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La persistencia en la generación y adopción de innovaciones de producto

Evidencia para las empresas manufactureras en un país en desarrollo

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Abstract

Purpose – The purpose of this paper is to test the existence of true persistence in the generation and adoption of product innovations in the context of a developing country.
Design/methodology/approach – A dynamic probit model with random effects is used to test true persistence relying on a panel data set constructed from three waves of the Colombian innovation survey (Encuesta de Desarrollo e Innvovación Tecnológica) covering the time span from 2003 to 2008.
Findings – This paper empirically shows the existence of true innovation persistence for two of the three types of product innovation studied: the adoption of product innovation that is new to the firm; and the adoption of product innovation that is new to the national market. However, the study could not confirm true persistence in the generation of product innovation.
Originality/value – To the best of our knowledge, this is the first study that systematically tests innovation persistence differentiating between the adoption of innovations that are new to the firm and innovation that is new to the national market. It is also the first study in this research area that uses a dynamic probit model with random effects according to the original specification by Wooldridge (2005).

Keywords Product innovation, Developing country, Manufacturing firms, Innovation persistence, Product adoption, True state dependence

Paper type Research paper

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Resumen

Propósito – En este trabajo se prueba la existencia de verdadera persistencia en la generación y adopción de innovaciones de productos en el contexto de un país en desarrollo.

Diseño/metodología – Para probar la existencia de verdadera persistencia se estima un modelo probit dinámico con efectos aleatorios utilizando tres cohortes de la Encuesta de Desarrollo e Innvovación Tecnológica (EDIT) que cubren el periodo de tiempo 2003-2008.

Resultados – Este trabajo muestra empíricamente la existencia de verdadera persistencia en dos de los tres tipos de innovación de productos estudiados: en i) la adopción de innovación de productos nuevo para la empresa, y ii) la adopción de innovación de productos nuevo para el mercado nacional. Sin embargo, el estudio no pudo confirmar la verdadera persistencia en la generación de innovación de productos.

Originalidad – Este es el primer estudio que evalúa sistemáticamente la persistencia en la innovación diferenciando entre la adopción de innovaciones que son nuevas para la empresa de las que lo son para el mercado nacional. También es el primer estudio en esta área de investigación que utiliza un modelo probit dinámico con efectos aleatorios de acuerdo con la especificación original de Wooldridge (2005).

Palabras claves Persistencia en innovación, dependencia verdadera, innovación de productos, adopción de productos, imitación, país en desarrollo, empresas manufactureras

Tipo de papel Trabajo de investigación

1. Introduction

Innovation persistence, the phenomenon of a firm that innovates in one time period and again in the subsequent time period, has gained importance in academic research as evidenced, for example by the special issue of Economics of Innovation and Technology in 2014. Various arguments justify this research interest: the frequency with which firms introduce innovations plays an important role in a country's technological and economic development (Duguet and Monjon, 2004); the growth and varying profitability of firms and industries is influenced by this phenomenon (Cefis and Ciccarelli, 2005); innovation persistence hints at the existence of creative accumulation (Malerba *et al.*, 1997); and empirical evidence suggests that persistent innovation is a source of competitive advantage (Cefis and Ciccarelli, 2005).

Innovation persistence can potentially be brought about by two different phenomena (Heckman, 1981): true state dependence, that is a causal behavioural effect where the decision to innovate in one period increases the likelihood to innovate in the subsequent period; and firms may exhibit certain characteristics that make them more likely to innovate such as strategic orientation, innovation capabilities development or R&D investments. In case that these characteristics are unobserved but correlated over time and at the same time not controlled for in an empirical estimation, spurious state dependency occurs (Peters, 2009). Empirical research has concentrated on analysing true state dependence (or true persistence in innovation) by controlling for the spurious effect by employing specific estimation techniques. The dynamic probit model with random effects according to the specification by Wooldridge (2005) is one of these and will be applied in the current study.

Despite ample empirical evidence regarding innovation persistence (Le Bas and Scellato, 2014), the phenomenon of innovation persistence is far from being completely understood and important research gaps remain (Ganter and Hecker, 2013). One of these research gaps is that only few of the empirical studies have included a comparison of product innovation persistence differentiating between the degrees of novelty. Most of the current research has used aggregated measures for product or process innovation (Raymond *et al.*, 2010), or even applied a general measure of innovation without differentiating between the different types of innovation

(Suárez, 2014). Other studies combined both innovation inputs and outputs in one single measure (Peters, 2009). Even though it can be argued that firms' general innovation activities are measured through these indices, the discrimination between innovation inputs and outputs, the different types of innovation, and their degree of novelty as we propose, is important because their determinants and effects differ. One of the consequences of this discrimination is that it allows a comparative study of the persistence in generating and adopting product innovation. In this sense, our research contributes to the literature by differentiating between the generation and adoption of product innovation. This differentiation is even more important in the context of a developing country, where our study is placed, whereby imitation, or the adoption of innovation generated outside the country, is widespread (Kim, 1997).

The low attention that so far has characterized the study of persistence in innovation adoption is surprising given that the generation and adoption of innovations is driven by different strategic goals and supported by diverging organizational capacities (Damanpour and Wischnevsky, 2006). Product innovations have the potential to transform existing markets or to create new market niches and generate technological discontinuities in the markets (Sorescu *et al.*, 2003). They are fundamental for the internationalization of firms (Pla-Barber and Alegre, 2007), and associated with obtaining a sustainable competitive advantage (Langerak and Hultink, 2006) and possibly disrupting the market competition (Tushman and Anderson, 1986). Achieving product innovation is based on the technological knowledge accumulated within the firm or acquired outside the firm but absorbed internally (Cohen and Levinthal, 1990). This technological knowledge needs to be accompanied by the possession of specialized resources and capabilities for its commercialization (Sorescu *et al.*, 2003; Damanpour and Wischnevsky, 2006).

The adoption of product innovations, on the other hand, enables a firm to remain competitive (Damanpour and Wischnevsky, 2006), and is frequently motived by the search for legitimacy and competitive parity with similar firms within referenced strategic groups (Massini *et al.*, 2005). Product innovation also provides an opportunity to deal with environmental uncertainty (Tschang, 2007). A firm that adopts product innovations relies mainly on capacities that allow the evaluation of new technologies, their assimilation and use as well as the knowledge to adapt them to the relevant context (Kim, 1997; Damanpour and Wischnevsky, 2006). Based on this discussion, it becomes clear that a differentiated study of persistence in the generation vs the adoption of product innovation is necessary.

