Latin American Economic Review (2022), volume 32, article 2
https://doi.org/10.47872/laer.v32.111

RESEARCH ARTICLE

The Role of Innovation in Employment Growth, Skills Demand, and Wages: Evidence from Ecuador

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Submission received: February 18, 2022
Final version received: September 6, 2022
Accepted: November 11, 2022
Published: January 30, 2023

Abstract

This study's main objective is assessing the effects of innovation on firms' employment growth. Further, we aimed to examine the quality of jobs in terms of skills and wages. By applying a structural modeling approach, four types of innovation were considered—namely, product, process, organizational, and marketing. This is the first study to evaluate the role of marketing in depth in this context. We predominantly utilized the database from Ecuador's 2013 National Survey of Innovation Activities (with firm-level information from 2009–2011). Our results show that innovation exhibits a net effect on employment and contributes to the improvement of job quality. Specifically, product and marketing innovations emerge as important tools for increasing employment in Ecuador. Moreover, product innovation favors high-skilled over low-skilled workers. Finally, innovative firms pay higher wages. Therefore, we provide evidence for a developing country on the relevant role of innovation in employment growth, skills demand, and the payment of higher wages.

Keywords: Innovation, employment growth, job quality, skills, wages, development.
JEL codes: O3, J23, O31, O33, C26.

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1. Introduction

This study's main objective is assessing the effects of innovation on firms' employment growth, considering the possible heterogeneous effects of different innovation types. Further, we aim to examine job quality in terms of skills and wages. Following the third edition of the Oslo Manual (OECD/Eurostat, 2005), we consider four innovation types— namely, product, process, organizational, and marketing innovations.[1] We apply the structural modeling approach of Harrison et al. (2014)—a key contribution to the literature on the innovation-employment nexus at the firm level—[2] because it focuses on the impact of different innovation types on firms' labor demand and describes it through the effects of innovation on firm's efficiency (productivity) and the demand for its products. Harrison et al. (2014) indicated that they developed a model based on economic theory, which was then adapted to the type of information in Community Innovation Surveys (CIS) databases. Due to the availability of information on firms' new products sales (present in CIS-type data), they could separate innovation's effects on employment operating through innovation's effects on productivity or firm demand.

The fundamental database utilized in our study is derived from Ecuador's 2013 National Survey of Innovation Activities (NIAS)—a survey of firm-level information from 2009–2011 sponsored by the National Statistics and Census Office of Ecuador (INEC) and the Secretary for Higher Education, Science, Technology, and Innovation (SENESCYT). It is a CIS-type database.

Harrison et al. (2014) central idea is that process and product innovations affect employment growth through displacement and compensation effects. In the case of process innovation, the labor displacement effect arises when introducing this innovation type generates efficiency (productivity) gains that save jobs. By contrast, the labor compensation effect, which could offset the displacement effect, arises when firms' sales grow as firms with greater efficiency lower their prices and pursue market expansion.

This study extends Harrison et al. (2014) empirical strategy, which only considered product and process innovations, to include organizational and marketing innovations. Although their model has been utilized in subsequent empirical research, most of these studies have focused on developed countries, have insufficiently incorporated organizational innovations, and have not considered marketing innovations.[3] [4]

In addition to process innovations, organizational and marketing innovations can exhibit a displacement effect on employment. In the case of organizational innovations, this might occur due to the reorganization of work and business practices. In the case of marketing innovations, it might also occur due to an increase in efficiency. In this sense, following Corrado et al. (2009), firms' specific investments in intangibles, such as brand name and advertising, can be considered intangible capital contributing to

[1]The Oslo Manual (OECD/Eurostat, 2005) highlighted the primary distinguishing factors between product and marketing innovations, or between process and organizational innovations. Thus, a significant change in a product's functions or uses should be termed a product innovation. However, innovation concerning firms' sales or marketing methods should be termed marketing innovation. Regarding the distinction between process and organizational innovations, the former mainly concerns the implementation of new equipment, software, and specific techniques or procedures, while the latter mainly concerns people and work organization (OECD/Eurostat, 2005).

[2]Some surveys on the innovation-employment nexus are Pianta (2005), Vivarelli (2014) and Calvino and Virgillito (2018).

[3]Several studies have applied Harrison et al. (2014) methodology to developed countries—Hall et al. (2008) to Italy, Peters et al. (2013) to 20 European countries, Dachs and Peters (2014) to 16 European countries, Dachs et al. (2017) to 26 European countries, and Damijan et al. (2014) to 28 European countries.

[4]Further, Harrison et al. (2014) model has been used as a basic framework in some studies on Latin American countries (see Appendix A1). Cirera and Sabetti (2019), who recently investigated low and middle-income countries in Africa, South Asia, the Middle East and North Africa, and Eastern Europe and Central Asia found a positive effect of product innovation on employment growth, but no effect of process or organizational innovations. This study includes the latter innovation type.

productivity growth. Corrado et al. (2009) estimated that approximately 60% of total advertising expenditure exhibits long-lasting effects (persist for more than one year).

Furthermore, Crass and Peters (2014) found that branding capital—measured by marketing expenditures and trademark stocks—exhibits strong positive effects on productivity. As a proxy for reputation or branding capital, they used marketing expenditure, which included advertising, the conceptual design of marketing strategies, market and customer demand research, and the establishment of novel distribution channels. Similarly, Bontempi and Mairesse (2015) termed advertising and branding as "intangible customer capital" and regarded these as productivity-enhancing investments. Therefore, marketing innovations can improve firms' branding capital and reputation and, consequently, productivity.

Similarly, a compensation effect for organizational and marketing innovations might occur when efficiency gains translate into price reductions, increased demand, and sales growth (market expansion). Furthermore, product and marketing innovations could exhibit a compensation effect on employment through the generation of new demand for the firm's products—representing additional market expansion. In the case of product innovation, a displacement effect on employment—caused by the substitution of old products with new ones, which, if produced more efficiently, require less labor—might occur.

All the aforementioned effects of innovation on employment growth at the microeconomic (firm) level contribute to explaining the net employment growth generated by innovation at the macroeconomic level. At a more aggregated level, along with the displacement and compensation effects described above, a new effect arises: the business stealing effect—that is, the act of product innovators stealing sales from firms that continue manufacturing old products.

The consideration of marketing innovations in Harrison et al. (2014) model estimation contributes to i) a better identification of model parameters capturing efficiency gains' effects on employment in the production of old products due to process and organizational innovations and ii) a better identification of relative efficiency's effects in the production of old products relative to new products in explaining employment growth (captured by the model parameter associated with sales growth caused by the introduction of new products). Additionally, the parameter associated with marketing innovations may reflect: 1) a displacement effect on employment due to efficiency gains over time in the production of old products and 2) a positive employment effect for financially constrained firms that raise new product prices and, consequently, profits, thus encouraging the hiring of new workers. An empirical question that requires investigation is which of these effects is most dominant.

Regarding the effects of innovation on job quality in terms of skills and wages, product innovation, for example, can increase product variety and quality and generate labor demand that tends toward higher skills and increases wages (technology-based wage premiums). Moreover, some studies in European countries have concluded that organizational innovation is more important than product and process innovation for skills upgrading—namely, Caroli and Van Reenen (2001) for France and the UK, Piva and Vivarelli (2002) and Piva et al. (2005) for Italy, and Greenan (2003) for France.[5] Additionally, technological change might potentially replace some tasks with others requiring more skilled labor (Vivarelli, 2013)).

While several studies have assessed technological change and skill bias in developed countries, such

[5] See the works by Acs and Audretsch (1988), Acemoglu (1998), Giuri et al. (2008), Bogliacino and Lucchese (2016), and Marouani and Nilsson (2016), among others, on the skill bias of technological change. Vivarelli (2014) found a positive relationship between innovation and skills in OECD countries.

research in developing countries has been scarce. An exception is De Elejalde et al. (2015) study in Argentina, which found that product innovation is skill-biased and process innovation exhibits no effect on skills.

In summary, we contribute to the related literature in several respects. First, we integrate both technological (product and process) and non-technological (organization and marketing) innovations in Harrison et al. (2014) framework. This study is the first to consider marketing innovations. Second, most evidence on innovation's effects on employment relates to developed countries. Third, we contribute to the understanding of the importance of innovation for development in several dimensions, including growth and quality of employment. Fourth, while several studies have evaluated technological change and skill bias in developed countries, such research has been scarce for developing countries. It would be worthwhile to investigate—especially in a middle-income developing country, such as Ecuador—whether different innovation types contribute to employment growth and whether these types relate to higher job quality in terms of skills and wages.

Generally, Latin American countries (LACs) have not demonstrated a "long tradition" of innovative activities. Lederman et al. (2013) reported that LACs exhibit less product innovation than European and North American countries. Similarly, the Global Innovation Index (WIPO, 2018) reported a lagging innovation performance for LACs.[6] Eight European countries (Switzerland, Netherlands, Sweden, United Kingdom, Finland, Denmark, Germany, and Ireland), one North American country (United States), and one Asian country (Singapore) appear as the leaders in innovation performance among 126 countries. Among LACs, Chile was ranked the highest at 47th, while Ecuador ranked 97th. Schwartz and Guaipatín (2014) highlighted that the primary factors that elucidate why Ecuador lags behind other comparable countries are as follows: insufficient private investments in RD, frictions caused by labor regulation, and deficiencies in education. However, Table 1 shows that Ecuador's overall (public and private) investment in RD as a percentage of GDP is the highest among the Andean countries (Colombia, Peru, Bolivia, and Ecuador); however, this does not hold when compared to other LACs—including Argentina, Brazil, Chile, Costa Rica, and Mexico.[7] The same is true for other innovation inputs.

Table 1: *Some aggregated innovation and employment indicators. Panel A: Andean Countries.*

Indicators	**Bolivia**				**Colombia**				**Ecuador**				**Peru**			
	2009	**2010**	**2011**	**2015**	**2009**	**2010**	**2011**	**2015**	**2009**	**2010**	**2011**	**2015**	**2009**	**2010**	**2011**	**2015**
R&D expenditure (% of GDP)	0.16	n/a	n/a	n/a	0.19	0.19	0.20	0.24	0.39	0.40	0.34	0.44*	n/a	n/a	0.08	0.12
Researchers in R&D (per million people)	145.71	165.95	n/a	n/a	172.03	182.27	168.04	114.89*	118.35	141.30	180.30	400.72*	n/a	n/a	n/a	n/a
Charges for the use of intellectual property, payments (in million US$)	18.65	19.80	20.80	83.56	298.56	362.40	424.66	471.320	47.45	54.05	65.76	72.45	152.41	196.76	215.80	302.156
Charges for the use of intellectual property, receipts (in million US$)	2.50	2.80	7.10	22.34	39.04	56.49	59.00	52.39	n/a	n/a	n/a	n/a	2.18	3.05	5.37	7.00
Patent applications, nonresidents	n/a	n/a	n/a	294*	1,551	1,739	1,770	1921	668	690	n/a	475	657	261	1,129	1,182
Patent applications, residents	n/a	n/a	n/a	9*	128	133	183	321	6	4	n/a	20	37	39	39	67
Unemployment, total (% of total labor force)	2.85	2.53	2.22	3.06	12.06	10.88	10.18	8.23	6.46	4.09	3.46	3.61	3.90	3.48	3.44	3
Part time employment, total (% of total employment)	25.75	n/a	n/a	n/a	19.72	21.04	21.87	21.5	19.29	18.09	16.45	20.80	20.28	18.62	17.59	16.09
Vulnerable employment, total (% of total employment)	35.16	35.47	35.76	32.09	47.71	47.93	48.38	46.74	40.10	40.78	41.94	41.28	51.04	51.13	51.49	49.93

Source: World Bank Indicators

* The last information for this indicator is from 2014.

