Laggards imitate, leaders innovate:
The heterogeneous productivity effect of imitation versus innovation

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Abstract

This study finds that imitation increases the productivity of laggards more than that of leaders, while innovation has the opposite effect. As firms approach the productivity frontier, the effect of imitation on productivity decreases, while that of innovation increases. The empirical evidence suggests that search costs are the mechanism underlying this effect. Firms increase their productivity by imitating productive firms. When they become more productive, search costs increase, because they have fewer opportunities to imitate.

Introduction

Innovative firms draw everyone's attention, and those that were previously imitators often generate discussions about how they turned themselves into innovators. Fast Company ranks Xiaomi (a Chinese firm) 13th on its list of the World's Most Innovative Companies of 2017 (Fast Company, 2017). Acknowledging Xiaomi's previous imitation, MIT Technology Review has described Xiaomi's achievement as going beyond a "cut-price Apple model" (MIT Technology Review, 2015). In spite of being ranked 12th on the same Fast Company list for its all-in-one app, WeChat, Tencent was initially an imitator. Its QQ messaging platform was copied from an Israeli company (The Economist, 2016). Within a decade, Xiaomi and Tencent have changed from imitators into innovators. The development of Xiaomi and Tencent is impressive, but not unprecedented. Asian Tiger firms took the same path during their catch-up process.

The notion that "laggards imitate and leaders innovate" inspires this study, which aims to explain why companies move from imitation to innovation. This move often goes with increased productivity and technological capability (Hobday, 1995; Kim, 2001). In other words, less productive firms often imitate, while productive firms tend to innovate. Using a formal modeling approach, Aghion and Howitt (2006) demonstrate that when a firm approaches the productivity frontier, innovation drives productivity improvements, but when far from the frontier, imitation mainly drives productivity improvements. While Aghion and Howitt (2006) developed this mechanism formally, little empirical evidence of the relationship has appeared. The observation that "laggards imitate and leaders innovate" is often made casually. This study suggests that the firms move from imitation to innovation because of the different effects of imitation and innovation on productivity. Firm-level empirical evidence shows that both imitation and innovation enhance productivity. However, the size of the effect depends on the firm's productivity level. This is consistent with previous formal models formulated by Nelson and Phelps (1966) and Acemoglu *et al.* (2006). Therefore, companies move from imitation to innovation when innovation begins to improve productivity more than imitation does.

My study uses two streams of literature. One compares and contrasts the concepts of imitation and innovation (Mansfield, 1963; Knight, 1967; Pierce and Delbecq, 1977; Mahmood and Rufin, 2005). These studies investigate the relationship between the concepts (Blumenthal 1976; Teece, 1986; Biggart and Guillén 1999; Aghion *et al.*, 2001; Raustiala and Sprigaman, 2012), choices between them (Aghion *et al.*, 2001; Vandenbussche *et al.*, 2006; Benhabib *et al.*, 2014; König *et al.*, 2016), and the catch-up process from imitation to innovation (Hobday,1995; Kim, 2001; Agénor and Dinh, 2013). Specifically, Benhabib *et al.* (2014) and König *et al.* (2016) proposed formal models associating the choice between imitation and innovation with the concept of leaders and laggards.

The other literature stream investigates various aspects of the differences between leaders and laggards. One common understanding is that the effect of a given practice on performance depends on whether the firm is a leader or a laggard. Researchers have shown that factors such as R&D activity (Coad, 2011; Zhang and Park, 2014; Chang *et al.*, 2015), firm size, firm growth (Coad, 2011), competition (Amable *et al.*, 2010), and collaboration (Triguero *et al.*, 2016) affect the performance of leaders and laggards differently, in terms of market value (Coad, 2011), firm growth (Zhang and Park, 2014), innovation (Amable *et al.*, 2010; Triguero *et al.*, 2016), and catch-up speed (Chang *et al.*, 2015).

