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Productivity, agglomeration, and diversity: A multilevel analysis of firms in ecuadorian regions

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Abstract:

This paper analyzes how territorial conditions influence the productivity of manufacturing and service firms in Ecuador. We employ multilevel models to estimate the effects of the urban population share and regional sectoral diversity on total factor productivity and labor productivity, also incorporating the moderating role of innovation. The results show that approximately 5% of the differences in productivity are attributable to geographic location. The share of urban population has a positive effect in both sectors, while sectoral diversity benefits manufacturing exclusively. Likewise, it is observed that innovative manufacturing firms enhance the benefits of both agglomeration and diversity, while service innovative firms obtain additional advantages from diversity.

Keywords: Productivity; agglomeration economies; sectoral diversity; multilevel models; developing countries.
JEL Classification: R11; O31; L60; L80; C21.

Productividad, aglomeración y diversidad: Un análisis multinivel de empresas en regiones del Ecuador

Resumen:

Este artículo analiza cómo las condiciones territoriales influyen en la productividad de empresas manufactureras y de servicios en Ecuador. A través de modelos multinivel, se estima el efecto del porcentaje de población urbana y de la diversidad sectorial regional sobre la productividad total de factores y la productividad laboral, incorporando también el papel moderador de la innovación. Los resultados muestran que cerca del 5% de las diferencias en productividad se deben a la ubicación geográfica. El porcentaje de población urbana tiene un efecto positivo en ambos sectores, mientras que la diversidad sectorial beneficia exclusivamente a la manufactura. Asimismo, se observa que las empresas manufactureras innovadoras potencian los beneficios tanto de la aglomeración como de la diversidad, mientras que las de innovadoras de servicios obtienen ventajas adicionales de la diversidad.

Palabras clave: Productividad; economías de aglomeración; diversidad sectorial; modelos multinivel; países en desarrollo.
Clasificación JEL: R11; O31; L60; L80; C21.

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1. Introduction

Understanding the determinants of firm productivity is a central issue in economic research. While traditional approaches emphasize firm-specific and sectoral factors (Syverson, 2011; Dvouletý and Blažková, 2021; Camino-Mogro, 2022), a growing body of work points to the critical role of geography. The analysis of the geographical component requires methodological approaches capable of disentangling firm-level determinants from those associated with sectors and territories. Multilevel models are particularly well suited for this task, as they explicitly capture the different sources of variation at each level of aggregation (Bullen et al., 1997; van Oort et al., 2012).

Multilevel studies on the determinants of productivity have examined the influence of a wide range of geographic characteristics (Lavoratori and Castellani, 2021; Guevara-Rosero, 2021; Stavropoulos et al., 2020; Bellmann et al., 2018). Among these, urban agglomeration and regional sectoral diversity have emerged as key factors (Combes and Gobillon, 2015; Ahrend et al., 2014).

This paper aims to analyze the geographic component of firm productivity, distinguishing between the manufacturing and service sectors in Ecuador, a middle-income Latin American country marked by strong territorial contrasts. Additionally, the study examines how urban agglomeration and regional sectoral diversity affect firm productivity and explores whether these effects differ between innovative and non-innovative firms. To address these questions, we estimate multilevel models that simultaneously accounts for cantonal location and sectoral affiliation. In Ecuador, a canton is a second-level political division, like a municipality. Its main responsibilities include managing public services, overseeing urban planning and land use, and maintaining local infrastructure.

Previous evidence for Ecuador is still scarce. Guevara-Rosero (2021), using a sample of manufacturing microenterprises, showed that they benefit from both agglomeration and diversity. The contribution of the present paper is twofold. First, it expands the scope of analysis by including the entire universe of manufacturing and service firms. Second, it makes an original contribution by introducing a distinction between innovative and non-innovative firms. This perspective captures how different types of firms exploit geographic externalities in distinct ways.

Beyond its analytical contribution, this paper provides useful insights for public policies aimed at fostering productive development. If urban agglomeration and sectoral diversity had a positive effect on productivity, this would suggest that local governments might orient their efforts towards strengthening urban agglomeration and productive diversification. In practice, this translates into territorial planning policies that ensure adequate infrastructure, housing supply, and quality urban services to accommodate population growth; as well as incentives for the establishment of new economic activities, the promotion of sectoral clusters, and the attraction of investment.

At the national level, however, the interpretation of such findings would require a more nuanced perspective. Even if evidence were to suggest that firms tend to be more productive in densely urbanized and sectoral diverse cantons, this would not necessarily imply that policies should privilege those territories. A strategy focused solely on the main urban centers could deepen regional inequalities. In this regard, the most suitable approach would be to advance toward a hybrid model.

The paper is organized as follows. Section 2 reviews the multilevel studies on the geographic determinants of productivity. Section 3 describes the data and the methodological strategy. Section 4 discusses the main results, and Section 5 concludes with policy implications.

2. Literature review

Over the past few decades, a line of research has emerged that incorporates geography as a central element in explaining productivity differences. It assumes that territories create differentiated conditions that shape firms' efficiency. The spatial concentration of firms and population, as well as the sectoral composition of regions influence productivity through knowledge spillovers, labor market pooling, and input–output linkages (Duranton and Puga, 2004; Combes and Gobillon, 2015).

The introduction of multilevel models in this field has represented a significant methodological advance (Bullen et al., 1997; van Oort et al., 2012). In developed economies, studies confirm that the largest share of variance in productivity is explained by firm-level characteristics, while sectoral and regional contexts nonetheless account for a meaningful portion. Backman (2014), analyzing Swedish firms, found that municipalities explained only 0.4–0.8 percent of the variance, industries accounted for 5–7 percent, and firms for about 86 percent, with notable differences between manufacturing and services. In Germany, Bellmann et al. (2018) reported that firms characteristics explained between 51 and 76 percent of the variance and regions accounted for 1.8–5.6 percent. Lavoratori and Castellani (2021), using UK data, similarly found that most of the variance was explained at the firm level, while the regional component was very small (0.34–0.40 percent).

In developing economies, multilevel studies also show that firm-level heterogeneity explains the largest share of productivity variance, although sectoral and regional contexts contribute non-negligible effects. For Ecuador, Guevara-Rosero (2021) reported that firms accounted for 90.1 percent of the variance, while cantons explained 4.1 percent and industries 5.8 percent. Amara and Thabet (2019), analyzing Tunisian firms, similarly found that firm-level factors dominated, but the regional component explained around 4 percent of the variance in total factor productivity and up to 10 percent in labor productivity. Sanfilippo and Seric (2016), using data from Sub-Saharan Africa, identified a stronger contextual role, with geographic location accounting for about 17.4 percent.