It is important to stress that in the literature reviewed, true state dependence is tested with a modification of the original model proposed by Wooldridge (2005). In this model, the within means of time-varying explanatory variables are included as part of the unobserved heterogeneity (Peters, 2009). In this respect, simulations show that this model provides biased results for short panels (Rabe-Hesketh and Skrondal, 2013). Consequently, our study – in contrast to most empirical studies in the area of innovation persistence – adopts the dynamic probit model with random effects according to the original specification by Wooldridge (2005).

The remainder of the paper is structured as follows. We first offer a literature review, highlighting the research gaps mentioned earlier. We then give a detailed description of the data, variables, and the statistical model employed. In Section 4, we present the results of our estimations and discuss them subsequently. Finally, we conclude this paper with a discussion of the theoretical and practical implications of this research.

2. Background

As mentioned above, research into innovation persistence has increased over recent years. A thorough revision of this literature reveals insights that are relevant for the current study. One of the main differences in the studies observed lies in the adoption of different measures of innovation, which we see as one of the determinants of differing results with regard to the degree of innovation persistence. This great diversity of innovation indicators seems to originate in the great difficulties that researchers have encountered when defining innovation and deciding upon relevant measurements (Freeman and Soete, 2009). This great diversity leads to a situation that makes a comparison of empirical results difficult if not impossible. As a consequence, knowledge about innovation persistence remains limited and needs to be amplified.

Reviewing the literature, we can identify some general conclusions. Studies, which adopt indicators that measure inputs of the innovation process, provide empirical evidence of a relatively high probability for innovation persistence. For example, Máñez *et al.* (2009) and Antonelli *et al.* (2012) observe a relatively high persistence in R&D investments, whereas Peters (2009) notes a relatively high persistence in all kinds of investments related to innovation activities (R&D, acquisition of machinery and technology, as well as external knowledge). These authors justify the existence of persistence in R&D investments with the existence of sunken costs in these kinds of activities.

The probability of innovation persistence when measured in terms of patents obtained is, however, comparatively very low (Geroski *et al.*, 1997). The main argument in favour of this low persistence lies in the fact that not all innovation is patented (Arundel and Kabla, 1998). A similar pattern can be detected when the empirical research focuses on other measures for radical product innovations (Geroski *et al.*, 1997). In line with the previous argument, only very few innovations clearly signify a disruption in the innovation path followed by the firm (Tushman and Anderson, 1986) and, as such, it is less likely to persist in time (Raymond *et al.*, 2010).

In contrast, empirical research, which uses other output criteria, generally shows a higher persistence. For example, Roper and Hewitt-Dundas (2008) and Antonelli *et al.* (2012) report a relatively high probability for innovation persistence in both product and process innovation. Contrary to that, Raymond *et al.* (2010) observe a relatively low-product and process innovations persistence despite the use of similar measures as the other two studies mentioned.

It is notorious to observe that most of the research on innovation persistence has taken place in the context of a developed country. We were able to identify two exceptions: Jang and Chen (2011) evaluate the determinants of patenting persistence in firms in Taiwan and based on a survival analysis were able to detect a relatively low persistence in innovation. As such, it follows the same line as earlier research regarding innovation persistence when measured in terms of patents. However, the study by Jang and Chen (2011) does not reflect the reality of most developing countries where patents are a rare exception. Suárez (2014) evaluated innovation persistence in Argentinian enterprises using an aggregated measure for all four types of innovation (product, process, organizational and market innovation) and found that the innovation persistence in this developing country depends, to a great extent, on the ability of the firms to adapt to the economic conditions in which the country finds itself. These findings need to be seen in the context of the Argentinian economy that, during the time of this analysis (1998-2006), was characterized by high economic instability (Suárez, 2014). We extend these findings by placing this research in the Colombian context, which for the time of the panel (2003-2008) was characterized by a relatively high economic stability.

Only two recent studies have evaluated the existence of innovation persistence depending on the degree of novelty. Clausen and Pohjola (2013) use a panel of four surveys applied to Norwegian enterprises, whereas Ganter and Hecker (2013) use a panel of three surveys applied to German enterprises. While Clausen and Pohjola (2013) provide empirical evidence that the introduction of an innovation in t is positively related to the introduction of subsequent innovations – new to the firm and new to the market – in $t+1$, Ganter and Hecker's (2013) study provides empirical evidence only for true state persistence of product innovation, which is new to the firm's market.

We extend these findings by amplifying the degree of novelty. We differentiate between adopting a product innovation, understood as the firm's imitation of an already existing innovation. We therefore define our measure for product adoption, distinguishing between products that are new to the firm (but not for the Colombian market) and products that are new to the Colombian market. The abovementioned studies do not differentiate between these two processes of product adoption. However, we consider this to be important in the context of a developing country, where firms do not base their innovation process on high levels of R&D investment. Rather, in these countries, inverse engineering and technology transfer by the means of purchasing machinery and equipments is the main source for developing innovation capabilities (Kim, 1997).

3. Data and methodology

3.1 Dynamic random effects probit

In order to evaluate true state dependence innovation persistence, we constructed three time-varying dummy dependent variables (one variable for each type of innovation analysed). For example, if one firm has introduced one innovation that is new to the market, the respective variable equals one. As a result, we need to apply a discrete regression model, i.e., a probit regression. Since true state dependence is defined with respect to the effect of past behaviours on current ones, a dynamic discrete model needs to be applied. This means that each binary dependent variable is regressed against its past value (dependent variable lagged) and relevant controls.

Our panel data have some restrictions, which need to be taken into account when choosing an adequate regression model. First, the beginning of our panel data does not necessarily coincide with the initiation of the firm's innovation process; that is, the measure for innovation results in 2003/2004 is not necessarily the first innovation result. Additionally, even though we control for a set of different variables, a number of non-observable factors may exist and influence the firm's innovation behaviour and results; e.g., firm's general manager's risk aversion. In such data with unobserved effects "[…] the treatment of the initial observations is an important theoretical and practical problem" (Wooldridge, 2005, p. 39). Accordingly, these conditions led us to choose a dynamic probit model with random effects according to the modification of the Heckman (1981) model as proposed originally by Wooldridge (2005).

The assumption that initial conditions are independent of unobserved heterogeneity (e.g. if it is assumed that the first result of innovation achieved by the firm is independent; for example, from the firm manager's level or risk aversion) is very strong and not enforced in practice (Wooldridge, 2005). According to Wooldridge (2005) "a better approach is to allow the initial condition to be random, and then to use the joint distribution of *all* outcomes on the response – including that in the initial time period – conditional on unobserved heterogeneity and observed strictly exogenous explanatory variables" (p. 40). This approach is reflected in our chosen model and described below.

