1376 | 1376 |
| Number of sectors | 24 | 24 | 24 |
| Year fixed effects | YES | YES | YES |
| Country fixed effects | YES | YES | YES |
| LR test vs logistic | 4.922 | 30.49 | 1.188 |
| P-value | 0.0133 | 1.67e-08 | 0.138 |

*Source:* Authors' own elaboration based on LAIS.
*Note:* All parameters were estimated employing a two-level random intercept model for binary responses. Standard errors are noted in parentheses. Significance levels are ** p<0.01, * p<0.05, + p<0.1

## 7. Conclusions

This study builds upon previous research examining the relationship between competition, distance to the technological frontier, and innovation, particularly the seminal work of Aghion et al. (2009). Our approach addresses important gaps in the literature by focusing on Latin American countries, a region relatively understudied in this context. Furthermore, we employ a multilevel analysis that considers factors at both the firm and sector levels, leveraging the novel LAIS database to provide comparative evidence across countries.

Our main objective was to answer how contextual characteristics affect firms' innovative performance, what the relationship is between foreign competition and the probability of innovation, and what role the distance to the technological frontier plays in these processes. The findings reveal that, while innovation is primarily driven by firm-level factors, sector characteristics play a crucial moderating role. In particular, the effect of foreign competition on innovation significantly depends on a sector's distance to the technological frontier. Firms in sectors closer to the technological frontier are more likely to innovate in response to competition, while for sectors further away, import tariffs can discourage innovation by limiting competitive pressure.

These conclusions have important implications for innovation policy and its interaction with trade policy. Firstly, they highlight the critical need to consider the interrelation between innovation policies and foreign trade policies, an area that has been insufficiently explored, especially in the context of Latin America and the Caribbean (LAC). Understanding this interaction is fundamental for designing effective interventions that promote greater technological innovation. Secondly, our findings underscore the importance of developing differentiated strategies that consider sectoral disparities in technological capabilities and competitive environments. The evidence suggests that generalized trade liberalization may not stimulate innovation uniformly across all sectors. On the contrary, specific and calibrated policies are required to boost innovation capacity, particularly in those sectors further from the technological frontier. This nuanced approach is essential to maximize the impact of innovation and trade policies, ensuring that they effectively complement each other to foster technological development and competitiveness across the diverse economic sectors of the region.

It is important to acknowledge the limitations of our study. We rely on self-reported innovation measures, and there is potential endogeneity in the relationship between competition and innovation. Additionally, our ability to establish causal relationships is limited by the nature of the data and study design.

These limitations point to fruitful opportunities for future research. Quasi-experimental methods could be employed to better establish causal effects, explore additional measures of competition and technological distance, and investigate how these relationships evolve over time as sectors develop. Moreover, it would be valuable to examine how specific innovation policies interact with sector characteristics to promote technological development and competitiveness. In sum, this study contributes to a more nuanced understanding of the determinants of innovation in Latin America, highlighting the importance of considering both firm-level factors and sector contexts in designing effective innovation policies.

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## Annex 1. Correspondence Between LAIS Dataset and SBO

### Table A1. Correspondence Table Between LAIS Dataset (ISIC rev4) and SBO (NAICS)

| LAIS | | | | SBO |
|---|---|---|---|---|
| ISIC rev. 4 – 1-digit | | ISIC rev. 4 – 1-digit and 2-digit manufacturing | | NAICS |
| Code | Name | Code | Name | Code |
| 1 | Agriculture, forestry, and fishing | 1 | Agriculture, forestry, and fishing | 11 |
| 2 | Mining and quarrying | 2 | Mining and quarrying | 21 |
| 3 | Manufacturing | 10 | Manufacturing of food products | 311 |
| | | 11 | Manufacturing of beverages | 312 |
| | | 12 | Manufacturing of tobacco products | 312 |
| | | 13 | Manufacturing of textiles | 314 |
| | | 14 | Manufacturing of wearing apparel | 315 |
| | | 15 | Manufacturing of leather and related products | 316 |
| | | 16 | Manufacturing of wood and of products of wood and cork | 321 |
| | | 17 | Manufacturing of paper and paper products | 322 |
| | | 18 | Printing and reproduction of recorded media | 323 |
| | | 19 | Manufacturing of coke and refined petroleum products | 324 |
| | | 20 | Manufacturing of chemicals and chemical products | 325 |
| | | 21 | Manufacturing of basic pharmaceutical products and preparations | 325 |
| | | 22 | Manufacturing of rubber and plastics products | 326 |
| | | 23 | Manufacturing of other non-metallic mineral products | 327 |
| | | 24 | Manufacturing of basic metals | 331 |
| | | 25 | Manufacturing of fabricated metal products | 332 |
| | | 26 | Manufacturing of computer, electronic, and optical products | 334 |
| | | 27 | Manufacturing of electrical equipment | 335 |
| | | 28 | Manufacturing of machinery and equipment NEC | 333 |