Multilevel studies in developed economies also provide nuanced evidence on how urban agglomeration and diversity affect firm productivity. Aarstad et al. (2016), analyzing Norwegian regions, found that while specialized regions enhance productivity, they may hinder innovation. Stavropoulos et al. (2020), focusing on European regions, similarly reported that related variety tends to improve firm productivity, though its impact differs between sectors and firms. Backman (2014), using Swedish data, emphasized the role of industrial diversity at the municipal level, showing that while the productivity of service firms depends primarily on internal human capital, it is reinforced when firms are located in municipalities with a high density of talent. In Germany, Bellmann et al. (2018) observed that industrial concentration, regional R&D expenditure, and cooperative networks in research activities do exert measurable effects on productivity. Finally, Lavoratori and Castellani (2021), with UK data, showed that the effects of location and diversity vary by spatial scale and firm characteristics.

Evidence in developing economies reveals that urban agglomeration and diversity exert measurable effects on firm productivity. Guevara-Rosero (2021), using data from Ecuadorian manufacturing microenterprises, showed that externalities linked to specialization and employment density contribute positively, whereas sectoral diversity has only a modest effect. Amara and Thabet (2019), studying Tunisian firms found that industrial density exerts a direct positive influence on productivity. Sanfilippo and Seric (2016), examining firms across Sub-Saharan Africa, found that urban diversity has a clear positive impact on productivity, particularly in manufacturing.

Despite significant progress, this literature faces several limitations. Endogeneity of location is a persistent challenge, since firms do not locate randomly across space. Measurement of diversity also poses difficulties, as different indices can yield conflicting results (Combes et al., 2010). Spatial scale is another critical issue: territorial effects may vary drastically depending on whether analysis is conducted at the neighborhood, city, or regional level.

A gap in the literature is that studies have not explicitly examined whether the effects of urban agglomeration and sectoral diversity differ between innovative and non-innovative firms. Theory suggests that firms' ability to benefit from externalities is not homogeneous. As argued by Beaudry and Breschi (2003), innovative firms rely more intensively on knowledge spillovers, localized learning, and interactions with diverse agents within clusters, which enhance their innovative capacity and, in turn, their productivity. In contrast, non-innovative firms are more likely to depend on the cost advantages associated with physical proximity, scale economies, or access to a larger pool of labor, rather than on the recombination of diverse knowledge bases.

3. Methodology

3.1. Data and variables

We use data from the 2010 National Economic Census (CENEC-2010) and complementary information from the 2010 Population and Housing Census (CPV-2010). Both datasets were produced by the National Institute of Statistics and Censuses of Ecuador. The CENEC-2010 collects economic information from all firms in the country and its geographic coverage includes all cantons nationwide.

Two alternative measures of productivity are used as the dependent variables: labor productivity and total factor productivity (TFP). The first is defined as the natural logarithm of the ratio between sales and the number of employees in the firm. TFP was estimated as the residual of a Cobb–Douglas production function in logarithmic form, where each firm's sales were modeled as a function of fixed capital and employment. This approach isolates the portion of output not explained by observable inputs, thereby capturing differences in productivity. However, the ordinary least squares estimation may be biased by endogeneity, as firms adjust their input decisions based on unobserved productivity shocks. To correct for this bias, an instrumental variables model was applied. Following Guevara-Rosero (2021), the instruments used—VAT withholdings per capita, tax revenue per capita, and inheritance tax per capita at the cantonal level—meet the conditions of relevance, as they are correlated with economic activity, and exogeneity, as they are independent of each firm's specific decisions. The estimation was implemented using two-stage least squares, and robustness tests confirmed the validity of the instruments: the Hausman test verified the endogeneity of capital and labor; the Kleibergen–Paap statistic rejected the weak instruments hypothesis; and the Hansen test did not reject the null hypothesis of exogeneity. The results are shown in Table A1 of the Appendix. Based on these results, the firm-specific residuals derived from the IV estimation are used as a measure of TFP in the multilevel models.

Table 1 describes all the variables used in this study, including the dependent and independent variables—at the firm, sector, and canton levels—employed in the multilevel model, as well as the variables and instruments used in the calculation of TFP. All variables are measured in the year 2010.

TABLE 1.
List of variables.

	Description	Mean	St.Dev	Min	Max
Dependent variables					
Labor productivity	Natural logarithm of sales divided by the number of employees	M: 8.853 S: 8.842	M: 1.110 S: 1.273	M: - 0.693 S: - 6.468	M: 19.320 S: 19.785
Total factor productivity (TFP)	Residual of a production function	M: $-1.3\text{x}10^{-11}$ S: $-1.1\text{x}10^{-10}$	M: 0.956 S: 1.202	M: - 8.866 S: - 13.383	M: 8.432 S: 9.138
Independent variables					
Firm Level					
Size	Natural logarithm of firms' number of employees	M: 0.773 S: 0.575	M: 0.865 S: 0.794	M: 0.000 S: 0.000	M: 8.541 S: 9.104
Age	Natural logarithm of firms' age	M: 1.758 S: 1.563	M: 1.101 S: 1.085	M: 0.000 S: 0.000	M: 6.118 S: 6.917
Web	Dummy variable equal to 1 if the firm has a website, and 0 otherwise.	M: 0.043 S: 0.037	M: 0.203 S: 0.189	0	1
Innov	Dummy variable equal to 1 if the firm invests in R&D or training; 0 otherwise.	M: 0.048 S: 0.043	M: 0.214 S: 0.203	0	1
Finan	Dummy variable equal to 1 if the firm received financing in the past year; 0 otherwise.	M: 0.244 S: 0.207	M: 0.430 S: 0.405	0	1
Sector level					
Sector	Sectoral classification based on ISIC Rev. 4.	M: 18.447 S: 51.725	M: 7.766 S: 14.31	M: 9 S: 33	M: 32 S: 86
Regional Level					
Diversity	See equation (1)	M: 4.315 S: 5.852	M: 1.765 S: 1.399	M: 1.324 S: 1.840	M: 12.434 S: 12.537
Agglomeration	Percentage of urban population in the canton.	0.388	0.228	0.000	1.00

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Table 1. cont.
List of variables.

	Description	Mean	St.Dev	Min	Max
Dependent variable for TFP estimation					
Sales	Natural logarithm of firm sales.	M: 9.629 S: 9.404	M: 1.573 S: 1.541	M: 0.000 S: 0.000	M: 22.821 S: 22.092
Independent variables for TFP estimation					
Capital	Natural logarithm of the value of fixed assets owned by the firm.	M: 8.176 S: 7.481	M: 1.804 S: 1.883	M: 0.000 S: 0.000	M: 20.972 S: 20.547
Size	Natural logarithm of the number of employees	M: 0.773 S: 0.575	M: 0.865 S: 0.794	M: 0.000 S: 0.000	M: 8.541 S: 9.104
Instruments for TFP estimation					
VAT withholding	Natural logarithm of the amount of VAT withholdings per capita in a canton.	-6.808	2.598	-12.626	-0.751
Tax revenue	Natural logarithm of total tax revenue per capita in a canton.	-4.670	2.777	-14.167	1.458
Inheritance tax	Natural logarithm of the inheritance tax revenue per capita in a canton.	3.462	1.085	0.419	7.520

Notes: M: manufacturing, S: services. The two regional variables are globally mean-centered and standardized using the standard deviation of regional data, considering a single observation per region. All variables are measured in the year 2010.
Source: Own elaboration using CENEC-2010.

