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Maximiliano Machado

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Maximiliano Machado*

Resumen

En este documento se investiga acerca de la persistencia en resultados innovadores para firmas uruguayas en el periodo 2004 – 2015. Empleando datos de panel de la Encuesta de Actividades de Innovación, se estima el grado de persistencia en productos y procesos indagando sobre efectos heterogéneos por tamaño y sector. Las estimaciones se hacen siguiendo la metodología de Wooldridge (2005) para controlar por heterogeneidad individual de las firmas. La evidencia obtenida muestra que los resultados innovadores no son persistentes, encontrando efectos nulos y negativos de innovaciones pasadas sobre futuras, indicando que la probabilidad de innovar en t no se ve afectada o se reduce para firmas que innovaron en t-1. Este resultado es contrario a lo habitual en la literatura especializada y, para profundizar su análisis se estudia el efecto de un segundo rezago en t-2. Los resultados indican que innovar en t-2 incrementa la probabilidad de innovar en t. Esto sugiere que las firmas uruguayas tienen un comportamiento innovador intermitente que puede redundar en una trayectoria de innovación errática. Estos resultados se distancian de la evidencia empírica usual para países desarrollados, aunque se alinean con algunos resultados para países de la región y con el caso de Portugal. Los altos costos de mantener una conducta innovativa constante y el escaso relacionamiento con el medio aparecen como algunas de las causantes de esta ausencia de persistencia innovadora.

Palabras clave: Innovación; Persistencia; Datos de Panel; Uruguay.

Código JEL: O31; O32; L25; C01.

(*) IECON, Universidad de la República, Uruguay, correo electrónico: mmachado@iecon.ccee.edu.uy

Abstract

This research addresses the persistence in innovation results for Uruguayan firms in the period 2004 – 2015. Using panel data from the Survey of Innovation Activities, persistence in products and process innovations is estimated, investigating also heterogeneous effects in size and sectors. The estimations were defined according to the methodology proposed by Wooldridge (2005) to control for firms' individual heterogeneity. The findings indicate that innovation results are not persistent in Uruguayan firms, showing null and negative effects of previous innovation on future innovation, indicating that the probability of innovating in t is non-affected or reduced for firms that innovated in t-1. Delving into these results, which is not usual in the literature in the field, the effects of the t-2 lag are estimated. Results indicate that innovating in t-2 increases the likelihood of persistence in innovation in t. This fact suggests that the Uruguayan firms innovate intermittently, contrary to what the literature states, arguably following an uneven innovation trajectory. Such results distance from empirical evidence for developed countries; although, they are in line with results for countries in the region and the case of Portugal. The effects may be related to the high costs of innovating continuously and the scarce relation with the environment, factors in which Uruguayan firms are lagging in relation to firms in developed countries.

Keywords: Innovation; Persistence; Panel Data; Uruguay.

JEL Classification: O31; O32; L25; C01

1 Introduction

Since the seminal works by Schumpeter (1934, 1942), the role of technological change on social welfare and economics has gained growing attention (Cohen, 2010). Following Schumpeter (1934), several authors highlighted innovation as a determinant of economic development (Aghion & Howitt, 1990; Aghion et al., 1997; Peters, 2009). On the other hand, it can also be seen as a determinant of a firm's performance, so that differences in a firm's achievement could be explained by heterogeneities in its innovative behavior (Tavassoli & Karlsson, 2015). Moreover, innovation studies have achieved a significant place in the academy, rising as its own field within economic science (Fagerberg & Verspagen, 2009).

Much of the effort has been focused on investigating the determinants of innovative behavior to understand what drives firms to innovate and how large such effects are. This topic has gained attention within the studies of industrial organization and management, particularly since innovation research began to be more appreciated (Shapiro, 2011). Along this line, it has been relevant to consider how much of the present innovation activity depends on previous innovation activity. Thus, much of the literature has advocated investigating how persistent innovation is and what causes it.

In this sense, innovation persistence implies the fact that firms obtain innovative results in a given moment of time and continue obtaining such results in subsequent periods. These types of practices generate a feedback mechanism, accumulating capital and knowledge and potentially creating a lock-in-effect, placing firms in advantageous positions for continuing with the process and obtaining future innovations (Juliao-Rossi et al., 2019; Suárez, 2014). Therefore, persistence can be framed in the theory of endogenous growth, such that sustainable growth emerges as a function of the abilities of firms to accumulate economic knowledge (Tavassoli & Karlssson, 2015). Regarding the analysis of this phenomenon, economic science may have contributed through empirical analysis by exploiting the rise and availability of surveys' microdata and patent registration data in recent years.

Concerning the measuring of persistence, two methods can be listed (Peters, 2009). On one hand, the measure of gross persistence, i.e. the influence of previous activity on the present, not considering other factors that can also affect current activity. Thus, persistence can be generated by the fact that firms have some characteristics that make them intrinsically prone to innovate. If such characteristics persist over time, they can induce a persistent innovative behavior. What is more, if such factors are unobservable – e.g. managerial decisions (Nelson, 1991) – and are correlated over time, not controlling for them in the estimations would imply that much of the estimated persistence levels actually correspond to these idiosyncratic elements. This type of persistence is usually called spurious persistence (Altuzarra, 2017; Peters, 2009; Raymond et al., 2010).

In contrast, the second method consists of identifying and measuring the genuine effect of past innovations on present innovation, generated due to a state dependence (Heckman, 1981). This means that the performance of innovative activity at a given moment of time would affect the probability of incurring such activities in the future, taking into consideration other variables that can also affect this probability. This expresses a level of real or net persistence, where the only observed effect is generated by previous innovation (Raymond et al., 2010). A causal relationship is then observed, which can also be seen as a path dependence.

The main challenge turns out to be the correct identification of real persistence, which is hampered by the existence of the mentioned idiosyncratic elements, confounding the effect of previous activities. At the moment, it leads to problems with elaborating public policies, making the identification of genuine persistence a tough task. Therefore, exploring if innovation is a persistent activity represents, in addition to a goal in terms of public policy, a methodological challenge. Understanding the elements behind the persistence phenomenon, the firms participating, and what type of persistence is observed – real or spurious – contribute to understanding the functioning of the industry and the potential results that could be obtained through policies to stimulate innovation and R&D (Le Bas & Scellato, 2014).

If innovation is persistent, policies designed to affect present innovation will also affect innovation in following periods (Tavassoli & Karlsson, 2015). An appropriate direction for these policies would contribute to improve the efficiency of expenditures, so that some firms do not need continuous financial aid, but only an impulse at one moment of time so that such behavior will persist by itself for subsequent periods. On the other hand, the identification of spurious persistence correlated to some variables would also be valuable, as policy makers could manage resources to stimulate such variables and thus improve innovative activities in the future.

Beyond the effort to measure persistence, the empirical evidence is still scarce (Peters, 2009), and the conclusions do not seem to be clear. Some authors consider that the evidence does not demonstrate in a consistent way the existence of persistence in innovation, and neither does it allow researchers to identify variables that affect it, discriminating effects in a proper way (Altuzarra, 2017; Juliao-Rossi et al. 2019; Mañez et al. 2015). Additionally, non-conclusive evidence has spurred the discussion that persistence depends on how it is measured (Duguet & Monjon, 2004; Juliao-Rossi et al., 2019; Le Bas & Scellato, 2014).

Identifying the existence of persistence and characterizing persistent firms is a key element of public policy formulation to improve firms' innovation and, indirectly, economic growth and development. Henceforth, this work represents significant progress on the mission of detecting persistent innovation in Uruguay, and it also contributes towards the academic evidence for the region, which is extremely limited in comparison to developed countries. Consequently, this work aims to answer the following question:

1. *Is innovation a persistent activity for Uruguayan firms in the period 2004–2015? Is evidence of persistence robust when different measures of innovation are used?*

As idiosyncratic elements may operate provoking divergent results, this research inquires on dissimilar effects for different type of firms and types of innovation (product and process). Henceforth, this document attempts to answer the questions below:

2. *Do different types of innovation present different degrees of persistence? Are these types complementary?*

3. *Are there differences in the degree of persistence according to firms' size and sectors?*

The objective is to investigate if innovation in a given moment of time has effects on the innovative firm's probability of innovation in the near future, for both manufacturing and service firms. This is done by working with the Uruguayan Innovation Survey (UIS) (*Encuesta de Actividades de Innovacion* in Spanish), allowing for a panel treatment. To estimate real persistence and address the problem of the initial condition, a methodology developed by Wooldridge (2005) and improved by Rabe-Hesketh and Skrondal (2013) is employed. In contrast, for the case of spurious – or gross – persistence, transition probability matrices are estimated to examine the probability of moving from one state (innovative or not innovative) to another (innovative or not innovative).

The results indicate that innovation has not been a persistent activity for Uruguayan firms during the analyzed period. When controlling the individual heterogeneity, the effect of previous innovation turns out to be negative in most of the regressions. However, this negative effect is not observed in large firms. Such an effect indicates that innovating in *t* reduces the likelihood of pursuing an innovative path in *t+1*. Even though this is a negative effect, some cases of complementarity are found in processes, as innovating in products in *t* increases the probability of innovating in processes in *t+1*. To dig deeper on these findings, a *t-2* lag is included, finding positive effects. This, together with the negative or null effects of persistence in *t-1*, show that Uruguayan firms' innovative behavior is intermittent, not innovating in a continuous way as the literature expects. To the best knowledge of the author, there is no strong evidence of cases where previous innovations affect present innovations negatively apart from Costa et al. (2018).

The results obtained are disruptive, contradicting most of the empirical literature. This innovative path can be explained through the high costs of innovating and maintaining it over a given time span. Once a firm innovates, its purpose for the next years may be to extract as much profits as possible from the innovation or reduce the costs of its production. The latter can explain the complementary effects. Firms in developing countries may not have the support and resources that European firms have, which may explain the differences in persistence with the literature revised for developed countries. On the other hand, the effects are consistent with the scarce empirical literature for the region.

After this Introduction, the document is structured as follows. In section 2 the Theoretical Framework is presented, exposing the definitions used and the potential theoretical explanations behind innovative activity and innovation persistence, and the empirical background. Section 3 describes the data employed, the variables used, and the econometric methodology. Section 4 includes the results of spurious persistence through transition probability matrices. Section 5 covers the real persistence estimations. The work closes with the conclusions in section 6.