We begin with model (1), where innovation in time t (y^*_{it}) depends on whether the firm innovated or not in t–1 ($y_{i,t-1}$), a set of observable variables z_{it} and a set of non-observable characteristics, which are represented by μ_i and are assumed to be constant over time. The remaining non-observable effects and variables are summarized in error term ε_{it}. According to Wooldridge (2005), it is assumed that the explicatory variables z_{it} are strictly exogenous with regard to μ_i:

$$y^*_{it} = \delta y_{i,t-1} + z_{it}\beta + \mu_i + \varepsilon_{it};\ i = 1, \ldots, N;\ t = 1, \ldots, T \quad (1)$$

where $y_{it} = 1(y^*_{it} > 0)$, and z_{it} is the vector of explanatory variables.

If the initiation of the firm's innovation process does not coincide with the beginning of the data obtained, that is to say when the process initiates in $w < 1$ and the innovation process observed in $t = 1, \ldots, T$, the initial observation y_{i0} "cannot be treated as a true exogenous factor and therefore its correlation with the error term could give place to biased estimations of the autoregressive parameterδ, which represents our measure of persistence" (Antonelli *et al.*, 2012, p. 348). In order to account for this problem, which is likely to occur when the start of the panel does not coincide with the founding of the firm, Wooldridge (2005) proposed to specify the distribution of μ_i as conditional on z_i and y_{i0}:

$$\mu_i = \alpha_0 + \alpha_1 y_{i0} + z_i\alpha_2 + a_i \quad (2)$$

where $z_i = z_{i2}, \cdots, z_{iT,}$ "z_i is the row vector of all (nonredundant) explanatory variables in all time periods" (Wooldridge, 2005, p. 46).

Under the assumption that the error term a_i is distributed normally (0, σa^2) and that $a_i \perp (y_{i0}, z_i)$, according to Wooldridge (2005) and based on (1) and (2), the probability to be an innovator is estimated from this latent dynamic probit model:

$$y^*_{it} = \delta y_{i,t-1} + z_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + z_i\alpha_2 + a_i + \varepsilon_{it} \quad (3)$$

where ε_{it} is normally distributed (0, 1).

3.2 Data description

The firm-level data on innovation behaviour and performance were given by the Colombian National Statistics Department (DANE), which collects data on Colombian manufacturing firms every two years. In contrast to most innovation surveys, the Encuesta de Desarrollo e Innvovación Tecnológica (EDIT) collects the information on the entire population of Colombian manufacturing firms with more than five employees or generated sales of above a threshold set for each survey wave[1]. We used the surveys carried out for three periods: 2003/2004 (EDIT II), 2005/2006 (EDIT III) and 2007/2008 (EDIT IV) and were able to obtain a balanced panel which included a total of 9,158 observations after eliminating those firms for which missing data were reported. Firms that were not included in all three surveys or those that presented missing values were excluded.

3.3 Dependent variables

In order to evaluate each kind of innovation persistence, we use three different dependent variables. Each of these dependent variables is a binary variable and indicates whether a firm introduced the type of innovation studied in period t. For the definition of our dependent variable, we relied on the definition of innovation as proposed by Schumpeter (1961), who associates it with the commercial exploitation of new products or processes. Based on this understanding, we define innovation as the development of a product, which has a reported positive impact on the conservation, amplification or the opening of a new market for the firm, and we differentiate between the following three innovations.

Innovation adoption – new to the firm (Inn_adop_Firm), takes the value of 1 if the firm, in *t,* introduced a product that was new to the firm or significantly improved, and 0 otherwise.

Innovation adoption – new for the national market (Inn_adop_Nat), takes the value of 1 if the firm, in *t,* introduced a product that was new to the Colombian market or significantly improved, and 0 otherwise.

Innovation generation – new for the international market (Inn_gen), takes the value of 1 if the firm, in *t*, introduced a product that was new to the global market or significantly improved, and 0 otherwise.

We present the descriptive statistics for each of the three variables in Tables I and II. As we can see, the adoption of innovation that is new to the firm or to the Colombian

	Inn_adop_Firm			Inn_adop_Nat			Inn_gen		
	Freq.	Per cent	Cum.	Freq.	Per cent	Cum.	Freq.	Per cent	Cum.
No	13,507	78.81	78.81	14,154	82.58	82.58	15,841	92.43	92.43
Yes	3,632	21.19	100	2,985	17.42	100	1,298	7.57	100
Total	17,139	100		17,139	100		17,139	100	

Notes: This table states the frequency, percentage and cumulative percentage for each of the three dependent variables across the three waves of the survey. Column 1 presents information regarding the adoption of innovation, which is new to the firm; column 2 provides information on the adoption of innovation which is new to the national market and column 3, the generation of innovation. While an average of over 21 vs 17.4 per cent of firms report the adoption of an innovation, which is new to the firm and new to the national market, only 7.6 per cent of the firms report the generation of an innovation

Table I. Descriptive summary for dependent variables – complete panel

	Frequency per survey			Descriptives			
Dependent variable	EDIT II	EDIT III	EDIT IV	Mean	SD	Between SD	Within SD
Inn_adop_Firm	1,459	771	1,402	0.21	0.41	0.27	0.31
Inn_adop_Nat	1,346	918	721	0.17	0.38	0.25	0.29
Inn_gen	568	458	272	0.08	0.26	0.18	0.20

Notes: This table provides further descriptive statistics for the three dependent variables. Column 1 provides information regarding the frequency of innovation adoption and generation for each of the three waves of the survey used, whereas the column 2 provides the mean, the general, between and within SD across the three surveys. As observed in Table I, the adoption of innovation new to the firm is most common with 21 per cent of the firms stating that they adopted an innovation during the 2003-2008 time span. This percentage drops to 17 per cent for the adoption of an innovation new to the national market and only 8 per cent of the firms state to have created an innovation during this time span. Provided that we have a balanced panel, the frequencies of the dependent variables are directly comparable. As such, during the period 2005/2006, the amount of firms adopting an innovation new to the firm was lowest, whereas the adoption of an innovation new to the national market as well as the generation of an innovation were lowest during the 2007/2008 period. The within standard deviation is generally higher than the between standard deviation for all three dependent variables, indicating that there exists more variation for the same firm across the three time spans than between the firms during the same time span

Table II. Descriptive summary for dependent variables – per survey market is relatively more common than the generation of innovation, which is reported for less than 8 per cent of all firms. Additionally, we can observe that, in general terms, variation for both types of product innovation adoptions (see Table II, between SD column and within SD column) is greater than for the generation of product innovation. At the same time, the respective within-variance is greater than the between-variance for all three cases indicating that there is more variation for the same Colombian manufacturing firm over time than between the different Colombian manufacturing firms for the same time period.