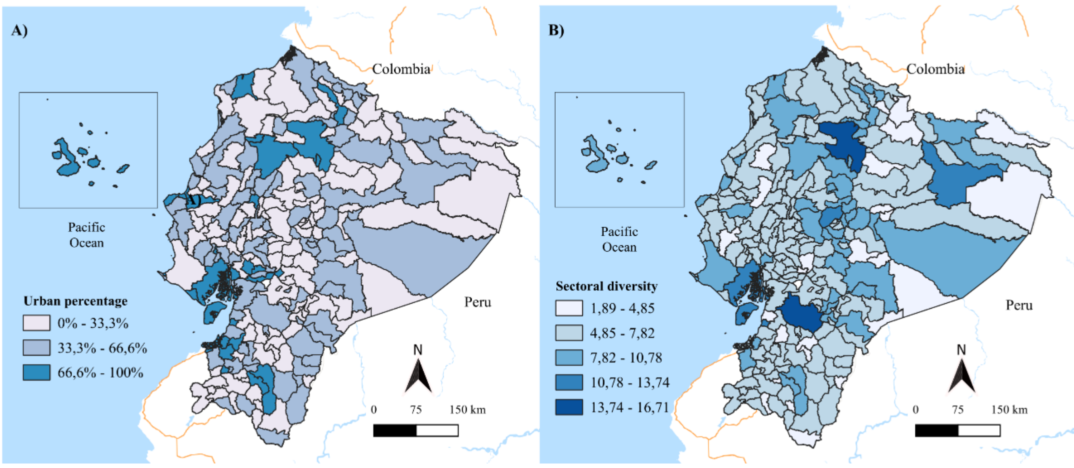
With regard to geographic variables, urban agglomeration is operationalized through the variable 'Agglomeration' defined as the percentage of urban population in the canton, while the sectoral diversity index at the cantonal level is calculated using which widely recognized in the literature as a standard measure: the inverse of the Herfindahl index, constructed from the employment shares of sectors 's' in canton 'j' (Combes and Gobillon, 2015):

$$Diversity_j = \left[\sum_i \left(\frac{emp_{s,j}}{emp_j}\right)^2\right]^{-1} \quad (1)$$

By inverting the sum of the squared employment shares, the resulting value increases when employment is more evenly distributed across many sectors and decreases when one or a few sectors dominate total employment. The higher the index, the greater the level of sectoral diversity.

Figure 1 shows the distribution of the urban population share and sectoral diversity across the cantons of Ecuador.

FIGURE 1.
Spatial Patterns of Urbanization and Sectoral Diversity



Source: Own elaboration using CENEC-2010 and CPV-2010

3.2. Method

The central objective is to determine the geographic component of productivity, understood as the proportion of productivity variability that can be attributed to the canton in which firms operate. To this end, multilevel models are estimated using two independent samples: one consisting of manufacturing firms and the other of service firms.

When estimating multilevel models, researchers face a fundamental choice between hierarchical and cross-classified structures. In hierarchical models, units are nested within a single higher-level classification, such sectors or regions, assuming a strictly nested relationship. By contrast, cross-classified models are designed for situations where each lower-level unit simultaneously belongs to two or more higher-level classifications that are not nested within each other. In such cases, the assumption of strict hierarchy is violated and it may lead to biased estimates of variance components and standard errors (Kim, et al., 2021; Doedens, et al. 2022).

Firms in this study are simultaneously classified by two non-hierarchical dimensions: the canton and the economic sector. Because the same sector can be present across multiple cantons, and each canton hosts firms from multiple sectors, the data structure is inherently cross-classified rather than strictly nested.

For this reason, the most appropriate specification is a cross-classified multilevel model with random effects for canton and sector.

Another relevant dimension is model selection based on information criteria. Information criteria are statistical tools used to compare competing models by balancing model fit and complexity. In this study, both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were computed. Lower AIC or BIC values indicate better model. While AIC is designed to optimize predictive accuracy in finite samples and therefore may favor more complex specifications, BIC penalizes complexity more strongly and is consistent in selecting the correct specification as sample size increases. Recent simulation evidence confirms this distinction: Kim, et al. (2021) show that across a wide range of data-generating conditions, BIC consistently outperformed AIC. In our estimations, AIC slightly favored the hierarchical specification, while BIC favored the cross-classified specification. Results are shown in Table A3 of the Appendix. Given both the theoretical appropriateness of cross-classification and the empirical robustness of BIC, we rely on the latter as a decisive criterion in justifying the final model choice. For transparency, both AIC and BIC are reported in the results tables. [1]

In the cross-classified structure, it is assumed that each firm 'i' is simultaneously influenced by a canton 'j' and a sector 's'. Sector and canton are treated as two independent levels. The crossed model is specified in the following four versions, for the manufacturing and service subsamples:

First, a null model without independent variables is estimated for each of the two productivity measures (y_{ij}), as described in Table 1, in the following way:

$$\boldsymbol{y_{ijs} = \beta_0 + u_{0j} + \mathrm{v}_{0s} + e_{ijs}} \tag{2}$$

With $u_{0j} \sim N(0, \sigma_u^2)$ as the random effect of canton 'j', $e_{ij} \sim N(0, \sigma_e^2)$ as the residual at the firm level, and $v_{0s} \sim N(0, \sigma_v^2)$ as the random component associated with sector 's'. Based on equation (6), the partial ICCs—cantonal and sectoral—are derived using the following expressions:

$$\mathbf{ICC_{cantonal}} = \boldsymbol{\sigma_u^2 / (\sigma_u^2 + +\sigma_v^2 + \sigma_e^2)} \tag{3}$$

$$\mathbf{ICC_{sectoral}} = \boldsymbol{\sigma_v^2 / (\sigma_u^2 + \sigma_v^2 + \sigma_e^2)} \tag{4}$$

These ICC measure the proportion of the total variance in y_{ij} that is attributable to differences between cantons and between sectors.

Second, equation (2) is re-estimated with the inclusion of firm-level covariates. Let $\mathrm{x}_{\mathrm{pij}}$ be the vector of P internal firm characteristics. The specification is then:

$$y_{ij} = \beta_0 + \sum_{p=1}^{P} \beta_0 x_{pij} + u_{0j} + \mathrm{v}_{0s} + e_{ijs} \tag{5}$$

In this model, the cantonal and sectoral ICC can be recalculated to assess whether cantonal and sectoral variance decreases or increases when controlling for these internal and sectoral variables.

