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The dynamic links between product and process innovations and productivity for Colombian manufacturing

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Abstract

Purpose – This paper aims to examine the interrelation between two innovating strategies (product and process) on total factor productivity (TFP) growth and the dynamic linkages between these strategies, for Colombia. The authors first explore whether ex ante more productive firms are those that introduce innovations (the self-selection hypothesis) and if the introduction of innovations boosts TFP growth (the returns-to-innovation hypothesis). Second, the authors study the firm's joint dynamic decision to implement process and/or product innovations. The authors use Colombian manufacturing data from the Annual Manufacturing and the Technological Development and Innovation Surveys.

Design/methodology/approach – This study uses a four-stage procedure. First, the authors estimate TFP using a modified version of Olley and Pakes (1996) and Levinsohn and Petrin (2003), proposed by De Loecker (2010), that implements an endogenous Markov process where past firm innovations are endogenized. This TFP would be estimated by GMM, Wooldridge (2009). Second, the authors use multivariate discrete choice models to test the self-selection hypothesis. Third, the authors explore, using multi-value treatment evaluation techniques, the life span of the impact of innovations on productivity growth (returns to innovation hypothesis). Fourth, the authors analyse the joint likelihood of implementing process and product innovations using dynamic panel data bivariate probit models.

Findings – The investigation reveals that the self-selection effect is notably more pronounced in the adoption of process innovations only, as opposed to the adoption of product innovations only or the simultaneous adoption of both process and product innovations. Moreover, our results uncover distinct temporal patterns concerning innovation returns. Specifically, process innovations yield immediate benefits, whereas implementing both product innovations only and jointly process and product innovations exhibit

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significant, albeit delayed, advantages. Finally, the analysis confirms the existence of dynamic interconnections between the adoption of process and product innovations.

Originality/value – The contribution of this work to the literature is manifold. First, the authors thoroughly investigate the relationship between the implementation of process and product innovations and productivity for Colombian manufacturing explicitly recognising that firms' decisions of adopting product and process innovations are very likely interrelated. Therefore, the authors start exploring the self-selection and the returns to innovation hypotheses accounting for the fact that firms might implement process innovations only, product innovations only and both process and product innovations. In the analysis of the returns of innovation, the fact that firms may choose among a menu of three innovation strategies implies the use of evaluation methods for multi-value treatments. Second, the authors study the dynamic inter-linkages between the decisions to implement process and/or product innovations, that remains under studied, at least for emerging economies. Third, the estimation of TFP is performed using an endogenous Markov process, where past firms' innovations are endogenized.

Keywords Product innovation, Process innovation, Self-selection, Returns-to-innovation, Dynamics

Paper type Research paper

1. Introduction

Innovation is essential for the development and progress of nations, as well as at the firm level as it increases the performance and competitiveness of companies (Schumpter, 1942; Griliches, 1979; Crépon *et al.*, 1998). Firms investing in knowledge increase their propensity to implement new technological advances and show higher productivity (Crespi and Zúñiga, 2012; Audretsch and Belitski, 2020, 2023; Segarra-Blasco *et al.*, 2022).

The relationship between innovation and productivity has been thoroughly examined in developed countries, but there are few studies in Latin America. The limited availability of comprehensive databases or consistent panel data sets and, more importantly, the low investment in R&D may have discouraged the investigation of this question (Demmel *et al.*, 2017). It is important to consider that the low investment in R&D (less than 1% of the GDP according to the World Bank) and the innovation deficit in Latin America are behind the stagnation of productivity (Pagés, 2010). Increasing productivity and inclusive growth is one of the major challenges facing Latin American countries, and innovation is crucial to improving productivity (OECD, 2019).

Earlier studies on firm growth analysed the impact of different production inputs (such as innovation) on productivity (Hall *et al.*, 2016; Corrado *et al.*, 2013; Mairesse and Mohnen, 2010; Mohnen and Hall, 2013). The most important model used to study this relationship uses data on product and process innovation (see Martínez-Ros and Labeaga, 2009; Hall, 2011; Ballot *et al.*, 2015; Zhang, 2022; and Godfrey and Tregenna, 2023, among others). The empirical evidence uncovers that innovative firms enjoy higher levels of productivity. And this higher productivity might be due either to the self-selection of the most productive firms into innovative activities or to the returns obtained through innovations, as innovators might enhance firms profits in the future in terms of productivity. These two hypotheses have been extensively explored; see Audretsch and Belitski (2020, 2023), Demmel *et al.* (2017), Rochina-Barrachina *et al.* (2010) and Mañez *et al.* (2013), among others.

For Colombia, the relation between innovation and productivity has only been explored through the impact of innovations on firm's productivity. The available studies differ in terms of the period analysed and how they relate R&D and productivity. See, for example, Ramírez *et al.* (2020), Busom and Vélez-Ospina (2017), Lambardi (2014), Eslava *et al.* (2013) and Crespi and Zúñiga (2012). The only study exploring the aforementioned hypotheses for Colombia is Demmel *et al.* (2017). However, this work does not find any evidence for self-selection or returns to innovation for Colombia.

The contribution of this work to the literature is manifold. First, we investigate the relationship between the implementation of process and product innovations and productivity for Colombian manufacturing, explicitly recognising that firms' decisions to adopt product and process innovations are very likely interrelated. Therefore, we start exploring the self-selection and returns to innovation hypotheses, accounting for the fact that firms might implement process innovations only, product innovations only and both process and product innovations. Thus, in the empirical analysis, we will use a multivariate probit to analyse the self-selection hypothesis. In the analysis of the returns to innovation, the fact that firms may choose among a menu of three innovation strategies implies the use of evaluation methods for multi-value treatments. Second, we study the dynamic interlinkages between the decisions to implement processes and/or product innovations that remain understudied in emerging economies. Third, we estimate total factor productivity (TFP) using a modified version of Olley and Pakes (1996) and Levinsohn and Petrin (2003), proposed by De Loecker (2010), that implements an endogenous Markov process where past firm innovations are endogenized. Finally, our analysis is performed using panel data techniques. For this purpose, we build a panel data set combining the Annual Manufacturing and the Technological Development and Innovation surveys, provided by the Colombian National Administrative Department of Statistics, for 2007–2016.