Using the *Technological Innovation Panel* (PITEC), the Spanish part of the

Community Innovation Survey (CIS), this study considers imitation as new-to-firm and innovation as new-to-market (Kleinknecht *et al.*, 2002; Köhler *et al.*, 2012; Arvanitis and Seliger, 2014; Cappelli *et al.*, 2014). I measure imitation and innovation by sales generated from new-to-firm and new-to-market products, respectively. Although not without limitation, such an operationalization enables me to measure and directly test the effect of imitation and innovation on productivity in a large sample of firms, which has rarely been done. Previous studies mainly test the effect of imitation by estimating the coefficient of the interaction term between distance to the frontier and innovation-related variables such as research intensity and quality of human capital (Vandenbussche *et al.*, 2006; Madsen *et al.*, 2010). They interpret a significant coefficient as evidence for the different effects of innovation and imitation on leaders and laggards.

Evidence from quantile regression shows that imitation and innovation have different effects on firm productivity. The relative importance of imitation and innovation varies, depending on the firm's productivity level. The effect of imitation decreases and the effect of innovation increases as the firm moves up in the productivity distribution. As a result, laggards improve their productivity more by imitating than by innovating, while leaders benefit more from innovation than from imitation. Therefore, as firms become more productive, imitation does not increase it so much, and they tend to move toward innovation.

I also investigate a possible mechanism underlying the relative importance of imitation and innovation. I argue that a key feature distinguishing imitation from innovation is the existence of a target. To imitate, firms need to locate appropriate targets—more productive firms. That is, the focal firm imitates productive firms to enhance its own productivity. As the focal firm becomes more productive, fewer productive firms remain to imitate. The availability of fewer imitation opportunities increases search costs. It is less expensive for firms that lag behind to find an appropriate target than for firms close to the frontier. Consequently, the cost of searching for an appropriate target increases along with the firm's productivity. Leaders have higher search costs than laggards, so they find imitation less beneficial than laggards, all else being equal. My empirical evidence supports the proposed mechanism—search costs.

In addition to combining two literature streams to explain an important phenomenon and search for an underlying mechanism, this study contributes to the literature in three more respects. First, it goes beyond estimating average effects, as in most previous studies, by using quantile regression. Unlike approaches such as ordinary least square (OLS) regression, which estimate average effects, quantile regression analyses can capture changes in the size of the productivity effect along the distribution. They reveal variations in the relative importance of imitation and innovation, in terms of productivity enhancement.

Second, this study directly measures and tests the effect of imitation. Previous studies find evidence that innovation affects performance more for leaders than for laggards, but have seldom measured or tested the effect of imitation directly. They assume that those who do not innovate, imitate. The conclusion that imitation enhances laggards' performance is often based on a non-significant coefficient of an innovation-related variable (Coad, 2011), or on a significant interaction term between an innovation-related variable and distance to the frontier (Vandenbussche *et al.*, 2006; Madsen *et al.*, 2010). Innovation and imitation are often considered as two sides of the same coin, and many assume that not innovating means imitating. However, the PITEC data reveal that about 26% of Spanish firms (nearly 8000) neither imitated nor innovated during the 9-year observation period. This shows that not innovating does not necessarily mean imitating. In addition, imitation is by no means the only alternative to innovation. For example, internationalization and diversification could also enhance performance. Even if we agree that not innovating means imitating, this approach still assumes a linear relationship between imitation and innovation effects, which deserves further clarification.

Coad (2011) uses quantile regression to show that R&D expenditure and patenting provide higher stock market returns for leaders than for laggards. He then suggests that the appropriate strategy for leaders is innovation and for laggards is imitation. Although his study does not assume a linear relationship between the effects of imitation and innovation, he still assumes that not innovating means imitating. Both assumptions (that not to innovate means to imitate, and that their effects on performance are linearly related) are debatable. Knowing only that innovation affects leaders and laggards differently, but not how the effect of imitation varies, we cannot confirm that laggards imitate and leaders innovate. Thus, this research is unique in explaining the phenomenon by measuring and testing the effects of both imitation and innovation.