Third, the two cantonal covariates are added in equation (5): let Z_{1j} be the standardized percentage of urban population and Z_{2j} the standardized sectoral diversity index; the model would be expressed as:

[1] Empirical evidence from our estimations also supports the cross-classified specification. The intraclass correlation coefficients (ICCs) are consistently larger at the sectoral than at the cantonal level, indicating that sectoral heterogeneity explains a meaningful share of productivity differences across firms. This further reinforces the choice of treating sector and canton as random factors in a cross-classified structure.

$$y_{ij} = \beta_0 + \sum_{p=1}^{P} \beta_0 x_{pij} + \gamma_1 Z_{1j} + \gamma_2 Z_{2j} + u_{0j} + v_{0s} + e_{ij} \tag{6}$$

In this model, the cantonal ICC can be recalculated to assess whether cantonal variance decreases when controlling for these contextual variables.

In this specification, the two cantonal-level predictors-urban agglomeration and sectoral diversity-were standardized prior to estimation, whereas firm-level covariates were included in their original scales. This decision reflects both analytical priorities and methodological considerations. First, the contextual variables are the core predictors of interest, and standardization makes it possible to directly compare their coefficients in terms of substantive importance, avoiding distortions due to differences in their original scales. Second, the standardization of higher-level predictors improves the stability of estimation and facilitates the interpretation of cross-level interactions. This is particularly relevant here, since the following model specification includes an interaction between cantonal characteristics and the firm-level indicator of Innov. Standardizing the contextual variables reduces collinearity between the main effects and the interaction term, yielding more reliable estimates and clearer substantive interpretation. Firm-level covariates, by contrast, are more interpretable in their natural units, and their inclusion without standardization preserves their direct substantive meaning.

Finally, the previous specification is extended by incorporating interactions between the firm-level binary variable 'Innov' -which distinguishes between firms that invest in innovation activities and those that do not- and the two cantonal covariates. This step allows for the assessment of whether the effect of territorial conditions on productivity varies depending on firms' innovation capacity. The model is expressed as:

$$y_{ij} = \beta_0 + \sum_{p=1}^{P} \beta_0 x_{pij} + \gamma_1 Z_{1j} + \gamma_2 Z_{2j} + \lambda_1 (Innov * Z_{1j}) + \lambda_2 (Innov * Z_{2j}) + u_{0j} + v_{0s} + e_{ij} \tag{7}$$

The introduction of the interaction terms $(Innov * Z_{1j})$ and $(Innov * Z_{2j})$ allows for the exploration of potential moderating effects; that is, whether the influence of urban agglomeration and sectoral diversity on productivity is conditioned by whether a firm invests in innovation activities. In this specification, the coefficients γ_1 and γ_2 capture the average effect of the percentage of urban population and sectoral diversity, respectively, on the productivity of non-innovative firms. In turn, the coefficients λ_1 and λ_2 measure the additional effect that these same territorial conditions have on innovative firms. Thus, a positive coefficient on the interaction term indicates that innovative firms benefit more from operating in cantons that are more urbanized or have a more diverse productive structure.

4. Results

Table 2 presents the cantonal ICCs from the null models for both dependent variables for manufacturing and service firms alike. The likelihood ratio tests provide strong statistical justification for adopting multilevel specifications. Even in cases where the cantonal ICC is relatively low—particularly in the TFP models, the LR tests show that a cross-classified model with canton and sector included as a random effect fits the data significantly better than a single-level specification.

The results of the null models show that the largest share of variance in productivity continues to be explained by internal firm-level characteristics, while sectoral and cantonal contexts contribute to a lesser but still significant extent. The cantonal ICCs indicate that the regional component is small—ranging from 1.7 to 4.1 percent in total factor productivity and from 3.7 to 4.1 percent in labor productivity—whereas the sectoral component is considerably more substantial, reaching values of 11.2 percent in manufacturing TFP and as high as 30.9 percent in service-sector TFP. These findings are consistent with previous evidence from both developed and developing economies, where the firm level generally dominates, but sectoral and territorial contexts account for a non-negligible portion of productivity differences (Backman, 2014; Bellmann et al., 2018; Amara and Thabet, 2019; Guevara-Rosero, 2021). Overall, the results position Ecuador within the broader international evidence, confirming the predominance of firm-level heterogeneity while also demonstrating that sectoral contexts, more than territorial ones, remain an essential dimension of productivity differences.

TABLE 2.
Null models

	TFP		Labor productivity	
	Manuf	**Serv.**	**Manuf.**	**Serv.**
Cantonal ICC	1.73	1.90	4.13	3.66
Sectoral ICC	11.19	30.92	26.07	20.67
LR test	1790.92***	$1.1x10^{5***}$	4919.84***	45205.02***

Note: *** p < 0.01.
Source: Own elaboration using CENEC-2010.

Table 3 presents the results when internal firm characteristics are included for both sectors.

TABLE 3.
Models with firm characteristics

	TFP		Labor productivity	
	Manuf	**Serv.**	**Manuf.**	**Serv.**
Constant	5.900*** (0.059)	5.589*** (0.076)	8.594*** (0.082)	8.257*** (0.076)
Size	-1.463*** (0.006)	-1.549*** (0.003)	0.139*** (0.006)	0.022*** (0.003)
Age	0.019*** (0.004)	0.118*** (0.002)	0.064*** (0.004)	0.145*** (0.002)
Web	0.415*** (0.032)	0.586*** (0.014)	0.680*** (0.035)	0.746*** (0.013)
Innov	0.239*** (0.022)	0.315*** (0.009)	0.514*** (0.023)	0.577*** (0.009)
Finan	0.059*** (0.010)	0.130*** (0.004)	0.220*** (0.011)	0.297*** (0.004)
Random effects				
Cantons	0.034 (0.005)	0.055 (0.006)	0.057 (0.008)	0.066 (0.007)
Sectors	0.068 (0.027)	0.287 (0.057)	0.137 (0.050)	0.286 (0.056)
Firms	0.827 (0.006)	1.197 (0.003)	0.957 (0.006)	1.279 (0.003)
Total	0.929	1.538	1.151	1.6304
ICC Cantonal	3.64	3.59	4.94	4.05
ICC Sectoral	7.33	18.63	11.93	17.51
LR test	2882.59***	65237.62***	3872.89***	47512.95***
AIC	120990	1228511	128316.1	1274182
BIC	121068.5	1228609	128394.7	1274280

Note: * p < 0.1; ** p < 0.05; *** p < 0.01.
Source: Own elaboration using CENEC-2010

Table 3 shows a consistent increase in the cantonal ICC when moving from the null model to Model 1 for both sectors. This variation indicates that, once observable differences between firms are controlled for, the proportion of variance explained by the cantonal context increases. In other words, the inclusion of individual-level covariates filters out the residual variance associated with idiosyncratic factors, allowing the latent effect of the territorial environment to emerge more clearly. Thus, the increase in the ICC does not imply that the canton has greater absolute influence, but rather that its relative weight on the residual variance is amplified when controlling for firm-level heterogeneity. This dynamic has been discussed in the methodological literature on hierarchical models (Snijders and Bosker, 2012; Bullen et al., 1997), where it is noted that the ICC may vary in a non-monotonic manner depending on the predictors included. In this case, the increase in the cantonal ICC suggests that territorial differences in productivity are not merely a reflection of firm composition but rather stem from intrinsic effects of the geographical context that become apparent only after accounting for observable differences between firms.