2. Theoretical Framework

2.1 Innovation: types and definitions

Innovation can be considered the result of the firms' capabilities to create knowledge and the skills to apply such knowledge to new products, processes, or organizational designs (Fagerberg et al., 2005; Tavassoli & Karlsson, 2015). This way, while innovating firms are immersed in a continuous-learning process, they emerge with novel ideas that result from the recombination of previous ideas (Tavassoli & Karlsson, 2015). Heterogeneity among firms leads them to employ different strategies, that will lead to different structures and capacities, within which R&D capacities can be highlighted (Nelson, 1991), therefore generating heterogeneous innovation results.

The mere production of a set of products through defined processes is not enough for ensuring permanence of firms in the market in the long run. For permanence to occur, it is necessary for a firm to incur some type of innovation (Nelson, 1991). Therefore, innovation can be viewed as a necessary condition for a firm's survival in the long run.

To distinguish clearly the diverse innovative results that firms can obtain, innovation surveys usually inquire about four types of results: in process, in products, in marketing, and organizational. In this study, only the first two types are considered. Process innovation refer to the introduction of a novel or improved product, while product innovation implies the use of a new or substantially improved method of production (OCDE, 2005). These results are the product of accumulated knowledge patterns and firms' learning dynamics (Colombelli & Von Tinzelmann, 2011).

As the academic literature posits different motives and levels for persistence, according to the type of innovation considered, it is necessary to discriminate between such types. According to Tavassoli and Karlsson (2015), the purpose behind process innovation is usually to achieve a reduction in the average production cost, e.g. by introducing new machinery or elaboration processes. This can lead to different persistence levels according to the type of innovation considered, though levels for different types can be correlated. In some sectors, firms may not invest in R&D to develop new processes, but they opt to directly incorporate capital to improve processes. Following this, a high degree of innovation processes can be expected – and thus, in persistence – just for the industries that develop their own capital for production processes.

The potential persistence effect may vary according to the degree of novelty of the innovation. Products that result in novelty only at the firm level are not comparable to innovations for the international market, as the first are the result of imitation or adaptation processes from other markets, whereas the second ones are a firm's own creations (Damanpour et al., 2009). Henceforth, discriminating between product and process innovations, as well as the market-scope of such innovations are both key elements for a proper interpretation of results.

2.2 Innovation persistence: external factors

Schumpeter (1934, 1942) can be considered the first to treat persistence, analyzing the link between market concentration and innovation. According to the author (Mark I), innovation is the outcome of entrepreneurs' activities, altering the circular trend of the economy, and pursuing profits. On the other hand, R&D activities are incorporated into productive routines, making innovation activities persistent over time (Mark II). According to this, firms will have incentives to undertake innovative activities in each period, aiming to achieve continuous monopoly power and profits.

Bartoloni (2012) states that the generation process of R&D is constantly influenced by market power and technology opportunities. The relation between past and future innovation is a crucial point in economies where the generation of new technologies does not emerge automatically. According to Ahuja et al. (2008), although the literature has made a huge effort to find a link between innovation and market structure, the current evidence is not conclusive. Even though it could be due to methodological problems, non-random samples, or inadequate controls, most of the obstacle lie in a lack of conceptual clarity.

In this sense, achieving monopoly power in its relevant market or part of it is one of the greatest incentives that innovative firms pursue. Monopolies allow to earning rents that may finance future innovation activities, which, in turn, contribute to maintain the monopoly power. This explanation of innovative persistence is known as the success-breeds-success approach (Duget & Monjon, 2004; Mansfield, 1968). Hence, firms obtaining successful innovations in a given moment of time could use the obtained profits to back future innovation activity (Flaig & Stadler, 1994). While there is empirical evidence that supports that firms with persistent innovation activities obtain profits over the average (Cefis, 2003; Cefis & Ciccarelli, 2005), a causal relation cannot be confirmed.

Another key element regarding the environment is the macroeconomic scenario in which firms are located. Suárez (2014) establishes the importance of the macroeconomic context in the persistence of innovation results for Argentinian firms. According to her, persistence is affected by macroeconomic stability, being stronger in more stable contexts. On the other hand, Triguero and Córcoles (2013) (based on Dosi, 1997) state the importance of market conditions, technological opportunities, and appropriability as external factors affecting firms' innovation. The authors employ a group of controls for the dynamics in the markets and region, the evolution of competitors' prices, and the number of patents awarded in each sector to control for external factors.

Beyond market dynamics and structures, the environment in which a firm is embedded plays a crucial role in determining its innovative behavior. Factors of knowledge externalities or relations with other firms or institutions may shape the way in which firms operate and thus, affect their innovative behavior. In particular, external sources of information and knowledge, e.g. searching knowledge, collaborative R&D, networking, (Antonelli et al., 2015), are necessary for the creation of a sort of knowledge reservoir, which is continuously renewed by acquiring, assimilating, and exploiting external knowledge (Adams, 2006; Antonelli et al., 2015; Johansson & Lööf, 2008).

The proposed theoretical foundations state that market power, stability, and relations with other agents affect innovation behavior, making it imperative to consider such elements when analyzing innovation persistence. As far as this is concerned, most of the empirical literature seems to fail in this aspect existing only a few studies that consider competitiveness (Le Bas & Poussing, 2014; Mañez et al., 2015) or macroeconomic stability (Suárez, 2014) when examining persistence.

While this work does not intend to identify a causal relationship between external elements and innovation persistence, it contributes to the literature in the field by taking into consideration the role of such factors on innovation persistence. For this purpose, it incorporates a measure of market concentration of the different sectors in the Uruguayan industry, as well as the cooperation agreements and sectorial GDP growth in order to capture for external factors shaping innovative behavior.

2.3 Innovation persistence: internal factors

Apart from external factors, the literature provides two main approaches related to internal characteristics of a firm as explanations of persistence (Le Bas & Scellato, 2014). The first one refers to knowledge accumulation, a driver of dynamic economies of scale, which allows firms to incorporate new ideas that improve products and processes (Duguet & Monjon, 2002; Georski et al. 1997). It is related to the phenomenon of learning-by-doing (Amara et al., 2008; Arrow, 1971; Jain, 2013) and learning-to-learn (Stiglitz, 1987), making the present knowledge accumulation not only increase the probabilities of using such knowledge in future periods, but also making such usage more efficient (Georski et al., 1997; Juliao-Rossi et al., 2019). Therefore, when innovating, firms are involved in a continuous learning process that allows the generation of new ideas contributing to future innovative activities (Le Bas & Scellato, 2014; Weitzman, 1996). Consequently, firms that generated a stock of knowledge and ideas in the past will be able to recombine them to engender new knowledge (Weitzman, 1998).

Secondly, the sunk costs approach is used to explain persistence (Sutton, 1991), usually related to costs associated with R&D activities (Le Bas & Scellato, 2014). These activities require an initial unrecoverable investment that endures in time so that it can be used in subsequent periods (Le Bas & Scellato, 2014; Sutton, 1991). These activities require a burden of valuable resources – e.g. R&D laboratories or qualified workforce – and the elaboration of routines that, once undertaken, the opportunity cost for stopping them can be extremely high due to increasing returns (Antonelli et al., 2012).

Following Le Bas and Scellato (2014), sunk costs represent incentives to employ new R&D activities, though they also embody motives for not stopping such activities, as the entrepreneur will attempt to extract the greatest possible profits. The opportunity cost of not innovating is high, due to the great disbursement of previous periods (Tavassoli & Karlsson, 2015). These costs then represent both barriers to entry and exit to innovation activities.

Both approaches can act simultaneously with each other and with external factors. The R&D investment that breeds incentives to innovate because of the sunk costs may create enough profits to invest in such activities in future periods, appearing then a success-breeds-success persistence. On the other hand, both sunk costs and economic success can set the proper conditions for knowledge accumulation.

Even though this study does not aim to identify the determinants of innovation persistence, understanding its potential causes contributes to the construction of ideas about which firms are expected to be persistent. Moreover, when estimating persistence, it becomes necessary to take into consideration those factors proposed by the theoretical approaches for a correct identification of real persistence. Previous economic results, R&D expenditures, and knowledge accumulation affect innovative behavior and thus must be included in any estimation for a proper identification of persistence. This identification is the main challenge when addressing persistence, as omitting potential causes of innovation conduct will lead to inconsistent persistence estimations. It is necessary to mention that the discussion about the determinants of persistence is not of interest in this case and, what is more, is not well addressed in the literature.

2.4 Empirical background

There are two widely employed strategies to study persistence. The first, which is employed in this case, is based on innovation surveys following the Oslo Manual (OECD, 2005), measuring innovation through the introduction of new products or processes. The second is based on patent records counting (Cefis, 1999, 2003; Cefis & Orsenigo, 2001; Geroski et al., 1997; Malerba et al., 1997). Both methodologies present limitations, although surveys provide more precise and consistent information about innovation activities (Raymond et al., 2010). It is also recognized that empirical analysis based on patent registration tends to observe lower persistence levels than analysis using survey data, especially for products and processes innovation (Le Bas & Scellato, 2014).

Raymond et al. (2010) base their study on the Dutch Community Innovation Surveys (CIS), working with an unbalanced panel of four waves. To identify real persistence, the authors employ a methodology developed by Wooldridge (2005) for controlling the overestimation effect and introducing initial conditions. The latter fact is crucial, as it is remarkable that persistence can only be identified if initial conditions related to firms' individual effects are correctly handled. The authors find that the effect of previous innovation on current performance is positive and significant in each of the models estimated, as well as other factors like firms' size, technology used, and previous R&D, among others. Hence, their results confirm the existence of persistence in innovation activities.

Peters (2009) analyzes innovative behavior of German firms between 1994 and 2002, measuring innovation as the realization of R&D (innovative effort) and innovation obtained (innovative results). The results suggest real persistence, being the probability of innovating in *t* 36 and 13 percentage points (pp) higher for firms that innovated in *t-1* compared to those that did not, for manufacturing and services, respectively. This article turns out to be one of the few that discriminates results between sectors, representing then a key antecedent for this study. Though the results seem to be encouraging, it is worth to mention that the author employs annual data, which can contribute to the high persistence level found. It contrasts with most of the reviewed literature where the data is usually biennial or triennial.

In a similar way, Tavassoli & Karlsson (2015) find evidence of innovation persistence in Swedish firms, using biennial data from CIS-type surveys. The authors document that obtaining innovation results in the previous period increases the probability of innovating in the present in 15 and 12 pp for product and process innovations, respectively. Such a result implies the existence of real persistence. In regard to spurious persistence, the authors find that the effects are of 55 and 31 pp for products and processes, respectively. As expected, the degree of spurious persistence is higher.