Third, my study provides firm-level empirical evidence about a topic that has been investigated theoretically rather than empirically. Most previous work on the relationship between imitation, innovation, and productivity comprises formal models (Aghion *et al.*, 2001; Vandenbussche *et al.*, 2006; Benhabib *et al.*, 2014; König *et al.*, 2016) or computer simulations (Chang *et al.*, 2015). Empirical studies are rare, and mainly limited to countries (Vandenbussche *et al.*, 2006; Madsen *et al.*, 2010) or industries, such as telecommunications (Lee and Lim, 2001; Guo *et al.*, 2015), electronics (Hobday, 1995; Kim, 1997; Lee and Lim, 2001), and the automotive industry (Lee and Lim, 2001). I know of no analyses of a large number of firms across a variety of industries—manufacturing, services, and other sectors. This is the first study to provide empirical evidence of how imitation and innovation affect firm-level productivity by directly measuring and testing their effect on a large sample of firms.

The next section outlines the theory on which this study is built. Next, I describe the data and the empirical strategy in the methodology section. The results section starts by showing that most of firms in the sample both imitate and innovate. It then provides descriptive statistics showing that laggards tend to imitate and leaders innovate. I obtain my main results from quantile regression with firm fixed effects (FE). By comparing their effects on productivity, I show that the relative importance of imitation and innovation varies, depending on the firm's rank in the conditional productivity distribution. I make several robustness checks, which are all consistent with my main analyses. I end my analysis by searching for the potential underlying mechanism, the evidence suggesting that search costs may be the key. Finally, I discuss the study's limitations and suggest future research opportunities.

Theoretical background

Academics agree that novelty distinguishes innovation from imitation. In their theoretical work, Mahmood and Rufin (2005) define a firm as an imitator when it expands its own knowledge set. Once a firm expands the world's knowledge set, it becomes an innovator. Pierce and Delbecq (1977) summarize the different conceptualizations of innovation. They note that Mansfield (1963) defines innovation as the "first ever use" of an idea and imitation as the "subsequent usage" of the idea (p. 28). Other scholars suggest boundary conditions for the concept of novelty. Knight (1967) proposes the concept, "new to an organization and to the relevant environment" (p. 478) as a requisite for innovation.

Becker and Whisler (1967) define innovation as "the first or early use of an idea by one of a set of organizations with similar goals" (p. 463). Accordingly, the adoption of ideas already used by competitors can be defined as imitation. In business, imitation can occur when a firm introduces products or services that resemble ones already in the market. Imitation could also involve adopting a production process, a managerial practice, or a marketing approach already used by competitors. Although imitation can take different forms, all require the identification of a target to imitate. Imitation is only possible when a target is identified. This is not the case for innovation. From this perspective, we can distinguish imitation from innovation by the existence of a target.

To operationalize imitation and innovation, studies mainly rely on the novelty level of new products. This is largely due to the availability of CIS-type data. Novelty ranges from new to the world to new to the market (or to the national context) or new to the firm. The highest degree of novelty—new to the world—is considered as innovation (Vinding, 2006), sometimes referred to as radical innovation (Laursen and Salter, 2006). However, the literature does not agree about the degree of novelty necessary for imitation. Seeing the market as a group of firms with similar goals, some scholars build on Becker and Whisler's (1967) idea of using the market as the boundary for imitation. They define new-to-firm as imitation and new-to-market as innovation (Kleinknecht *et al.*, 2002; Köhler *et al.*, 2012; Arvanitis and Seliger, 2014; Cappelli *et al.*, 2014).

Other scholars argue that even when products are only new-to-firm, they often need modification and improvement over products already offered by competitors (Schnaars, 1994). Niosi (2017) points out that the development of biosimilar drugs requires both research and clinical trials. These scholars recognize that firms imitate when introducing new-to-firm products, but emphasize that developing such products also involves novelty. They describe new- to-firm products as imitative innovation (Vinding, 2006), incremental innovation (Laursen and Salter, 2006), or minor innovation (Vega-Jurado *et al.*, 2008). In contrast to new-to-firm, they describe new-to-market products as major innovation (Vega-Jurado *et al.*, 2008).