To anticipate our main results, our research underscores the relevance of conducting a comprehensive analysis that considers the joint process of self-selection in the adoption of processes and/or product innovations. Our investigation reveals that the self-selection effect is notably more pronounced in the adoption of process innovations only, as opposed to the adoption of product innovations only or the simultaneous adoption of both process and product innovations. Moreover, our results reveal distinct temporal patterns concerning innovation returns. Specifically, process innovations yield immediate benefits, whereas implementing both product innovations only and jointly process and product innovations exhibit significant, albeit delayed, advantages. Finally, our analysis confirms the existence of dynamic interconnections between the adoption of processes and product innovations. Past product (process) innovations stimulate the subsequent adoption of process (product) innovations. Importantly, the fostering effect of past product innovations on the adoption of process innovations is more pronounced than the reciprocal influence of past process innovations on product innovation adoption.

The remainder of the paper is organised as follows. Section 2 reviews the related theoretical and empirical literature. Section 3 describes the data and introduces the method used to estimate productivity. Section 4 presents the empirical strategy and discusses the empirical results. Finally, Section 5 presents some concluding remarks.

2. Literature review: innovation and productivity

The national innovation system in Colombia differs significantly from those of industrialised countries (Hall and Mairesse, 2006). The absence of resources for businesses to support science, technology and innovation activities as well as the lack of highly skilled individuals are the main and most important differences.

The Colombian private and public financial system supporting small and medium enterprises (SMEs) aiming at investing in R&D is quite precarious. Given that SMEs make up 92% of manufacturing companies in Colombia, getting innovations and improving future performance appear to be significantly hampered by the lack of resources. This shortage of funds is an important obstacle for setting up R&D facilities, hiring qualified staff and importing foreign raw materials and/or intermediate inputs. The inadequate legal framework for knowledge protection makes this issue worse.

In Colombia, 75% of the financial resources devoted to science are private resources. The absence of public support implies that the majority of manufacturing firms lack strong incentives to participate in R&D. Companies in Latin America place more emphasis on obtaining or implementing foreign technologies than on creating their own innovations (Pagés, 2010; Crespi *et al.*, 2016). As a result, the innovations obtained are essentially incremental changes that have minimal impact on global markets. Because the process of obtaining technology differs from that in developed countries, there is not a strong correlation between innovation and productivity (Mohan *et al.*, 2016).

In this context, we aim at investigating the dynamic relationship between productivity and innovations in Colombia. We will analyse the potential for a bidirectional relationship between process and product innovations and productivity, as well as the dynamic linkages between process and product innovations. To achieve this, we first analyse the self-selection into process and/or product innovations as well as the returns-to-innovation hypotheses. In a second step, we will focus on the analysis of the dynamic interactions between processes, product innovations and productivity.

We start by testing the self-selection of the more productive firms into innovations. The primary argument supporting the existence of a self-selection process is that the investment associated with innovative activities involves sunk costs (Sutton, 1991). For many Latin American countries, innovation activities are mainly related to the adoption or acquisition of external innovations rather than producing them internally (Pagés, 2010). Thus, many innovations consist of incremental improvements with a low impact on international markets and/or are the result of an imitation or copying process and/or technology transfers (Crespi and Zúñiga, 2012). Nevertheless, the implementation of these innovations may still involve sunk costs associated with searching for suppliers, customs procedures, contract formulation, taxation and searching for high-skilled employees, among others. Furthermore, and according to Demmel *et al.* (2017), these firms will have to face additional issues specific to Latin America: higher uncertainty about the returns to innovation because of market volatility, the precarious financial system, and the lower absorptive capacity of firms in these countries. All these elements imply important expenditures only affordable by the most productive firms.

The existence of a process of self-selection into processes and product innovations should be considered in the analysis of the impact of innovations on productivity. A simple comparison of TFP growth for innovators and non-innovators after the former start implementing innovations does not allow determining whether the observed differences are due to self-selection or returns to innovation. This is because of the fact that more productive enterprises self-select into the implementation of innovations rather than being selected at random. Even if they do not implement any innovation, firms that are ex ante more productive and start to innovate may show higher productivity in the future. A novelty in the analysis of the returns-to-innovation hypothesis is that we explicitly consider that firms may choose among four innovation strategies. We will consider three out of these four "active" innovation strategies: implementing process innovations only, implementing product innovations only and implementing both process and product innovations. The final strategy corresponds to a situation in which the firm does not introduce any innovation. Therefore, if we consider each innovation strategy as a treatment, we face a multi-valued treatment. Thus, to analyse the impact of active innovation strategies on productivity, we resort to treatment evaluation techniques that consider multi-valued treatments (see, for example, Cattaneo, 2010; Imbens, 2000; or Wooldridge, 2010). This will allow us to determine the average productivity growth for firms implementing a given active innovation strategy, which will be calculated as the difference between the productivity growth of an innovator following the implementation of a given active innovation strategy and its productivity growth if it had not introduced any innovation.

We will examine the dynamic links between the firm's decisions to implement process and/or product innovations after analysing the self-selection and returns-to-innovation hypotheses. In this analysis, we will contemplate that these two strategies might be correlated and study them jointly, accounting for the potential existence of sunk costs associated with these decisions. A firm would implement a process and/or product innovation in a given year whenever the current increase in gross operating profits associated with that decision plus the discounted expected future returns in that year exceeded the sunk costs. The existence of such costs implies that a firm's current innovation strategy will depend on past choices of these strategies; see, for example, Aw *et al.* (2011) or Mañez *et al.* (2009).

Implementing a process (product) innovation may also increase the likelihood that a product (process) innovation will be adopted. Once businesses start innovating, they may gain knowledge from doing so, which will make it simpler for them to engage in new forms of innovation. This might be explained by the fact that businesses may profit from a learning process because they have mastered a variety of skills, such as acquiring innovations from abroad, investing in and managing R&D labs, hiring skilled labour, managing the legal framework surrounding the acquisition of new knowledge and innovation marketing.