Making use of the Survey on Entrepreneurial Strategies (ESEE, by its acronym in Spanish), Triguero and Córcoles (2013) discover complementary effects of persistence between results and effort. According to the authors, the realization of R&D activities during the previous year increases the probability of incurring such activities in the present in 50 pp, while it increases the probability of achieving innovation results in 26 pp. Moreover, persistence in results is observed, so that obtaining results in *t-1* increases the probability of re-obtaining these results in *t* in 36 pp. In the same way as Peters (2009) described, these results are based on annual data, which can contribute to the high levels observed.

In the Italian industry, Antonelli et al. (2012) find complementarity in product and process innovations, using a three-wave balanced panel. The results show that probability of innovating in process increases significantly for firms that accomplished innovations in the past. The explanation lies in that, once a firm achieves product innovation, the future objective is to identify new processes to improve the productive efficiency. Otherwise, the authors observe spurious persistence for different types of innovation, finding the greater marginal effects for R&D activities and product innovation.

Haned et al. (2014) study the link between persistence and organizational innovation, finding a positive and significant relation for French firms. This effect is valid for several measures of innovation, being greater for complex innovations. In this line, Manez et al. (2015) find, for Spanish firms, that the factors influencing persistent R&D realization in small and medium business are different from those of large firms. However, the authors consider only innovative effort, representing a key difference with the articles mentioned above. For French firms, Duguet and Monjon (2002) find that the persistence determinants depend on firms' sizes.

The articles cited correspond to studies from advanced economies called 'Innovation Leaders' (Costa et al., 2018), embodied in relatively similar economic contexts. To break this chain, Suárez (2014) investigates innovation persistence in the Argentinean manufacturing industry between 1998 and 2006. A novel aspect of this study is the differentiation between periods of different economic contexts, which, according to the author, can affect innovation activities through variations in exchange rates. The main result indicates that innovation is not a persistent activity, which can be explained mainly by unstable economic contexts affecting innovative paths through firms' exogenous characteristics.

Costa et al. (2018) do not find evidence of persistence for Portuguese firms. What is more, the authors find a negative effect of previous innovation for both sporadic and continuous innovative firms. Such results strongly differ from those found in other European countries, which may be explained by the fact that Portugal is a 'Moderate Innovator' country, opposed to 'Leading Innovators' (Finland, Sweden, UK, Germany or Netherland). The authors conclude that their results are in line with those of Suárez (2014), considering Argentina as a similar case to Portugal.

Juliao-Rossi and Schmutzler (2016) and Juliao-Rossi et al. (2019) examine persistence and its drivers for Colombian firms. The first one studies persistence in the generation and adoption of innovation results, employing data from CIS-type surveys. These authors find that there exists persistence in the new products adoption, where firms imitate external innovative products, adapting such innovations to the firms' own markets. However, there is no evidence of persistence in the generation of new products. For this case, the authors work with three periods between 2003 and 2008, choosing such periods mainly because of the economic stability observed in Colombia in these years. Contrasting with the previous article, Juliao-Rossi et al. (2019) look for the verification of theoretical drivers of persistence in Colombian firms. They find evidence that the three theoretical explanations (success-breeds-success, sunk costs, and knowledge accumulation) affect the persistence level, varying according to the definition considered. The authors recognize that measurement of persistence in the context of developing countries – where not many firms obtain innovation – is not straightforward.

Those articles for the Colombian case are some of the few that discriminate among the novelty degree of innovations. This strategy allows a more precise identification of the degree of persistence, being a key element in the policy design. Along this line, the studies of Clausen and Pohjola (2013) for Norway and Ganter and Hecker (2013) for Germany can also be quoted.

A direct precedent for persistence in Uruguay can be found in Muinelo and Suanes (2018), which offers relevant findings on the topic but some differences regarding the present research. Firstly, they employ a balanced panel with only 400 manufacturing firms from 2001 to 2009, whereas here the estimations are done with both an unbalanced and a balanced panel from 2004 to 2015. On the other hand, they handle a different set of control variables to those used here, not controlling for most of the theoretical explanations. Their findings indicate that innovation results are persistent in time, so that the probability of innovating in *t* is 58.2 pp higher for firms that innovated in *t-1* compared to those that did not. Such a high persistence level can be explained by the fact that the authors employed a selected balanced panel, where firms should be more prone to innovate than the whole set of firms in the industry.

In light of this direct background and the others listed in this section, the following hypothesis is proposed to answer the main research question about the existence of innovation persistence:

Hypothesis 1: *Innovation is a persistent activity, in both types spurious and real, for Uruguayan firms in the period 2004–2015. This is valid for product and process innovations.*

2.5 Innovation in the Uruguayan economy: Stylized Facts

Along with the literature mentioned above, other results that illustrate the state of innovation in Uruguay can be emphasized. It has been found that a positive relation between innovation and productivity exists (Muinelo & Suanes, 2018) and between innovation and the creation of qualified employment (Aboal et al., 2011). In addition, a recent study by Laguna and Bianchi (2020) confirmed that innovation generates an increase in demand for the workforce. On the other hand, innovation activities based on incorporated knowledge (capital goods acquisition) are more common than disincorporated (R&D) (Berrutti & Bianchi, 2020), while products and processes are the most frequent innovative results.

As opposed to developed countries, Uruguay lacks a critical mass of innovative firms. In the manufacturing sector, barely 26% of firms incur some innovative activity, which is a low proportion when compared to other countries in the region, such as Brazil (36%), Ecuador (59%), and Costa Rica (81%) or most Asian and European countries (ANII, 2015). It is also observed that the number of innovative projects and national effort destined to innovation are below the regional average (Aboal et al., 2014). In addition to the struggles to innovate, the scope of Uruguayan innovations is mainly the national market, with only 7% of it reaching the international market (Cassoni & Ramada-Sarasola, 2015). Concerning innovative activities, the most frequent is capital goods acquisition (Berrutti & Bianchi, 2020), with external R&D being less frequent (ANII, 2015). This latter fact can be explained by the low demand of knowledge from Uruguayan firms, where R&D is not usual (Arocena & Sutz, 2011).

Regarding the external factors affecting innovative activities, Ponce and Roldan (2015) find positive effects of competition intensity on the probability of achieving innovative results. However, for those firms incurring innovative activities, the effort dedicated to such activities is greater in more concentrated sectoral markets. Both conclusions exhibit the need to control for market concentration when estimating innovation persistence. On the other hand, connection with the National System of Innovation (NSI) is low, as only about 20% of innovative firms reported some linkage for R&D purposes (Arocena & Sutz, 2011). Additionally, the most required agents in these linkages were suppliers and clients, whereas knowledge providers – i.e. universities, laboratories, or R&D agencies – were the least required.

Berrutti and Bianchi (2020) shed light on the link between innovation activity and public financial support. Moreover, in line with other research in the region (Pereira & Suárez, 2018), these authors find that previous innovation experience is a key determinant of access to public support. Moreover, if such support is granted with the purpose of boosting innovation activity, it can be related to the idea of success-breeds-success, so that innovating today eases access to funding for future innovation.

Process innovations, even being historically more frequent than product innovations, have increased since the economic crisis of 2002 (Cassoni & Ramada-Sarasola, 2015). This fact, along with the idea that the acquisition of capital goods is done to reduce production costs (Tavassoli & Karlsson, 2015), allows the following hypothesis to be stated:

Hypothesis 2: *Persistence is stronger for process than for product innovation.*

The service industry, despite representing – for most of the Latin American countries – the largest proportion of the GDP, does not receive as much support as the manufacturing industry (Aboal et al., 2014), which may generate heterogeneity in the realization of innovative activities among sectors. Given that innovative results strongly depend on R&D, the fact that services receive less support to perform this type of activity can lead to scarcer results compared to manufacturing (Peters, 2009). Otherwise, within sectors, firms labeled as high technology tend to expend more on innovative activities than low-tech firms do. As this type of public support is weak in Uruguay (Aboal et al., 2014; Aboal & Garda, 2015), it can broaden differences in the propensity to innovate between manufacturing and services. Based on the latter argument, an additional hypothesis about differences in persistence among sectors is presented:

Hypothesis 3.1: *The degree of persistence in products and processes is greater in the manufacturing than in the services sector.*

Idiosyncratic elements can be behind the different levels of persistence observed between firms. To investigate this aspect, it is of interest to look for differences between large and small firms. As proposed by the literature, large firms may have elements – e.g. managerial decisions or greater budget – that make them more persistent in innovation than small and medium firms. Thus, the following hypothesis is proposed:

Hypotheses 3.2: *The degree of persistence in products and processes differs by firms' size.*

According to Cassoni and Ramada-Sarasola (2015), small and local-market-oriented firms follow different innovative behaviors than large firms in terms of innovation. The first group will focus on processes to reduce production costs, whereas the second will boost their innovative products to reach international markets. To inquire on these topics, following Peters (2009), the whole sample is split into subsamples, distinguishing firms according to sector (manufacturing and services) and size (large versus small and medium), to analyze persistence according to these specific firm's features.

3. Methodological Design and Data

3.1 Data

Working with the innovation survey data allows us to obtain information about firms' efforts, results, and obstacles, which cannot be obtained through patent data. Indicators generated from patents capture just a fraction of firms' total innovative activity (Antonelli et al., 2012), not allowing us to discriminate among different types of innovation. The patent registration process is financially expensive and time consuming, which can create incentives to only patent those products with high-expected profits. Otherwise, not every registered patent is carried out with the purpose of protecting innovations (Aboal et al., 2014; Cohen et al. 2000), and in some cases, firms may prefer not to patent their products in order to keep them secretly (Archibugi & Planta, 1996).

The main data source employed in this study is the Uruguayan Innovation Survey (UIS), which follows the guidelines of the Oslo Manual (OECD 2005), having a structure similar to the CIS. This survey has a triennial frequency, starting in 1998–2000 and with the last available wave in 2013–2015. It collects data on manufacturing and service firms' innovative activities for both the reference year and the two previous years. The survey is designed by the National Agency of Research and Innovation (ANII by its acronym in Spanish).

In addition, data from the Annual Survey of Economic Activities (ASEA) is used, which collects data on firms' economic performance. Such data allows us to assess precisely both a firm's performance and the sector characteristics. Both UIS and ASEA use firms of five or more employees as a sample unit and are executed by the National Institute of Statistics (INE by its acronym in Spanish) (for a detailed description of the sampling and the data collected, see Appendix A1). As these surveys are part of the official statistics of compulsory response, their response rate is assured to be high. Finally, data from the Central Bank of Uruguay (BCU) is used to control for macroeconomic sectorial performance.