| LAIS | | | | SBO |
|---|---|---|---|---|
| ISIC rev. 4 – 1-digit | | ISIC rev. 4 – 1-digit and 2-digit manufacturing | | NAICS |
| Code | Name | Code | Name | Code |
| | | 29 | Manufacturing of motor vehicles, trailers, and semi-trailers | 336 |
| | | 30 | Manufacturing of other transport equipment | 336 |
| | | 31 | Manufacturing of furniture | 337 |
| | | 32 | Other manufacturing | 339 |
| | | 33 | Repair and installation of machinery and equipment | 333 |
| 4 | Electricity, gas, steam, and AC | 4 | Electricity, gas, steam, and AC | 22 |
| 5 | Water supply, sewerage | 5 | Water supply, sewerage | 22 |
| 6 | Construction | 6 | Construction | 23 |
| 7 | Wholesale and retail trade | 7 | Wholesale and retail trade | 42-44 |
| 8 | Transportation and storage | 8 | Transportation and storage | 48-49 |
| 9 | Accommodation and food service | 9 | Accommodation and food service | 72 |
| 10 | Information and communication | 10 | Information and communication | 51 |
| 11 | Financial and insurance | 11 | Financial and insurance | 52 |
| 12 | Real estate | 12 | Real estate | 53 |
| 13 | Professional, scientific, and technical | 13 | Professional, scientific, and technical | 54 |
| 14 | Administrative | 14 | Administrative | 55 |
| 16 | Education | 16 | Education | 61 |
| 17 | Human health and social work | 17 | Human health and social work | 62 |
| 18 | Art, entertainment, and recreation | 18 | Art, entertainment, and recreation | 71 |
| 19 | Other services | 19 | Other services | 81 |

*Source:* Authors' elaboration based on International Standard Industrial Classification (ISIC) and North American Industry Classification System (NAICS).
*Notes:* (1) ISIC Rev. 4 and Rev. 3 refer to the International Standard Industrial Classification (ISIC), Revision 4 and Revision 3 respectively. (2) NAICS refers to the North American Industry Classification System, (3) NEC stands for "Not Elsewhere Classified." (4) The tables show the correspondence between ISIC codes used in the LAIS dataset and NAICS codes used in the U.S. Survey of Business Owners (SBO).

Table A2. Correspondence Table Between LAIS Dataset (ISIC Rev 3) and SBO (NAICS)

| LAIS | | | | SBO |
|---|---|---|---|---|
| ISIC rev 3 – 1-digit | | ISIC rev 3 – 1-digit and 2-digit manufacturing | | NAICS |
| Code | Name | Code | Name | Code |
| 1 | Agriculture, hunting, and forestry | 1 | Agriculture, hunting, and forestry | 11 |
| 2 | Fishing | 2 | Fishing | 11 |
| 3 | Mining and quarrying | 3 | Mining and quarrying | 21 |
| 4 | Manufacturing | 15 | Manufacturing of food products and beverages | 311-312 |
| | | 16 | Manufacturing of tobacco products | 312 |
| | | 17 | Manufacturing of textiles | 313-314 |
| | | 18 | Manufacturing of wearing apparel; dressing and dyeing of fur | 315 |
| | | 19 | Tanning and dressing of leather; manufacturing of luggage | 316 |
| | | 20 | Manufacturing of wood and of products of wood and cork | 321 |
| | | 21 | Manufacturing of paper and paper products | 322 |
| | | 22 | Publishing, printing, and reproduction of recorded media | 323 |
| | | 23 | Manufacturing of coke, refined petroleum products | 324 |
| | | 24 | Manufacturing of chemicals and chemical products | 325 |
| | | 25 | Manufacturing of rubber and plastics products | 326 |
| | | 26 | Manufacturing of other non-metallic mineral products | 327 |
| | | 27 | Manufacturing of basic metals | 331 |
| | | 28 | Manufacturing of fabricated metal products | 332 |
| | | 29 | Manufacturing of machinery and equipment NEC | 333 |
| | | 30 | Manufacturing of office, accounting, and computing machinery | 334 |
| | | 31 | Manufacturing of electrical machinery and apparatus NEC | 335 |
| | | 32 | Manufacturing of radio, television, and communication | 334 |
| | | 33 | Manufacturing of medical, precision, and optical instruments | 334 |
| | | 34 | Manufacturing of motor vehicles, trailers, and semi-trailers | 336 |