The firm's decision to innovate may also be influenced by international trade, including previous imports of intermediates and export expertise. According to Aghion *et al.* (2018), companies' prior exporting efforts may have expanded their market reach, which may encourage innovation. In addition, especially in developing nations, imports enable businesses to introduce product innovations stemming from foreign knowledge embodied in machinery or equipment (Crespi and Zúñiga, 2012). Importing also implies that firms would need to implement/improve some process innovations to gain access to international suppliers.

The empirical evidence on the link between innovations and productivity in Latin America is heterogeneous in terms of statistical methodologies, the data used and the innovation definitions. Furthermore, the results are mixed and inconclusive. For Colombia, the few empirical studies have three things in common: first, they are based on the CDM traditional model; second, with some exceptions, they use cross-sectional data; and third, productivity is measured using labour productivity, and the studies that use TFP consider an exogenous Markov process for the law of motion for productivity. Some recent studies are Gómez and Borrastero (2022), Atayde *et al.* (2021), Ramírez *et al.* (2020) and Busom and Vélez-Ospina (2017). These find a positive link between R&D, innovation and labour productivity. Furthermore, Ramírez *et al.* (2020), Crespi *et al.* (2016) and Crespi and Zúñiga (2012) applying the CDM model and using panel data, find similar results.

3. Data

We use manufacturing and innovation data from the Annual Manufacturing (EAM) and the Technological Development and Innovation (EDIT) surveys for the years 2007–2016 to analyse the relationship between productivity and innovation. These data sets are provided by the Colombian National Administrative Department of Statistics.

The EAM is the annual census for industrial establishments (identified according to ISIC Rev. 3, adapted for Colombia) with ten or more employees or, failing that, firms that report an annual production value above a threshold set by the EAM. This survey collects yearly firms' information for variables such as value added, number of employees, intermediate and energy consumption, among others. The EDIT is a biannual survey aimed at characterising the technological dynamics, innovation activities and technological development of Colombian manufacturing (using ISIC Rev. 3, adapted for Colombia). It is a census of firms that follows the same criteria as the EAM.

The innovation variables we use come from five waves of the EDIT (from EDIT IV, for 2007–2008, to EDIT VIII, for 2015–2016). We exclude previous versions of the EDIT as there were important changes in the process of gathering information on innovations. Using the EAM survey, we calculate firms' TFP for the years 2007–2016.

Because the EDIT is a biennial survey and does not specify the precise year in which a firm introduces an innovation, merging the EAM and EDIT databases presents certain challenges. Thus, if a firm declares to have introduced an innovation in the last two years, we will consider the firm an innovator in the second year. This will guarantee that the company has implemented the innovation in the year we consider it to be an innovator. After merging ten EAM waves with five EDIT waves, we end up with an unbalanced panel data of 10 years (2007–2016) with 76,031 observations corresponding to 11,051 firms. Table 1 displays several descriptive statistics regarding innovation by the technological intensity sector using the OECD technological intensity classification (ISIC Rev. 3) (Hatzichronoglou, 1997).

In columns 1 and 2, we display the number of observations and firms, respectively. Column 3 reports the average number of employees. As an emerging economy, Colombian manufacturing firms concentrate in low-tech industries (58.1%). Furthermore, 28.3% of the manufacturing firms operate in the med-low technological industries. In the case of med-high technological industries, we observe a lower participation of firms (12.2%). Finally, the lowest representation is observed in the high-tech industries (less than 2%).

Furthermore, we characterise firms' innovation profiles. Column 4 presents the average percentage of firms investing in R&D activities. We observe that 23.55% of the firms invest in R&D activities. In general, the data show that the proportion of companies with positive R&D investments increases with the degree of technology intensity, although the larger percentage of companies investing in R&D belongs to the med-high tech sector.

In Columns 5 and 6, we report the average percentage of innovative firms among firms non-investing in R&D and firms investing in R&D, respectively. We consider a firm a *product innovator* if it has obtained at least one new or significantly improved good or service, or a *process innovator* if it has introduced a new or significantly improved method for providing services, production, distribution, delivery or logistic systems [1]. We observe that among those not investing in R&D, 3.79% implement innovations. However, 61.87% of firms performing R&D implement innovations.

Industries	N. observations	N. firms	Average no. employees	% R&D	% innovators Non-R&D firms	% innovators R&D firms	R&D employees in R&D firms
Low-tech sectors	42,350	6,417	85.73	21.22	3.92	63.17	9.30
Med-low-tech sectors	22,458	3,128	95.49	23.05	3.51	61.52	10.21
Med-High-tech sectors	9,980	1,349	102.28	34.00	4.01	58.54	11.10
High-tech sectors	1,243	157	96.76	27.92	2.90	66.28	10.25
Total	76,031	11,051	95.06	23.55	3.79	61.87	10.21

Source: Authors' own work

Table 1. Innovation activities by technological intensity sectors

Column 7 refers to the average number of employees in R&D activities for firms with positive R&D expenditures. In general, the average number of R&D employees is higher in more technologically advanced industries.

To estimate TFP, we use Wooldridge (2009), who argues that the semi-parametric estimation methods of Olley and Pakes (1996) and Levinsohn and Petrin (2003) can be reconsidered as consisting of two equations that can be jointly estimated by GMM. This estimation procedure is described in the online Appendix 2, and the estimated input elasticities are reported in Table B1 of the same appendix.

4. Empirical model and results

In this section, we first introduce the empirical procedure to analyse the relationship between innovations and productivity, and then we present the specification to explore the dynamic links between process and product innovations. We also present the results concerning these two analyses [2].

4.1 On the relationship between innovations and productivity

The fact that innovators – either process/product or both – have higher productivity levels could stem from two factors, as discussed in Section 2: either they were already more productive before introducing the innovation (i.e. the most productive firms self-select into the introduction of innovations); or, implementing innovations has an enhancing effect on firms' productivity (returns-to-innovation hypothesis). We explain the empirical methods we use to investigate these hypotheses and present the corresponding results in the next two sub-sections.