3.4 Independent variables

In order to assure that the obtained persistence is not spurious, we need to include a series of control variables. In this research, we identified these control variables relying on three different sets of explications of innovation persistence. The first approach to explain innovation persistence is based on the concept of sunken costs generated by previous investments in R&D (Máñez *et al.*, 2009). The second, the financial restrictions approach, takes into consideration the disposable capital for new investments in innovation activities (Ganter and Hecker, 2013). Lastly, the learning process generated through innovation processes within the firm leads – through economies of scales – to the accumulation of innovation capabilities which may cause innovation persistence (Geroski *et al.*, 1997). In Table III, we define the included set of control variables and present their descriptive statistics in Tables IV and V. Table VI presents the correlation matrix of the variables considered in this study.

4. Empirical results

4.1 Descriptive statistics and transition probabilities

Transition probabilities are descriptive tools traditionally used to analyse innovation persistence. We report these transition probabilities in Table VII. We can observe that the transition probability for adopting innovations new to the firm is lowest in the first transition with 20.9 per cent (from Survey 1 to 2), even lower than for the generation of a product innovation, which reaches 21.5 per cent. At the same time, this kind of innovation adoption presents the highest probability of persistence in the second transition as well as in the transition from Survey 1 to 3. A general trend which we can observe is that the probability of persistent innovation generation is lower in the second transition and in the long run (transition from Survey 1 to 3) than in the first transition. This is also true for the transition probability of adopting innovation at the national level.

Generally, we can observe that all transition probabilities are well below 50 per cent. In comparison, the majority of those studies which use a measure that aggregates different types of innovation, report transition probabilities that are far higher than the ones reported in Table VII (e.g. Peters, 2009; Raymond *et al.*, 2010). However, compared with those found by Suárez (2014), who reported transition probabilities of >46 per cent for Argentinian manufacturing enterprises operating in a technological and economical context similar to the Colombian one, we can observe that they are closer. At the same time, >46 per cent is higher than most of the transition probabilities we reported which might be an indicator that aggregated measures of innovation tend to generate higher transition probabilities.

We can also observe that the transition probability of not adopting or generating an innovation is relatively high with levels beyond 75 per cent. This probability

Variable name	Short description	Detailed description
Sunken costs		
Invest_R&D	R&D investments	Investments in R&D realized by the firm during the time period *t*, divided by the number of employees
Financial restrictions		
Inv_internal	Innovation investment intensity financed by own resources	The amount of innovation investment, which was financed with resources from the firm during the period *t*, divided by the number of employees
Inv_internal_cont	Continuity in internal innovation investment	The variable takes the value of 2 if the firm has generated innovation investment relying on own resources for two consecutive periods prior to *t*. It takes the value of 1 if the investment was undertaken only one period prior to *t* and a value of 0 otherwise
Inv_external	Innovation investment intensity financed by external resources	The amount of innovation investment, which was financed with external resources (public, private banks, venture capital) amount of externally financed resources (public, private bank, capital funds) during the period *t*, divided by the amount of employees
Inv_external_cont	Continuity in external innovation investment	The variable takes the value of 2 if the firm has generated innovation investment relying on external resources for two consecutive periods prior to *t*. It takes the value of 1 if the investment was undertaken only one period prior to *t* and a value of 0 otherwise
Capacities for innovation		
Educ	Educational level of employees	The proportion of employees which possess at least a university degree in period *t*
Learn_Train	Learning by training	Investment in technological training realized by the firm in period *t*, divided by the amount of employees
Learn_Doing	Learning by doing	Investment in machinery and technology realized by the firm in period *t*, divided by the amount of employees
Learn_Using	Learning by using	Investment in the acquisition of technologies in the form of ownership, licenses and inventions not patented realized by the firm in period *t*, divided by the amount of employees
Learn_Inter	Learning by interacting	A count variable indicating the use of one or more of the following external information sources: clients, suppliers, competitors, universities and research centres, centres of technological development, chamber of commerce and industry associations. The value ranges from 1 to 7

(*continued*)

Table III. Definition of independent and control variables

Variable name	Short description	Detailed description
Control variables		
Size	Firm size	Natural logarithm of the number of employees for the firm in period *t*
Foreign	Foreign ownership	If 25% or more of the firm's capital is of foreign ownership in period *t*, the variable takes the value 1, and a value of 0 otherwise
Pavitt_sup	Supplier-based industrial segment according to Pavitt	Depending on the industry classification CIIU in period *t*, the firms were grouped according to the classic segmentation of Pavitt (1984) into four groups, each corresponding to one dummy variable taking the value of 1 if the firm belonged to that industry segment and 0 otherwise
Pavitt_scale	Scale-intensive industrial segment according to Pavitt	
Pavitt_special	Specialized industrial segment according to Pavitt	
Pavitt_science	Science-based industrial segment according to Pavitt	
Dummy04	Time period	A dummy variable for the time 2003/2004 period
Dummy06	Time period	A dummy variable for the time 2005/2006 period
Dummy08	Time period	A dummy variable for the time 2007/2008 period
InnNatFirm		Binary variable used in the model where the dependent variable is the generation of product innovations (Inn_gen). This variable controls for the case that the firm has adopted any kind of product innovation in the same time period. It takes the value of 1 if the firm adopted a product innovation new to the firm and the national market in period *t*
InnIntFirm		Binary variable used in the model where the dependent variable is the adoption of product innovations new to the national market (Inn_adop_Nat). This variable controls for the case that the firm has adopted a product innovation new to the firm or generated a product innovation in the same time period. It takes the value of 1 if the firm adopted a product innovation new to the firm or generated a product innovation in period *t*
InnIntNat		Binary variable used in the model where the dependent variable is the adoption of product innovations new to the firm (Inn_adop_Firm). This variable controls for the case that the firm has adopted a product innovation new to the national market or generated a product innovation in the same time period. It assumes the value of 1 if the firm has adopted a product innovation new to the national market or generated a product innovation in period *t*

Note: This table states the name of the independent and control variables used for this research, a short description and a corresponding detailed description

Table III.

increases even further with an increase in the degree of novelty. This suggests the existence of a large inertia of non-adopters or non-innovative firms, which might be the result of a series of obstacles which act as barriers to initiate any kind of innovation process.