For this case, the last four waves of the UIS are used, corresponding to years between 2004 and 2015. Even though it is possible to include data from previous years, such editions lack relevant data due to changes in the questions included. Moreover, considering the influence of macroeconomic stability on innovation persistence in Latin American economies (Juliao-Rossi et al., 2019; Suárez, 2014), the selected years represent a period of macroeconomic stability and growth, conversely to the previous years – 1998 to 2003.

Henceforth, we have an unbalanced panel for the period 2004–2015. Table 1 shows comparisons in the number of observations and firms between the unbalanced panel of the global sample, the unbalanced panel with only firms with two or more observations, and the balanced panel. The first sample includes every firm surveyed, while the second includes only the firms included in the estimations. It is useful to compare the structure of firms included in the estimations with the global sample and with firms in the balanced panel. Estimations are done with both the balanced and unbalanced panel. Moreover, for testing Hypothesis 3, the samples are divided according to sectors and size.

Table 1: Number of firms and observations in different samples.

	Manuf.	Services	Total
(a) Global Sample			
Number of obs.	3,600	4,322	7,922
Number of firms	1,618	2,346	3,964
Mean employees	90.8	158.4	127.4
Mean firm age (years)	34.1	23.9	28.5
Mean obs. by firm	2.2	1.8	2.0
Median obs. by firm	2.0	1.0	1.0
(b) Unbalanced panel			
Number of obs.	1,920	1,864	3,784
Number of firms	847	882	1,792
Mean employees	108.2	229.0	159.5
Mean firm age (years)	39.7	29.4	35.4
Mean obs. by firm	2.7	3.1	2.9
Median obs. by firm	3.0	3.0	3.0
(c) Balanced panel			
Number of obs.	1,552	1,180	2,732
Number of firms	388	295	683
Mean employees	152.6	336.3	231.9
Mean firm age (years)	48.1	33.8	41.9
Mean obs. by firm	4.0	4.0	4.0
Median obs. by firm	4.0	4.0	4.0

Source: Author based on UIS data.

As can be seen in Table 1, by using the unbalanced panel, more than 2,000 firms are lost, corresponding to firms that have only one observation during the period. This means a loss of more than the 50% of the firms. In the unbalanced panel, at least half of the firms have three observations. It can also be noted than, when dropping firms with only one observation, the average number of employees and firms' age increases, showing a process of selection. This latter fact is interesting, as in Uruguay the larger and older firms have a higher propensity to innovate than younger firms and SMEs (small and medium enterprises) (Berrutti & Bianchi, 2020).

Table 2 shows, for every wave, the number of firms surveyed for the first time and the number of firms that were already in the previous wave. As expected, 2009 is the year with a larger proportion of new firms due to the modification in the sampling, where more than half of the firms were not observed in 2006. What is more, a larger loss is observed from 2006 to 2009, when 52% of the firms are missing. After 2009, a better stability is observed, as the loss proportion is about 20% for the mentioned year and the subsequent. For all these disappearances, about 80% correspond to small firms, and as the survey is mandatory for the selected enterprises, it is proper to suppose that the ones not responding – after 2009 – ceased activities.

Table 2: New firms included by wave (proportion from the whole year in parentheses)

	2006	**2009**	**2012**	**2015**
Firms from previous wave	-	841	1,493	1,472
	-	(0.43)	(0.84)	(0.65)
New firms	-	1098	313	1,004
	-	(0.57)	(0.16)	(0.35)
Total firms	1,752	1,939	1,806	2,476
	(1.00)	(1.00)	(1.00)	(1.00)
Firms disappearing in the following wave	911	446	334	-
	(0.52)	(0.22)	(0.18)	-
Firms with less than 50 employees disappearing	746	327	280	-
in the following wave	(0.82)*	(0.76)*	(0.84)*	-

Source: Author based on UIS data.

Notes: *Proportion with respect to firms disappearing

These statistics can shed some light on the fact that the firms considered in the estimations are not representative of the entire firms in the industry. Thus, the conclusions derived here should be handled with care, even more so the balanced-panel results. As the results embrace a group of firms, on average, different from the whole, the presented results lack external validity. Thus, an extrapolation to the global Uruguayan economy is not possible. It is worth noting that the extant literature on innovation studies using innovation survey data face these external validity limitations. In this regard, this study is framed in the current debates that focus on the study of microeconomic explanations of innovation behavior rather than on an explanation and statement of general patterns.

Table 3: Average number of firms incurring in effort activities and obtaining innovative results by year (from innovative firms).

	2006	**2009**	**2012**	**2015**
Effort				
Total innovative activities	0.42	0.42	0.36	0.41
R&D (internal and/or external)	0.15	0.14	0.13	0.16
Capital goods acquisition	0.21	0.25	0.21	0.21
Innovation results				
Products	0.21	0.2	0.17	0.23
Processes	0.26	0.3	0.22	0.27
Total number of innovative firms	1,752	1,939	1,806	2,476

Source: Author based on UIS data.

When looking at firms that incur innovative activities and those that obtain innovative results (Table 3), we can appreciate that these proportions remain relatively stable during the period. Similarly, firms obtaining results in products are about half of the firms that incur results in innovative activities during the years considered. For innovation in processes, the proportion is even greater. Additionally, R&D activities are less frequent than capital goods acquisition, exposing the higher occurrence rate of the latter as mentioned in the previous section. Besides the research limitations imposed by the available data, it is worth recognizing that it allows the investigation of a group of heterogeneous firms operating in different sectors, where the results are internally valid. Furthermore, estimations for the balanced panel shed light on the behavior of a group of mainly large and well-profited firms. Thus, this research represents a remarkable starting point for analyzing innovation persistence in a developing country like Uruguay.

3.2 Variables

This study aims to investigate the persistence of both innovations in products and processes. The dependent variables, $prod_{i,t}$ and $proc_{i,t}$ indicate if the firm obtained innovation results, taking the value of 1 if the firm i innovates in products or process in time t respectively, and 0 otherwise. The variables of interest, which indicate the persistence effect, are the lagged dependent variables $prod_{i,t-k}$ and $proc_{i,t-k}$ with $k \in [1,2,3]$.

The control variables set is formed, firstly, by the following: number of employees, presence of foreign capital, exporting firm, belonging to networks, and belonging to groups (for a specific description of the variables, see Appendix A2). To control for the theoretical hypotheses of persistence, the following variables are included: turnover results in the previous period (success-breeds-success), investment in R&D in the previous period (sunk costs), and the expenditures in machinery and physical capital in the previous period (knowledge accumulation). The sectorial GDP growth rate and a competitiveness index (Lerner Index) are used to control for factors external to the firms (see Appendix A2 for a description of this index). Descriptive statistics are described in Appendix A4 for the different sample structures.

3.3 Methodology

3.3.1 Gross Persistence

Gross persistence is estimated through Transitions Probability Matrices (TPM). This method estimates the probability of moving from a state i_0 to other state i_1 not considering the different covariables that can affect the passage. In this case, the two states are innovator (IN) and not innovator (NIN). Following Cefis (2003) and assuming a set of random variables $\{Y_1, Y_2, \dots, Y_n\}$ that follow a Markov process, we have:

$$p_{ij} = P(Y_t = j \mid Y_{t-1} = i) = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{1}$$

where p_{ij} is the probability of moving from state i to state j in one period. The Y variables are two innovation indicators: Y_1 for product and Y_2 for processes innovations. This methodology assumes that, for every firm, the innovation indicators are independent in each period (Cefis, 2003), which can be considered a strong postulation.

The unknown parameters p_{ij} can be estimated by Maximum Likelihood, and it is possible to show that $p_{ij} = n_{ij}/n_i$ where n_{ij} is the number of observed transitions from states i to j and n_i is the total number of transitions from state i (Tavassoli and Karlsson, 2015). The literature establishes that, through the results obtained with this methodology, persistence can be feasibly classified as weak or strong (Cefis & Orsenigo, 2001; Tavassoli & Karlsson, 2015). Persistence is considered to be weak if the sum of the elements on the main diagonal (p_{11} and p_{22}) is equal to or greater than 1, but one of the elements is less than 0.5. On the other hand, there is strong persistence if the number of elements on the main diagonal is equal to or greater than 1 and both elements are greater than 0.5. Otherwise, there is no persistence.

Additionally, the methodology permits the calculation of the unconditional state dependence (USD) as:

$$USD = p_{IN,IN} - p_{IN,NIN} = P(Y_t = IN \mid Y_{t-1} = IN) - P(Y_t = IN \mid Y_{t-1} = NIN) \tag{2}$$

This would indicate that part of the probability of being an innovator in any period t is explained by the fact of being an innovator in a previous period.

3.3.2 Real Persistence

To estimate real persistence, a parametric approach similar to Peters (2009), Raymond et al. (2010), or Tavassoli and Karlsson (2015) among others is employed.

It is assumed that firm i would innovate in period t if the expected value to obtain this innovation, y_{it}^*, is positive (Tavassoli & Karlsson, 2015). Additionally, y_{it}^* is supposed to depend on previous innovation realization $y_{i,t-1}$, a set of observable characteristics of the firm X_{it}, unobservable firms effects that do not vary across the time u_i, unobservable time effects δ_t and other unobservable effects illustrated as an error term ϵ_{it}. This can be modeled as:

$$y_{it}^* = \gamma y_{i,t-1} + \beta X_{it} + u_i + \delta_t + \epsilon_{it} \tag{3}$$

where y_{it}^* is a latent variable that, when observed $y_{it} = 1$, implying that the firm got innovative results in t and $y_{it} = 0$ otherwise.

The main problem with this estimation is that most firms do not start their activities with the first registered observation. This causes the initial condition y_{i0} to be correlated with the vector of unobservable firms' characteristics u_i, thus generating inconsistent estimations. In addition, an incorrect treatment of the initial conditions and the individual effects could lead to overestimation of the lagged variable (Peters, 2009; Raymond et al., 2010; Tavassoli & Karlsson, 2015). As a solution to this issue, Wooldridge (2005) proposes to model the distribution of $\{y_{i0}, y_{i1}, \dots, y_{iT}\}$ conditional on the initial condition y_{i0} assuming the unobservable firms' characteristics can be proxied by a lineal function of observable variables (Suárez, 2014). Rabe-Hesketh and Skrondal (2013) go one step further and improve the specifications of Wooldridge (2005) by also controlling for the initial condition of explanatory variables. Hence, the vector u_i can be modeled as:

$$u_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{X}^*{}_i + \alpha_3 X^*{}_{i0} + c_i \tag{4}$$

with $\bar{X}^*{}_i$ as a vector of explanatory variables for each period, with no time variations – e.g. Tavassoli and Karlsson (2015) suggest using average values of time-invariant variables included in X_{it}, with $t \in \{1, \dots, T\}$-, $X^*{}_{i0}$ as the initial values of the variables included and $c_i \sim N(0, \sigma^2)$ independent of the initial condition y_{i0}, $X^*{}_{i0}$ and $\bar{X}^*{}_i$. Replacing equation (3) in (2):

$$y_{it}^* = \gamma y_{i,t-1} + \beta X_{it} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{X}^*{}_i + \alpha_3 X^*{}_{i0} + c_i + \delta_t + \epsilon_{it} \tag{5}$$

Obtaining then for variable y_{it}:

$$prob(y_{it} = 1 | y_{i,0}, \dots, y_{i,t-1}, X_{it}, X_i, c_i) = \Phi(\gamma y_{i,t-1} + \beta X_{it} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{X}^*{}_i + \delta_t) \tag{6}$$

where Φ refers to a normal cumulative distribution function (cdf). Thus, γ indicates the effect of previous innovation on present innovation.