| LAIS | | | | SBO |
|---|---|---|---|---|
| ISIC rev 3 – 1-digit | | ISIC rev 3 – 1-digit and 2-digit manufacturing | | NAICS |
| Code | Name | Code | Name | Code |
| | | 35 | Manufacturing of other transport equipment | 336 |
| | | 36 | Manufacturing of furniture; manufacturing NEC | 337 |
| 5 | Electricity, gas and water supply | 5 | Electricity, gas, and water supply | 22 |
| 6 | Construction | 6 | Construction | 23 |
| 7 | Wholesale and retail trade | 7 | Wholesale and retail trade | 42-44 |
| 8 | Hotels and restaurants | 8 | Hotels and restaurants | 72 |
| 9 | Transport, storage | 9 | Transport, storage, and communications | 48-49 |
| 10 | Financial Intermediation | 10 | Financial intermediation | 52 |
| 11 | Real estate, renting | 11 | Real estate, renting, and business activities | 53 |
| 13 | Education | 13 | Education | 61 |
| 14 | Health and social work | 14 | Health and social work | 62 |
| 15 | Social and personal services | 15 | Social and personal services | 62 |
| 18 | Others | 18 | Others | 81 |

*Source:* Authors' elaboration based on the International Standard Industrial Classification (ISIC) and the North American Industry Classification System (NAICS).
*Notes:* (1) ISIC Rev. 4 and Rev. 3 refer to the ISIC, Revision 4 and Revision 3 respectively. (2) NAICS refers to the North American Industry Classification System. (3) NEC stands for "Not Elsewhere Classified." (4) The tables show the correspondence between ISIC codes used in the LAIS dataset and NAICS codes used in the U.S. Survey of Business Owners (SBO), (5) NEC stands for "Not Elsewhere Classified."

## Annex 2. Robustness Check for the Probability to Innovate

### Table A3. Probability to Innovate: Micro and Meso Determinants

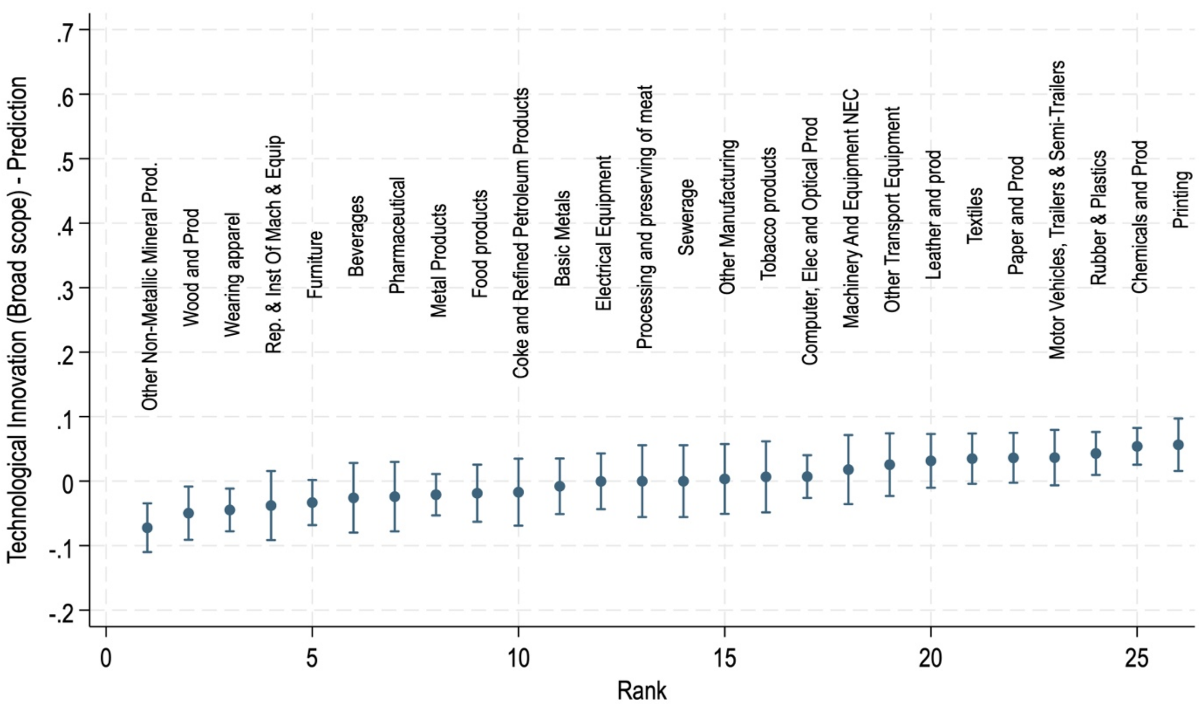
| | TPP_inno_broad | TPP_inno_narrow | NonTech_inno |
|---|---|---|---|
| Firm-level covariates | | | |
| Innovative firm | 0.283** | 0.303** | 0.324** |
| | (0.003) | (0.004) | (0.003) |
| R&D department | 0.046** | 0.020** | 0.003 |
| | (0.004) | (0.004) | (0.005) |
| Cooperation with competitors, clients, suppliers | 0.052** | 0.043** | 0.030** |
| | (0.004) | (0.004) | (0.004) |
| Cooperation with universities and R&D laboratories | 0.013** | 0.002 | 0.025** |
| | (0.005) | (0.005) | (0.005) |
| =1 if access to public funding to innovation | 0.020** | -0.007 | 0.024** |
| | (0.007) | (0.007) | (0.007) |
| bin_share | 0.008 | 0.013+ | 0.015** |
| | (0.005) | (0.007) | (0.006) |
| Sector-level covariates | | | |
| Productivity gap (US$ millions) | 0.001 | 0.007** | -0.003 |
| | (0.002) | (0.002) | (0.002) |
| HHI[18] index at sector level | -0.043* | -0.016 | -0.081** |
| | (0.017) | (0.023) | (0.020) |
| Prod. Gap * Concentration Index (HHI) | -0.003 | -0.015** | 0.007 |
| | (0.004) | (0.005) | (0.005) |
| Observations | 33,024 | 33,024 | 33,024 |
| Number of firms | 1376 | 1376 | 1376 |
| Number of sectors | 24 | 24 | 24 |
| Year fixed effects | YES | YES | YES |
| Country fixed effects | YES | YES | YES |