Independent variable	Mean	SD	Descriptives Between SD	Within SD
Invest_R&D	1,085,725	1,862,507	1,057,276	1,493,351
Inv_internal	2,353,744	13,976	8,497,139	10,999
Inv_external	1,440,431	8,545,908	5,990,062	6,486,321
Educ	0.12	0.14	0.11	0.09
Learn_Train	8,814,173	9,923,287	5,664,435	7,982,245
Learn_Doing	2,801,135	16,009	11,127	11,769
Learn_Using	9,363,761	1,333,365	7,933,889	1,071
Learn_Inter	0.98	1.88	1.25	1.42
Size	3,604,058	1,299,464	1,277,433	0.29

Notes: This table contains the descriptive statistics (mean, standard deviation, between and within SD) of the independent variables. In general terms, we can observe that the within SD is greater than the between SD with the exception of education, size and learning by using

Table IV. Summary statistics of independent variables

Variable		Observed value 0	1	2
Inv_internal_cont	Freq	4,713	8,415	2,463
	Perc	30.23	53.97	15.8
Inv_external_cont	Freq	9,861	4,725	1,005
	Perc	63.25	30.31	6.45
Foreign	Freq	15,979	1,160	
	Perc	93.23	6.77	
Pavitt_sup	Freq	10,635	6,504	
	Perc	62.05	37.95	
Pavitt_scale	Freq	10,949	6,190	
	Perc	63.88	36.12	
Pavitt_special	Freq	16,019	1,120	
	Perc	93.47	6.53	
Pavitt_science	Freq	13,795	3,344	
	Perc	80.49	19.51	
InnNatFirm	Freq	12,807	4,332	
	Perc	74.72	25.28	
InnIntFirm	Freq	13,196	3,943	
	Perc	76.99	23.01	
InnIntNat	Freq	13,990	3,149	
	Perc	81.63	18.37	

Notes: This table contains descriptive statistics (frequency and percentages) for all binary and ordered independent and control variables. While the majority of firms use own capital to invest in innovation-related activities at least for two consecutive years, 63 per cent of the firms do not rely on external sources for innovation-related investments. More than one-third of the firms in this panel belong either to the supplier-based or the scale-intensive industrial sectors. Only 6.5 per cent belong to the specialized and almost 20 per cent to the science-based industrial sector

Table V. Descriptive statistics of the independent binary or ordered variables

4.2 Econometric results

In order to determine the existence of true state persistence, we estimated three models for each dependent variable. In the first model, the base model, we included the size of the firm, foreign ownership, the sectorial control variables and the dummies to control for time effects. In the second model, we additionally included the suggested

Table VI.
Correlations between the explicative panel variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Invest_R&D	1																		
2. Inv_internal	0.1580*	1																	
3. Inv_external	0.0383*	0.2535*	1																
4. Inv_internal_cont	0.0240*	0.0943*	0.0184*	1															
5. Inv_external_cont	0.0334*	0.0451*	0.1942*	0.1442*	1														
6. Educ	0.0205*	0.0626*	0.0563*	0.0201*	0.0089	1													
7. Learn_Train	0.0132	0.0626*	0.0441*	0.013	0.0300*	0.0437*	1												
8. Learn_Doing	0.0234*	0.4543*	0.4049*	0.0612*	0.0942*	0.0616*	0.0525*	1											
9. Learn_Using	0.0133	0.3536*	0.2423*	0.0211*	0.0260*	0.0557*	0.0203*	0.3138*	1										
10. Learn_Inter	0.0379*	0.0834*	0.0920*	0.1243*	0.1654*	0.0404*	0.0401*	0.0870*	0.0193*	1									
11. Size	0.0489*	0.1003*	0.0815*	0.2284*	0.2880*	−0.0754*	0.0229*	0.1089*	0.0046	0.2018*	1								
12. Foreign	0.0212*	0.1061*	0.0745*	0.0564*	0.0326*	0.1405*	0.0431*	0.1123*	0.0364*	0.0767*	0.3223*	1							
13. Pavitt_sup	−0.0289*	−0.0432*	−0.0167*	−0.0434*	−0.0146	−0.0861*	−0.0318*	−0.0391*	0.0026	−0.0342*	−0.0446*	−0.0709*	1						
14. Pavitt_scale	−0.0025	0.0047	0.0066	0.0228*	−0.0323*	−0.0648*	−0.0069	0.0161*	−0.0215*	−0.0095	0.0236*	−0.0227*	−0.5880*	1					
15. Pavitt_special	−0.006	−0.0055	−0.0173*	0.0183*	0.0114	0.0215*	0.0202*	−0.0134	0.0018	0.012	−0.0396*	−0.0017	−0.2068*	−0.1988*	1				
16. Pavitt_science	0.0422*	0.0522*	0.0229*	0.0173*	0.0511*	0.1707*	0.0350*	0.0381*	0.0225*	0.0463*	0.0522*	0.1176*	−0.3850*	−0.3702*	−0.1183*	1			
17. InnNatFirm	0.0748*	0.1187*	0.1138*	0.1598*	0.2005*	0.0375*	0.0363*	0.1126*	0.0383*	0.3438*	0.2563*	0.0838*	−0.0495*	−0.0063	0.0065	0.0640*	1		
18. InnIntFirm	0.0780*	0.1136*	0.1104*	0.1442*	0.1914*	0.0302*	0.0362*	0.1037*	0.0293*	0.3339*	0.2517*	0.0862*	−0.0409*	−0.0081	0.0069	0.0559*	0.9035*	1	
19. InnIntNat	0.0489*	0.1065*	0.1112*	0.1398*	0.1857*	0.0554*	0.0355*	0.1038*	0.0370*	0.3474*	0.2441*	0.0971*	−0.0506*	−0.0192*	0.0209*	0.0717*	0.7762*	0.6879*	1

Notes: The table presents the correlation matrix. The only correlation coefficient which might be of concern in terms of potential multicollinearity problems are the correlation coefficients for the last three variables which are higher than 0.65. However, these variables are not included in the same model but are used separately. *,**,***Correlation coefficients statistically significant at the 10, 5 and 1 per cent confidence levels, respectively

		Survey 2: EDIT III				Survey 3: EDIT IV				Survey 3: EDIT IV	
		0	1			0	1			0	1
Innovation adoption – firm level											
Survey 1:	0	87.06	12.94	Survey 2:	0	75.09	24.91	Survey 1:	0	75.17	24.83
EDIT II	1	79.1	20.9	EDIT III	1	59.21	40.79	EDIT II	1	67.9	32.1
Innovation adoption – national level											
Survey 1:	0	84.5	15.5	Survey 2:	0	88.27	11.73	Survey 1:	0	87.28	12.72
EDIT II	1	74.85	25.15	EDIT III	1	74.91	25.09	EDIT II	1	83.05	16.95
Innovation generation											
Survey 1:	0	92.56	7.44	Survey 2:	0	95.81	4.19	Survey 1:	0	95.6	4.4
EDIT II	1	78.5	21.5	EDIT III	1	82.68	17.32	EDIT II	1	87.72	12.28