The results on internal firm characteristics reveal consistent and statistically robust patterns in explaining both total factor productivity and labor productivity. Firm size exhibits a negative association with total factor productivity. This result suggests that, in the Ecuadorian context, larger firms face diminishing returns in the combined use of inputs. In contrast, when analyzing labor productivity, firm size has a positive effect, indicating that larger firms tend to generate more value per worker. The remaining internal characteristics exhibit positive and significant effects across all models. Innovative firms, in turn, exhibit superior productivity performance compared to their non-innovative counterparts. Collectively, these findings highlight the critical role of internal firm characteristics in explaining business productivity.

Table 4 presents the results when, in addition to internal characteristics, the two standardized regional variables are included.

Table 4.
Models with firm and regional characteristics

	TFP		**Labor productivity**	
	Manuf	**Serv.**	**Manuf.**	**Serv.**
Constant	5.874*** (0.059)	5.587*** (0.076)	8.567*** (0.081)	8.253*** (0.076)
Size	-1.463*** (0.006)	-1.549*** (0.003)	0.138*** (0.006)	0.022*** (0.003)
Age	0.019*** (0.004)	0.118*** (0.002)	0.064*** (0.004)	0.145*** (0.002)
Web	0.416*** (0.032)	0.586*** (0.014)	0.681*** (0.035)	0.746*** (0.013)
Innov	0.238*** (0.022)	0.315*** (0.009)	0.514*** (0.023)	0.577*** (0.009)
Finan	0.059*** (0.010)	0.130*** (0.004)	0.221*** (0.011)	0.297*** (0.004)
Agglomeration	0.086*** (0.014)	0.048*** (0.017)	0.087*** (0.018)	0.084*** (0.017)
Diversity	0.032*** (0.014)	0.013 (0.017)	0.054*** (0.018)	0.025 (0.018)
Random effects				
Cantons	0.024 (0.004)	0.053 (0.006)	0.045 (0.007)	0.057 (0.006)
Sectors	0.068 (0.027)	0.287 (0.057)	0.137 (0.050)	0.285 (0.056)

TABLE 4. CONT.
Models with firm and regional characteristics

	TFP		Labor productivity	
	Manuf	**Serv.**	**Manuf.**	**Serv.**
Firms	0.827 (0.005)	1.197 (0.003)	0.957 (0.006)	1.2789 (0.003)
Total	0.920	1.536	1.139	1.621
ICC Cantonal	2.63	3.42	3.97	3.51
ICC Sectoral	7.39	18.66	12.03	17.60
LR test	2273.79***	63292.30	3012.82***	43907.76***
AIC	120945.3	1228505	128280.6	1274156
BIC	121041.3	1228625	128376.6	1274276

Note: * p < 0.1; ** p < 0.05; *** p < 0.01. The two regional variables are globally mean-centered and standardized using the standard deviation of regional data, considering a single observation per region.
Source: Own elaboration using CENEC-2010.

In both sectors, the percentage of urban population emerges as a consistent determinant of productivity. Operating in cantons with a higher percentage of urban population implies superior access to advanced infrastructure, efficient transportation networks, specialized labor markets, and more diversified demand, which benefits both manufacturing and service sectors. However, the positive impact of sectoral diversity is observed exclusively in manufacturing, while it was not statistically significant in the services sector. This sectoral asymmetry is consistent with the experience of other developing countries, where economic diversity often does not translate into higher productivity levels (Amara and Thabet, 2019; Lall et al., 2004). Frenken et al. (2007) argue that diversity yields advantages only when local firms possess the capacity to absorb external knowledge, and that in sectors dominated by low-tech firms such benefits may be negligible or limited.

Our findings support this interpretation: the absence of a positive effect of diversity in services may be because the bulk of the Ecuadorian service sector consists of activities with low knowledge intensity. These activities derive their advantage primarily from market scale and proximity to consumers (i.e., urban agglomeration), rather than from intersectoral complementarities. In contrast, manufacturing does manage to take advantage of the inter-sectoral synergies offered by a diversified environment. This differentiation is consistent with studies indicating that the benefits of variety tend to concentrate in knowledge-intensive services, particularly when these are sufficiently developed and integrated into the local economic environment (Cainelli et al., 2019).

The comparison between the models in Table 3 and Table 4 allows for an assessment of the explanatory contribution of regional variables to cantonal variance in firm productivity. In both sectors and for both types of productivity, the inclusion of cantonal covariates leads to a systematic reduction in the ICCs at the cantonal level, indicating that a substantial portion of the variability initially attributed to territorial factors can be explained by these two specific regional characteristics. This reduction suggests that urban agglomeration and sectoral diversity not only exert a direct influence on productivity but also contribute to a more precise decomposition of the sources of spatial variation.

Table 5 presents the results when the interaction terms $(Innov * Z_{1j})$ and $(Innov * Z_{2j})$ are included.

The inclusion of interactions between innovation status and territorial variables reveals that urban externalities do not operate uniformly across all firms but rather depend critically on their internal capabilities. In the case of the manufacturing sector, the results show that innovative firms significantly amplify the benefits derived from both urban agglomeration and sectoral diversity. This finding is consistent with the principles of the literature on absorptive capacity and learning regions, which argues that firms with greater technological capabilities are better equipped to internalize the knowledge available in their geographical environment (Cohen and Levinthal, 1990; Feldman and Audretsch, 1999).

Table 5.
Models with Innov and Regional characteristics interactions

	TFP		Labor productivity	
	Manuf	**Serv.**	**Manuf.**	**Serv.**
Constant	5.875*** (0.058)	5.589*** (0.076)	8.567*** (0.080)	8.254*** (0.076)
Size	-1.465*** (0.006)	-1.55*** (0.003)	0.136*** (0.007)	0.022*** (0.003)
Age	0.019*** (0.004)	0.118*** (0.002)	0.064*** (0.004)	0.146*** (0.002)
Web	0.404*** (0.032)	0.577*** (0.014)	0.668*** (0.035)	0.740*** (0.013)
Innov	0.078* (0.046)	0.218*** (0.018)	0.309*** (0.049)	0.517*** (0.018)
Finan	0.060*** (0.010)	0.130*** (0.004)	0.221*** (0.011)	0.297*** (0.004)
Agglomeration	0.086*** (0.014)	0.047*** (0.017)	0.085*** (0.018)	0.084*** (0.017)
Diversity	0.032*** (0.014)	0.012 (0.017)	0.054*** (0.018)	0.024 (0.018)
Innov x Agglomeration	0.051* (0.027)	0.015 (0.011)	0.119*** (0.029)	0.011 (0.011)
Innov x Diversity	0.031*** (0.010)	0.028*** (0.004)	0.017 (0.011)	0.016*** (0.004)
Random effects				
Cantons	0.024 (0.004)	0.052 (0.006)	0.045 (0.007)	0.057 (0.006)
Sectors	0.065 (0.026)	0.284 (0.057)	0.132 (0.049)	0.284 (0.055)
Firms	0.827 (0.005)	1.196 (0.003)	0.957 (0.006)	1.279 (0.003)
Total	0.917	1.533	1.134	1.620
ICC Cantonal	2.63	3.42	4.00	3.51
ICC Sectoral	7.13	18.55	11.67	17.56
LR test	2263.15***	63111.70***	3002.17***	43789.35***
AIC	120932.5	1228453	128260.7	1274141
BIC	121045.9	1228595	128374.2	1274283

Note: * p < 0.1; ** p < 0.05; *** p < 0.01. The two regional variables are globally mean-centered and standardized using the standard deviation of regional data, considering a single observation per region.
Source: Own elaboration using CENEC-2010.