The estimations are done using only one lag, observing the effect of $y_{i,t-1}$ over y_{it}. This methodology allows the observation of persistence caused by a real state dependence and/or to a type of unobservable heterogeneity attributable to a firm's characteristics (Antonelli et al., 2012). Even though for the balanced panel more lags can be employed, two lags imply a period of 6 years while three lags imply 9 years. As those time spans could be excessive to find causal effects, only one lag is considered.

In this study, two types of innovation are treated in the analysis of each of the innovation results – products or processes –, bring also interesting to include the other type to investigate for complementarity effects.

Tavassoli and Karlsson (2015) highlight the straightforward calculation of marginal effects as one of the main advantages of this methodology. According to the authors, the marginal effect on means (MEM) of $y_{i,t-1}$ can be computed as:

$$\widehat{MEM} = \Phi(\hat{\gamma} + \hat{\beta}X_{it} + \hat{\alpha}_0 + \hat{\alpha}_1\bar{y}_{i0}) - \Phi(\hat{\beta}X_{it} + \hat{\alpha}_0 + \hat{\alpha}_1\bar{y}_{i0}) \quad (7)$$

This is the prevailing approach in the literature based on survey data, having a great advantage in the control of the initial condition through a simple-to-use methodology. However, it is not free of critics. According to Juliao-Rossi et al. (2019) the coefficients generated with this method are the result of changes in the variable of interest between individuals (between effects), but also by variations within the individuals (within effects). It turns out to be impossible to discriminate between both effects. This results in difficulty identifying adequately the origins of persistence. On the other hand, it has been shown to generate biased results for a panel with less than five waves (Akay, 2012; Rabe-Hesketh & Skrondal, 2013). Finally, much of the criticism resides in the methodology's incapacity to take into account the number of zeroes – i.e. no-innovative firms – which increases as more zeroes are detected (Hua & Zang, 2012) as in cases of developing countries, where the number of non-innovators is large.

Despite the mentioned setbacks, and as the purpose of this research is not to identify persistence causes but its existence and degree of persistence, such methodological criticisms do not represent a relevant obstacle here.

4. Results: Spurious Persistence

In this subsection, the estimation of TPMs showing the passage from the different states are exposed. The transitions are calculated for the entire sample and for subsamples of large firms (those with 50 or more employees), SMEs (those with less than 50 employees), manufacturing, and services firms. As the sample suffers from attrition, the transitions are also calculated for the balanced panel. The results are displayed in Tables 4 and 5, along with the USD.

Table 4: Transition probability matrices: product innovations.

		Unbalanced panel			Balanced panel		
		Status in *t*			**Status in *t***		
	Status in *t* – 1	NIN	IN	USD	NIN	IN	USD
Global	NIN	0.86	0.14	32 pp	0.82	0.18	33 pp
	IN	0.54	0.46		0.49	0.51	
Manufacturing	NIN	0.84	0.16	32 pp	0.81	0.19	35 pp
	IN	0.52	0.48		0.46	0.54	
Services	NIN	0.88	0.12	31 pp	0.85	0.15	32 pp
	IN	0.57	0.43		0.53	0.47	
Large	NIN	0.78	0.22	31 pp	0.78	0.22	31 pp
	IN	0.47	0.53		0.47	0.53	
SMEs	NIN	0.89	0.11	29 pp	0.88	0.12	32 pp
	IN	0.60	0.40		0.55	0.45	

Notes: The number of transitions in the unbalanced (U) and balanced panel (B) are: 3,971 (U) and 2,049 (B) in the global sample; 1,985 (U) and 1,161 (B) in the manufacturing sample; 1,975 (U) and 882 (B) in the services sample; 1,242 (U and B) in large firms' sample; and 2,729 (U) and 807 (B) in the SMEs sample.

The main findings from the matrices is that, conditional on innovating in any period, firms are more prone to not innovate in the subsequent period in the unbalanced panel. This can be seen as the fact that $P(IN_t|IN_{t-1}) < P(NIN_t|IN_{t-1})$ in all cases but large firms. Moreover, this difference is extremely large for Services (14 and 24 pp for products and process, respectively) and SMEs (20pp and 26pp for products and process, respectively). This could indicate that innovation is not just not persistent, but also that innovating in a given moment of time reduces the probability of innovating in the future for some firms. In balanced panel, persistence in products changes for manufacturing firms, where the probability of innovating in t is greater than the probability of not innovating for previous innovators. However, these differences are not as large as in the unbalanced panel.

These results do not allow for an accurate conclusion about persistence, as the differences in probabilities are not large enough and change when going from the unbalanced to the balanced panel. When comparing these results to the ones obtained in other previous articles (Peters, 2009; Raymond et al., 2010; Tavassoli & Karlsson, 2015; Triguero & Córcoles, 2013), one can appreciate that the difference $P(IN_t|IN_{t-1}) - P(NIN_t|IN_{t-1})$ found in these studies is always positive and with higher magnitudes than the ones found here. This indicates that Uruguayan firms' innovative behavior is different from that of European firms. Additionally, it is possible to infer that only large firms experience a strong persistence behavior in both cases, whereas in the balanced panel, persistence is strong for manufacturing. This latter result deviates from the revised empirical background.

The USD is similar across the samples employed, being between 29 and 35 pp in products, far away from the 50 pp observed in Tavassoli and Karlsson (2015) or the 70 pp from Peters (2009). Nonetheless, for process, the USD found between 27 and 31 pp, which is similar to the findings in other cases (Antonelli et al., 2012; Tavassoli & Karlsson, 2015).

Table 5: Transition probability matrices: process innovations.

		Unbalanced panel			Balanced panel		
		Status in *t*			**Status in *t***		
	Status in $t-1$	NIN	IN	USD	NIN	IN	USD
Global	NIN	0.80	0.20	27 pp	0.73	0.27	28 pp
	IN	0.52	0.47		0.45	0.55	
Manufacturing	NIN	0.76	0.24	30 pp	0.68	0.32	27 pp
	IN	0.46	0.54		0.41	0.59	
Services	NIN	0.83	0.17	31 pp	0.77	0.23	25 pp
	IN	0.62	0.38		0.52	0.48	
Large	NIN	0.66	0.34	25 pp	0.66	0.34	25 pp
	IN	0.41	0.59		0.41	0.59	
SMEs	NIN	0.84	0.19	28 pp	0.80	0.20	25 pp
	IN	0.63	0.37		0.55	0.45	

Notes: The number of transitions in the unbalanced (U) and balanced panel (B) are: 3,971 (U) and 2,049 (B) in the global sample; 1,985 (U) and 1,161 (B) in the manufacturing sample; 1,975 (U) and 882 (B) in the services sample; 1,242 (U and B) in large firms' sample; and 2,729 (U) and 807 (B) in the SMEs sample.

5. Results: Real Persistence

5.1 One-period persistence

This subsection includes the results from real persistence estimation through the methodology proposed by Wooldridge (2005), aiming to solve the individual heterogeneity drawback. Here persistence is addressed immediately, from *t-1* to *t*, as observed in the literature. The coefficients estimated through a probit model are presented firstly, and then corrected with the proposed methodology. It allows for analyzing the misspecification that arises when the initial condition is not controlled. Different robustness checks are presented showing the same estimation in both panels and different subsamples, with more than one lag of the dependent variable.

The estimations' results for product and process innovation persistence are shown in Table 6, where the results for unbalanced and balanced panels are reported in panel (a) and (b). Columns (1) and (4) show the effects of previous innovation activity in the present, not taking into account the initial condition issue. As can be seen, product innovation is persistent in a way that obtaining an innovative product in *t-1* increases the likelihood of obtaining it again in *t* in 13 and 11 pp for products and process, respectively. However, as stated in the previous sections, this leads to biased estimations due to unobserved heterogeneity. In columns (2), (3), (5) and (6) this heterogeneity is incorporated using the method developed by Wooldridge (2005), with the improvements suggested by Rabe-Hesketh and Skrondal (2013).

In panel (a), contrary to what is observed in column (1), previous innovations in *t-1* reduce the probability of obtaining innovative results in *t*, for both innovation types. Such an effect is maintained when complementary effects are considered, though complementary effects are not significant for products. This disruptive result is contrary to the revised empirical literature. A hypothesis for it can be the high costs faced by firms when conducting innovation activities. As it is costly to invest in fixed capital and R&D, once firms innovate, they may dedicate efforts to exploit and improve these products for a period greater than three years. It is worth mentioning that, although such an effect is not observed in the empirical literature, most of the articles, except for Suárez (2014) and Juliao-Rossi and Schmutzler (2016), correspond to European countries where the entrepreneurial structure is quite different from developing countries. What is more, both of these articles do not find significant persistence as the literature from developed nations. In addition, these results confirm the findings from spurious persistence, where it was seen that once firms innovate, they are more prone to not innovate in the subsequent period. Henceforth, innovation seems to be a non-persistent activity for Uruguayan firms.

Table 6: Real persistence in the whole sample (marginal effects).