Notes: This table contains the transition probabilities for the three dependent variables. Row 1 contains the transition probabilities regarding the adoption of innovation new to the firm; row 2 for the adoption of innovation new to the national market; and row 3, the generation of innovation. Column 1 contains the transition probability from EDIT II (2003/2004) to EDIT III (2005/2006), column 2 from EDIT III (2005/2006) to EDIT IV (2007/2008), and column 3 from EDIT II (2003/2004) to EDIT IV (2007/2008). The persistence of not adopting or producing an innovation is very high with percentages ranging between 75 and 96 per cent. The transition probabilities for the adoption of innovation (rows 1 and 2) tends to be higher than for the generation of innovation (row 3) with the exception of the transition for innovation adoption at firm level from EDITs II to III, which is lower than the transition for the same time period for the generation of innovation

Table VII. Transition probabilities per type of innovation

independent variables by the three different research streams that explain innovation persistence. The third model takes into consideration the unobserved individual heterogeneity according to Wooldridge (2005). In order to control for the effects of past investment and financial decisions and the historical accumulation of innovation capacities, we include the lagged version of the independent and control variables in all these models. It is important to note that based on significant correlations of 0.57 or higher, we excluded the corresponding z_i for the first and second survey for the following variables: educational level, learning by doing, learning by using, learning by interacting, size of the firm and foreign capital.

Table VIII reports the results of the dynamic probit regression with random effects, which models the innovation persistence separately for the generation of product innovation, adoption at national level, and adoption at firm level. Conditional on the observed and non-observed firm characteristics, there is evidence that point to true persistence in the adoption of product innovations, which are new to the firm. The significance of the coefficient for the dependent lagged variable for adoption ($\text{Inn\_adop\_Firm}_{-1}$) remains even after controlling for the non-observed heterogeneity, implying that having adopted an innovation in $t-1$ significantly and positively influences the innovation adoption in t. We can additionally observe, for this case, that the initial status ($\text{Inn\_adop\_Firm}_{-\text{initial}}$) does not exercise a significant effect on the adoption of innovation in time t, implying that having initially adopted an innovation (i.e. in 2003/2004) does not significantly influence the adoption of an innovation in t.

The same observations can be made for the case of an adoption of product innovations new to the national (Colombian) market. True state persistence exists for this case, as is evidenced by the significant lagged dependent variable (Inn_adop_Nat_{-1}) in model 6,

Table VIII. Results of the dynamic probit model with random effects

Variables	Adoption of innovation – new to firm (1)	(2)	(3)	Adoption of innovation – new to national market (4)	(5)	(6)	Innovation generation (7)	(8)	(9)
Dependent variables									
Inn_adop_Firm$_{-1}$	0.168 (0.0501)***	0.123 (0.0509)**	0.137 (0.0574)**						
Inn_adop_Nat$_{-1}$				0.199 (0.0589)***	0.145 (0.0604)**	0.149 (0.0625)**			
Inn_gen$_{-1}$							0.372 (0.0766)***	0.341 (0.0788)***	0.18 (0.131)
Independent variables									
Invest_R&D$_{-1}$		0.0919 (0.0519)*	0.0346 (0.0748)		0.0255 (0.0522)	−0.00555 (0.0738)		0.0617 (0.0584)	−0.0379 (0.0947)
Inv_internal$_{-1}$		−0.0120 (0.0146)	−0.00873 (0.0155)		−0.00413 (0.0145)	−0.00299 (0.0154)		0.00538 (0.0152)	0.00498 (0.0168)
Inv_internal_cont$_{-1}$		0.157 (0.0237)***	0.156 (0.0247)***		0.161 (0.0263)***	0.151 (0.0265)***		0.0873 (0.0339)**	0.0761 (0.0375)**
Inv_external$_{-1}$		−0.00575 (0.0152)	−0.00154 (0.0160)		−0.0196 (0.0161)	−0.0193 (0.0172)		−0.000776 (0.0168)	−0.000907 (0.0188)
Inv_external_cont$_{-1}$		0.220 (0.0251)***	0.215 (0.0265)***		0.234 (0.0281)***	0.233 (0.0280)***		0.212 (0.0352)***	0.208 (0.0399)***
Educ$_{-1}$		0.0728 (0.0161)***	0.0622 (0.0165)***		0.105 (0.0175)***	0.0939 (0.0176)***		0.110 (0.0227)***	0.102 (0.0244)***
Learn_Train$_{-1}$		−0.00968 (0.0135)	−0.0154 (0.0169)		0.00137 (0.0121)	0.00523 (0.0146)		0.00302 (0.0148)	−0.00167 (0.0185)
Learn_Doing$_{-1}$		0.0353 (0.0186)*	0.00655 (0.0219)		0.00552 (0.0207)	−0.0298 (0.0248)		0.0222 (0.0207)	−0.00121 (0.0251)
Learn_Using$_{-1}$		−0.0180 (0.0172)	−0.00895 (0.0208)		−0.0156 (0.0210)	−0.0135 (0.0247)		−0.0170 (0.0230)	−0.00923 (0.0269)
Learn_Inter$_{-1}$		0.0152 (0.0136)	0.0104 (0.0141)		0.00951 (0.0148)	0.00510 (0.0150)		0.000967 (0.0189)	−0.00403 (0.0204)
Unobserved heterogeneity u_i									
Inn_adop_Firm$_{\text{initial}}$			0.0212 (0.0413)						
Inn_adop_Nat$_{\text{initial}}$						−0.0587 (0.0470)			
Inn_gen$_{\text{initial}}$									0.186 (0.110)*
Invest_R&D _EDITIII			0.165 (0.0859)*			0.190 (0.0839)**			0.268 (0.0992)***
Invest_R&D _EDITIV			0.000876 (0.00892)			−0.0123 (0.00759)			−0.0196 (0.0121)
Inv_internal_EDITIII			−0.0483 (0.0359)			−0.00930 (0.0344)			−0.0225 (0.0409)
Inv_internal_EDITIV			0.159 (0.0232)***			0.159 (0.0240)***			0.0992 (0.0265)***
Inv_external _EDITIII			0.00603 (0.0336)			0.00972 (0.0355)			0.0486 (0.0406)
Inv_external _EDITIV			0.113 (0.0190)***			0.0927 (0.0189)***			0.0981 (0.0226)***
Learn_Train_EDITIII			0.00904 (0.0124)			−0.00186 (0.0130)			0.00751 (0.0145)
Learn_Train_EDITIV			0.103 (0.0658)			0.0801 (0.0642)			0.104 (0.0756)

(continued)

Table VIII.