In addition to clarifying the concepts of imitation and innovation, previous studies point out that these concepts are related in different ways. In terms of antecedence, the performance improvements generated by innovation trigger imitation (Lieberman and Asaba, 2006). Depending on conditions such as product market competition (Aghion *et al.*, 2001) and the nature of the industry (Raustiala and Sprigaman, 2012), imitation may encourage or discourage innovation. Regarding consequences, imitation may reduce the profits generated by innovation (Teece, 1986). As to diffusion, the impact of an innovation often depends on the extent of its adoption, or the degree to which agents imitate each other in adopting the innovation (Blumenthal, 1976; Biggart and Guillén, 1999).

Of the various relationships between imitation and innovation, this study focuses on the idea that "laggards imitate and leaders innovate." Most studies investigating this phenomenon take one of two approaches. One literature stream suggests that learning by imitation leads to innovation. This work mainly comprises qualitative case studies or formal modeling. Kim (2001) proposes a three-stage framework of technological development—duplicative imitation, creative imitation, and innovation—to account for the industrialization of developing countries. Studying one firm in each Asian Tiger country, Hobday (1995) shows how latecomer firms build up their innovation capacity by acquiring, assimilating, and adapting foreign technology. Agénor and Dinh (2013) develop a formal model showing that, through reverse engineering and learning by doing, unskilled laborers in imitative sectors become familiar with technology and gain cognitive skills that favor innovation. Chang *et al.* (2015) use a computational model to simulate the catch-up process. Before attempting to innovate, laggards should first invest in imitative R&D to develop their technological capability.

An alternative approach is based on the idea of the advantage of backwardness (Gerschenkron,1962). According to the catch-up hypothesis formalized by Nelson and Phelps (1966), the extent to which imitation contributes to productivity depends on where the imitation occurs. The lower the productivity level, the more it can be improved by imitating existing innovations. Aghion and Howitt (2006) use the concept of distance to the technology frontier—the distance between an agent's productivity and that provided by the most advanced technology—to pin down "where" imitation occurs. The relative importance of imitation and innovation is determined by distance to the technology frontier. Assuming that the benefits of imitation decrease as the technology frontier approaches, they show that lead- ers mainly grow through innovation, and laggards through imitation.

To study why leaders and laggards choose imitation or innovation, Benhabib *et al.* (2014) present a formal model in which firms can grow by imitating or innovating. In an equilibrium, not all imitators become innovators. Some choose to fall back and continue imitating, and others choose to catch-up by investing in innovation. The differences between the returns on innovation and imitation drive the results. A closely related model by König *et al.* (2016) suggests that the availability of imitation opportunities affects the choice between imitation and innovation.

Empirical studies in this area are mostly country- and industry-level analyses. They operationalize the concept of distance to the technology frontier in different ways, mostly measured by total factor productivity (Nicoletti and Scarpetta, 2003; Vandenbussche *et al.*, 2006; Madsen *et al.*, 2010) and labor productivity (Amable *et al.*, 2010). This approach considers that productivity fairly reflects technology level—they are often closely related—so that distance to the technology frontier can be captured by relative productivity. Applying the concept of distance to the technology frontier to firm data, Coad (2011) uses quantile regression to show the effect of R&D investment on firms' market value. Concerning the time lag between R&D investment and performance gains, he argues that Tobin's *q* reflects firms' distance to the frontier better than productivity does. This is because the stock market often anticipates future performance gains resulting from R&D investment. Moreover, high-technology firms might be less productive when introducing new products. Consequently, productivity and technology level might not correspond.