	Product Innovation			Process Innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
			(a) Unbalanced Panel			
$prod_{t-1}$	0.1298***	-0.0619***	-0.0656***			0.0406***
	(0.0151)	(0.0161)	(0.0160)			(0.0155)
$proc_{t-1}$			0.0168	0.1136***	-0.0628***	-0.0690***
			(0.0125)	(0.0148)	(0.0179)	(0.0180)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Obs.	3,784	3,784	3,784	3,784	3,784	3,784
#firms	1,729	1,729	1,729	1,729	1,729	1,729
			(b) Balanced Panel			
$prod_{t-1}$	0.1485***	-0.0109	-0.0143			0.0435
	(0.0322)	(0.0278)	(0.0184)			(0.0249)
$proc_{t-1}$			0.0168	0.0914***	-0.0038	-0.0096
			(0.0125)	(0.0315)	(0.0286)	(0.0289)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Obs.	2,049	2,049	2,049	2,049	2,049	2,049
#firms	683	683	683	683	683	683

Notes: The coefficients are obtained through dynamic probit estimations. The set of control variables include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$, $hightech$, inc_1, $expend\_1$, $practices$, $comp$ and $sgdp$. The individual heterogeneity is given by the initial values of the dependent variable along with the inital value and the time-average values of $pers$, $prof$, $R\&D\_1$, inc_1, $expend\_1$. Robust standard errors in parentheses. Marginal effects are shown. ** $p < 0.05$, *** $p < 0.01$.

Table 7: Real persistence for SME and large firms (marginal effects).

	SME				Large			
	Products		Process		Products		Process	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(a) Unbalanced Panel				Balanced Panel			
$prod_{t-1}$	-0.1043***	-0.1111***		-0.0327	0.0183	0.0173		0.0057
	(0.0203)	(0.0204)		(0.0207)	(0.0394)	(0.0394)		(0.0321)
$proc_{t-1}$		0.0315***	-0.1040***	-0.1100***		0.0093	0.0041	-0.0043
		(0.0140)	(0.0171)	(0.0174)		(0.0253)	(0.0338)	(0.0338)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Indiv. heter.	YES	YES	YES	YES	YES	YES	YES	YES
# Obs.	2,542	2,542	1,228	1,228	1,242	1,242	828	828
# firms	1,315	1,315	959	959	414	414	414	414
	(b) Balanced Panel							
$prod_{t-1}$	-0.0339	-0.0461		0.0229				
	(0.0369)	(0.0371)		(0.0413)				
$proc_{t-1}$		0.0543**	-0.0069	-0.0106				
		(0.0251)	(0.0433)	(0.0438)				
Controls	YES	YES	YES	YES				
Year FE	YES	YES	YES	YES				
Indiv. heter.	YES	YES	YES	YES				
#Obs.	807	807	807	807				
#firms	269	269	269	269				

Notes: The coefficients are obtained through dynamic probit estimations. The set of controls include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$,$hightech$, inc_1, $expend\_1$, $practices$, $comp$ and $sgdp$. Individual heterogeneity is given by initial values of the dependent variable along with the initial value and the time-average values of $pers$, $prof$, $R\&D\_1$, inc_1, $expend\_1$. Robust standard errors in parentheses. Marginal effects are shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To test for the robustness of the previous results, the same regressions are carried out for the balanced panel. The results are shown in panel (b) of Table 6. Again, when individual heterogeneity is not considered, significant persistence is observed. However, after controlling for it, significance disappears. Even though the effect is not negative as in the previous case, it is not significant, showing that previous innovation does not affect present innovation. Thus, innovation is proved to not being persistent for both the balanced and the unbalanced panel.

As the sample of firms is heterogeneous, to investigate more about these effects, the sample of firms is divided by size, looking for idiosyncratic differences. Larger firms are expected to behave differently than SMEs, as unobserved elements – e.g. managerial skills or own funding – may be operating to make large firms more innovative. Persistence is then estimated for firms with at least 50 employees (large)[1] and firms with less than 50 employees (SME), with the same methodology as before. The results for products and process are displayed in Table 7. For SMEs, the effect is negative for both types of innovation, whereas for large firms the effects are not significant. The results observed for SMEs are estimated for an unbalanced panel, while the results for large firms imply a balanced one. In panel (b) the persistence for the balanced sample of SMEs is shown. Though the complementary effects of process in products is significant, there is no evidence of real persistence for both types of innovations. Therefore, innovation seems to not be a persistent activity in either large or SME firms.

Now, to continue inquiring about idiosyncratic elements affecting persistence, the sample is divided in manufacturing and services firms (Peters, 2009), and the results are displayed in Table 8. For manufacturing firms, there is no significant effect of previous innovation, either in process or in products, although there is a complementary effect from products to process. However, for service firms, there are negative effects in both types of innovation. These results show heterogeneous effects between sectors, as innovation in one period reduces the likelihood of future

[1] Firms with 50 or more employees are included in every wave of the survey, forming then a balanced panel.

innovations, whereas for manufacturing the effect is null. These results are observed also for the balanced panel as shown in panel (b).[2] However, persistence is not observed in any sector.

The results exposed here show that innovation is not a persistent activity for Uruguayan firms, so that obtaining innovative results reduces or has no effect on the probability of obtaining it again in the next period. The first results are consistent with the findings of Suárez (2014) and Juliao-Rossi and Schmutzler (2016) for countries in the region and Costa et al. (2018) for Portugal, a European but non-leading innovator country. However, the evidence of negative effects is scarcer, being only found in Costa et al. (2018). These outcomes deviate from the theory, representing a disruptive finding when compared to the current empirical literature. However, these results are in line with the existing literature for countries in the region, more similar to Uruguay than the mentioned leading innovators. Robustness checks with the scope of innovations are presented in the Appendix, where persistence is estimated for innovations at the international, national, and firm level. Non-persistence effects remain in all the estimates, supporting the previous findings.

The results presented contradict those found by Muinelo and Suanes (2018). However, the methodology employed here differs from the methodology used by Muinelo and Suanes in several aspects. First, they control individual heterogeneity by including only the initial condition of the dependent variable, not including either the time-invariant term $\bar{X}^*{}_i$ or the initial condition of such variables $X^*{}_{i0}$. Second, they employ three waves of the UIS, whereas here four waves are employed, from a more recent period. Third, they work with a balanced panel of 400 manufacturing firms, not considering the service sector. Fourth, their set of control variables differs substantially with the one employed here. To make a clearer comparison, their estimations are

[2] The persistence for product innovations in significant only at the 10% level

replicated, using a balanced panel of manufacturing firms for the period 2004–2015, controlling for the same variables as they do. The results are presented in the Appendix A.3 and show that neither product nor process innovation is persistent when applying the methodology proposed by Muinelo and Suanes (2018).

Table 8: Real persistence for manufacturing and service firms (marginal effects).

	Manufacturing				Services			
	Products		Process		Products		Process	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				(a) Unbalanced Panel				
$prod_{t-1}$	-0.0196	-0.0231		0.0701***	-0.1139***	-0.1171***		-0.0003
	(0.0284)	(0.0285)		(0.0253)	(0.0214)	(0.0215)		(0.0212)
$proc_{t-1}$		0.0217	-0.0261	-0.0370		0.0225	-0.1254***	-0.1254***
		(0.0188)	(0.0289)	(0.0290)		(0.0158)	(0.0218)	(0.0221)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Indiv. heter.	YES	YES	YES	YES	YES	YES	YES	YES
#Obs.	1,920	1,920	1,920	1,920	1,864	1,864	1,864	1,864
#firms	847	847	847	847	882	882	882	882
				(b) Balanced Panel				
$prod_{t-1}$	0.0807	0.0805		0.0748**	-0.0759**	-0.0806***		0.0169
	(0.0478)	(0.0481)		(0.0350)	(0.0306)	(0.0306)		(0.0335)
$proc_{t-1}$		0.0270	0.0196	0.0103		0.0315	-0.0845**	-0.0818**
		(0.0262)	(0.0434)	(0.0436)		(0.0249)	(0.0332)	(0.0336)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Indiv. heter.	YES	YES	YES	YES	YES	YES	YES	YES
#Obs.	1,164	1,164	1,164	1,164	885	885	885	885
#firms	388	388	388	388	295	295	295	295

Notes: The coefficients are obtained through dynamic probit estimations. The set of controls include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$,$hightech$, inc_1, $expend\_1$, $practices\ comp$ and $sgdp$. Services firms are controlled by $kibs$ whereas manufacturing by $tecn$. Individual heterogeneity is given by initial values of the dependent variable along with the initial value and the time-average values of $pers$, $prof$, $R\&D\_1$, inc_1, $expend\_1$. Robust standard errors in parentheses. Marginal effects are shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Besides the internal cause for non-persistence related to high costs, external factors can also be acting. Firms tend to exploit opportunities in their environments, absorbing information coming from spillovers, cooperating with other agents – i.e. competitors, suppliers, government, etc. – or being part of groups of firms. These activities represent opportunities to access resources that will contribute to boost the development of innovations, access to markets, economies of scale, and risk spreading (Ahuja, 2000; Faria et al., 2010), affecting the degree of innovation persistence (Triguero et al., 2013). However, the degree in which Uruguayan firms interact with the environment is low. The average level of cooperation is 13%, which is more than half lower than leading countries such as Sweden (30%) (Faria et al., 2010) or the Netherlands (34%) (Raymond et al., 2010). The level of belonging to groups is also low (16%) in reference to Germany (36%) (Ganter & Hecker, 2013; Peters, 2009) or Sweden (66%) (Faria et al., 2010).

5.2 Two-periods persistence

To shed more light on the innovative behavior of Uruguayan firms, persistence with regards to a two period lag is calculated. As the innovation process can be long and expensive, firms that obtain innovative results in one period can need more the one period to innovate again. For this, the interest variable is the dependent variable lagged two periods, while all the variables that were lagged one ($R\&D\_1$, inc_1, $expend\_1$) period in the latter regressions are replaced by the two-period lags ($R\&D\_2$, inc_2, $expend\_2$). The equation to be estimated is (8).

$$y_{it}^{*} = \gamma y_{i,t-2} + \beta X_{it} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \bar{X}^{*}{}_{i} + \alpha_3 X^{*}{}_{i0} + c_i + \delta_t + \epsilon_{it} \tag{8}$$

The results for the global sample are reported in Table 9. As can be seen, after controlling for individual heterogeneity, the lagged innovation is still significant and positive, contrary to what was observed for *t-1* in Table 6. Persistence for products is clearer, as the results maintain for both the balanced and the unbalanced panel, and it does not change when complementary effects are considered. However, persistence for process is only significant at 5% in the balanced panel. Innovation from two periods ago seems to affect present innovation, contrary to what was observed for *t-1*. Such a result may indicate that Uruguayan firms innovate erratically, so that after innovating in *t*, firms skip the subsequent period and get back into the innovation trail in *t+2*.

Table 9: Real persistence in the whole sample for two-period lag (marginal effects).