4.1.1 The analysis of the self-selection hypothesis. The traditional approach for examining the presence of a self-selection process in the implementation of process (product) innovations involves regressing a first-time innovator dummy variable on the firm's past productivity and a set of control variables. However, previous studies using this approach overlook the likelihood that firms make decisions regarding process and product innovation jointly, resulting in correlated outcomes. Neglecting this interrelation when examining the self-selection hypothesis might introduce a significant bias in the results. To address this issue, we propose estimating a bivariate probit model, as outlined in equation (1), which explicitly considers the simultaneous nature of the decisions regarding process and product innovations:

$$FTI_{it}^{prc} = \begin{cases} 1 & \text{if } \beta_0^{prc} + \beta_1^{prc} TFP_{it-2} + \gamma^{prc} Z_{it-2} + \mu_t^{prc} + s_j^{prc} + \epsilon_{it}^{prc} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$FTI_{it}^{prd} = \begin{cases} 1 & \text{if } \beta_0^{prd} + \beta_1^{prd} TPF_{it-2} + \gamma^{prd} Z_{it-2} + \mu_t^{prd} + s_j^{prd} + \epsilon_{it}^{prd} \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where FTI_{it}^{prc} (FTI_{it}^{prd}) is a dummy variable capturing that the firm is a first-time process (product) innovator. We include past productivity ($TFP_{\mathrm{it}-2}$) to test for self-selection and a set of other variables, $Z_{\mathrm{it}-2}$, that may potentially affect the innovation decisions (firm size, export and import dummies and firm's R&D intensity). Finally, we control for industry, s_{j}, and time effects, μ_{t} [3].

The EDIT survey is conducted biennially without specifying the precise year in which a firm introduces an innovation. This will determine both our definition of a first-time innovator and the timing of productivity and the other control variables in equation (1).

Consequently, the dependent variable in our bivariate probit model $FTI_{it}^{process}$ $\left(FTI_{it}^{product}\right)$ will take a value of 1 in period t (which falls within the biennium $t-1/t$) if firm i has not introduced any process (product) innovation since its initial observation in the sample but if does introduce a process (product) innovation in the biennium $t-1/t$. We consider this firm a first-time process (product) innovator in t and not $t-1$ to guarantee that the firm has already introduced the innovation the year we consider it as a first-time process (product) innovator [4]. The $FTI_{it}^{process}$ $\left(FTI_{it}^{product}\right)$ dummy takes value 0 in t if firm i declares neither having introduced a process (product) innovation in the previous biennia to $t-1/t$ nor does it in such a biennium. Given our definition of first-time innovators, we have to lag TFP and the rest of the control variables by two periods, as one-period lag could be affected by the potential adoption of innovations in $t-1$ for first-time innovators.

The estimation results of equation (1) are shown in Table 2. Interestingly, the Wald test for the correlation of these two decisions strongly rejects the null hypothesis of no correlation (with a p-value of approximately 0). This finding confirms the interrelationship between firms' choices in adopting process and product innovations for the first time. Consequently, it suggests that the proper estimation technique is to use a bivariate probit model.

The average marginal effects corresponding to the estimation of equation (1), shown in Columns 1–3 of Table 2, provide evidence supporting a self-selection process in the firm's adoption of only process and only product as well as jointly process and product innovations for the first time, as indicated by the positive average marginal effects associated with $TFP_{\mathrm{it}-2}$. Specifically, a 10% increase in TFP leads to a 0.042 (0.007) percentage point increase in the probability of becoming a first-time process (product) innovator [5]. As for the effect of TFP on the probability of adopting both process and product innovations for the first time, as observed in Column 3, the average marginal effect associated with $TFP_{\mathrm{it}-2}$ is positive, albeit small. Thus, a 10% increase in productivity increases the likelihood of becoming both a process and product innovator in the same period by 0.0009 percentage points.

Consequently, based on the results obtained from the estimation of the bivariate probit model (1), we can conclude that the self-selection effect is more pronounced when implementing process innovations only than when implementing product innovations alone. We also observe a self-selection effect in the joint implementation of both process and product innovations, albeit with a much smaller intensity as compared with only product or only process innovations. This might suggest that in the more complex strategy of implementing process and product innovations simultaneously, there might be other factors relevant beyond productivity.

These estimated effects of productivity on the probability of becoming a first-time process and/or product innovator may seem small, but it should be considered that in our sample, the probabilities of being a first-time process innovator only, a first-time product innovator only or a first-time process and product innovator are also quite small, 6.43%, 0.40% and 0.63%, respectively [6].

Finally, we extend equation (1) to examine whether past process (product) innovations influence the likelihood of becoming a first-time product (process) innovator. In doing so, we introduce a past product (process) innovation dummy into the equation for first-time process (product) innovators. We will refer to these two variables as past cross-effects. As it is possible to observe in Columns 4 and 5 in Table 2, both the presence of past process and product innovations positively affect the probability of becoming a first-time product and process innovator, respectively.

Table 2.
Self-selection into process/product innovations: marginal effects

Variables	Process innovations	Product innovations	Both	Process innovations	Product innovations	Both
$TFP_{\mathrm{it}-2}$	0.0042*** (0.0016)	0.0007* (0.0004)	0.00009* (0.00006)	0.0038* (0.0026)	0.00004* (0.00003)	0.00005* (0.00003)
$Process\ in._{\mathrm{it}-2}$					0.05690*** (0.0046)	
$Product\ in._{\mathrm{it}-2}$				0.2425*** (0.0129)		
$Size_{\mathrm{it}-2}$	0.0232*** (0.0016)	0.0010*** (0.0003)	0.0017*** (0.0003)	0.0227*** (0.0016)	0.0021*** (0.0010)	0.0004*** (0.0001)
$X_{\mathrm{it}-2}$	0.0028 (0.0043)	0.0002 (0.0007)	0.0002 (0.0006)	0.0033 (0.0044)	0.0002 (0.0003)	0.0002 (0.0002)
$M_{\mathrm{it}-2}$	−0.0046 (0.0046)	0.0001* (0.0007)	0.0006 (0.0006)	−0.0052 (0.0047)	0.0027 (0.0026)	0.0001 (0.0002)
$R\&D_{\mathrm{it}-2}$	0.0015 (0.0040)	−0.0002 (0.0042)	−0.0001 (0.0034)	0.0013 (0.0022)	0.0001 (0.0016)	0.0000 (0.0001)
Year/sector dummies		YES			YES	
N. observ.		20,582			20,582	
Log-L		−4,213.855			−3987.559	
ρ		0.427*** (0.047)			0.852*** (0.021)	
Wald test $\rho = 0$						
χ^2		214.683			212.353	
p-value		0.000			0.000	

Notes: We report cluster adjusted standard errors. *** and * indicate significance at the 1 and 10%, respectively
Source: Authors' own work

Furthermore, the positive impact of past product innovations on the probability of becoming a first-time process innovator surpasses that associated with past process innovations on the probability of implementing a product innovation for the first time. Specifically, while past product innovations increase the likelihood of introducing a process innovation for the first time by 24 percentage points, past process innovations raise the probability of implementing product innovations for the first time by only 5.7 percentage points.