In the case of services, although the interaction with urban agglomeration is not statistically significant, innovative firms do obtain a positive differential return from sectoral diversity. This suggests that even within the service sector, the heterogeneity of the productive environment can stimulate productivity if firms possess the capabilities to capitalize on it. This finding suggests that investment in innovation activities enables service firms to capture opportunities associated with environmental diversification such as new ideas and technologies from other industries that would otherwise go unnoticed. At the same time, it explains why non-innovative service firms do not benefit from regional diversity, as they lack the necessary competencies to absorb external knowledge. Taken together, these findings reinforce the idea that agglomeration economies are neither automatic nor universal but are mediated by the organizational and technological characteristics of productive units. Several studies have reached similar conclusions, showing that the returns from locating in urban environments depend critically on internal firm factors (Crescenzi and Gagliardi, 2018).

5. Conclusions

This paper has examined how territorial conditions—specifically urban agglomeration and sectoral diversity—affect firm productivity in a developing country, with a distinction between the manufacturing and service sectors. Using multilevel models that simultaneously account for the geographical and sectoral structure of firms, it has been shown that territorial characteristics explain a limited yet significant share of the variability in productivity. Although internal firm factors predominantly explain performance, geographical location introduces a non-trivial productivity differential. These findings are in line with previous research identifying economic geography as a relevant source of competitive advantages (Combes and Gobillon, 2015; Duranton and Puga, 2004).

The results confirm that urbanization exerts a systematic positive effect on productivity in both manufacturing and services, highlighting the importance of urban environments as spaces that facilitate access to markets, infrastructure, and specialized human capital. However, sectoral diversity showed a positive and statistically significant effect only in the manufacturing sector, suggesting that intersectoral linkages and knowledge externalities are more influential in industrial activities than in tertiary activities, where proximity to final demand appears to be more critical.

A central contribution of this study is the identification of firms' innovative capacity as a moderating mechanism of territorial externalities. In manufacturing, innovative firms significantly amplify the benefits of both urbanization and diversity, suggesting that innovation functions as a mechanism for absorbing knowledge and seizing environmental opportunities (Cohen and Levinthal, 1990). This nuance enriches our understanding of spatial returns: not all firms benefit equally from their surroundings; those that invest in innovation activities are better positioned to more fully exploit available externalities. In the services sector, however, the role of innovation appears more limited: while it enhances the benefits of diversity, it does not do so with respect to urban agglomeration.

Despite its contributions, this study presents several methodological limitations that must be acknowledged with due rigor. First, the estimation is based on a single cross-sectional dataset, which prevents drawing causal inferences or assessing dynamic effects. The inability to control for unobserved temporal heterogeneity limits the capacity to identify structural relationships between location and productivity. Second, firm innovation is approximated using a binary variable, which does not capture its intensity, modality, or technological orientation. This simplification may underestimate the complexity and heterogeneity of innovation processes and their differentiated territorial effects.

An additional limitation concerns the potential endogeneity in the relationship between territorial characteristics and productivity. Although productivity was estimated using robust semiparametric methods, the study does not explicitly model firm location as an endogenous decision. This could introduce selection bias if, for instance, more productive firms tend to locate in more urbanized or diverse cantons. Similarly, the analysis does not incorporate direct measures of human capital or regional infrastructure, which could bias the effects attributed to urban agglomeration if these factors act as omitted variables that are correlated with both location and productivity.

A final limitation of this study is the temporal dimension of the data, which from the 2010. The structural context of firms and territories has evolved considerably over the last decade, and especially after the COVID-19 pandemic. The crisis accelerated digitalization processes, altered global value chains, and reshaped the spatial organization of production and services. These changes tend to reduce the centrality of geographic location as a determinant of productivity, by enabling new forms of remote work, offshoring, and the reorganization of productive and commercial flows. Although the core mechanisms identified in this study—agglomeration and sectoral diversity—remain theoretically robust, the magnitude of their effects may have changed.

From a public policy perspective, the results underscore the need for territorial development strategies that are sensitive to sectoral dynamics and firm-level heterogeneity. Both urban agglomeration and sectoral diversity are positively associated with productivity, although their effects vary in magnitude and significance across manufacturing and services and between innovative and non-innovative firms. The consistent and robust impact of agglomeration supports policies that reinforce the role of cities as productive hubs, through investments in infrastructure, transportation, and services that facilitate dense economic interactions. The more selective influence of sectoral diversity highlights the value of fostering cross-sector linkages, knowledge exchange, and collaborative networks, particularly in manufacturing, where the benefits are most pronounced. This can be pursued through the promotion of multisectoral industrial clusters, the development of mixed-use industrial zones, and the creation of platforms that facilitate inter-firm cooperation and knowledge flows.

The interaction estimates further indicate that innovative firms benefit disproportionately from territorial conditions, especially from agglomeration in manufacturing and from sectoral diversity in both manufacturing and services. These findings suggest that urbanized and diverse environments function as catalysts of innovation, amplifying spillovers and localized learning for innovative firms. Accordingly, urban development and regional diversification strategies should be closely tied to innovation policy—for example, by supporting technology parks, university–industry partnerships, and cross-sectoral research platforms.

More broadly, these results call for a nuanced approach to regional policy that avoids one-size-fits-all interventions. While prioritizing more urbanized and more diverse territories may appear efficient from a productivity standpoint, such strategies carry the risk of reinforcing spatial inequalities. Concentrating resources on established poles could deepen disparities between regions. In this sense, the alignment between innovation policy and territorial planning requires careful calibration between centralized strategies that promote development poles and decentralized initiatives that empower local governments. Finding this balance is essential for bridging spatial productivity gaps, stimulating inclusive growth, and ensuring that the advantages of agglomeration and diversity are shared more widely across the productive structure.