| | | | |
|---|---|---|---|
| LR test vs logistic | 3.188 | 26.23 | 3.653 |
| P-value | 0.0371 | 1.51e-07 | 0.0280 |

*Source:* Authors' elaboration based on LAIS database, U.S. Census Bureau's Survey of Business Owners (SBO), and the World Bank's World Integrated Trade Solution (WITS).
*Notes:* (i) All parameters were estimated employing a two-level random intercept model for binary responses. (ii) Standard errors are noted in parentheses. (iii) Significance levels: ** p<0.01, * p<0.05, + p<0.1. (iv) HHI refers to the Hirschman-Herfindahl Index HHI, a measure of market concentration. (v) LR test vs logistic refers to the Likelihood Ratio test comparing the multilevel model to a standard logistic regression.

## Annex 3. Random Intercept by Sector

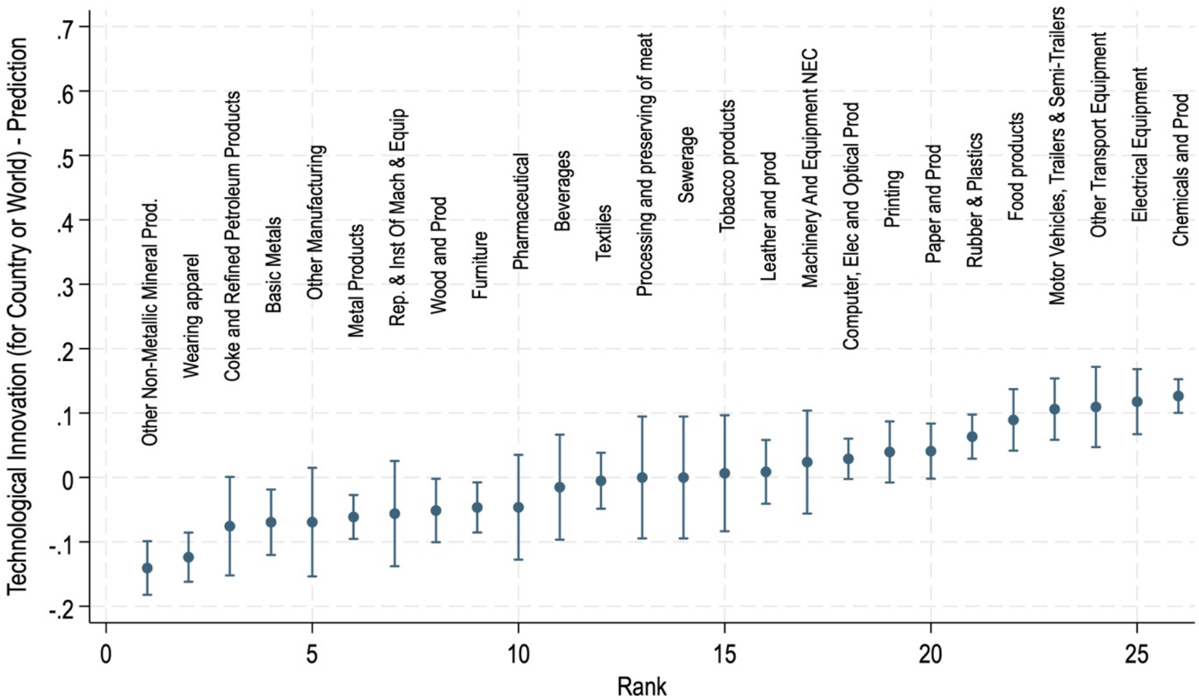
### Figure A1. Technological Innovation (Broad Scope): Rank of Predicted Intercept by Sectors