The positive and statistically significant average marginal effects associated with TFP_{it-2} in the estimation that incorporates cross effects (Columns 4–6) reinforce the evidence of a self-selection effect in the introduction of both process-only and product-only innovations, as well as in the joint implementation of process and product innovations. Interestingly, the average marginal effect of TFP_{it-2} in Column 4 is higher than that in Columns 5 and 6, indicating that, even in the presence of cross effects, the self-selection effect appears to be greater in the implementation of process innovations only rather than in the other strategies.

Regarding the quantitative impact of including past cross-effects in the self-selection specification, the average marginal effect associated with past productivity in the process equation remains largely unchanged (varying from 0.0042 to 0.0038). However, the inclusion of past process innovations in the product innovation equation significantly reduces the influence of past productivity on the probability of implementing a product innovation. In the estimation without past cross effects, a 10% increase in TFP leads to a 0.007 percentage point increase in the probability of implementing a product innovation. However, with the inclusion of past cross-effects, the corresponding effect reduces to 0.0004 percentage points. A possible explanation for this reduction is that firms that have introduced process innovations in the past have already surpassed the productivity threshold required for implementing product innovations for the first time, and the past process innovation dummy captures this effect. Consequently, the average marginal effect of past productivity diminishes.

As for the control variables, the average marginal effect of firm size is positive and significant in both equations, suggesting that, in emerging economies, large enterprises may have better access to financial resources to acquire technology or technologically embodied goods from abroad [7]. Furthermore, the estimates corresponding to R&D intensity are never significant, which might be explained by the limited number of firms investing in these activities (23.5% on average), the important gap from the technological frontier, and the limited incentives to invest in these activities (Crespi *et al.*, 2016). These findings are in line with those found for some countries in Latin America; see Asiedu *et al.* (2023), Alvarez *et al.* (2010), Pérez *et al.* (2005) and Crespi and Zúñiga (2012).

In summary, our findings underscore that considering past cross-effects between process and product innovations also plays a crucial role in determining the magnitude of the estimated effects. Hence, it is crucial to account for both factors when examining the self-selection dynamics in firms' adoption of process and product innovations. In general, our results are aligned with other studies on Latin America. There is evidence of self-selection into the implementation of product innovations for Brazil and Argentina (Chudnovsky *et al.*, 2006; Raffo *et al.*, 2008), while for Chile and Mexico (Alvarez *et al.*, 2010; Brown and Guzmán, 2014), there is evidence of self-selection into the implementation of process innovations. For Colombia, our findings are similar to those by Ramírez *et al.* (2020), Crespi and Zúñiga (2012), Crespi *et al.* (2016) or Gallego *et al.* (2013), among others.

4.1.2 Innovation returns. To examine the returns to innovation hypothesis, it involves comparing the productivity growth of firms that refrain from implementing any process or product innovation with that of firms getting involved in "active" innovative strategies.

Newly innovative firms (first-time innovators) can be categorized into three groups: first-time process-only innovators (those introducing process innovations but not product innovations for the first time), first-time product-only innovators (those introducing product innovations but not process innovations for the first time) and first-time process and product innovators (those simultaneously implementing both process and product innovations for the first time).

However, the presence of self-selection in the adoption of process and/or product innovations complicates the assessment of returns to innovation through a simple comparison of productivity growth between non-innovators and the three possible categories of innovators. This is because the self-selection into implementing innovations is not a random process; rather, the most productive firms tend to self-select into adopting innovation strategies. As a consequence, self-selection must also be considered in order to fully account for the observed productivity growth differences between first-time innovators and non-innovators. Different methodologies are required to accurately disentangle the effects of self-selection from the actual returns on innovation.

To simultaneously address these issues and account for the existence of multiple innovation strategies, we resort to the treatment evaluation literature that considers multi-value treatments (Cattaneo, 2010; Imbens, 2000; Wooldridge, 2010). This procedure to test for returns to innovations is described in the online Appendix 2.

Table 3 presents the estimations of the average treatment effect (ATE) for three groups of firms: first-time process-only innovators, first-time product-only innovators and first-time process and product innovators. These values are computed based on the methods described, taking as reference non-innovator firms. The ATEs are reported for three consecutive periods: $t/t + 1$, $t + 1/t + 2$ and $t + 2/t + 3$, offering insights into the productivity growth dynamics across these time intervals [8].

The results of our analysis reveal that the benefits of innovation are more immediately evident when firms implement process innovations. Specifically, for first-time process-only innovators the ATE during period t to $t + 1$ is 1.6% compared to both non-innovators and firms adopting alternative active innovation strategies.

In contrast, the rewards from implementing product innovations or implementing both process and product innovations jointly do not emerge immediately but rather materialize

Observations	Period	ATE	SE
First-time process only innovators			
1,480 (27,238)	$t/t+1$	0.016*	0.009
1,131 (22,325)	$t+1/t+2$	0.001	0.013
1,061 (16,858)	$t+2/t+3$	0.017*	0.009
First-time product only innovators			
62 (27,238)	$t/t+1$	0.002	0.060
51 (22, 325)	$t+1/t+2$	0.121*	0.064
49 (16,858)	$t+2/t+3$	0.015	0.045
First-time process and product innovators			
71 (27,238)	$t/t+1$	−0.014	0.044
59 (22, 325)	$t+1/t+2$	0.229	0.281
55 (16,858)	$t+2/t+3$	0.075*	0.040

Notes: ATE stands for average treatment effect for FTI process, product or process-product innovators over non-innovators. The first column reports the number of FTI (process, product or both) and the number of control observations in parentheses. * indicate significance at the 10%
Source: Authors' own work

Table 3.
Returns to innovations

with some time lag. For first-time product-only innovators, the ATE becomes significant after one year, whereas for first-time process and product innovators, it becomes significant after two periods. However, despite the delayed appearance, the ATE associated with these innovation strategies is substantially greater than that associated with implementing process innovations. For instance, during the period $t+1$ to $t+2$, the ATE for first-time product innovators is a remarkable 12.1% over that of firms pursuing any other innovation strategy. The ATE observed for first-time product-only innovators is limited in time and extends only to the period $t+1$ to $t+2$.