References

Aarstad, J., Kvitastein, O., & Jakobsen, S. (2016). Related and unrelated variety as regional drivers of enterprise productivity and innovation: *A multilevel study. Research Policy*, *45*(4), 844-856. https://doi.org/10.1016/j.respol.2016.01.013

Ahrend, R., Farchy, E., Kaplanis, I., & Lembcke, A. C. (2014). *What Makes Cities More Productive? Evidence on the Role of Urban Governance from Five OECD Countries* (OECD Regional Development Working Papers). https://doi.org/10.1787/5jz432cf2d8p-en

Amara, M., & Thabet, K. (2019). Firm and regional factors of productivity: a multilevel analysis of Tunisian manufacturing. *Annals of Regional Science*, *63*(1), 25-51. https://doi.org/10.1007/s00168-019-00918-x

Backman, M. (2014). Human capital in firms and regions: Impact on firm productivity. *Papers in Regional Science*, *93*(3), 557-576. https://doi.org/10.1111/pirs.12005

Beaudry, C., & Breschi, S. (2003). Are firms in clusters really more innovative? E*conomics of Innovation and New Technology*, *12*(4), 325-342. https://doi.org/10.1080/10438590290020197

Bellmann, L., Evers, K., & Hujer, R. (2018). Regional and firm-specific effects on innovations using multi-level methods. *Annals of Regional Science*, *61*(2), 319-349. https://doi.org/10.1007/s00168-018-0869-2

Bullen, N., Jones, K., & Duncan, C. (1997). Modelling complexity: analysing between-individual and between-place variation - a multilevel tutorial. *Environment and Planning A*, *29*(4), 585-609. https://doi.org/10.1068/A290585

Cainelli, G., De Marchi, V., & Grandinetti, R. (2019). Do knowledge-intensive business services innovate differently? *Economics of Innovation and New Technology*, *29*(1), 48-65. https://doi.org/10.1080/10438599.2019.1585639

Camino-Mogro, S. (2022). TFP determinants in the manufacturing sector: the case of Ecuadorian firms. *Applied Economic Analysis*, *30*(89), 92-113. https://doi.org/10.1108/AEA-10-2020-0142

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128-152.

Combes, P. P., & Gobillon, L. (2015). The Empirics of Agglomeration Economies. In *Handbook of Regional and Urban Economics* (Vol. 5, pp. 247-348). Elsevier B.V. https://doi.org/10.1016/B978-0-444-59517-1.00005-2

Combes, P. P., Duranton, G., Gobillon, L., & Roux, S. (2010). Estimating Agglomeration Economies with History, Geology, and Worker Effects. *Agglomeration Economics*, 15-66. https://doi.org/10.7208/CHICAGO/9780226297927.003.0002

Crescenzi, R., & Gagliardi, L. (2018). The innovative performance of firms in heterogeneous environments: The interplay between external knowledge and internal absorptive capacities. *Research Policy, 47*(4), 782-795. https://doi.org/10.1016/j.respol.2018.02.006

Doedens, P., ter Riet, G., Boyette, L.-L., Latour, C., de Haan, L., & Twisk, J. (2022). Cross-classified multilevel models improve standard error estimates of covariates in clinical outcomes – A simulation study. *Journal of Clinical Epidemiology, 145*, 39-46. https://doi.org/10.1016/j.jclinepi.2022.01.005

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In: Henderson, J.V., Thisse, J.F. (Eds.), *Handbook of Regional and Urban Economics* (vol. 4, pp. 2063-2117). North-Holland.

Dvouletý, O., & Blažková, I. (2021). Exploring firm-level and sectoral variation in total factor productivity (TFP). *International Journal of Entrepreneurial Behavior and Research*, *27*(6), 1526-1547. https://doi.org/10.1108/IJEBR-11-2020-0744

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review, 43*(2), 409-429. https://doi.org/10.1016/S0014-2921(98)00047-6

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*(5), 685-697. https://doi.org/10.1080/00343400601120296

Guevara-Rosero, G. C. (2021). Determinants of manufacturing micro firms' productivity in Ecuador. Do industry and canton where they operate matter? *Regional Science Policy and Practice*, *13*(4), 1215-1248. https://doi.org/10.1111/rsp3.12399

Kim, S., Jeong, Y., & Hong, S. (2021). The impact of ignoring a crossed factor in cross-classified multilevel modeling. *Frontiers in Psychology, 12*, 637645. https://doi.org/10.3389/fpsyg.2021.637645

Lall, S. V., Shalizi, Z., & Deichmann, U. (2004). Agglomeration economies and productivity in Indian industry. *Journal of Development Economics*, *73*(2), 643-673. https://doi.org/10.1016/J.JDEVECO.2003.04.006

Lavoratori, K., & Castellani, D. (2021). Too close for comfort? Microgeography of agglomeration economies in the United Kingdom. *Journal of Regional Science*, *61*(5), 1002-1028. https://doi.org/10.1111/jors.12531

Sanfilippo, M., & Seric, A. (2016). Spillovers from agglomerations and inward FDI: a multilevel analysis on sub-Saharan African firms. *Review of World Economics*, *152*(1), 147-176. https://doi.org/10.1007/s10290-015-0237-6

Snijders, T., & Bosker, R. (2012). *Multilevel Analysis. An introduction to basic and advanced multilevel modeling*. SAGE Publications.

Stavropoulos, S., van Oort, F. G., & Burger, M. J. (2020). Heterogeneous relatedness and firm productivity. *Annals of Regional Science*, *65*(2), 403-437. https://doi.org/10.1007/s00168-020-00988-2

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature*, *49*(2), 326-365. https://doi.org/10.1257/JEL.49.2.326

van Oort, F. G., Burger, M. J., Knoben, J., & Raspe, O. (2012). Multilevel approaches and the firm-agglomeration ambiguity in economic growth studies. *Journal of Economic Surveys*, *26*(3), 468-491. https://doi.org/10.1111/j.1467-6419.2012.00723.x

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Appendix

Table A1.
TFP estimation using OLS and IV methods

Sales (dependent variable)	**OLS**	**IV MC2E**	
Constant	7.1266 *** (0.009)	5.3679*** (0.250)	
Capital	0.2401*** (0.001)	0.3741*** (0.038)	
Size	0.8808*** (0.004)	2.2107*** (0.088)	
N	466324	342826	
R^2	0.413	-0.093	
Root MSE	-	1.657	
Instruments	-	VAT withholding per capita. tax collection per capita. inheritance tax per capita	
Sub identification (p-value)			
Kleibergen-Paap	-	706.734	(0.000)
Weak instrument test			
F of Cragg-Donald	-	239.49 > 13.43	
Overidentification Test			
Hansen (p-value)	-	0.959	(0.3275)

Note: Robust standard errors in parenthesis. ***p < 0.01, **p < 0.05, *p < 0.1.
Source: Own elaboration using CENEC-2010.