My study also applies the concept of distance to the technology frontier. Unlike Coad (2011), I use relative labor productivity to measure distance to the frontier. Coad's (2011) chooses Tobin's *q* for two main reasons. First, firms are likely to use different production technologies and second, R&D affects performance some time after the initial investment. To address the first concern, I use quantile regression with firm FE. By controlling for time-invariant firm characteristics, I show within subjects (firm) effects. In addition to firm FE, I also control for time-variant characteristics of capital and knowledge stock. This also deals with the possibility that the same firm might use different production technology during the observation period. I deal with the second concern by measuring imitation and innovation using sales generated from imitative and innovative products, rather than R&D investment. The time lag between sales from new products and productivity gains is shorter than that between R&D investment and productivity gains. In the main analysis, I lag the independent variable for 1 year. An additional robustness check with 2-year lag shows consistent results.[1]

[1] The results are not presented in the article but available upon request.

Although previous studies demonstrate that leaders benefit from innovation more than laggards do, the effect of imitation has rarely been tested directly. Coad (2011) estimates the effects of R&D investment and patenting on firms' market value. Quantile regression shows that innovation, measured by R&D investment and patenting, affects firms with a higher market value more than firms with a lower value. Assuming that not innovating means imitating, he interprets the results as showing that imitation benefits laggards, and innovation benefits leaders. Analyzing a panel of 55 countries from 1970 to 2004, Madsen *et al.* (2010) measure the effect of imitation by interacting distance to the technology frontier with research intensity, and then educational level. Based on the significant coefficient of the interaction term, they conclude that OECD countries rely more on innovation to grow, while developing countries grow mainly by imitation. By testing the interaction term between distance to the technology frontier and the proportion of the population reaching higher education, Vandenbussche *et al.* (2006) provide evidence that skilled labor improves growth in countries closer to the technology frontier. Assuming that innovation is more skill-intensive than imitation, they interpret the results as showing that innovation helps leaders grow more than it helps laggards. In addition to assuming that not innovating means imitating, as Coad (2011) does, the studies of both Madsen *et al.* (2010) and Vandenbussche *et al.* (2006) imply that the relationship between the growth effects of imitation and innovation is linear, which is debatable. None of these studies directly measured or tested the effect of imitation.

A recent formal model endogenizes choices between imitation and innovation (König *et al.*, 2016). Given the objective of maximizing profits and resource constraints, ex-ante, identical firms will choose imitation or innovation depending on their overall productivity level. Imitation is possible only if they find a target. The target-searching process is modeled as a random matching process. Two firms are matched when the focal firm locates another firm with higher productivity. If we assume random matching, firms far from the frontier are more likely to find a target to imitate than those close to the frontier.

In this model, the likelihood of successful imitation depends on the productivity gap between the focal and target firms. The larger the gap, the less likely a successful imitation. When successful, the focal firm improves its productivity to the level of the target firm. When it fails, the focal firm remains at its original productivity level. In addition to imitation, firms can also improve productivity via innovation. If the focal firm innovates successfully, its productivity increases, but it will be likely to make limited rather than considerable improvement. Given their resource constraints, firms maximize profits by choosing between imitation and innovation. The outcome shows that less productive firms are more likely to choose imitation, and more productive firms are more likely to choose innovation.

Inspired by their model, I propose search costs as the mechanism explaining the different importance of imitation and innovation in improving productivity. I define search costs as the resources spent by the focal firm on locating an “appropriate” target for imitation. A target firm is “appropriate” when the focal firm would increase its productivity in the case of successful imitation. When it is unaware of a potential target’s productivity, the focal firm might select a target that is no more productive than itself. In this case, it would not improve its productivity, even with successful imitation. Thus, the selected target is inappropriate.