The ATE for first-time process and product innovators in the period $t+2$ to $t+3$ is 7.5% over both non-innovators and first-time product-only innovators. Although in the period $t+2$ to $t+3$, first-time process innovators also experience a positive and significant ATE (1.7%) over both non-innovators and first-time product-only innovators, this is 5.8% smaller than that corresponding to first-time process and product innovators. The ATE of first-time process and product innovators becomes evident at a later stage, which could be attributed to the implementation of more complicated innovations that require additional time to be fully integrated within the firm. However, once these innovations are in effect, they generate higher returns than introducing process innovations for the first time [9].

These findings highlight the varying temporal patterns of innovation returns, with process innovations yielding immediate benefits and product innovations, as well as joint process and product innovations, showing significant but delayed benefits. These insights shed light on the distinct dynamics of different innovation strategies and their implications for firms' productivity growth over time [10].

Similar empirical studies for developing countries are pretty scarce. However, our results can be compared with Demmel *et al.* (2017). They found that Argentina and Mexico obtain returns to innovation in terms of productivity for all innovation types, but they do not find evidence for process or product innovation rewards for Colombia and Peru.

4.2 Dynamic links between process and product innovations

After studying the self-selection and returns-to-innovation hypotheses, we now analyse the dynamic links between the firm's decisions to implement process and/or product innovations. For this purpose, we estimate a dynamic panel data discrete choice model for the two decisions, in which the choice probabilities in year t are conditioned on the previous vector of state variables for that year:

$$Process_{it} = \begin{cases} 1 \text{ if } \theta_0^{prc} Proc_{it-2} + \theta_1^{prc} Prod_{it-2} + \beta^{prc} Z_{it-2}^{prc} + \mu_t^{prc} \\ +s_j^{prc} + \alpha_i^{prc} + \epsilon_{it}^{prc} \geq 0 \\ 0 \quad \text{otherwise} \end{cases}$$

$$Product_{it} = \begin{cases} 1 \quad \text{if } \theta_0^{prd} Prod_{it-2} + \theta_1^{prd} Proc_{it-2} + \beta^{prd} Z_{it-2}^{prd} + \mu_t^{prd} \\ +s_j^{prd} + \alpha_i^{prd} + \epsilon_{it}^{prd} \geq 0 \\ 0 \quad \text{otherwise} \end{cases} \tag{2}$$

where θ_0 identifies the sunk costs and possible path dependence or learning effects; θ_1 captures the cross-impact of introducing a process (product) innovation in a previous year on the likelihood of introducing a product (process) innovation today. By introducing cross-effects, we aim at capturing the possibility that accruing experience implementing product (process) innovations can encourage the implementation of process (product) innovations, as explained in Section 2. $Z_{\mathrm{it}-2}$ is a vector of control variables that accounts for TFP [11], size, R&D intensity, exports and imports; μ_t are year dummies and s_j are industry dummies. In addition, we also account for unobserved firm-specific effects (α_i). Finally, the error term ϵ_{it} summarizes the impact of additional time and firm-specific unobservable factors. Our estimation methodology will consider the potential simultaneity of the two decisions through the estimation of a bivariate probit specification.

As we do not observe firms' process and product innovation choices before they appear in the data set, a potential concern in estimating equation (2) is the bias arising from the initial conditions problem and the correlation between the unobserved heterogeneity term (i.e. α_i) and the explanatory variables. To solve this problem, we follow Wooldridge's (2005) approach and model the distribution of α_i^{type} as:

$$\alpha_i^{type} = \delta_0^{type} + \delta_1^{type}\overline{q}_i + \gamma_2^{type} innov_{io} + \nu_{it}^{type} \tag{3}$$

where *type* indicates the process or product innovations, $\overline{q}_i$ is the vector including Mundlak–Chamberlain means (Chamberlain, 1980; Mundlak, 1978). Thus, it includes the means of all exogenous control variables. The variable $innov_{io}$ represents the initial condition of either process or product innovations and ν_{it}^{type} is the error term, which is assumed to be independent of the initial conditions, the explanatory variables and the idiosyncratic error term of our main estimation equation (2).

Table 4 presents the bivariate probit estimation results (calculating average marginal effects). We have estimated two specifications: first, without accounting for TFP, and second, including TFP. In general, the results are quite stable, except for the fact that when we include TFP the marginal effects are slightly lower. Therefore, we will discuss only the results for the specification with TFP. As we report marginal effects, we have three types of marginal effects in each of the two specifications: for the process only innovators (1,0); for the product only innovators (0,1); and for both process and product innovators (1,1).

Our findings reveal that the marginal effect of lagged process (product) innovation (associated with coefficients $\hat{\theta}_0^{prc}$ and $\hat{\theta}_0^{prd}$) in the process (product) equation is always positive and statistically significant, providing evidence of persistence in the probability to implement process (product) innovation activities. The observed persistence may be caused by path dependence, learning effects, and sunk costs associated with the introduction of (process and/or product) innovations. Once a firm overcomes the initial sunk costs associated with implementing a process/product innovation for the first time, continuing to do so may be easier. We are unable to discriminate between these various hypotheses, which are not necessarily mutually exclusive in our setup.

It is important to note that, according to our estimates, process innovation is more persistent than product innovation. Thus, whereas firms that implemented process innovations in $t-2$ are 9.3 percentage points more likely to implement process innovations in t, the increase in the likelihood of introducing product innovations in t for firms that implemented product innovations in $t-2$ is 0.57 percentage points. The initial conditions (pre-sample means of the dependent variables), capturing the long-term influence through the firm's individual effects, further support the importance of persistence. These results are, as far as we are aware, the first empirical proof of innovation persistence for Colombian manufacturing.