An example of innovation outcomes is the number of patent applications. Ecuador, with only 20 patent applications in 2015, is far behind leading LACs and other developing nations.

On the contrary, considering a few characteristics of the labor market, Table 1 shows that Ecuador

[6]The GII (Global Innovation Index) is a report that provides information on innovation performance at the aggregate level for countries. Specifically, the GII incorporates information on the innovation process' inputs and outputs, and also considers issues related to institutions, human capital, infrastructure, market and firm sophistication, and scientific and creative output. See WIPO (2018) for methodological details and a complete ranking of countries.

[7]For example, Ecuador exhibited 0.40% of RD expenditure over GDP in 2010, which was higher than that of other Andean countries, while for the 2009–2011 period, only Chile exhibited lower values among LACs.

Table 1: *Some aggregated innovation and employment indicators. Panel B: Other Latin American Countries.*

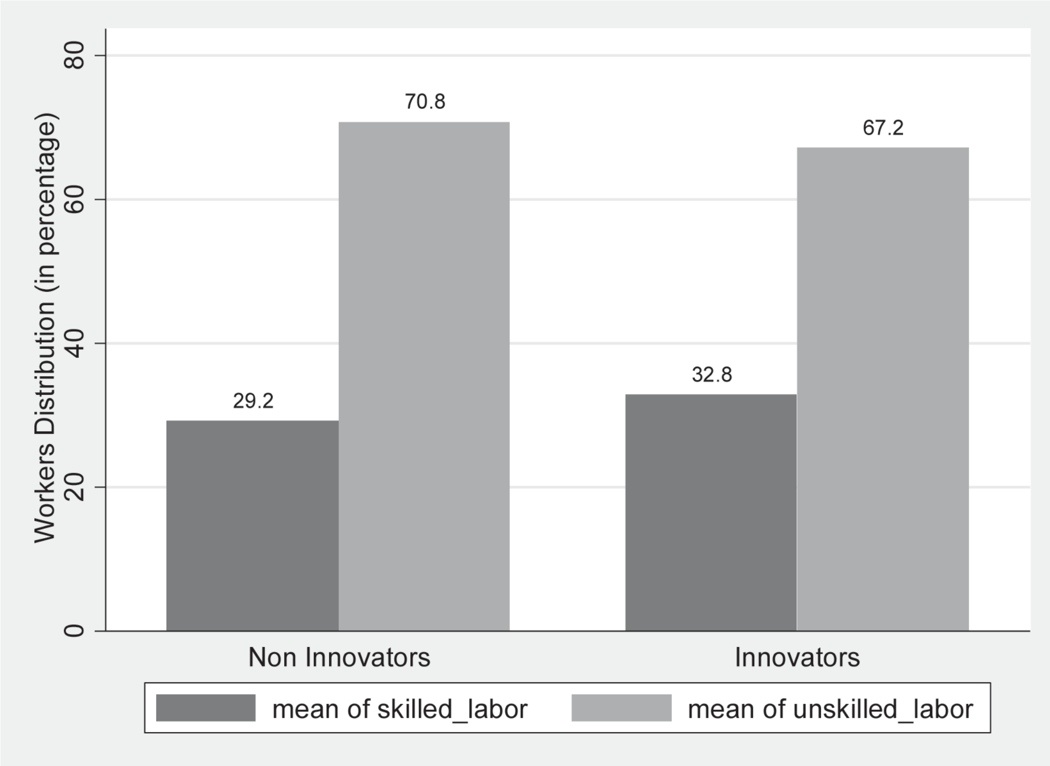
2*Indicators	Argentina				Brazil				Chile				Costa Rica				Mexico			
	2009	2010	2011	2015	2009	2010	2011	2015	2009	2010	2011	2015	2009	2010	2011	2015	2009	2010	2011	2015
R&D expenditure (% of GDP)	0.59	0.56	0.57	0.59*	1.12	1.16	1.14	1.17**	0.35	0.33	0.35	0.38	0.52	0.48	0.47	0.58**	0.52	0.54	0.51	0.55
Researchers in R&D (per million people)	1,032.77	1,120.71	1,177.00	1,202.07*	656.34	698.10	n/a	n/a	288.71	319.72	353.37	455.50	342.00	384.58	409.09	572.98**	367.87	324.55	330.87	241.80+
Charges for the use of intellectual property, payments (in million US$)	1,526.89	1,712.21	2,079.13	2178.06	2,512.04	3,225.74	3,747.622	5250.45	596.53	726.28	773.55	1,557.77	119.40	158.85	214.77	495.82	278.54	293.69	283.73	259.558
Charges for the use of intellectual property, receipts (in million US$)	105.96	152.18	155.39	161.74	433.80	189.60	300.800	581.08	25.42	36.13	55.29	41.95	n/a	n/a	n/a	0.43	0.005	8.76	5.89	7.40
Patent applications, nonresidents	4,336	4,165	4,133	3,579	18,135	20,771	23,954	25,578	1,374	748	2,453	2,831	n/a	1,212	630	584	13,459	13,625	12,990	16,707
Patent applications, residents	640	552	688	546	4,271	4,228	4,695	4,641	343	328	339	443	n/a	8	14	17	822	951	1,065	1364
Unemployment, total (% of total labor force)	8.64	7.71	7.17	7.15	8.27	7.25	6.69	8.43	9.68	8.42	7.34	6.51	7.71	8.92	10.18	9.26	5.38	5.32	5.19	4.34
Part time employment, total (% of total employment)	25.72	24.62	24.01	25.84**	n/a	n/a	n/a	18.07	15.97	23.53	24.54	24.67	n/a	19.96	21.81	22.12	19.45	19.55	19.22	18.98
Vulnerable employment, total (% of total employment)	19.67	19.48	19.67	21.40	26.23	25.98	25.56	27.02	26.86	22.72	22.97	22.76	20.12	20.48	14.33	14.88	29.77	28.79	28.75	27.66

Source: World Bank Indicators
* The last information for this indicator is from 2014.
+ The last information for this indicator is from 2013.

does not exhibit a high unemployment rate. Nevertheless, in 2015, vulnerable employment constituted, on average, 40.94% of total employment. Employment vulnerability is an indicator that measures job quality. The United Nations—as part of its Millennium Development Goals—established this indicator in 2009 (International Labour Office, 2009). This indicator measures the sum of own-account workers and contributing family members over the total number of workers. The high value of this indicator for Ecuador indicates that numerous workers have "poor quality" jobs. Based on this indication, it seems reasonable to consider that innovation may also affect employment quality. The first piece of evidence in this direction is derived from the latest Economic Census of Ecuador (2010), which covers the universe of firms and provides information regarding wages and RD. According to census data, firms investing in RD pay higher wages. [8] The second piece of evidence is presented in Figure 1, which, following De Elejalde et al. (2015) definition of skilled labor, presents the percentage of employees with basic education (primary and secondary) and the percentage of those with higher education (PhD., Master, Bachelor, Specialists, and Technicians— university degrees or tertiary education related to technical professions). Ecuadorian innovative firms have a higher proportion of workers with higher education (approximately 4% more: 1% more specialists and technicians, 2% more other university graduates, and 1% more postgraduates). Figure 1 displays data from the National Survey of Innovation Activities in Ecuador (NIAS, 2013), which provides information on workers' skills. In this Figure, innovative firms are defined as those performing any of the four innovations considered in this study—product, process, organizational, or marketing innovations.

This study's results are manifold in terms of the effects of different innovation types on firms' employment growth. First, process innovation increases production efficiency over time, thus justifying a decrease in firms' employment (displacement effect). By contrast, the estimated negative effect on organizational innovation is not statistically significant. Second, sales growth due to new products generates a gross increase in firms' employment because efficiency in the production of old products is higher than in the production of new ones (the opposite of displacement effect). Moreover, the net effect of product innovation on employment growth at the micro level remains positive, large, and highly significant, but smaller than the gross effect. This is caused by the cannibalization of old products by new ones in product-innovative firms (to a certain extent), which experience a decline in demand for old products. Third, we find that innovation in marketing increases employment, possibly due to increased profits as a consequence of higher prices of new products compared to old ones. Fourth, non-product innovators exhibit sales growth of existing products, thus stimulating employment growth in the absence of business stealing by product innovators. Finally, at the macroeconomic level, innovation's positive effects on employment (due to product and marketing innovations) outweigh the negative effects (due to process innovations and the cannibalization of old products by new ones in product-innovative firms).

[8] This result is obtained by performing a mean test of wages between innovative and non-innovative firms. The null of equal wages is rejected (at a 1% level) in favor of innovative firms. The difference in log wages is 1.668.



Note: Own elaboration based on data from the Ecuadorian National Innovation Activities Survey (NIAS, 2013).

Figure 1: *Distribution of workers' education by firm innovative status.*

In terms of job quality, we found that innovative employment growth positively influences the skill composition of the firm's workforce as a result of the positive effect of sales growth due to new products' introduction. Process innovation exhibits the opposite effect. By contrast, these effects are not significant for marketing and organizational innovations. Finally, the results indicate that innovative firms pay higher wages. Therefore, in Ecuador, innovation not only exhibits net positive effects on employment but also positively affects employment quality.

Our results have interesting policy implications. First, both product and marketing innovations are relevant tools for increasing employment in the short and medium-term in Ecuador. Second, product innovation is seemingly an innovation type positively associated with skills, thereby highlighting product innovation's relevance in promoting the demand for human capital in developing countries. In Ecuadorian firms, such innovation could be associated with greater complexity than process innovation, which would require more skilled workers. Moreover, since innovative firms pay higher wages, the public sector could improve workers' living standards through firm-level innovation policies.

The remainder of the paper is organized as follows: Section 2 presents the structural modeling approach; Section 3 presents the empirical model; Section 4 presents the data; Section 5 reveals and discusses the results obtained; and Section 6 concludes.