Variables	Adoption of innovation – new to firm (1)	(2)	(3)	Adoption of innovation – new to national market (4)	(5)	(6)	Innovation generation (7)	(8)	(9)
Other control variables									
Size_1	0.255 (0.0128)***	0.216 (0.0136)***	0.194 (0.0142)***	0.275 (0.0153)***	0.241 (0.0161)***	0.218 (0.0152)***	0.309 (0.0215)***	0.284 (0.0224)***	0.271 (0.0253)***
Foreign_1	−0.0506 (0.0574)	−0.0491 (0.0595)	−0.0778 (0.0617)	0.0140 (0.0586)	0.0200 (0.0614)	−0.00911 (0.0634)	0.153 (0.0681)**	0.131 (0.0718)*	0.127 (0.0785)
Pavitt_science	0.249 (0.0407)***	0.198 (0.0418)***	0.172 (0.0428)***	0.377 (0.0438)***	0.318 (0.0452)***	0.288 (0.0454)***	0.267 (0.0556)***	0.197 (0.0576)***	0.184 (0.0628)***
Pavitt_scale	0.0605 (0.0357)*	0.0531 (0.0362)	0.0406 (0.0371)	0.0772 (0.0391)**	0.0678 (0.0399)*	0.0469 (0.0408)	−0.0780 (0.0527)	−0.0971 (0.0541)*	−0.140 (0.0595)**
Pavitt_special	0.206 (0.0615)***	0.171 (0.0621)***	0.175 (0.0627)***	0.387 (0.0644)***	0.348 (0.0654)***	0.349 (0.0652)***	0.422 (0.0801)***	0.391 (0.0816)***	0.406 (0.0886)***
Dummy06	−0.467 (0.0305)***	−0.472 (0.0313)***	−0.450 (0.0322)***	0.171 (0.0333)***	0.182 (0.0342)***	0.203 (0.0342)***	0.321 (0.0459)***	0.335 (0.0472)***	0.353 (0.0500)***
InnNatFirm_1							0.0465 (0.0539)	−0.0182 (0.0561)	−0.00786 (0.0601)
InnIntFirm_1				0.0691 (0.0534)	0.0170 (0.0543)	0.0603 (0.0553)			
InnIntNat_1	0.128 (0.0486)***	0.0613 (0.0496)	0.0325 (0.0509)						
Constant	−1.714 (0.0553)***	−1.783 (0.0583)***	−1.677 (0.0619)***	−2.366 (0.0800)***	−2.481 (0.0894)***	−2.350 (0.0704)***	−3.071 (0.136)***	−3.156 (0.147)***	−3.139 (0.182)***
Observations	9,662	9,650	9,158	9,662	9,650	9,158	9,662	9,650	9,158
ρ	1.21E-07	0.0000166	0.0000127	0.0021454	0.0125044	0.0000161	0.0170172	0.0315494	0.1037871
	−0.000106	−0.000171	−0.000127	−0.040536	−0.044358	−0.000147	−0.061361	−0.06424	−0.083476
Wald χ^2	802.4	936.64	948.14	646.89	702.69	851.7	507.25	501.97	435.01
Prob > χ^2	0	0	0	0	0	0	0	0	0
Log pseudolikelihood	−45.323.405	−44.397.720	−42.519.941	−38.788.872	−37.880.551	−35.848.573	−21.523.760	−21.048.274	−19.745.266
Maximum likelihood R^2	0.087	0.091	0.109	0.087	0.106	0.115	0.135	0.149	0.154

Notes: This table presents the regression coefficients for the three different dependent variables. The respective first model only includes the control variables, whereas the second includes the control variables and the independent variables. The third model for each independent variable additionally takes into consideration the unobserved heterogeneity where the non-observed heterogeneity is taken into account. Additionally, the initial status of the firm (Inn_adop_Nat$_{_initial}$) does not influence whether or not a firm adopts a product new to the national market.

Finally, we cannot observe true persistence for the generation of product innovation. Even though models 7 and 8 report a significant effect (at the 1 per cent significance level) for the lagged dependent variable (Inn_gen$_{_1}$), at the moment where the unobserved heterogeneity is taken into account, this variable ceases to be significant. At the same time, the variable representing the initial status (Inn_gen$_{_initial}$) is significant at a 10 per cent level. These two observations combined indicate that the probability to generate a new product innovation increases in time. Based on these results, we can therefore conclude that the firm's behaviour differs with respect to adopting vs generating product innovation.

The estimated models suggest that firms which have continuity in both external and internal investments related to innovation activities and that present higher levels of educational attainment among their employees increase the probability for innovation persistence. At the same time, we were not able to detect differential effects of the different independent variables with respect to the three types of innovation persistence studied.

4.3 Robustness checks

We subjected these results to various robustness checks which all generated the same findings[2]. First, we obtained the same pattern for innovation persistence and significant variables when estimating the probit regressions with robust standard errors. Second, we did not observe important changes when we progressively excluded the part of the model that represents non-observed heterogeneity, which are the z_i variables with the highest correlation levels with respect to their corresponding z_{it}. In our case, these were learning by training (Learn_Train_EDITIII: correlation of 0.5570 with Learn_Train) and the R&D investment intensity (Invest_R&D_EDITIII: 0.5080 with Invest_R&D). Our third robustness check consisted in estimating the modified specification of Wooldridge (2005), in which the average of the dependent variables instead of z_i are included to account for non-observed heterogeneity (Peters, 2009). Again, we were able to observe similar results regarding the innovation persistence for each type of innovation studied. In the fourth check, we obtained the initial results when replacing the assumption of normally distributed error terms with the assumption of a logistic distribution. Finally, the dynamic probit estimation was based on the Gauss-Hermite quadrature approach. The accuracy of the results was tested with 8, 12 and 16 quadrature points using the STATA command quadchk.

5. Discussion and conclusion

In this paper, we empirically evaluated the existence of true state persistence in product innovation. We found that true state persistence exists for both the adoption of product innovations that are new to the firm or new to the national market while it does not exist for the generation of innovation. This result may not be surprising in light of the reviewed literature. Past research has shown very low rates of innovation persistence whenever innovation is measured in terms of patents or radical innovation (Geroski *et al.*, 1997). Additionally, theoretical arguments from within evolutionary economics suggest that innovation persistency exists for incremental innovations with a low degree of novelty because the generation of such innovation is based on local search and exploitation of existing competencies and skills (e.g. Nelson and Winter, 1982; Stuart and Podolny, 1996). At the same time, these findings partially contradict the empirical results of Clausen and Pohjola (2013) as well as those of Ganter and Hecker (2013). These authors observed true state persistence for new to the market innovations. In part, this finding is theoretically supported by the resource constraint perspective, which argues that innovation success sends positive signals, facilitating access to capital markets and other external sources of financing (Czarnitzki and Hottenrott, 2010; Flaig and Stadler, 1994). However, this driver of persistence in the generation of innovation is likely to be weaker in the context where this study takes place. Colombia is a developing country with underdeveloped financial markets, meaning that access to external resources is generally limited (Conpes, 2007).