A second important result is related to the existence of cross-effects between processes and product innovations. In fact, the marginal effects for cross-product and process innovations (associated with the estimated parameters $\hat{\theta}_1^{prc}$ and $\hat{\theta}_1^{prd}$) are positive and statistically significant in all cases, suggesting that implementing one of the innovation

Table 4.
Biprobit estimates of product and process innovators: marginal effects

Variables	(1) Process (1,0)	(1) Product (0,1)	(1) Both (1,1)	(2) Process (1,0)	(2) Product (0,1)	(2) Both (1,1)
$Process_{it-2}$	0.0936*** (0.0042)	0.0003* (0.0002)	0.0069*** (0.0009)	0.0935*** (0.0042)	0.0003* (0.0002)	0.0069*** (0.0008)
$Product_{it-2}$	0.0313*** (0.0093)	0.0057*** (0.0010)	0.0092*** (0.0013)	0.0313*** (0.0092)	0.0057*** (0.0010)	0.0091*** (0.013)
TFP_{it-2}	–	–	–	0.0106** (0.0052)	0.0007** (0.0004)	0.0016*** (0.0006)
$Size_{it-2}$	−0.0318*** (0.0053)	0.0010*** (0.0002)	−0.0010*** (0.0002)	−0.0315*** (0.0053)	0.0010*** (0.0002)	−0.0010*** (0.0002)
X_{it-2}	0.0081** (0.0046)	0.0016*** (0.0008)	0.0025*** (0.0009)	0.0075* (0.0046)	0.0016*** (0.0008)	0.0025*** (0.0009)
M_{it-2}	0.0048*** (0.0009)	0.0042*** (0.0008)	0.0048*** (0.0009)	0.0047*** (0.0009)	0.0042*** (0.0008)	0.0047*** (0.0047)
R&D $int._{it-2}$	−0.0061 (0.0052)	−0.0001 (0.0008)	−0.0005 (0.0010)	−0.0061 (0.0052)	−0.0001 (0.0008)	−0.0005 (0.0010)
$\overline{Prc_{io}}$	0.0390*** (0.0039)	–	0.0012*** (0.0001)	0.0388*** (0.0039)	–	0.0012*** (0.0001)
$\overline{Prd_{io}}$	–	0.0049*** (0.0008)	0.0056*** (0.0008)	–	0.0049*** (0.0008)	0.0056*** (0.0008)
$\overline{Size_i}$	0.0746*** (0.0057)	0.0012* (0.0009)	0.0067*** (0.0011)	0.0738*** (0.0057)	0.0012* (0.0009)	0.0066*** (0.0011)
$\overline{R\&D\ int._i}$	0.0520*** (0.0091)	0.0022** (0.0013)	0.0063*** (0.0016)	0.0516*** (0.0091)	0.0024** (0.0012)	0.0065*** (0.0015)
Year/sector	YES	YES	YES	YES	YES	YES
Observations		30,119			30,119	
Log-L		−11934.859			−11929.676	
P		0.415*** (0.025)			0.416*** (0.024)	
Wald test $\rho = 0$						
χ^2		207.537			206.952	
p-value		0.000			0.000	

Notes: We follow Wooldridge (2005) to deal with the bias arising from the initial conditions problem and the correlation between the unobserved heterogeneity term and the explanatory variables. ***, ** and *indicate significance at the 1, 5 and 10%, respectively
Source: Authors' own work

activities increases the probability of implementing the other one. Furthermore, the nurturing effects of past product innovations both on the likelihood of implementing process innovations and both process and product innovations are greater than those corresponding to process innovations. Specifically, while past product innovations increase the likelihood of introducing a process innovation by 3.1 percentage points, past process innovations raise the probability of implementing product innovations by only 0.03 percentage points. Analogously, whereas past product innovations increase the likelihood of implementing both process and product innovations by almost one percentage point (0.91), the increase associated with past process innovation is about 0.69 percentage points. A possible explanation of this fact could be that introducing new products increases the attractiveness of Colombian manufacturing firms' output and allows them to generate the necessary resources to implement process innovations. This has important implications for innovation policy, as providing firms incentives to implement product innovations would very likely foster the introduction of process innovations that could result in enhanced productivity and improvements in firms' competitiveness.

As regards the control variables, our estimates show evidence of the self-selection of the more productive firms into the implementation of innovations. The marginal effects of lagged TFP are positive and statistically significant for both types of innovations. However, the impact of past productivity is greater for process than for product innovations or for implementing both activities. More specifically, a 10% increase in TFP raises the probability of introducing process innovations by 0.106 percentage points, by 0.007 percentage points the probability of implementing product innovations and by 0.016 percentage points the probability of implementing both types of innovations [12].

As for the impact of firms' internationalisation strategies, our estimates confirm that past importing intermediates and exporting have a positive impact on the likelihood of implementing process innovations only, product innovations only, or both innovation activities. Interestingly, whilst the impact on the likelihood of implementing process innovation is greater for exporting than for importing, for product innovations (or for both), the opposite is true. As Colombia is an emerging economy, the higher impact of exporting on the probability of implementing process innovations could be related to the need to adopt productivity-enhancing (cost-reducing) process innovations that may allow firms to remain competitive in international markets [13]. As for the higher impact of importing intermediates on the probability of implementing product innovations, it could be signalling that importing intermediates grants access to a wider range of (very likely) higher-quality inputs that eases the introduction of product innovations.

Finally, as we consider simultaneously both innovative decisions, at the bottom of Table 4, we report the Wald test for the correlation of these activities. We strongly reject the null of no correlation between process and product innovation (with a p-value of about 0). Therefore, the joint estimation of the two equations is the correct estimation strategy.

5. Concluding remarks

This article has thoroughly analysed the dynamic relationship between process and product innovations, and productivity in Colombian manufacturing. We have explored the hypotheses of self-selection and returns-to-innovation and the linkages between process and product innovations. For this purpose, we have endogenized firms' innovation strategies in the Markov process to estimate productivity, following the De Loecker (2010) approach and the Wooldridge (2009) estimation procedure.