In addition, search costs differ for laggards and leaders. As long as they do not know whether the potential target is more productive than themselves, laggards will have lower search costs than leaders. This holds, no matter how they undertake their search. The model by König *et al.* (2016) depicts a random search. In a local search, the focal firm finds a target in its own environment. If the number of potential targets remains constant, an already productive focal firm will find it more difficult to find a more productive target. Another strategy might be to imitate the frontier firm—the most productive firm. In this case, the focal firm will know for certain that the frontier firm is more productive than itself. Search costs are similar for focal firms with different productivity levels. However, the further it is from the frontier, the more a firm can improve by imitating the frontier firm, if its imitation is successful. This is the case in the Aghion and Howitt (2006) model.

By proposing search costs as the mechanism, I expect that the importance of imitation and innovation, in terms of improved productivity, will vary between firms. Imitation is more beneficial than innovation for less productive firms, because they will find it less expensive to locate an appropriate target. On the other hand, innovation is more likely to be beneficial for more productive firms, because their search costs will be higher if they imitate.

Methodology

Data

The data used in this study come from the PITEC. Since 2004 (collecting data for 2003), firm-level information has been collected annually, based on the methodology suggested by the *Oslo Manual* (see OECD and Eurostat, 2005). Due to the increasing size of the sample, cross-year comparison is only feasible from 2005. I excluded firms that have merged, shut down, split up, or gone through other significant events during the survey period. I obtained 71,202 firm-year observations from 2005 to 2013, in 44 industries, including both manufacturing and services.

Since the study measures imitation and innovation by sales generated from new products, I further excluded 2087 firms (about 26% of the original dataset) that did not introduce any new products during the 9-year period. As a result, the final dataset comprises 52,500 firm-year observations.[2] For the regression analysis, I reduced the number to 46,476 firm-year observations, due to the use of lagged variables and missing values.

Empirical strategy

Most studies of the link between innovation and productivity use one of two approaches: the Cre´pon *et al.* (1998) model—the CDM approach—(Griffith *et al.*, 2006; Parisi *et al.*, 2006; Hall *et al.*, 2009) or the production function framework (Griliches, 1986; Hall and Mairesse, 1995). Due to the structure of my data and the purpose of the study, the CDM approach was unusable.[3] Thus, I used the production function framework, considering innovation efforts as a production input, in addition to labor and capital.

Rather than focusing on the average effect, I argue that the effect of imitation and innovation on productivity vary between firms, depending on their productivity level. Therefore, I used a quantile regression, to estimate a coefficient for the regressor at each selected quantile. When estimated at the qth quantile, the coefficient of a particular regressor can be interpreted as the marginal change in the qth conditional quantile of the dependent variable, due to the marginal change in the particular

[2] Each year the number of unique firms contained in the dataset varies slightly. From 2005 to 2013, the numbers are 5826, 5826, 5830, 5831, 5831, 5834, 5838, 5842, and 5842, respectively.

[3] The study compares the productivity effects of imitation and innovation. Applying the CDM approach, I need to have two productivity equations—one for imitation and another for innovation. To model imitation and innovation as two dis- tinct processes, the approach requires separate data on imitation and innovation inputs. PITEC, however, does not pro- vide such information. It does not distinguish between resources spent on imitation and innovation.

regressor (Yasar *et al.*, 2006). At firm level, quantile regression has been applied to different topics, such as estimating the production function (Yasar *et al.*, 2006; Montresor and Vezzani, 2015), productivity (Bartelsman *et al.*, 2015), and firm growth (Coad and Rao, 2008; Bianchini *et al.*, 2014; Coad *et al.*, 2016; Santi and Santoleri, 2017).

The choice of imitation or innovation is also likely to be driven by unobservable characteristics associated with productivity level. To deal with this potential endogeneity, I conducted FE quantile regressions. Canay (2011) pro- poses a simple transformation to eliminate time-invariant effects by viewing these as "location shift variables (i.e. variables that affect all quantiles in the same way)" (p. 368). This method has been used in studies on R&D and in- novation (Bianchini *et al.*, 2014; Bartelsman *et al.*, 2015; Coad *et al.*, 2016). I made the transformation in two steps.