*Source:* Authors' calculations based on LAIS database.

*Notes:* (1) The figures show the ranking of predicted random intercepts by sector for different types of innovation. (2) The horizontal axis represents the deviation from the overall mean intercept. (3) Positive values indicate sectors with above-average propensity to innovate, while negative values indicate below-average propensity.

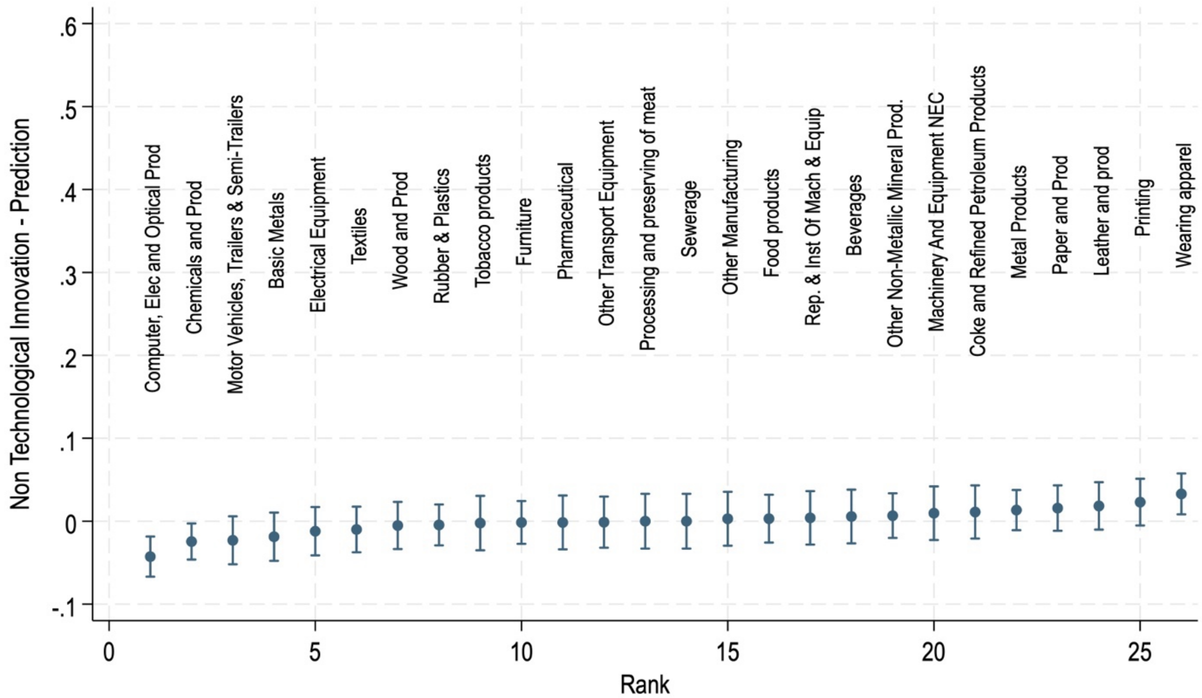
Figure A2. Technological Innovation (Narrow Scope) prediction by sector




*Source:* Authors' calculations based on LAIS database.

*Notes:* (i) The figures show the ranking of predicted random intercepts by sector for different types of innovation. (ii) The horizontal axis represents the deviation from the overall mean intercept. (iii). Positive values indicate sectors with above-average propensity to innovate, while negative values indicate below-average propensity.

Figure A3. Non-Technological Innovation Prediction by sector




*Source*: Authors' calculations based on LAIS database.

*Notes:* (i) The figures show the ranking of predicted random intercepts by sector for different types of innovation. (ii) The horizontal axis represents the deviation from the overall mean intercept. (iii) Positive values indicate sectors with above-average propensity to innovate, while negative values indicate below-average propensity.