	Product Innovation			Process Innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
			(a) Unbalanced Panel			
$prod_{t-2}$	0.1205***	0.0632***	0.0556***			0.0425**
	(0.0203)	(0.0222)	(0.0229)			(0.0242)
$proc_{t-2}$			0.0321**	0.0752***	0.0334*	0.0320
			(0.0175)	(0.0196)	(0.0191)	(0.0223)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Obs.	2,061	2,061	2,061	2,061	2,061	2,061
#firms	1,378	1,378	1,378	1,378	1,378	1,378
			(b) Balanced Panel			
$prod_{t-2}$	0.1422***	0.0818***	0.0776***			0.0176
	(0.0261)	(0.0298)	(0.0301)			(0.0375)
$proc_{t-2}$			0.0227	0.0461**	0.0618*	0.0833**
			(0.0225)	(0.0230)	(0.0355)	(0.0428)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Obs.	1,366	1,366	1,366	1,366	1,366	1,366
#firms	683	683	683	683	683	683

Notes: The coefficients are obtained through dynamic probit estimations. The set of control variables include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$, $hightech$, inc_1, $expend\_1$, $practices$, $comp$ and $sgdp$. The individual heterogeneity is given by the initial values of the dependent variable along with the initial value and the time-average values of $pers$, $prof$, $R\&D\_2$, inc_2, $expend\_2$. Robust standard errors in parentheses. Marginal effects are shown. ** $p < 0.05$, *** $p < 0.01$.

As in the previous subsection, heterogeneous persistence among size and sectors is discussed. Table 10 displays the persistence coefficients for SMEs and large firms. Large firms are persistent in product innovations, with marginal effects of previous innovation on the present of 11.6 pp, almost doubling those observed in Table 9 and tripling the persistence for SMEs. Both outcomes are consistent with the expected results, as unobservable characteristics of large firms are supposed to make them more innovative than SMEs. In addition, the marginal effect for large firms should be larger than those observed for the entire sample, as SMEs are included in the latter. When comparing types of innovation, it is clear that product innovations are persistent in SMEs and large firms, whereas the case of process innovations is not clear.

Finally, heterogeneous effects by sector are addressed in Table 11. The most evident outcome is that process innovation is persistent in manufacturing firms, which holds for both panels. Persistence in product innovation is not so clear, as it is significant in the balanced sample but not in the unbalanced.[3] In service firms, persistence is only observed in the unbalanced panel and for product innovations, which does not allow for a correct conclusion about persistence in the sector. The persistence in the innovation process for manufacturing firms is consistent with the idea that they tend to develop new processes with the objective of reducing costs of production, which may not be true for service firms as their productive process is quite different.

[3] In the unbalanced panel, it is significant at a 10% level, though it vanishes when process is considered.

Table 10: Real persistence for SME and large firms for two-period lag (marginal effects).

	SME				Large			
	Products		Process		Products		Process	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(a) Unbalanced Panel				Balanced Panel			
$prod_{t-1}$	0.0454*	0.0289		0.0408	0.1159***	0.1160***		0.0329
	(0.0262)	(0.0267)		(0.0297)	(0.0405)	(0.0409)		(0.0410)
$proc_{t-1}$		0.0522**	0.0539**	0.0446*		-0.0003	0.0087	0.0049
		(0.0206)	(0.0251)	(0.0260)		(0.0310)	(0.0406)	(0.0409)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Indiv. heter.	YES	YES	YES	YES	YES	YES	YES	YES
# Obs.	1,297	1,297	1,297	1,297	828	828	828	828
# firms	1,028	1,028	1,028	1,028	414	414	414	414
	(b) Balanced Panel							
$prod_{t-1}$	0.0762*	0.0640		0.0386				
	(0.0452)	(0.0423)		(0.0502)				
$proc_{t-1}$		0.0248	0.0862*	0.0797				
		(0.0306)	(0.0480)	(0.0488)				
Controls	YES	YES	YES	YES				
Year FE	YES	YES	YES	YES				
Indiv. heter.	YES	YES	YES	YES				
#Obs.	538	538	538	538				
#firms	269	269	269	269				

Notes: The coefficients are obtained through dynamic probit estimations. The set of controls include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$,$hightech$, inc_1, $expend\_1$, $practices$, $comp$ and $sgdp$. Individual heterogeneity is given by initial values of the dependent variable along with the initial value and the time-average values of $pers$, $prof$, $R\&D\_2$, inc_2, $expend\_2$. Robust standard errors in parentheses. Marginal effects are shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Real persistence for manufacturing and service firms for two-period lag (marginal effects).

	Manufacturing				Services			
	Products		Process		Products		Process	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(a) Unbalanced Panel							
$prod_{t-1}$	0.0580*	0.0443		0.0247	0.0664**	0.0612**		0.0458
	(0.0329)	(0.0332)		(0.0356)	(0.0302)	(0.0307)		(0.0325)
$proc_{t-1}$		0.0526**	0.0863***	0.0817**		0.0211	-0.0181	-0.0249
		(0.0250)	(0.0318)	(0.0325)		(0.0238)	(0.0298)	(0.0302)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Indiv. heter.	YES	YES	YES	YES	YES	YES	YES	YES
# Obs.	1,099	1,099	1,099	1,099	1,026	1,026	1,026	1,026
# firms	711	711	711	711	731	731	731	731
	(b) Balanced Panel							
$prod_{t-1}$	0.0942**	0.0840**		0.0317	0.0582	0.0598		0.0203
	(0.0431)	(0.0431)		(0.0441)	(0.0411)	(0.0419)		(0.0450)
$proc_{t-1}$		0.0540*	0.0865**	0.0812**		-0.0019	-0.0461	-0.0482
		(0.0305)	(0.0417)	(0.0422)		(0.0326)	(0.0457)	(0.0459)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Indiv. heter.	YES	YES	YES	YES	YES	YES	YES	YES
# Obs.	776	776	776	776	590	590	590	590
# firms	388	388	388	388	295	295	295	295

Notes: The coefficients are obtained through dynamic probit estimations. The set of controls include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$,$hightech$, inc_1, $expend\_1$, $practices\ comp$ and $sgdp$. Services firms are controlled by $kibs$ whereas manufacturing by $tecn$. Individual heterogeneity is given by initial values of the dependent variable along with the initial value and the time-average values of $pers$, $prof$, $R\&D\_2$, inc_2, $expend\_2$. Robust standard errors in parentheses. Marginal effects are shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Concluding Remarks

This article investigates persistence in innovation results in Uruguayan firms between 2004 and 2015, using rich panel data from manufacturing and services firms. The analysis allows us to conclude that innovation is not a persistent activity, as the probability of innovating in a given period is not affected – in some cases is negatively affected – by previous innovation results. However, when the path is tracked two periods back, the effects observed are – in most cases – positive. These findings together indicate that firms follow an erratic innovative behavior, innovating in *t*, skipping *t+1,* and going back to innovate in *t+2* in most of the cases.

Interpretation of this behavior can be twofold. First, innovation is costly in terms of financial resources. To get a new product, it is necessary to hire employees, support R&D laboratories, or invest in fixed capital. Thus, firms may not be able to sustain such expenses continuously, and after getting a new product (or process), future efforts can be aimed towards selling the product (or developing and using the process) properly. Second, innovation takes time. Three years may be not enough to develop and commercialize innovations, and the efforts carried on in *t* may be still on work in *t+1*. On the other hand, it is worth considering that the definition of the periods used is decided by the organism in charge of the survey, and may not be the same as the ones defined by the firms.

The main contributions of this research are the findings that, in line with the scant evidence for the region, corroborate that innovation persistence in the Latin American context deviate from the expected findings according to the literature from developed countries. The findings on negative effects is not observed in previous articles, and these findings help to show differences with developed economies. Even though a negative effect is not expected, it is consistent with the ideas defined above: firms may not have enough resources to persist in innovative results. Despite this, a better analysis with more data is essential. The panel structure here is not the best, as almost half of the observations are lost when lagging the dependent variable. In addition, some results are not maintained when going from the unbalanced to balanced panel, which can be attributed to the reduction of firms and endogenous differences in firms that suffer from attrition.

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Appendix

A.1 UIS and ASEA sampling description

Both surveys employ the same sampling frame, being possible to merge the data sets, obtaining data from innovation and economic activities. In this frame, for each wave until 2009 a random stratified sampling was done for firms with less than 50 employees, while firms with 50 or more employees or with income of at least $25,000,000 Uruguayan pesos were included forcibly. However, in 2012 a panel structure started to being employed based on the sampling frame of 2009. Thus, the firms included in 2009 are followed until 2015. Hence, most of the firms included in 2006 -mostly those of less than 50 employees- are not included in the 2009 edition, generating then an important unbalance in the panel. Moreover, as the methodology applied here requires the use of lagged variables, any firm that has only one observation will be lost. Those firms sampled in 2006 but not in 2009 are not taking into account for the estimations. Henceforth, the results shown correspond to manufacturing and services firms with presence in at least two periods from 2006 and 2015.

In the considered period some firms died or ceased to being eligible -e.g. reducing the number of employees to less than five. For these cases, where the sample would lose representativeness, those disappeared firms are replaced by others of similar characteristics for maintaining the representativeness.

The Lerner index is defined by:

$$L_i = \frac{P_i - MC_i}{P_i} \tag{9}$$

where P is the marginal income for selling the product and CM is the marginal cost of producing it. However, both elements are not observable in the data registered. Hence, assuming threefold: (i) the firms employ linear prices, (ii) the marginal cost is constant and (iii) and the observed costs actually reflect the opportunity costs of firms, the equation below can be rewritten as:

$$L_i = \frac{P_i * q_i - MC_i * q_i}{P_i * q_i} = \frac{Y_i - C_i}{Y_i} \tag{10}$$

where Y is the total income from sales and C is the total variable cost related to the product sold. Both Y and C are observed. Then, the competition in the sector j and time t can be computed as the average Lerner index across firms in the sector (Aghion et al., 2005):

$$c_{jt} = 1 - \frac{1}{N_{jt}} \sum_{i \in j} L_{ijt} \tag{11}$$

where N_{jt} reflects the number of firms in sector j and period t. Given the index construction, a value of 1 implies perfect competition, while 0 implies a monopoly.

A.2 Variables

Table A.1: Description of variables.