2. Structural modeling approach

We rely on Harrison et al. (2014) structural model, which focuses on the impact of different innovation types on firms' labor demand and describes it through the effects of innovation on firms' productivity (efficiency) and the demand for their products. In a structural model, the estimated parameters of the employment growth equation allow for an economic interpretation. Therefore, we can determine whether innovation stimulates a firm's labor demand and identify and understand channels through which this occurs; for this purpose, the structural model is particularly relevant. The structural model can distinguish the effects on labor demand arising from changes in efficiency (productivity)—for a given level of output—from the effects arising due to changes in a firm's demand for a given efficiency level. Regarding efficiency gains resulting from innovation while maintaining a fixed output, the structural model predicts a displacement effect on labor (reduction in labor demand). On the contrary, if efficiency gains translate into lower prices, leading to an increased demand for the firm's products, this would increase output and justify an increase in the demand for labor (compensation effect). Harrison et al. (2014) argued that unlike studies based on simple correlations or those estimating reduced-form relationships (capturing only net employment effects resulting from the complex interaction of different forces), their structural framework disentangled the theoretical productivity (displacement) effects of innovation from those of demand expansion (compensation effects).

Harrison et al. (2014) developed a model based on economic theory and adapted it for the information contained in CIS-type databases. Thus, given that a wave of CIS represents three years, their model captures innovation's short-term effects on employment. Therefore, the model, which is not a complete dynamic specification based on data spanning numerous years, considers two periods and two goods (old and new products). Furthermore, due to this short period and a lack of factor price data in CIS-type databases, they assume that relative input prices are roughly constant over time (from $t-2$ to t) and are equal for old and new products in the second period (t). This assumption allows—using an output conditional or Hicksian demand for labor—the separation of productivity effects for a given output from the demand effects of a firm's output for a given efficiency level.

In notation, the two periods of the model are $t = 1$ and $t = 2$. The two goods are old $(j = 1)$ and new products $(j = 2)$. Production in $t = 1$ applies to old products (i.e., $Y_{jt} = Y_{11}$). By contrast, in $t = 2$ the firm produces a mixture of old and new products (hence, $Y_{j2} = Y_{12} + Y_{22}$, with $Y_{j2} > 0$, $Y_{12} \geq 0$, and $Y_{22} \geq 0$). Product innovation can be zero, in which case, in period 2, the firm produces only old products; alternatively, product innovation can be positive, in which case, the firm will produce a mix of old and new products or only new products. This will depend on the degree of complementarity or substitutability between the two product types.

Specific production functions are assumed to produce old products in periods 1 and 2, and to produce new products in period 2:

$$
\begin{aligned}
Y_{11i} &= \theta_{11} F(K_{11i}, L_{11i}, M_{11i}) e^{\eta_i} \\
Y_{12i} &= \theta_{12} F(K_{12i}, L_{12i}, M_{12i}) e^{\eta_i - u_i} \\
Y_{22i} &= \theta_{22} F(K_{22i}, L_{22i}, M_{22i}) e^{\eta_i - v_i}
\end{aligned} \tag{1}
$$

where i represents the firm; θ_{jt} reflect productivity (efficiency) terms; andη_i allows for firm's fixed effects in the production technology. Further, unanticipated productivity shocks (u_i or v_i) may occur in the production of both product types in period 2. A firm varies efficiency in producing old products (θ_{1t}) by introducing process innovations between periods 1 and 2. However, as new products do not exist in period 1, such innovations cannot affect the efficiency in new products' production. This model allows for factors other than innovation possibly affecting efficiency in old products' production.

Cost-minimizing firms exhibit the following relative labor demands:

$$\begin{aligned} \frac{L_{12i}}{L_{11i}} &= \frac{\theta_{11}}{\theta_{12}} \cdot \frac{Y_{12i}}{Y_{11i}} \cdot e^{u_i} \\ \frac{L_{22i}}{L_{11i}} &= \frac{\theta_{11}}{\theta_{22}} \cdot \frac{Y_{22i}}{Y_{11i}} \cdot e^{v_i} \end{aligned} \tag{2}$$

where the first corresponds to the labor demand for the production of old products in period 2 relative to that in period 1, and the second to the labor demand for the production of new products in period 2 relative to that in period 1 for the production of old products. Notably, in the presence of relative labor demands, firms' individual effects η_i disappear. This is highly relevant for estimation, as it allows for the correlation between explanatory variables and individual firm effects.

The change from period 1 to period 2 in the firm's labor demand is decomposed into the change in employment to produce old and new products as follows:

$$\frac{\Delta L_i}{L_i} = \frac{(L_{12i} + L_{22i}) - L_{11i}}{L_{11i}} = \frac{L_{12i} - L_{11i}}{L_{11i}} + \frac{L_{22i}}{L_{11i}} \simeq ln\left(\frac{L_{12i}}{L_{11i}}\right) + \frac{L_{22i}}{L_{11i}} \tag{3}$$

Next, combining (2) and (3), we obtain the equation for the firm's labor demand growth:

$$\frac{\Delta L_i}{L_i} = -[ln(\theta_{12}) - ln(\theta_{11})] + [ln(Y_{12i}) - ln(Y_{11i})] + \frac{\theta_{11}}{\theta_{22}} \cdot \frac{\bar{Y}_{22i}}{Y_{11i}} + u_i \tag{4}$$

where $\bar{Y}_{22i} = Y_{22i} \cdot e^{v_i}$ is the production of new products excluding the unanticipated productivity shock v_i. This is relevant for estimation, as unforeseen productivity shocks affecting the production of new products, which appear in period 2, is not a concern. The last term u_i is the unanticipated productivity shock affecting the production of old products in period 2. In Harrison et al. (2014) model, the assumptions regarding the timing of investment decisions preclude u_i foresight in advance and, thus, rule out the simultaneity of investment decisions and productivity shocks in the production of old products in period 2. The model assumes that, before period 2, firms decide on their RD and other investment types to obtain innovations. In the literature on the estimation of production functions, Olley and Pakes (1996) make a similar assumption that current investment decisions depend on past productivity shocks.[9]

In (4), since the growth of demand for old products contributes directly (with a coefficient equal to one) to the growth of the firm's demand for labor, this component can be shifted to the left-hand side to obtain:

$$\frac{\Delta L_i}{L_i} - [ln(Y_{12i}) - ln(Y_{11i})] = -[ln(\theta_{12}) - ln(\theta_{11})] + \frac{\theta_{11}}{\theta_{22}} \cdot \frac{\bar{Y}_{22i}}{Y_{11i}} + u_i \tag{5}$$

The error of the employment equation (u_i) is correlated with Y_{12i}; however, this does not imply an estimation problem since no coefficient exists to estimate for the term $[ln(Y_{12i}) - ln(Y_{11i})]$, which is

[9]Due to the model's assumptions, u_i cannot be forecasted at the time of investment. However, if firms—in real-life scenarios—were to make investments to obtain innovations within the period affected by the shocks u_i, the resulting innovations could be endogenous and would require the use of instruments.

shifted to the left-hand side. Additionally, the ratio $(\bar{Y}_{22i}/Y_{11i})$ is uncorrelated with u_i.

Therefore, through the estimation of the model's parameters, Harrison et al. (2014) structural model identifies the following: 1) the increase (or decrease) in the firm's labor demand when there is an increase (or decrease) in efficiency (productivity) in the production of old products from period 1 to period 2 (i.e., $-[ln(\theta_{12}) - ln(\theta_{11})]$, with $\theta_{12} < \theta_{11}$ or $\theta_{12} > \theta_{11}$); and 2) the effect on the firm's labor demand generated by an increase in the demand (production) of new products $(\bar{Y}_{22i}/Y_{11i})$ that did not exist in period 1. This effect depends on the initial productivity in the production of old products compared to that of new products appearing in period 2 $(\theta_{11}/\theta_{22})$.

3. Empirical model and interpretation of coefficients

To obtain the empirical version of (5), the model is expressed as follows:

$$l_i - y_{1i} = \alpha + \beta \cdot y_{2i} + u_i \tag{6}$$

where $l_i = \Delta L_i/L_i$; $\alpha = -[ln(\theta_{12}) - ln(\theta_{11})]$; $y_{1i} = [ln(Y_{12i}) - ln(Y_{11i})]$; $y_{2i} = \bar{Y}_{22i}/Y_{11i}$; and $\beta = \theta_{11}/\theta_{22}$. Furthermore, the change in efficiency in the production of old products (α) is decomposed into three terms—namely, the change in efficiency due to factors other than firm innovation (α_0); change in efficiency due to process innovations (α_1); and change in efficiency due to organizational innovations (α_2):[10]

$$l_i - y_{1i} = \alpha_0 + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i + \beta \cdot y_{2i} + u_i \tag{7}$$

Finally, we incorporate marketing innovations to the empirical model in (7).[11] Hence, our empirical model to be estimated in this study is as follows:[12]

$$l_i - y_{1i} = \alpha_0 + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i + \alpha_3 \cdot Marketing_i + \beta \cdot y_{2i} + u_i \tag{8}$$

The coefficient α_0 is expected to be negative when efficiency gains occur over time in the production of old products unrelated to the firm's innovation. The coefficients α_1 and α_2 are expected to be negative when the replacement of labor with machines and the reorganization of work and business practices increase efficiency in the production of old products over time. The above coefficients identify labor displacement effects due to the passage of time, process innovations, or organizational innovations, respectively. These represent gross effects because they identify the effects of efficiency changes in the production of old products—while keeping their output fixed—on firms' labor demand. Their compensation effects, which appear when firms lower their prices and increase the demand for their product by increasing their efficiency, are included in y_{1i} in (8). Non-structural models usually estimate a net effect

[10] Peters et al. (2013), Damijan et al. (2014), Dachs et al. (2017), and Cirera and Sabetti (2019) extend Harrison et al. (2008, 2014) empirical model by incorporating organizational innovations, which are treated like process innovations. Evangelista and Vezzani (2012) studied the impact of product, process, and organizational innovations on firm employment for European countries, but adopted a different methodology. They found that organizational innovation positively affects employment.

[11] Employing a different approach, Falk (2015), studying Austrian data, added organizational and marketing innovations to technological innovations. He found that both non-technological innovations exhibit no effect on employment.

[12] Although the dependent variable is $l_i - y_{1i}$, the estimation results are interpreted on employment growth as the coefficient of variable y_{1i} is equal to 1.

that combines the two aforementioned effects.

Additionally, by estimating β , we identify the relative efficiency in the production of old products compared to that of new ones. This coefficient is used to evaluate how a given increase in sales due to new products, y_{2i}, translates into growth in the firm's demand for labor. Again, it captures a gross effect, since compensation effects are included in y_{2i} or even in y_{1i} in (8).[13] If new products are produced relatively more efficiently than old ones ($\beta < 1$), the increase in sales due to new products will facilitate less growth in the firm's labor demand than would have occurred with the same increase in sales of old products (assuming for them the productive efficiency in period 1). The opposite will be the case when new products are produced relatively less efficiently.