Our main empirical results may be summarized as follows: First, our findings shed light on the importance of conducting a joint analysis of the self-selection process in the implementation of process and/or product innovations, since the estimates measuring the intensity of self-selection are significantly affected when accounting for the correlation between the adoption of product and process innovations. Furthermore, we find that the self-selection effect is more intense in the adoption of process innovations only than in the adoption of product innovations only or the joint adoption of process and product innovations. Second, our results reveal the varying temporal pattern of innovation returns. Thus, process innovations yield immediate benefits, whereas product innovations and implementing both process and product innovations show significant but delayed benefits. Finally, our analysis confirms the existence of dynamic links between process and product innovations: past product innovations foster the implementation of process innovations and vice versa, but the nurturing effect of past product innovations on process innovation is larger than that of past process innovations on product innovations.

Implementing process and product innovations is crucial for Colombian manufacturing despite the low percentage of innovative enterprises, the modest expenditures on R&D activities, the low percentage of qualified people and the sparse connections with international markets. We uncovered that process and product innovation improve future firms' performance (in the short term), which in turn will increase the likelihood of future process and product innovations (in the medium to long term). Furthermore, there exists a two-way relationship between process and product innovations, which implies that a firm implementing process and/or product innovations is more likely to implement product and/or process innovations in the future. This is significant in emerging economies where process innovations are more common than product innovations.

Our findings suggest that there is high potential in the local industry as a source of economic growth despite the poor indicators of innovation. The processes of self-selection and returns-to-innovation exist and can be reinforced to achieve greater impacts in the economy if the innovation policy is appropriate. In this regard, we advocate expanding public funding for innovation, strengthening the patent system, and providing lending options through private banking, particularly for SMEs, to enable them to acquire new and improved technology. Their productivity and competitiveness in both the domestic and global markets will increase as a result. In addition, this virtuous cycle might be reinforced if companies recognize the benefits associated with using innovations in the production process and the impact these innovations might have on the future performance of their companies.

Notes

1. The Colombian national institute of statistics defines product innovations as "new or significantly improved goods or services for the national market or the international market", and process innovation as "Introduction of new or significantly improved methods of production and distribution systems, new organisational methods, new marketing techniques, and improvement in the quality of goods or services".
2. Table A2 in the online Appendix 2 presents the descriptive statistics for the estimation sample. It is important to stress that in our working sample, only 13.3% (1.52%) of the firms are process (product) innovators.
3. The definitions of the variables can be found in Table A1 in Appendix 1.
4. Using the first year of the biennium to define a first-time process/product innovator could imply classifying firms as first-time process/product innovators firms that have not introduced an innovation yet.

5. As TFP is measured in logs, to interpret the average marginal effect, it is useful to multiply it by 0.1. After this transformation, the resulting coefficients may be interpreted as the average change in the probability of introducing an innovation for the first time when TFP in levels increases by about 10% (an increase in the log of TFP of 0.1 is about a 10% increase in the TFP in levels). Hence, if the average marginal effect is 0.0042, a 10% increase in TFP increases the probability of implementing a process innovation for the first time by 0.00042, or 0.042 percentage points. We would like to point out that in our sample period, the average yearly variation of productivity is about 10.35% for innovators, whereas it is only 0.44% for non-innovators. Therefore, we consider that an increase of 10% in TFP is quite feasible.

6. Therefore, an increase of 0.042 percentage points in the probability of becoming a first-time process innovator implies an increase in the actual probability of becoming a first-time process innovator of 0.65% ((0.042/6.43) × 100). Analogously, an increase of 0.007 percentage points in the probability of becoming a first-time product innovator implies an increase of 1.75% in the actual probability of becoming a first-time product innovator. Finally, an increase of 0.001 percentage points in the probability of becoming a first-time process and product innovator implies an increase in the actual probability of becoming a first-time product and product innovator of 0.16%.

7. Griffith *et al.* (2006) or Benavente (2006) also found that the likelihood of implementing product innovations is directly related to the size of the firm.

8. The scarce number of first-time innovators beyond $t + 3$ advises not expanding our analysis further because the results would be unreliable.

9. An additional aspect worthy of consideration relates to the observational evidence that indicates a significant ATE for first-time process-only innovators during periods $t/t + 1$ and $t + 2/t + 3$, but not during the period $t + 1/t + 2$. This disparity may arise from the changing composition of the sample over time. A number of factors, including firm attrition, non-response to surveys and cases where some firms move forward with a second innovation, excluding them from the pool of first-time process-only innovators, cause the number of first-time process innovators to decline over time.

10. Similar results have been found in Spain for process innovations (Mañez *et al.*, 2013).

11. We include TFP to capture self-selection of the more productive firms into implementing process and/or product innovations.

12. We consider it might be informative to analyse the magnitude of these productivity effects, considering the sample probabilities of being a process innovator only (14.11%), a product innovator only (1.49%) and both a product and process innovator (1.87%). Thus, a 10% productivity improvement increases the actual probability of implementing process innovations only, product innovations only and both process and product innovations by 0.75% ((0.106/14.11) × 100), 0.47% (0.007/1.49) × 100) and 0.86% ((0.016/1.87) × 100), respectively.

13. It should be considered that price (and so cost) is a crucial determinant for exporting in an emerging country like Colombia.

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Appendix 1. Definitions of the variables

FTI	First-time innovator. A firm that declares to have introduced an innovation in a period, not having implemented any innovation since the first year it is observed in the sample
TFP	Logarithm of total factor productivity
Size	Logarithm of the number of employees
Export	Dummy variable that takes value 1 if the firm exports output in period *t*, and 0 otherwise
Import	Dummy variable that takes value 1 if the firm imports intermediates in period *t*, and 0 otherwise
R&D	R&D expenditures over sales
Process	Dummy variable that takes value 1 if the firm obtains a process innovation in period *t*, and 0 otherwise
Product	Dummy variable that takes value 1 if the firm obtains a product innovation in period *t*, and 0 otherwise
Year dummies	Dummy variable taking value 1 for the corresponding year, and 0 otherwise
Industry dummies	Industry dummies accounting for 19 industrial sectors (OECD classification)

Source: Authors' own work

Table A1.
Variable definitions

Appendix 2

URL: https://drive.google.com/file/d/1uOzHm7RfvN1NlMM2H_Ahum-qozkQ6EsX/view?usp=sharing

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