Variable	Type	Description	Source
$prod_{it}$	Dummy	=1 if firm *i* introduced a product innovation in the period *t*, =0 otherwise.	UIS
$proc_{it}$	Dummy	=1 if firm *i* introduced a process innovation in the period *t*, =0 otherwise.	UIS
$pers_{it}$	Continuous	Number of employees occupied in firm *i* in *t* (log).	UIS
$prof_{it}$	Continuous	Number of professional employees occupied in firm *i* in *t* (log).	UIS
$capx_{it}$	Dummy	=1 if firm *i* has foreign capital in the period *t*, =0 otherwise.	UIS
$expo_{it}$	Dummy	=1 if firm *i* is an exporting firm in the period *t*, =0 otherwise.	UIS
net_{it}	Dummy	=1 if firm *i* declares to participate in a regional or international network in the period *t*, =0 otherwise.	UIS
$coop_{it}$	Dummy	=1 if firm *i* declares to have done cooperation agreements in the period *t*, =0 otherwise.	UIS
$R\&D\_1_{it}$	Dummy	=1 if firm *i* declares to have invested in R&D in the previous period *t-1*, =0 otherwise.	UIS
$manufact_{it}$	Dummy	=1 if firm *i* belongs to manufacturing sector in the period *t*; =0 otherwise.	UIS
$kibs_{it}$	Dummy	=1 if firm *i* is classified as Knowledge Intensive Based Services (KIBS) in period *t*; =0 otherwise.	UIS
$hightech_{it}$	Dummy	=1 if firm *i* is classified as high technology manufacturing in period *t*; =0 otherwise.	UIS
$financ_{it}$	Dummy	=1 if firm *i* declared to have financial obstacles for innovating in period *t*.	UIS
inc_1_{it}	Continuous	Sales income per employee in Uruguayan pesos, obtained by firm *i* in the previous period *t-1*.	ASEA
$expend\_1_{it}$	Continuous	Expenditures per employee in machinery and physical capital in Uruguayan pesos of firm *i* in the period *t-1*.	ASEA
$practices_{it}$	Continuous	Number of organizational practices carried by firm *i* in period *t* from: continuous improvement groups, collective	UIS

		organs, level reductions, systems for collecting opinions and result-based incentives.	
$comp_{it}$	Continuous	Lerner Index at the sector where firm i operates in period t, at three digit SIC level.	ASEA
$sgdp_{it}$	Continuous	Sectorial GDP growth rate between the first and the last year of period t at the sector where firm i operates, at two-digits SIC level.	BCU

Source: Author.

Table A.2: Variables descriptive statistics

Variable	Mean	Standard. Dev.	Median	Minimum	Maximum	Observations
$prod$	0.206	0.404	0.000	0.000	1.000	7922
$proc$	0.266	0.442	0.000	0.000	1.000	7922
$pers$	3.676	1.394	3.584	0.000	9.208	7922
$prof$	0.628	1.247	0.000	0.000	8.602	7922
$capx$	0.126	0.332	0.000	0.000	1.000	7922
$expo$	0.242	0.428	0.000	0.000	1.000	7922
net	0.149	0.356	0.000	0.000	1.000	7922
$coop$	0.127	0.333	0.000	0.000	1.000	7922
$R\&D\_1$	0.184	0.388	0.000	0.000	1.000	4683
$manufact$	0.454	0.498	0.000	0.000	1.000	7922
$kibs$	0.445	0.497	0.000	0.000	1.000	4322
$hightech$	0.224	0.417	0.000	0.000	1.000	3600
inc_1	2,982	31,503	850.813	0.000	1,833,176	4648
$expend\_1$	27.087	271.555	0.000	0.000	13073	4669
$practices$	1.226	1.403	1.000	0.000	5.000	7922
$comp$	0.791	0.092	0.792	0.251	1.000	7922
$sgdp$	0.078	0.254	0.053	-0.567	3.828	7922

Source: Author based on UIS, ASEA and BCU data.

A.3 Muinelo and Suanes (2018): Replication

Table A.3: Real persistence in product and process innovations, emulating Muinelo & Suanes (2018).

	Process Innovation		Product Innovation	
	(1)	(2)	(3)	(4)
$prod_{t-1}$			-0.004	0.057
			(0.034)	0.058
$proc_{t-1}$	0.042	0.086		
	(0.030)	(0.051)		
R&D intensity	0.001	0.001	0.004***	0.003*
	(0.001)	(0.001)	(0.001)	(0.002)
Physical capital intensity	0.001***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Foreign direct investment	-0.025	-0.103**	-0.009	-0.026
	(0.031)	(0.040)	(0.030)	(0.045)
Hardware and software investment	0.106***	0.093**	0.049*	0.018
	(0.027)	(0.039)	(0.026)	(0.037)
TC and ID investment	-0.005	-0.098	0.090	0.059
	(0.081)	(0.085)	(0.063)	(0.076)
Training	0.081***	0.008	0.102***	0.096**
	(0.029)	(0.041)	(0.025)	(0.036)
Information sources: market	0.229***	0.066	0.232***	0.171
	(0.057)	(0.123)	(0.075)	(0.120)
Information sources: scientific	0.190***	0.416***	0.150**	0.304**
	(0.059)	(0.149)	(0.067)	(0.121)
Information sources: public	0.048	0.176	-0.007	0.024

	(0.055)	(0.120)	(0.056)	(0.085)
Obstacles 1	-0.012	0.009	0.033	0.022
	(0.026)	(0.054)	(0.025)	(0.043)
Obstacles 2	-0.020	-0.017	-0.011	-0.044
	(0.030)	(0.058)	(0.031)	(0.051)
Obstacles 3	0.006	-0.085	0.081**	0.107*
	(0.035)	(0.077)	(0.038)	(0.063)
Size 20-49	-0.010	0.086	0.211***	1.549***
	(0.049)	(0.117)	(0.072)	(0.096)
Size 50-149	0.099**	0.257**	0.225***	1.508***
	(0.048)	(0.110)	(0.069)	(0.078)
Size 150 or more	0.076	0.258**	0.228***	1.466
	(0.052)	(0.112)	(0.072)	(0.084)
$prod_{t0}$			0.140***	0.144***
			(0.027)	(0.046)
$proc_{t0}$	0.051**	0.053		
	(0.023)	(0.045)		
Temporal effects	Yes	Yes	Yes	Yes
W_industry	0.232	0.234	0.381	0.644
Log-likelihood	-457.3	-127.9	-449.2	-232.1
Observations	1,164	352	1,164	521

Notes: Robust std. errors are shown in parentheses. The term W_industry gives the probability value of the joint significance test of the industry binary variables. *Significance 10%, **Significance 5%, ***Significance 1%.

A.4 Robustness Checks: Innovation Scope

Table A.4: Real persistence in product and process innovations (international level).

	Product Innovation			Process Innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
	(a) Unbalanced Panel					
$prod_{t-1}$	0.017**	-0.005	-0.006			0.003
	(0.008)	(0.008)	(0.004)			(0.007)
$proc_{t-1}$			0.004	0.005	-0.001	-0.003
			(0.010)	(0.008)	(0.008)	(0.008)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Observations	3,784	3,784	3,784	3,784	3,784	3,784
#firms	1,729	1,729	1,729	1,729	1,729	1,729
	(b) Balanced Panel					
$prod_{t-1}$	0.013	0.002	0.002			-0.004
	(0.011)	(0.011)	(0.012)			(0.012)
$proc_{t-1}$			0.003	0.014	0.018	0.020
			(0.015)	(0.011)	(0.034)	(0.037)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Observations	2,049	2,049	2,049	2,049	2,049	2,049
#firms	683	683	683	683	683	683

Notes: The coefficients are obtained through dynamic probit estimations. The set of control variables include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$, $hightech$, inc_1, $expend\_1$, $practices$, $comp$ and $sgdp$. The individual heterogeneity is given by the initial values of the dependent variable along with the inital value and the time-average values of $pers$, $prof$, $R\&D\_1$, inc_1, $expend\_1$. Robust standard errors in parentheses. Marginal effects are shown. ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Real persistence in product and process innovations (national level).

	Product Innovation			Process Innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
			(a) Unbalanced Panel			
$prod_{t-1}$	0.097	-0.079***	-0.084***			0.012
	(0.123)	(0.015)	(0.015)			(0.012)
$proc_{t-1}$			0.036	0.040***	-0.039***	-0.040***
			(0.013)	(0.016)	(0.013)	(0.014)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Observations	3,784	3,784	3,784	3,784	3,784	3,784
#firms	1,729	1,729	1,729	1,729	1,729	1,729
			(b) Balanced Panel			
$prod_{t-1}$	0.010	-0.065***	-0.075***			0.011
	(0.029)	(0.024)	(0.025)			(0.018)
$proc_{t-1}$			0.056***	0.024	-0.037*	-0.038*
			(0.019)	(0.023)	(0.021)	(0.021)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Observations	2,049	2,049	2,049	2,049	2,049	2,049
#firms	683	683	683	683	683	683

Notes: The coefficients are obtained through dynamic probit estimations. The set of control variables include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$, $hightech$, inc_1, $expend\_1$, $practices$, $comp$ and $sgdp$. The individual heterogeneity is given by the initial values of the dependent variable along with the inital value and the time-average values of $pers$, $prof$, $R\&D\_1$, inc_1, $expend\_1$. Robust standard errors in parentheses. Marginal effects are shown. ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Real persistence in product and process innovations (firm level).

	Product Innovation			Process Innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
	(a) Unbalanced Panel					
$prod_{t-1}$	0.044***	-0.061***	-0.067***			-0.022
	(0.015)	(0.017)	(0.017)			(0.018)
$proc_{t-1}$			0.027**	0.062***	-0.089***	-0.086***
			(0.011)	(0.020)	(0.018)	(0.018)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Observations	3,784	3,784	3,784	3,784	3,784	3,784
#firms	1,729	1,729	1,729	1,729	1,729	1,729
	(b) Balanced Panel					
$prod_{t-1}$	0.047***	-0.003	-0.010			-0.016
	(0.020)	(0.061)	(0.034)			(0.026)
$proc_{t-1}$			0.033	0.038	-0.050*	-0.048*
			(0.058)	(0.031)	(0.028)	(0.028)
Controls	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES
Indiv. heter.	NO	YES	YES	NO	YES	YES
#Observations	2,049	2,049	2,049	2,049	2,049	2,049
#firms	683	683	683	683	683	683

Notes: The coefficients are obtained through dynamic probit estimations. The set of control variables include $pers$, $prof$, $capx$, $expo$, net, $coop$, $R\&D\_1$, $manufact$, $hightech$, inc_1, $expend\_1$, $practices$, $comp$ and $sgdp$. The individual heterogeneity is given by the initial values of the dependent variable along with the initial value and the time-average values of $pers$, $prof$, $R\&D\_1$, inc_1, $expend\_1$. Robust standard errors in parentheses. Marginal effects are shown. ** $p < 0.05$, *** $p < 0.01$.