To explain marketing innovations' role in the model, two estimation issues must be introduced. First, (8) is not yet our equation to estimate because growth rates of old and new products' sales must be in real terms, and therefore, deflators must be used. Following the usual practice in this literature, we use industrial deflators (ISIC Rev.4) for Ecuador (at three digits for manufacturing and two digits for services) in the calculation of the growth rate in real terms of old products' sales (g_{1i}). However, no suitable deflator calculates real sales growth rate due to new products; in (8), we simply enter its observed value $g_{2i} = (1 + \pi_{2i})y_{2i}$, where π_{2i} is the difference between prices of new products in period 2 and old products in period 1 over the price of old products in period 1 ($(P_{22} - P_{11})/P_{11}$). This pricing information is unavailable, even at the industry level. Therefore, our labor demand equation to be estimated becomes:

$$l_i - g_{1i} = \alpha_0 + \alpha_1 \cdot Process_i + \alpha_2 \cdot Organizational_i + \alpha_3 \cdot Marketing_i + \beta \cdot g_{2i} + \epsilon_i \quad (9)$$

where $\epsilon_i = -\beta\pi_{2i}y_{2i} + u_i$.

The second estimation issue is the endogeneity caused by the measurement error affecting the variable g_{2i} in (9). Considering that the nominal growth rate of production due to new products is $g_{2i} = P_{22}\bar{Y}_{22i}/P_{11}Y_{11i}$, this regressor is correlated with the error term, ϵ_i. A measurement error will cause an attenuation bias in the estimation of β in (9) by OLS.[14] This problem can be solved by finding instruments correlated with y_{2i} but uncorrelated with the price differential component that would remain in the error term. To this end, we used four instruments: The first two instruments—an *increased range of products* and *clients as an information source*—have been used in numerous studies (Harrison et al., 2014, 2008; Peters, 2008; Peters et al., 2013; Dachs and Peters, 2014; Jaumandreu, 2003; Dachs et al., 2017). The first instrument is derived from a survey question on the importance of increasing firms' product range for product innovation. The variable has a five-level Likert scale—with low values indicating no or low relevance and high values indicating high relevance. Arguably, when a firm introduces new products to increase its range, this will positively affect the increase in new products' sales. The second instrument is a dummy variable based on a survey question about the importance of clients' opinions in introducing product innovations (takes the value of 1 when this source of information is of high relevance to the firm and 0 otherwise). If clients' opinions are considered in product innovation, new products can be expected to contribute in increasing sales. Third, we introduce the variable *replacement of outdated products*, which is derived from a survey question on the importance of replacing outdated products for product innovation. It is a dummy variable that takes the value of 1 when this purpose is of high relevance for product innovation in the firm and 0 otherwise. Arguably, when a firm introduces

[13] A certain degree of substitution ("cannibalization") of old products for new ones might occur.

[14] Notably, this coefficient will reflect both the relative efficiency in the production of old and new products and unobserved information on the relative prices of these two product types.

new products to replace outdated ones, this will positively affect the increase in sales due to the new products. Finally, we introduce another dummy variable, *reaction to the market*, which is derived from the information in the survey regarding the introduction of product innovations even though the market suffers from demand uncertainty or is dominated by established firms. Arguably, a firm introduces new products even in an undesirable market scenario because it expects an increase in sales due to the new products.

Although these instruments were initially selected because they are expected to be related to sales growth due to new products, their validity—an empirical question—will be formally assessed in the results section. This will involve checking that they are exogenous to the error term in the employment equation, positively and significantly correlated with the potentially endogenous regressor in the first stage reduced-form regression (i.e., not weak instruments), and not redundant (i.e., favor efficiency in the estimation of the employment equation).

Next, we discuss the role of introduction of marketing innovations in the model estimation in (9). Marketing innovations' potential effects on employment growth are manifold. First, if marketing innovations predominantly affect old products (products already produced in period 1), with the coefficient α_3, the model identifies the effect of the change in efficiency over time in the production of old products produced by marketing innovations (i.e., a similar effect captured by α_1 and α_2 for process and organizational innovations, respectively). Their inclusion would contribute to a better identification of efficiency changes' employment effects precipitated by process and organizational innovations. Marketing innovations are expected to increase productivity (see Corrado et al. (2009), Crass and Peters (2014), and Bontempi and Mairesse (2015), who consider marketing as a productivity-enhancing intangible investment); thus, the expected sign for α_3 is negative. This is a labor displacement effect. Second, as in the case of process and organizational innovations, a labor compensation effect may also occur when more efficient firms lower prices and expand demand for old products. Additionally, another labor compensation effect may appear if they contribute to old products' commercial success. [15] In either case, the increase in old products' sales would be captured by g_{1i} in (9). Third, if marketing innovations affect new products' sales (produced only in period 2), this is already incorporated in g_{2i} in (9).

In the case of marketing innovation affecting new products, its inclusion in the model would correct for a potential omitted variable bias affecting the estimation of β in (9). This bias may occur if marketing innovation is positively correlated with nominal output growth due to new products (i.e., with $g_{2i} = P_{22}\bar{Y}_{22i}/P_{11}Y_{11i}$ that implies with $P_{22}\bar{Y}_{22i}$, since $P_{11}Y_{11i}$ is a fixed value in period 1) and both nominal output growth due to new products (g_{2i}) and marketing innovation positively affect employment (i.e., $\beta > 0$ and $\alpha_3 > 0$). When do these conditions for marketing innovation occur? When marketing innovation positively affects the firm's profits—beyond the possible increase in real sales of new products—by enhancing consumers' quality perception of new products, strengthening the brand image, and fostering consumer loyalty. In this case, on the one hand, new products' prices are likely to increase relative to old ones in period 1, which affects the value of the regressor g_{2i} and contributes to its measurement error problem due to the absence of a deflator. On the other hand, when firms' profits increase due to new products' higher prices, those firms asymmetrically affected by the economic cycle—or with financial restrictions—can alleviate their internal funding limitations and, thus, hire new workers. The aforementioned omitted variable bias will overestimate the coefficient $\beta = (\theta_{11}/\theta_{22})$, thereby increasing the probability of concluding that output growth of new products generates greater employment than would a similar increase in output of old products.

Summarizing marketing innovation's (when it mainly affects new products) contribution to the esti-

[15] Marketing innovation can influence employment through firms' sales growth (Som et al., 2012; Evangelista and Vezzani, 2012).

mation of (9), we conclude the following: First, α_3 captures factors such as employment growth associated with an increase in profits. Second, it solves the possible problem of overestimation bias in the model parameter β. Third, it helps partially eliminate from the error term in (9), $\epsilon_i = -\beta\pi_{2i}y_{2i} + u_i$, the unobserved price differential between new and old products (P_{22}/P_{11})—behind the deflator π_{2i}, which is due to marketing innovation. This helps mitigate potential endogeneity problems.

When marketing innovation affects both old and new products, an empirical question arises: Which effect dominates in α_3? Notably, it could reflect both the (negative) displacement effect on employment due to efficiency gains over time in old products' production and the positive effect on employment that the relaxation of financial constraints may precipitate—due to increased profits originating from an improvement in perceived quality, reputation, brand, and consumer loyalty.

4. Data and descriptives

The main database used in this study is the Ecuadorian National Survey of Innovation Activities NIAS (2013). This survey is sponsored by the Ecuadorian National Statistics and Census Office ("Instituto Nacional de Estadísticas y Censos", INEC), and the Secretary of Superior Education, Science, Technology and Innovation ("Secretaría de Educación Superior, Ciencia, Tecnología e Innovación", SENESCYT). NIAS provides information regarding firms' characteristics related to innovation activities, following the Frascati and Oslo Manuals given by the OECD (OECD, 2002; OECD/Eurostat, 2005). Hence, it has information on the performance of product, process, organizational, and marketing innovations. This survey's information corresponds to the 2009–2011 period and is similar—in terms of structure and variables—to the Community Innovation Surveys (CIS) for European countries. Further, NIAS includes other firms' characteristics, including the sector of activity, sales, and employment. The survey, which includes 2,815 firms extracted from the population in the last Economic Census of Ecuador (2010), covers all regions in the country and represents industry-size strata. Moreover, NIAS provides information on the composition of the firm's workforce in terms of skills (a measure of job quality in this study), but does not provide wage-related information (another quality measure used here). Therefore, for the part of our study focusing on the quality of jobs generated, we will combine information from NIAS (referring to the 2009–2011 period) and from the 2010 Economic Census (referring to 2009). Unfortunately, the Economic Census does not include information on innovative outputs but only on RD investment.

NIAS includes all sectors following the ISIC Rev. 4 classification from the United Nations, except the agricultural sector. Additionally, the survey excludes firms with less than 10 employees. Answering the questionnaire is compulsory for firms. In this study's analysis, we further exclude mining and quarrying, construction, and utilities (water supply and electricity, gas, steam, and air conditioning supply). Subsequently, our sample comprises 2,502 firms. Following the additional cleaning of missing values in the variables relevant to our analysis, we obtain an estimation sample of 2,437 firms.

Similar to CIS data, NIAS further provides information on firms' employment and sales for the initial and final years of the period covered in the survey wave (2009–2011). Moreover, it provides information on the proportion (S) of new product sales over total sales in the given period. Per the model assumptions, products existing in 2009 are considered old products. All this information allows us to calculate the growth in sales due to new products (g_2), which, when subtracted from the (nominal) growth in total sales ($\hat{g}$), provides the (nominal) growth in old products' sales ($\hat{g}_1$).[16] To obtain $\hat{g}$ and $\hat{g}_1$

[16] For more detailed information on calculating these growth measures with CIS-type databases, see Appendix A of Harrison et al. (2014).

in real terms (g and g_1), we use industry s deflators π_{1s}.[17][18] However, g_2 cannot be deflated because new products' prices and their difference from the old ones are unavailable. The dependent variable in (9), $l_i - g_{1i}$, is then calculated as the growth in employment minus the real growth in sales of old products for the 2009–2011 period.

Table 2: *Growth of employment and sales, 2009-2011.*

Variables	% of firms (over total)	Employment growth	Sales Growth[a]	Sales growth old products[a]	Sales growth new products[a]
Product innovation (0/1)	0.432	0.217	0.632	0.031	0.600
Process innovation (0/1)	0.421	0.219	0.670	0.208	0.462
Organizational innovation (0/1)	0.239	0.272	0.738	0.300	0.437
Marketing innovation (0/1)	0.250	0.206	0.513	0.138	0.375
Product-only innovation (0/1)	0.073	0.178	0.525	-0.019	0.544
Process-only innovation (0/1)	0.065	0.169	0.813	0.813	0
Organizational-only innovation (0/1)	0.036	0.189	0.291	0.291	0
Marketing-only innovation (0/1)	0.041	0.106	0.234	0.234	0
Innovation in all types simultaneously (0/1)	0.071	0.270	0.561	-0.0815	0.642
Absence of innovation (0/1)	0.358	0.148	1.179	1.179	0

Notes: [a] Total sales growth, sales growth for old products and sales growth for new products.