On the other hand, we did not find empirical evidence for true state persistence in the generation of product innovation while at the same time the variable representing the initial status ($\text{Inn\_gen}_{\text{initial}}$) is significant. These results combined indicate that the greater the time passed since its last innovation, the higher the probability of a firm to successively generate product innovations. In contrast, for the adoption of innovations both new to the firm and new to the national market, the lesser the time passed since the last innovation, the greater the probability to innovate. These findings are coherent with the results found by other authors. For example, Eisenhardt and Tabrizi (1995) argue that product innovations with a high degree of novelty require a far greater time span to be generated due to the higher difficulties encountered throughout the innovation process. Furthermore, Arrow (1962) argues that the introduction of new innovations into the market may generate an erosion of the profits generated by the past innovation. In other words, it may initiate a cannibalization process, meaning that firms tend to avoid the persistent generation of innovations. Finally, it has been argued that due to the greater risk and higher investment requirements for the generation of product innovations, firms become financially more vulnerable in the period immediately after innovation investments which leads to a situation where only financially very solid firms can and should strategically pursue innovation persistence (Buddelmeyer *et al.*, 2010).

In addition, two research strands within the organizational theories might explain the empirical results. The first of these is the punctuated approach to innovation (Tushman and Anderson 1986). These authors propose that after an innovation with a high degree of novelty has been introduced, firms dedicate the subsequent time period (s) to incremental and complementary innovation in order to exploit the successful introduction of an innovation to its fullest. Only when the underlying technology starts to be imitated by others, does the firm need to initiate a new cycle of the innovation process; a highly novel innovation which will help avoid inefficiencies, obsolescence or the loss of competiveness (Tushman and Anderson, 1986).

According to the organizational ecology theory (Hannan and Freeman, 1984), disruptive changes in the central structure of the organization[3] threaten the performance, legitimacy and the survival of a firm. These kinds of negative effects are amplified when the disruptive changes occur repeatedly (Amburgey *et al.*, 1993). The persistent generation of radical innovation is an organizational change, which has the potential to disrupt both the technological structure and the marketing strategy (Dowell and Swaminathan, 2000). As a consequence, it is very likely that after the generation of a radical product innovation, the firm pauses in order to readjust its strategic orientation, and its processes and routines before intending to generate a new innovation with the same degree of novelty (Dowell and Swaminathan, 2000).

The persistence in adopting a product innovation is a process that can be developed in a more agile way; firms that adopt innovation are in a much better position to search for existing and relevant information which can reduce uncertainty in terms of the innovation's characteristics, costs and benefits (Rogers, 2003). As a result, the disruptive effects on the central structure of the firm are more reduced than the effects of generating a product innovation. Teece (2010) mentions that as the firm guides the adoption processes based on the evaluation of the firm's resource compatibility, the organizational change will be incremental with a low financial and moral impact. Additionally, these kinds of innovation processes are usually financially less restricted as public information about the innovation allows the reduction of the potential asymmetry between the innovator and the investor (Mansfield *et al.*, 1981).

The stated results have several implications for public policy. Product innovations are of utmost importance for the competitiveness and the economic development of a country. The first observation of great relevance is the notable low proportion of firms, which persistently adopt product innovation and the even lower proportion of those which persistently generate it. This has direct consequences: not only is the impact that these few persistent innovators have on the technological evolution and thus the competitiveness of the country likely to be low, but processes of knowledge accumulation and capability building caused through persistent innovation activities (Dosi, 1988; Nelson and Winter, 1982) are not taking place, inducing a potentially vicious circle. At the same time, R&D investments once entailed are sunk; created capital goods for the innovation processes are not taken advantage of once the innovation process ceases to continue (Máñez *et al.*, 2009). As such, R&D investments pose both a barrier to entry into and to exit out of innovation activities. Therefore, the aim of public policy with respect to the persistence of innovation should be twofold, increasing the critical mass of those firms that initiate innovation activities. On the other hand, it should also support firms to persistently innovate.

When contrasting the innovation persistence depending on the degree of novelty, this discussion becomes even more eminent. While the percentage of persistent innovation adopters is low, the percentage of persistent innovation generators is extremely low. Even though imitation plays a substantial role as a precondition for learning and catching up (Bell and Pavitt, 1997), radical product innovations are the main driver of economic development and growth. Public policy should therefore aim at enabling innovation adopters in their transition towards innovation generators.

This research has several limitations, which should be mentioned. The first lies in the difficulty – as mentioned by (Suárez, 2014) – of all empirical research investigating innovation persistence to establish with certainty the time necessary to convert an investment made in order to develop technological and innovation capabilities into the generation of an innovation. This situation is even more complex in the case whereby – as in this study – innovation is differentiated according to its degree of novelty. A second limitation lies in the data employed for this research. We relied on the Colombian innovation survey, carried out every two years. However, relying on this data allowed us to place it in the context of a developing country with a relatively stable economic context. Consequently, our results are shielded from sudden economic changes. We are thus able to extend the findings of Suárez (2014) which is so far the only study of innovation persistence in the context of a developing country.

Our results have some implications for future research. Most importantly, we show that a differentiation in terms of degree of novelty when investigating innovation persistence matters. Future research should therefore continue in this sense and differentiate between degrees of novelty. This differentiation with respect to the degree of novelty allows us to observe varying innovation behaviours and evaluate the innovation persistence of firms in different stages of their technological development. However, we are not able to take into account when a firm adopts an innovation new to the firm in period 1, and then one that is new to the market in period 2. This evolution in terms of technological capabilities which represents a different kind of persistence provides interesting possibilities for future research. Additionally, we were not able to identify differential drivers for each type of innovation persistence. This is surprising in light of theoretical discussions which argue that each kind of innovation relies on different kinds of capabilities and pursues different strategic goals (Amara *et al.*, 2008). Future research could try to identify a wider array of potential drives in order to determine whether or not these differ in terms of influencing the different kinds of innovation persistence. Our research does not take into consideration process innovations as a potential complementary type of technological innovation (Mantovani, 2006). It may very well be that a firm adopts a product innovation in period 1, and in the subsequent period, adjusts its processes to the new product instead of adopting yet another product. These interactions and complementarities between product and process innovations should play a role in future research as well. Our panel data are relatively limited in terms of the time it spans. Our results need to be interpreted in light of this limitation, especially when trying to evaluate what role time spans play for the different type of innovation persistence. Future research should attempt to include a much broader time span and evaluate the importance and length of time for innovation persistence.

Notes

1. In 2008, the threshold was at COP$130.5 million.
2. This robustness checks can be provided upon request.
3. The central structure of an organization constitutes the mission and objectives, the structure of authority, the technology structure and marketing strategies (Hannan and Freeman, 1984).

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