Table A1.a
Sectoral classification for manufacturing firms

ISIC cod.	Description of sector	Number of firms
C19	Manufacture of coke and petroleum refining products	18
C21	Manufacture of pharmaceuticals. medicinal chemicals and botanicals for pharmaceutical use	65
C20	Manufacture of substances and chemical products	365
C10	Manufacture of food products	9838
C12	Manufacture of tobacco products	3
C23	Manufacture of other non-metallic mineral products	2614
C24	Base Metal Fabrication	224
C26	Manufacture of computer. electronics and optical products	58
C15	Manufacture of leather and related products	1254
C22	Manufacture of rubber and plastic products	507
C30	Manufacture of other types of transport equipment	55
C27	Electrical Equipment Manufacturing	160
C17	Manufacture of paper and paper products	268
C29	Manufacture of motor vehicles. trailers and semi-trailers	401
C25	Manufacture of processed metal products. except machinery and equipment	8021
C32	Other manufacturing industries	1543
C13	Textile manufacturing	1466
C31	Furniture Manufacturing	5663
C28	Manufacture of NCP machinery and equipment	404
C11	Beverage Brewing	202
C33	Repair and installation of machinery and equipment	1355
C16	Production of wood and manufacture of wood and cork products. except furniture; manufacture of straw articles and plaiting materials	3109
C18	Printing and Playback of Recordings	2001
C14	Garment Manufacturing	8273

Source: Own elaboration using CENEC-2010

Table A2.b.
Sectoral classification for services firms

ISIC cod.	Description of sector	Number of firms
G46	Wholesale trade. except motor vehicles and motorcycles	8190
H51	Transportation by air	177
F42	Civil engineering works	286
F41	Building Construction	492
K65	Insurance. reinsurance and pension funds. except compulsory social security schemes	523
H50	Water transport	96
G47	Retail trade. except motor vehicles and motorcycles	232760

TABLE A2.B. CONT.
Sectoral classification for services firms

ISIC cod.	Description of sector	Number of firms
K66	Ancillary activities of financial services activities	254
I56	Food and beverage service	48385
E39	Decontamination activities and other waste management services	11
N79	Activities of travel agencies. tour operators. reservation services and related activities	855
D35	Supply of electricity. gas. steam and air conditioning	273
E38	Waste collection. treatment and disposal. material recovery	127
F43	Specialized Construction Activities	772
K64	Financial services activities. except insurance and pension funds	2589
M75	Veterinary activities	598
M73	Advertising and market research	1051
M70	Main office activities; Management consulting activities	488
M71	Architecture and engineering activities; Technical Testing and Analysis	1332
H53	Postal and courier activities	705
G45	Wholesale and retail trade; repair of motor vehicles and motorcycles	28801
J62	Computer programming. computer consulting and related activities	272
N80	Security and research activities	514
H52	Storage and transport support activities	1509
N81	Building Services and Landscaping Activities	196
N78	Employment activities	83
J63	Information Services Activities	50
H49	Transport by land and by pipeline	2741
L68	Real estate activities	1706
J58	Publishing activities	463
M69	Legal and accounting activities	7775
M72	Scientific research and development	130
E36	Water collection. treatment and distribution	172
S95	Repair of computers and personal effects and household goods	15037
N82	Office and other business support activities	2841
Q86	Human health care activities	13942
M74	Other professional. scientific and technical activities	1950
J59	Motion picture production. video and television program production. sound recording. and music editing	190
S96	Other personal service activities	18092
J61	Telecommunications	18188
R92	Gambling and betting activities	2387
N77	Rental and leasing activities	1328
R90	Creative. artistic and entertainment activities	356
J60	Programming and Streaming Activities	598
O84	Public administration and defense; Compulsory social security schemes	4009

TABLE A2.B. CONT.
Sectoral classification for services firms

ISIC cod.	Description of sector	Number of firms
R93	Sports. leisure and recreational activities	2516
I55	Accommodation activities	3430
Q87	Care activities in institutions	605
Q88	Social assistance activities without accommodation	1362
R91	Library. archive. museum and other cultural activities	367
P85	Teaching	13081
S94	Partnership activities	6502
E37	Wastewater disposal	21
U99	Activities of offshore organizations and bodies	34

Source: Own elaboration using CENEC-2010

TABLE A3.
Hierarchical and cross-classified model fit

	TFP				Labor productivity			
	Hierarchical		Crossed		Hierarchical		Crossed	
	Manuf.	Serv.	Manuf	Serv.	Manuf.	Serv.	Manuf.	Serv.
Constant	6.034*** (0.019)	5.932*** (0.019)	5.900*** (0.059)	5.589*** (0.076)	8.689*** (0.023)	8.479*** (0.089)	8.594*** (0.082)	8.257*** (0.076)
Size	-1.463*** (0.006)	-1.549*** (0.003)	-1.463*** (0.006)	-1.549*** (0.003)	0.138*** (0.006)	0.022*** (0.003)	0.139*** (0.006)	0.022*** (0.003)
Age	0.019*** (0.004)	0.118*** (0.002)	0.019*** (0.004)	0.118*** (0.002)	0.064*** (0.004)	0.146*** (0.002)	0.064*** (0.004)	0.145*** (0.002)
Web	0.409*** (0.032)	0.586*** (0.014)	0.415*** (0.032)	0.586*** (0.014)	0.675*** (0.035)	0.746*** (0.013)	0.680*** (0.035)	0.746*** (0.013)
Innov	0.236*** (0.022)	0.315*** (0.009)	0.239*** (0.022)	0.315*** (0.009)	0.512*** (0.023)	0.577*** (0.009)	0.514*** (0.023)	0.577*** (0.009)
Finan	0.059*** (0.010)	0.13*** (0.004)	0.059*** (0.010)	0.130*** (0.004)	0.22*** (0.011)	0.297*** (0.004)	0.220*** (0.011)	0.297*** (0.004)
Sector dummies	Included	Included	-	-	Included	Included	-	-
Random effects								
Cantons	0.034 (0.005)	0.055 (0.006)	0.034 (0.005)	0.055 (0.006)	0.056 (0.008)	0.066 (0.007)	0.057 (0.008)	0.066 (0.007)
Sectors	-	-	0.068 (0.027)	0.287 (0.057)	-	-	0.137 (0.050)	0.286 (0.056)
Firms	0.827 (0.005)	1.196 (0.003)	0.827 (0.006)	1.197 (0.003)	0.957 (0.006)	1.279 (0.003)	0.957 (0.006)	1.279 (0.003)
Total	0.860	1.251	0.929	1.538	1.013	1.344	1.151	1.6304
ICC Cantonal	3.90	4.39	3.64	3.59	5.57	4.88	4.94	4.05

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TABLE A3. CONT.
Hierarchical and cross-classified model fit

	TFP				Labor productivity			
	Hierarchical		Crossed		Hierarchical		Crossed	
	Manuf.	Serv.	Manuf	Serv.	Manuf.	Serv.	Manuf.	Serv.
ICC Sectoral	-	-	7.33	18.63	-	-	11.93	17.51
LR test	978.09***	6421.43***	2882.59***	65237.62***	1359.72***	8597.89***	3872.89***	47512.95***
AIC	120912.4	1228288	120990	1228511	128229.7	1273959	128316.1	1274182
BIC	121182.9	1228954	121068.5	1228609	128500.4	1274626	128394.7	1274280

Note: * p < 0.1; ** p < 0.05; *** p < 0.01.
Source: Own elaboration using CENEC-2010.