In Table 2, we present the descriptive statistics of relevant variables for our analysis. For firms' innovation statuses, we construct dummy variables for product, process, organizational, and marketing innovations, and for the corresponding exclusive categories. We further construct dummies for non-innovators and all-type innovators. We observe that non-innovators represent approximately 36% of the firms and that the most common innovative activities are product (43%) and process (42%) innovations, followed by marketing (25%) and organizational (24%) innovations. Additionally, employment growth over the period is about one and a half times higher for innovators than for non-innovators; however, no notable differences exist between product, process, and marketing innovators, but the growth rate is higher for organizational innovators. Observing the exclusive categories reveals that employment growth is highest for all-type innovators. However, while sales growth is high for innovators, it is even higher for non-innovators. This result indicates that not all growth in firms' sales is due to the introduction of innovations and, therefore, highlights the need for an econometric analysis that controls for other factors. Further, according to the information broken down into old and new product sales growth, for product innovators, new product sales' growth is the most important component of their total sales growth. Finally, for only-product innovators, the contribution of old products' sales growth to total sales growth is negative. This could indicate some degree of cannibalization of old products by new ones, though it is not a sufficient condition for this to occur.

Moreover, Table 3 presents mean tests comparing firm size in 2011 with firm size in 2009 and whether firms that engage in innovation activities are larger in 2011 than firms that do not. Clearly, firms are larger in 2011 than in 2009, and firms that innovate are larger in 2011 than those that do not.

In our econometric analysis in Section 5, we further include some controls that may affect firms' employment growth. First, we control for technological intensity with dummy variables according to the OECD (2002, 2007) technological classification for manufacturing and services industries. Manufacturing is classified as follows: High-tech, Medium-high-tech, Medium-low-tech, and Low-tech. There is

[17] $g = \hat{g} - \pi_1$ and $g_1 = \hat{g}_1 - \pi_1$

[18] In the case of manufacturing, they are constructed with the Producer Price Indices (PPI) published by INEC (the Ecuadorian statistical office) at three digits. Due to the lack of data, we apply the average PPIs of manufacturing to services (as do other related works in the literature).

a distinction between Knowledge-intensive and Less knowledge-intensive services.[19] The largest number of firms is concentrated in Low-tech manufacturing (26.4%, mainly comprising firms in the food, beverage, and tobacco sectors) and in Knowledge-intensive services (30.1%, with service firms dedicated to information, communication, or finance, among others). Second, we control for firms' size. On the one hand, Gibrat's law states that a firm's proportional growth rate is independent of its absolute size (Gibrat, 1931). On the other hand, there is no consensus on this law's validity because numerous studies have found that smaller firms grow faster (Audretsch et al., 2004). In this study, given that the production laws in Ecuador—Production Code 2010 and Production Regulation Code 2011 (Registro Oficial, 2010; Presidencia de la República del Ecuador, 2011)—classify firm size into four groups, four dummy variables corresponding to Micro, Small, Medium and Large firms are used.[20] According to this classification, 14.4%, 44.7%, 22.0%, and 19.0% of our firms are Micro, Small, Medium, and Large, respectively.[21]

Table 3: *Mean Test for employment differences by type of innovation.*

	Difference	Std. Err.
workers 2011 vs 2009	0.112 ***	0.006
Product innovation (1) vs Product innovation (0)	0.389 ***	0.051
Process innovation (1) vs Process innovation (0)	0.520 ***	0.051
Marketing innovation (1) vs Marketing innovation (0)	0.165 ***	0.059
Organizational innovation (1) vs Organizational innovation (0)	0.422 ***	0.060
Innovation in all types simultaneously (1) vs Innovation in all types simultaneously (0)	0.404 ***	0.100
Absence of innovation (1) vs Absence of innovation (0)	-0.343 ***	0.053

Notes: H0 = difference 1 – difference 0; *, ** and ***significant at 10%, 5% and 1% level, respectively.

Appendix A2 presents the mean values and standard deviations of the relevant variables in our econometric analysis in Section 5

5. Results

5.1. Innovation and employment growth

Table 4 presents the results of estimating model (9), using OLS and IV methods. The instruments for the *sales growth due to new products* variable are: the *increased range* indicator in column 2; the *increased range* and *clients as information source* indicators in column 3; the *increased range*, *clients as an information source* and *replacement of outdated products* indicators in column 4; and the *increased range*, *clients as an information source*, *replacement of outdated products*, and *reaction to the market* indicators in column 5. The IV estimation is performed by combining the corresponding moment conditions utilizing heteroscedastic GMM.[22] The results of four testing procedures on our instruments and the instrumented regressor (sales growth due to new products) are presented at the bottom of Table 4.

First, we use Hansen's test of overidentification restrictions, whose null hypothesis (H0) is that the instruments are uncorrelated with the error term (i.e., they are exogenous). Under H0, the test statistic is χ^2(m) distributed with the number m of overidentification restrictions. Since the p-values associated

[19] Since the model already eliminates firm-specific factors, the objective for including some sectoral controls in the employment growth equation is gaining flexibility by allowing their effects to change during the study period.

[20] Micro firms (with sales under 100,000 USD), Small firms (with sales between 100,001 to 1,000,000 USD), Medium firms (with sales between 1,000,001 to 5,000,000 USD), and Large firms (with sales over 5,000,001 USD). The classification is based on 2009 data.

[21] Notably, NIES excludes firms with less than 10 employees.

[22] Efficiency in GMM is robust to heteroscedasticity of the unknown form.

with the statistic are invariably well above 10%, H0 is never rejected (see columns 3, 4, and 5; this test is not available for column 2, since no overidentification is present). Therefore, Hansen's tests indicate that our four excluded instruments are accurately excluded from the equation estimated in (9). Second, we apply the endogeneity test of the regressor sales growth due to new products. The null hypothesis is regressor's exogeneity. The statistic is distributed as $\chi^2(1)$ and is defined as the difference between two Hansen statistics. Since the p-values associated with the statistic are invariably less than 5%, the difference in Hansen's tests rejects the regressor's exogeneity (see columns 2 to 5). Third, we use the IV redundancy test, which helps determine whether a subset of excluded instruments is "redundant." They are redundant if using them fails to improve the estimate's asymptotic efficiency. The test statistic is an LM test. Under the null hypothesis that the specified instruments are redundant, the statistic is distributed as χ^2 (with degrees of freedom=(number of endogenous regressors)*(number of instruments tested)). In columns 3–5, we test the redundancy of the subset of instruments added to the baseline in column 2 (increased range). With the p-values obtained, which are invariably less than 1%, we reject the null hypothesis, which suggests that our instruments are not redundant and that their inclusion improves estimation efficiency. Notably, from column 2–5, the p-values of the statistically significant regressors decrease, which increases the significance levels, especially in column 5, which uses our four proposed instruments. Finally, we use the first-stage F-test of excluded instruments. This test's null hypothesis is that instruments must be uncorrelated with the instrumented regressor, sales growth due to new products. This test requires a first-stage estimator of a reduced-form regression, wherein the dependent variable is sales growth due to new products and the regressors are the other regressors in (9), plus the corresponding excluded instruments. The first-step regressions' results associated with columns 2–5 of Table 4 are shown in columns 2–5 of Table 5. Table 5 and the bottom of Table 4 show that the excluded instruments are both individually (with a positive sign) and jointly significant (the F-test, with a p-value=0.000, causes the null hypothesis to be rejected), indicating that they are not weak instruments.

Table 4: *The effects of innovation on employment growth.*

Dependent variable: Employment growth $(l - g_1)^a$	(1) OLS Estimation	(2) IV Estimation^b	(3) IV Estimation^c	(4) IV Estimation^d	(5) IV Estimation^e
Process innovation	0.381*	-0.257†	-0.255†	-0.234†	-0.246*
	(0.075)	(0.130)	(0.104)	(0.119)	(0.099)
Organizational innovation	0.157	-0.112	-0.109	-0.138	-0.107
	(0.438)	(0.533)	(0.509)	(0.372)	(0.468)
Sales growth due to new prod. (g_2)	-0.249	1.636*	1.624*	1.400*	1.444**
	(0.394)	(0.081)	(0.061)	(0.061)	(0.050)
Marketing innovation	0.355*	0.304†	0.303†	0.282†	0.324**
	(0.072)	(0.114)	(0.102)	(0.117)	(0.050)
Micro firms2009	-0.171	-0.625**	-0.621***	-0.659***	-0.619***
	(0.504)	(0.015)	(0.009)	(0.003)	(0.004)
Small firms2009	-0.663	-0.874	-0.867	-0.713	-0.781
	(0.282)	(0.219)	(0.203)	(0.243)	(0.194)
Medium firms2009	0.123	0.002	0.002	-0.007	0.004
	(0.285)	(0.981)	(0.985)	(0.932)	(0.956)
OECD_high_technology_manufacturing	1.118	1.319	1.304	1.032	1.187
	(0.363)	(0.318)	(0.297)	(0.360)	(0.283)
OECD_med_high _technology_manufacturing	1.401	1.277	1.263	1.001	1.155
	(0.303)	(0.328)	(0.309)	(0.376)	(0.297)
OECD_med_low_technology_manufacturing	1.266	1.353	1.337	1.039	1.251
	(0.358)	(0.340)	(0.320)	(0.391)	(0.286)
OECD_low_technology_manufacturing	1.254	1.303	1.286	1.017	1.176
	(0.337)	(0.327)	(0.301)	(0.365)	(0.285)
OECD_knowledge_intensive_services	1.462	1.454	1.439	1.159	1.316
	(0.289)	(0.290)	(0.269)	(0.326)	(0.255)
Constant	-1.229	-1.208	-1.193	-0.916	-1.112
	(0.350)	(0.354)	(0.335)	(0.410)	(0.322)

Observations	2,437	2,437	2,437	2,437	2,437
Hansen test χ^2(m=1, 2, or 3)			0.001	0.262	0.806
P-value Hansen test[f]			0.9720	0.8774	0.841
Endogeneity test of regressor g_2 χ^2(1)		4.208	5.794	5.436	5.982
P-value endog. test[g]		0.0402	0.0161	0.0197	0.0145
IV redundancy test, χ^2(m=1, 2, or 3)			7.031	11.542	19.151
P-value redund. test[h]			0.0080	0.0031	0.0003
F test of excluded instruments, F(1,2,3, or 4; 2421)		117.81	61.45	41.85	31.41
P-value F test[i]		0.0000	0.0000	0.0000	0.0000

Notes: *, ** and *** significant at 10%, 5% and 1% level. † slightly above 10% level of significance.
[a] Coefficients and p-values (in parenthesis) robust to heteroscedasticity.
[b] Method: GMM instrumental variables estimation. Unique instrument used is increased range.
[c] Method: GMM instrumental variables estimation. Instruments used are increased range and clients as information source.
[d] Method: GMM instrumental variables estimation. Instruments used are increased range, clients as information source and replacement of outdated products.
[e] Method: GMM instrumental variables estimation. Instruments used are increased range of products, clients as information source, replacement of outdated products and reaction to the market.
[f] Hansen test denotes the test of overidentifying restrictions. The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null hypothesis the test statistic is χ^2(m) distributed with the number m of overidentifying restrictions. Ho always non-rejected.
[g] The endogeneity test tests the null hypothesis of exogeneity of the regressor g2. The statistic is distributed as a χ^2(1). It is defined as the difference of two Hansen statistics. Ho is always rejected.
[h] The redundancy test is a test of whether a subset of excluded instruments is "redundant". Excluded instruments are redundant if the asymptotic efficiency of the estimation is not improved by using them. The test statistic is an LM test. Under the null that the specified instruments are redundant, the statistic is distributed as χ^2(with degrees of freedom=(endogenous regressors)*(instruments tested)). Rejection of the null indicates that the instruments are not redundant.
[i] The first stage F test of excluded instruments allows detecting "weak instruments". Since the p-values are close to zero, the excluded instruments are "relevant", meaning correlated with the endogenous regressor.

In sum, the tests performed confirm our instruments' validity, their contribution to estimation efficiency, and that the regressor sales growth due to new products is endogenous and must be instrumented. However, should we be concerned about instrumenting process, organizational, or marketing innovations? Appendix A3 presents the results of the tests reported in Table 4 when in the estimation of column 5 of Table 4, in addition to the regressor sales growth due to the new products, the regressors process, organizational, and marketing innovations are instrumented one at a time. The results indicate that our four instruments are exogenous, not redundant, not weak, and that the null of exogeneity of process, organizational, and marketing innovations is not rejected.

Therefore, we now interpret our preferred estimates—those in column 5 of Table 4, wherein the sales growth variable due to new products is instrumented using our four instruments. For process innovation, we obtain a negative and significant coefficient. This reflects the existence of efficiency gains in old products' production, which is associated with process innovations that reduce labor requirements (displacement effect). We find that the labor demand growth for process innovators is about 0.25 percentage points lower than that for non-process innovators. However, for organizational innovation, the sign is negative, but not significant.

Table 5: *First stage regressions for the IV method in columns 2-5 of Table 4*

Dependent variable: Sales growth due to new prod. $(g_2)^a$	(2) OLS Estimation	(3) OLS Estimation	(4) OLS Estimation	(5) OLS Estimation
Process innovation	0.076†	0.069†	0.053	0.0503
	(0.113)	(0.141)	(0.247)	(0.272)

Organizational innovation	0.113**	0.112**	0.098*	0.095*
	(0.035)	(0.035)	(0.059)	(0.071)
Marketing innovation	-0.025	-0.031	-0.040	-0.044
	(0.531)	(0.457)	(0.347)	(0.300)
Micro firms2009	0.249***	0.254***	0.250***	0.239***
	(0.000)	(0.000)	(0.000)	(0.000)
Small firms2009	0.116***	0.116***	0.114***	0.107***
	(0.001)	(0.001)	(0.001)	(0.003)
Medium firms2009	0.061**	0.063**	0.061**	0.058**
	(0.031)	(0.028)	(0.032)	(0.037)
OECD_high_technology_manufacturing	-0.068	-0.048	-0.047	-0.043
	(0.334)	(0.484)	(0.499)	(0.531)
OECD_med_high _technology_manufacturing	0.058	0.053	0.053	0.0456
	(0.494)	(0.530)	(0.534)	(0.592)
OECD_med_low_technology_manufacturing	-0.057	-0.051	-0.052	-0.053
	(0.361)	(0.405)	(0.399)	(0.383)
OECD_low_technology_manufacturing	-0.033	-0.034	-0.035	-0.041
	(0.560)	(0.551)	(0.539)	(0.467)
OECD_knowledge_intensive_services	-0.019	-0.022	-0.025	-0.0263
	(0.743)	(0.705)	(0.677)	(0.659)
(excluded) Instruments (IVs)				
Increased range of products	0.115***	0.092***	0.087***	0.084***
	(0.000)	(0.000)	(0.000)	(0.000)
Clients as information source		0.136***	0.124**	0.120**
		(0.008)	(0.015)	(0.020)
Replacement of outdated products			0.119**	0.118**
			(0.024)	(0.025)
Reaction to the market				0.078*
				(0.100)
Constant	-0.078**	-0.082**	-0.082**	-0.080**
	(0.024)	(0.016)	(0.017)	(0.018)
Observations	2,437	2,437	2,437	2,437
F test of excluded instruments				
F(1,2,3, or 4; 2421)	117.81	61.45	41.85	31.41
P-value F test[b]	0.0000	0.0000	0.0000	0.000

Notes: *, ** and *** significant at 10%, 5% and 1% level. † slightly above 10% level of significance.
[a] Coefficients and p-values (in parenthesis) robust to heteroscedasticity.
[b] The first stage F test of excluded instruments allows detecting "weak instruments". Since the p-values are close to zero, the excluded instruments are "relevant", meaning correlated with the endogenous regressor.

Innovation's strongest effect on labor demand growth is for product innovations, as the sales growth variable due to new products exhibits a significant and positive coefficient (β) greater than one.[23] As this coefficient estimates the relative efficiency in the production of old versus new products, our results indicate that the former are produced more efficiently than the latter. Therefore, no displacement effect occurs due to higher productivity in new products' production. This result for Ecuadorian firms is similar to that obtained by Crespi et al. (2019) for Argentina, Chile, and Costa Rica; Monge-González et al. (2011) for Costa Rica; and De Elejalde et al. (2011, 2015) for Argentina. Our estimate indicates that

[23]The OLS estimator for this variable is not significant, which is consistent with an attenuation bias due to a measurement error.

a 1% increase in sales due to new products generates a 1.4% increase in gross labor demand. As the model coefficients do not identify the extent to which new products displace existing ones, conclusions on the net effect on labor demand of product innovation will be obtained by applying the methodology for decomposing labor demand growth at the firm level—as described in section 5.2.

For marketing innovations, the estimated coefficient α_3 is positive and significant. It captures a labor displacement effect due to efficiency gains in the production of old products as well as a positive effect from higher profits due to improved perceived quality, reputation, brand image and consumer loyalty and the consequent relaxation of financial constraints; thus, we find that the latter effect dominates.[24][25]

The model constant (α_0)—though with the expected negative sign —is statistically non-significant, which may indicate that efficiency in old products' production does not simply evolve through mechanisms such as "learning by doing" or spillovers. Furthermore, the firms' technological classification is not statistically significant. Finally, a negative and statistically significant coefficient is obtained for Micro firms, indicating that for this size group, the efficiency in the production of old products increases over time— possibly due to the mechanisms indicated above, thus justifying a lower demand for labor.

5.2. Average employment growth decomposition

In this section, using the coefficient estimates from (9) in column 5 of Table 4, we apply an employment growth decomposition methodology to determine the percentage of employment growth that is derived from different sources. Since in (9), α_0 has been replaced in estimation by $\alpha_{00} + \sum_j \alpha_{0j} \cdot d_{industry_j} + \sum_s \alpha_{0s} \cdot d_{size_s}$, and shifting the sales growth of old products back to the right-hand side, (9) can be written as:

$$\begin{aligned} l_i &= (\alpha_{00} + \sum_j \alpha_{0j} \cdot d_{industry_j} + \sum_s \alpha_{0s} \cdot d_{size_s}) + \alpha_1 \cdot Process_i \\ &+ \alpha_2 \cdot Organizational_i + \alpha_3 \cdot Marketing_i + g_{1i} + \beta \cdot g_{2i} + \epsilon_i \end{aligned} \tag{10}$$

where if coefficients are replaced by their estimates and variables by their means over i, we obtain (assuming a zero-mean residual) the following:

[24] If we exclude marketing innovation from the regression, the estimated coefficients for process or organizational innovations are not affected. By contrast, the coefficient associated with increased sales due to new products rises from 1.44 to 1.64. This highlights the existence of an omitted variable bias that leads to the overestimation of this coefficient when marketing innovation is eliminated from the regression. This may occur if marketing innovation is positively correlated with nominal output growth due to new products.

[25] Comparing the results of a regression of nominal sales growth due to new products on marketing innovations—including controls for technological classification and firm size—with the results of the same regression, but additionally including the four instruments considered in this study as additional regressors, shows that marketing innovation increases profits by increasing new products' prices relative to old products' initial prices. The second regression assumedly cleans g_{2i} from prices and can, therefore, serve as a proxy for real sales growth due to new products. From the first regression, we obtain that the coefficient of the marketing innovation variable is positive and statistically significant (with a value of 0.151), but in the second regression, it is not statistically significant (with a p-value of 0.524). This is in line with the fact that marketing innovation affects the nominal growth rate of sales due to new products, but not its real growth rate. As the difference between the two growth rates stems from the ratio P_{22}/P_{11}, the results obtained indicate that marketing innovation increases this ratio, thus favoring new products' prices.

$$\begin{aligned} \bar{l} &= \hat{\alpha}_0 + \hat{\alpha}_1 \cdot \bar{P} + \hat{\alpha}_2 \cdot \bar{O} + \hat{\alpha}_3 \cdot \bar{M} + \bar{g}_1 + \hat{\beta} \cdot \bar{g}_2 \\ 18.5 &= -57.9 - 10.3 - 2.6 + 8.1 + 43.7 + 37.5 \end{aligned} \tag{11}$$

If we further decompose in (11) the average contribution to the employment growth of old products ($\bar{g}_1$) for firms that are not product innovators and for firms that are product innovators, we obtain the following:

$$\begin{aligned} \bar{l} &= \hat{\alpha}_0 + \hat{\alpha}_1 \cdot \bar{P} + \hat{\alpha}_2 \cdot \bar{O} + \hat{\alpha}_3 \cdot \bar{M} + N\bar{P}D \cdot \bar{g}_{1,NPD} + Y\bar{P}D \cdot \bar{g}_{1,YPD} + Y\bar{P}D \cdot \hat{\beta} \cdot \bar{g}_{2,YPD} \\ 18.5 &= -57.9 - 10.3 - 2.6 + 8.1 + 47.6 - 3.9 + 37.5 \end{aligned} \tag{12}$$

where NPD and YPD are the share of non-product and yes-product innovators, respectively. Notably, $\hat{\beta} \cdot \bar{g}_2$ in (11) is substituted in (12) by $Y\bar{P}D \cdot \hat{\beta} \cdot \bar{g}_{2,NPD}$ because the two are identical due to $\bar{g}_{2,NPD} = 0$ (i.e. non-product innovators have, by definition, zero sales growth due to new products). This new decomposition indicates that the 43.7 percentage points in (11), by which old product growth contributes to employment growth, are composed of 47.6 percentage points from non-product innovators and -3.9 percentage points from product innovators.

Next, we interpret the complete decomposition's results shown in the second row of (12). The first element ($\hat{\alpha}_0$) measures the contribution to the employment growth of efficiency changes in old products' production that do not stem from the firm's innovations. Its negative value, combined with the results in column 5 of Table 4, reflects an increase in efficiency (labor-saving) in old products' production in Micro firms. The second and third elements ($\hat{\alpha}_1 \cdot \bar{P}$ and $\hat{\alpha}_2 \cdot \bar{O}$) measure the contribution to employment growth of efficiency changes in old products' production stemming from the proportion of process or organizational innovators in the sample, respectively. Their negative values highlight efficiency gains (labor savings) in old products' production as a consequence of the introduction of process and organizational innovations. However, considering the results in Table 4, this is statistically true for process innovation (as the estimated coefficient for organizational innovation is negative but not significant). The fifth element ($N\bar{P}D \cdot \bar{g}_{1,NPD}$) measures the contribution to employment growth from the growth in old product output that is derived from non-product innovators' share. Its positive value indicates that non-product innovators experience an increase in demand for old products. Thus, they do not seem to suffer from a business stealing effect of product innovators; on the contrary, they probably face an elastic demand reacting to probable price reductions of old products. The sixth element ($Y\bar{P}D \cdot \bar{g}_{1,YPD}$) measures the contribution to employment growth from the growth in old products' production for the share of yes-product innovators. Its negative value captures the indirect negative effect of new products' introduction on the demand for old products. Therefore, cannibalization—instead of complementarity in the firm between old and new products—occurs. The seventh element ($\hat{\beta} \cdot \bar{g}_2 = Y\bar{P}D \cdot \hat{\beta} \cdot \bar{g}_{2,YPD}$) measures the contribution to employment growth of sales growth due to new products from the share of product innovators. Its positive value suggests that firms with increased sales due to new products contribute to employment growth. This result is driven by the degree of success of product innovations, as measured by $\bar{g}_{2,YPD}$, by the higher relative efficiency in old products' production relative to new products' production ($\hat{\beta} > 1$), and by the existing share of product innovating firms ($Y\bar{P}D$). Finally, the fourth element ($\hat{\alpha}_3 \cdot \bar{M}$) exhibits a positive value and, therefore, supports the idea that firms can alleviate the financial constraints affecting their hiring if marketing innovation increases their profits. By influencing perceived quality, reputation, brand image, and consumer loyalty, they can charge higher prices for new products. Table 6 shows the summary of the results of the decomposition analysis of this section.

What does this section add to this study's previous results? Before performing the decomposition in this subsection, we could only elucidate the gross effects of product innovation on employment growth, i.e., $\hat{\beta} \cdot \bar{g}_2$. Now, however, we can effectively discuss the net contribution of product innovation to employment growth, which is determined by $Y\bar{P}D \cdot \bar{g}_{1,YPD} + Y\bar{P}D \cdot \hat{\beta}\bar{g}_{2,YPD}$, i.e., the contribution of the growth in old products' sales plus the growth in new products' sales for product innovators. Further, the net effect includes the cannibalization of old products in firms introducing new products.

Table 6: *Decomposition of employment growth.*

Variables	Percentage
Employment growth ($\bar{l}$)	18.5
General productivity trend old products ($\hat{\alpha}_0$)	-57.9
Productivity effect of process innovations ($\hat{\alpha}_1 \cdot \bar{P}$)	-10.3
Productivity effect of organizational innovations ($\hat{\alpha}_2 \cdot \bar{O}$)	-2.6
Effect of output growth of old products (for non-product innovators, $N\bar{P}D \cdot \bar{g}_{1,NPD}$)	47.6
Net employment effects of product innovations:	33.6
Effect of output growth of old products (for product innovators, $Y\bar{P}D \cdot \bar{g}_{1,YPD}$)	-3.9
Effect of the increase in production due to new products ($Y\bar{P}D \cdot \hat{\beta}\bar{g}_{2,YPD}$)	37.5
Effect of the increase in profits from marketing innovations (consumers' willingness to pay, $\hat{\alpha}_3 \cdot \bar{M}$)	8.1

5.3. Two dimensions of the quality of jobs created: skills and wages

We intend to ascertain whether firms' innovation activities affect employment growth and its composition in terms of skills and wages. Unfortunately, the Ecuador's National Survey of Innovation Activities does not enable us to determine how employment changes (from 2009–2011) are associated with different skill levels. The survey provides a distribution of the firm's employees in 2011 by skill level. The survey, however, does not provide wage-related information, which must be derived from a complementary database, i.e., the latest Economic Census of Ecuador (2010) with information on firms in 2009.[26]

Table 7: *Effects of innovation on firms' skill labor composition and wages.*

Dependent variables[a]	(1)[b] Skill labor (log%) OLS	(2)[c] Skill labor (log%) IV	(3)[d] Log wages per worker OLS	(4)[e] Log wages per worker OLS
Innovative employment growth	0.002***			
	(0.002)			
Process innovation		-0.224**		
		(0.023)		
Organizational innovation		0.131		
		(0.131)		
Sales growth due to new prod.(g_2)		0.415**		
		(0.039)		
Marketing innovation		-0.014		
		(0.852)		
(Yes/no) R&D			0.855***	
			(0.000)	
Log R&D expenditure				0.133***

[26]See Rodríguez-Moreno and Rochina-Barrachina (2015, 2019) for further details concerning this dataset.

				(0.000)
OCDE_group_high[f]	1.779***	1.750***	0.599***	0.597***
	(0.000)	(0.000)	(0.000)	(0.000)
Micro firms	0.347***	0.270**	-2.126***	-2.107***
	(0.002)	(0.032)	(0.000)	(0.000)
Small firms	0.093	0.053	-0.656***	-0.643***
	(0.287)	(0.557)	(0.000)	(0.000)
Medium firms	-0.106	-0.120	0.925***	0.921***
	(0.281)	(0.228)	(0.000)	(0.000)
Constant	-1.329***	-1.330***	10.506***	10.487***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,437	2,437	126,737	126,737
Hansen test χ^2 (3)		3,355		
P-value Hansen test[g]		0.3401		
Endogeneity test of regressor g_2, $\chi^2(1)$		3.350		
P-value endog. test[h]		0.0672		
IV redundancy test, $\chi^2(3)$		20.258		
P-value redund. test[i]		0.0002		
F test of excluded instruments, F(4, 2425)		31.80		
P-value F test[j]		0.0000		

Notes: *, ** and *** significant at 10%, 5% and 1% level.
[a] Coefficients and standard errors (in parenthesis) robust to heteroscedasticity.
[b,c] The dependent variable is the log transformation of the percentage of the firm's skill workers. Skill workers are employees with PhD, master, university degree, specialists and technicians as level of education.
[d,e] Log wages per employee and all the information about RD performance and expenditures for these regressions is taken from the last Ecuadorian Economic Census (2010).
[f] Following the OECD classification for manufacturing and services as regards knowledge intensity, we have created a dummy variable with value 1 if the sector belongs to the high classification for manufacturing and to the one of knowledge intensive sectors for services.
[g] Method: GMM instrumental variables estimation. The four instruments increased range of products, clients as information source, reaction to the market and replacement of outdated products, are used. Hansen test denotes the test of overidentifying restrictions. The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null hypothesis the test statistic is $\chi^2(3)$ distributed with the number 3 of overidentifying restrictions. Ho always non-rejected.
[h] The endogeneity test tests the null hypothesis of exogeneity of the regressor g_2. The statistic is distributed as a $\chi^2(1)$. It is defined as the difference of two Hansen statistics. Ho is rejected.
[i] The redundancy test is a test of whether a subset of excluded instruments is "redundant". Excluded instruments are redundant if the asymptotic efficiency of the estimation is not improved by using them. The test statistic is an LM test. Under the null that the specified instruments are redundant, the statistic is distributed as χ^2(with degrees of freedom=(endogenous regressors)*(instruments tested)). Rejection of the null indicates that the instruments are not redundant.
[j] The first stage F test of excluded instruments allows detecting "weak instruments". Since the p-value is close to zero, the excluded instruments are "relevant", meaning correlated with the endogenous regressor.

In the first part of the analysis in this section, we used the definition of skilled labor given by De Elejalde et al. (2015), who defined skilled labor as the percentage of employees with more than basic education (including primary and secondary education). In our survey, this percentage would include employees with doctoral, master's, bachelor's, specialist, and technical degrees (i.e., university or higher education degrees related to technical professions). We estimated two specifications of a regression in which the dependent variable is the logarithm of the skilled labor variable. In the first specification, we used the predicted value of innovative employment growth—derived from the estimates in column 5 of Table 4—as the main regressor. In the second specification, we replaced this regressor with our four innovation variables. In both cases, we included size and technological classification controls. The results are shown in the first two columns of Table 7. The regressors related to innovation refer to the 2009–2011 period, while the dependent variable of skill composition represents 2011. The first specification is estimated by OLS. In the second specification, we instrumented the variable of sales growth due to new products with the same instruments as in column 5 of Table 4.[27] Our results indicate that employment growth due to innovation positively affects firms' skill composition. Moreover, this effect stems from sales growth due to new products. However, process innovation exhibits a negative effect, while organizational and marketing innovations are not significant.

In the second part of the analysis in this section (the last two columns of Table 7), we used the Economic Census of Ecuador because it includes information on the average wage per worker. This forced us to utilize—as measures of firms' innovation—whether they conduct RD or make RD investments. Both the dependent variable and RD expenditure are in logs. The results indicate that innovative firms, on average, pay higher wages to their employees.[28]

In summary, the results in this section indicate that innovation affects not only job creation by firms but also job quality—as measured by skills and wages.

6. Conclusions

Our results indicate that different types of innovations may exhibit different effects on firms' labor demand. Process innovation, by increasing efficiency in production, exhibits a labor demand displacement effect. Firms in sectors with homogeneous products may have incentives to increase their competitiveness accordingly. By contrast, there was no statistically significant effect of organizational innovation on labor demand. Further, sales growth due to new products generates a gross increase in firms' labor demand because efficiency in old products' production is higher than that in new products' production—the opposite of a displacement effect; and firms must increase the number of employees to meet new "demand". Moreover, the net effect of product innovation on employment growth, which considers the cannibalization of old products by new ones in product innovating firms, remains positive, large, and highly significant, but smaller than the gross effect. This shows that product innovators suffer from a decline in demand for old products (in line with Schumpeter (1942), and creative destruction). However, there was no evidence of business stealing by product innovators from non-product innovators. Finally, the study results clarified that marketing innovation generates firms' labor demand. Such innovation possibly favors firms' profits by allowing an increase in new products' prices, compared to old ones. Marketing innovation is a novelty in this literature, as previous related studies have not considered it.

Generally, innovation's positive effects (from product and marketing innovations) on firms' labor demand outweigh the negative ones (from process innovation and some cannibalization of old products by new ones within a firm).

What can be stated regarding the quality of the jobs generated by innovation activities? Innovative firms require a higher proportion of skilled labor (a result of product innovations) and pay higher average wages *per* worker. However, process innovation seemingly requires fewer skills. Process innovations in Ecuador might be aimed at improving the efficiency of repetitive, automatic, and simple tasks, which are not highly demanding in terms of skills. These innovations displace workers in a biased manner

[27] Information on the first-stage regression for the IV method in column 2 of Table 7 is found in Appendix A4.

[28] Regarding control variables, firms belonging to knowledge-intensive sectors have a higher proportion of skilled workers and pay, on average, higher wages. On the contrary, medium-sized firms—followed by large firms—pay higher wages. By contrast, micro firms exhibit a higher share of skilled labor, which probably indicates that skills are more than proportional to firm size.

against higher skills. By contrast, product innovation in Ecuador is seemingly related to more complex innovations that in the short- and medium-term, decrease efficiency, but require greater skilled labor. They increase firms' labor demand such that it is biased toward higher qualification of workers.

Our study does not determine the origin of the most skilled workers required by product-innovator firms, but it highlights the possibility that some such workers come from firms introducing process innovations predominantly affecting older products with a greater chance of being automated in the short- to medium-term than new ones. Process innovation increases efficiency in old products' production and displaces skilled labor, which is absorbed by firms performing product innovation, thus effectively compensating for the previous displacement effects and favoring skills. This is an interesting dynamic mechanism. Moreover, today's new products will be tomorrow's old products. This highlights the important combined role of process and product innovations for society to reconcile efficiency gains with employment growth, skilled labor generation, and higher wages.

Acknowledgements and Funding

M.E. Rochina Barrachina acknowledges financial support from Grant ECO2017-86793-R funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe", from Grant PID2021-124266OB-I00 funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe" and Grant TED2021-130232B-I00 funded by MCIN/AEI/10.13039/501100011033 and the "European Union NextGenerationEU/PRTR", and from Grant PROMETEU/2019/095 (Generalitat Valenciana). J.A. Rodríguez Moreno gratefully acknowledges financial support from research funds from the Universidad del Río-Ecuador period 2019-2023.

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A. Appendix

Table A1: *Evidence from several countries on the impact of innovation on labor following the Harrison et al. (2014) methodology.*

Country **1. European Countries**	 α_0	Sales growth new prod. (g_2) β	Process innov. α_1	Organiz. innov. α_2	Market. innov. α_3	Paper
Italy	-2.80***	0.95***	-1.22*	n/a	n/a	Hall et al. (2008). The paper only includes manufacturing.
20 European Countries	-20.889*** -27.574***	0.989*** 0.968***	-2.475*** 0.308	-0.621 -0.939	n/a	Peters et al. (2013). We reproduce here results in columns 4 and 6 of Table 9 in the paper (first row manufacturing, second row services). Countries included: Bulgaria, Cyprus, Czech Republic, Germany, Estonia, Spain, France, Hungary, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Portugal, Romania, Slovenia, Slovakia, UK, and Ireland.
16 European Countries	-14.015*** -10.375***	1.011*** 0.903***	-1.973** -1.603	n/a	n/a	Dachs and Peters (2014). We reproduce here results in column 4 of Table 3 in the paper (first row manufacturing, second row services). Countries included: Bulgaria, Czech Republic, Denmark, Estonia, Spain, France, Greece, Hungary, Italy, Luxembourg, Latvia, Norway, Portugal, Romania, Slovenia, and Slovakia.
28 European Countries	11.486***	0.676***	-0.001	0.307***		Damijan et al. (2014). Organizational and Marketing innovations are jointly treated. We reproduce here results in column 2 of Table 6 in the paper (joint results for manufacturing and services).
France	-3.52*** -5.25**	0.98*** 1.16***	-1.31 -1.45	n/a	n/a	Harrison et al. (2014). We reproduce here results in B and D of Table 3 in the paper (first row manufacturing, second row services).
Germany	-6.95*** -3.36	1.01*** 0.92***	-6.19** 1.54	n/a	n/a	
Spain	-6.11*** -4.04*	1.02*** 0.99***	2.46 -0.38	n/a	n/a	
UK	-6.30*** -5.51***	0.99*** 1.05***	-3.51* 3.21	n/a	n/a	

26 European Countries	-67.158*** -15.094***	0.991*** 1.003***	-1.665** -1.816*	-2.284*** -1.393**	n/a n/a	Dachs et al. (2017). We reproduce here results in Table 4 of the paper (first row for upturns and second row for downturns; the paper only includes manufacturing).
2. Latin American Countries						
Chile	-0.790**	0.545***	0.096	n/a	n/a	Benavente and Lauterbach (2008). We reproduce here results from Table 4 (Panel C) in the paper (the paper includes jointly manufacturing, mining and power industry).
Chile	-1.989	1.740***	0.297	n/a	n/a	Álvarez et al. (2011). We reproduce here results in column 1 of Table 8 in the paper (the paper only includes manufacturing).
Costa Rica	-12.160**	1.015***	18.413*	n/a	n/a	Monge-González et al. (2011). We reproduce here results in column 4 of Table 8 in the paper (the paper only includes manufacturing).
Argentina	-0.994	1.170***	1.398	n/a	n/a	De Elejalde et al. (2011). We reproduce here results in column 4 of Table 12 in the paper (the paper only includes manufacturing).
Argentina	-6.887***	0.631***	-2.947	n/a	n/a	Crespi et al. (2019). We reproduce here results in columns 1-4 of Table 3 in the paper (the paper only includes manufacturing).
Chile	-2,016	1.751***	0.333	n/a	n/a	
Costa Rica	-12.160**	1.015***	18.413*	n/a	n/a	
Uruguay	1.402**	0.961***	-2.716**	n/a	n/a	
Argentina	n/a	1.151***	1.252	n/a	n/a	De Elejalde et al. (2015). We reproduce here results in column 1 of Table 3 in the paper (the paper only includes manufacturing).
Uruguay	1.544**	0.964***	-2.610**	n/a	n/a	Aboal et al. (2015). We reproduce here results in column 4 of Table 2 in the paper (the paper only includes manufacturing).

Table A2: Summary statistics.

Variable	Mean (sd)
Employment growth (l, not in %)	0.185
	(0.540)
Sales growth of old prod. (g_1, not in %)	0.437
	(15.012)
Process innovation dummy	0.422
	(0.494)
Organizational innovation dummy	0.239
	(0.427)
Marketing innovation dummy	0.250
	(0.433)
Sales growth due to new prod. (g_2, not in %)	0.260
	(0.765)
Micro firms	0.144
	(0.351)
Small firms	0.447
	(0.497)
Medium firms	0.220
	(0.414)
Large firms	0.190
	(0.392)
OECD_high_technology_manufacturing	0.009
	(0.095)
OECD_med_high_technology_manufacturing	0.048
	(0.215)
OECD_med_low_technology_manufacturing	0.158
	(0.365)
OECD_low_technology_manufacturing	0.264
	(0.441)
OECD_knowledg_intensive_services	0.301
	(0.459)
OECD_non_knowledge_intensive_services	0.219
	(0.414)
Increased range of products	1.783
	(1.763)
Clients as information source	0.362
	(0.481)
Reaction to the market	0.190
	(0.392)
Replacement of outdated products	0.241
	(0.428)
Observations	2,437

Table A3: *Testing exogeneity of other innovation types.*

(In the estimations in column 5 of Table 4, in addition to the regressor *sales growth due* to the new products, the regressors *process innovation*, *organizational innovation* and *marketing innovation* are instrumented one at a time)

Dependent variable: Employment growth $(l - g_1)^a$	(5) Process[b]	(5) Organizational[c]	(5) Marketing[d]
Hansen test $\chi^2(2)$	0.383	0.222	0.028
P-value Hansen test[e]	0.8259	0.8948	0.9861
Endogeneity test of regressor process, organiz. or marketing, $\chi^2(1)$	0.508	0.555	0.758
P-value endog. test[f]	0.4762	0.4561	0.3839
IV redundancy test, $\chi^2(4)$	33.943	36.676	26.798
P-value redund. test[g]	0.0000	0.0000	0.0000
F test of excluded instruments for process, organiz. or marketing, F(4, 2422)	415.82	11.05	16.48
P-value F test[h]	0.0000	0.0000	0.0000
Observations	2,437	2,437	2,437

Notes:
[a] Method: GMM instrumental variables estimation. Instruments used are increased range of products, clients as information source, replacement of outdated products and reaction to the market.
[b] Instrumented regressors: *sales growth due to new products* g_2 and *process innovation*.
[c] Instrumented regressors: *sales growth due to new products* g_2 and *organizational innovation*.
[d] Instrumented regressors: *sales growth due to new products* g_2 and *marketing innovation*.
[e] Hansen test denotes the test of overidentifying restrictions. The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null hypothesis the test statistic is $\chi^2(2)$ distributed with the number 2 of overidentifying restrictions. Ho always non-rejected.
[f] The endogeneity test tests the null hypothesis of exogeneity of the regressor *process*, *organizational* or *marketing innovation*. The statistic is distributed as a $\chi^2(1)$. It is defined as the difference of two Hansen statistics. Ho always non-rejected.
[g] The redundancy test is a test of whether the subset of excluded instruments *replacement of outdated products* and *reaction to the market* is "redundant". Excluded instruments are redundant if the asymptotic efficiency of the estimation is not improved by using them. The test statistic is an LM test. Under the null that the specified instruments are redundant, the statistic is distributed as χ^2(with degrees of freedom 4=(endogenous regressors 2)*(instruments tested 2)). Rejection of the null indicates that the instruments are not redundant, which is the case.
[h] The first stage F test of excluded instruments allows detecting "weak instruments". Since the p-values are close to zero, the excluded instruments are "relevant", meaning correlated with the endogenous regressor *process*, *organizational* or *marketing innovation*.

Table A4: First stage regression for the IV method in column 2 of Table 7.

Dependent variable: Sales growth due to new prod. $(g_2)^a$	(2) OLS Estimation
Process innovation	0.046
	(0.295)
Organizational innovation	0.096*
	(0.075)
Marketing innovation	-0.045
	(0.310)
Micro firms_{2009}	0.238***
	(0.001)
Small firms_{2009}	0.107***
	(0.003)
Medium firms_{2009}	0.060**
	(0.034)
OECD_group_high[b]	-0.002
	(0.938)
(excluded) Instruments (IVs)	
Increased range of products	0.083***
	(0.000)
Clients as information source	0.123**
	(0.017)
Replacement of outdated products	0.118**
	(0.025)
Reaction to the market	0.078*
	(0.100)
Constant	-0.102***
	(0.000)
Observations	2,437
F test of excluded instruments F(4, 2425)	31.80
P-value F test[c]	0.0000

Notes: *, ** and *** significant at 10%, 5% and 1% level.
[a] Coefficients and p-values (in parenthesis) robust to heteroscedasticity.
[b] Following the OECD classification for manufacturing and services as regards knowledge intensity, we have created a dummy variable with value 1 if the sector belongs to the high classification for manufacturing and to the one of knowledge intensive sectors for services.
[c] The first stage F test of excluded instruments allows detecting "weak instruments". Since the p-value is close to zero, the excluded instruments are "relevant", meaning correlated with the endogenous regressor.