First, I estimated a firm effect for each firm (which remains constant over the observation period) using a firm FE panel regression:

$$y_{it} = \alpha + \beta X_{it} + u_i + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome variable, b is the vector of parameters to be estimated, X_{it} is the vector of regressors (including independent and control variables), and u_i is the firm fixed effect. I transformed the dependent variable by subtracting the estimated firm effect from equation (1):

$$y'_{it} = y_{it} - \hat{u}_i \tag{2}$$

where $\hat{u}_i$ is the estimated firm effect. The transformed dependent variable (y'_{it}) is then used in the quantile regression:

$$y'_{it} = \alpha'_\theta + \beta'_\theta X_{it} + \epsilon'_{\theta it} \text{ with } Q_\theta(y_{it}|X_{it}) = \beta'_\theta X_{it} \tag{3}$$

where $Q_\theta(y_{it}|X_{it})$ denotes the θth conditional quantile of y_{it}, given X_{it}.

Canay's (2011) approach is computationally simple, because it eliminates the firm FE beforehand. However, it relies on the assumption that firm FE are location shifters. In addition, the estimator is consistent and asymptotically normal when both the number of firms (*N*) and the number of periods (*T*) approach infinity. Although PITEC data covers almost 6000 unique firms and a 9-year observation period, this remains far from infinity. Nevertheless, using Monte Carlo simulations, Canay (2011) shows that when the number of periods increases, the bias decreases. With *T* equaling 10, the bias is low, regardless of N.[4] PITEC covers a 9-year period (eight periods in effect, due to lagged variables), so the bias is probably limited. Although Canay's (2011) approach has been applied to previous studies using the same PITEC dataset to investigate the relationship between innovation and growth (Bianchini *et al.*, 2014; Coad *et al.*, 2016), such a limitation needs to be borne in mind when interpreting the results.

Operationalization of imitation and innovation

Imitation and innovation can be distinguished by the novelty level (Mansfield, 1963; Knight, 1967; Mahmood and Rufin, 2005) and by the existence of a target (Becker and Whisler, 1967). This study operationalizes imitation as (only) new-to-firm and innovation as new-to-market. Such an operationalization reflects the different novelty level. It also implicitly assumes that all new-to-firm products result from imitation. The focal firm needs first to identify a target to imitate, and then introduce the new-to-firm product. This assumption is debatable. For example, it is possible that two firms work independently during the R&D process, but develop the same product.[5] According to my operationalization, the firm that first introduces the new product to the market is considered an innovator, while the other is an imitator, as it arrives on the market later. In this case, the operationalization is limited, as it does not adequately capture the distinction between imitation and innovation.

I use sales generated from new-to-firm and new-to-market products to measure the extent of imitation and innovation, respectively. Previous studies have taken the same approach, including Kleinknecht *et al.* (2002), Köhler *et al.* (2012), Arvanitis and Seliger (2014), Cappelli *et al.* (2014), and Arora *et al.* (2016). Distinguishing between imitative (new-to-firm) and innovative (new-to-market) sales, Cappelli *et al.*, (2014) demonstrate that the R&D spillovers from diverse sources contribute differently to imitative and innovative sales. Köhler *et al.* (2012) analyze how different search strategies influence the success of imitative and innovative products. Both studies found that successful imitative and innovative products rely on distinct types of spillovers and knowledge search. In particular, spillovers from competitors and a

[4] Using Monte Carlo simulation, Canay (2011) shows that with N = 5000 and T = 10, the percentage of bias ranges from 0.03% to 0.08%, depending on the assumed distribution of other relevant parameters.
[5] I thank the reviewer for pointing out this particular scenario.

market-driven knowledge search contribute to imitative but not innovative sales. Arvanitis and Seliger (2014) found similar results. Using Swiss CIS data, they show that imitative firms are more likely to source knowledge externally through contractual R&D and cooperation. Innovative firms mainly rely on internal knowledge for their R&D.

All of these studies provide evidence that operationalizing imitation and innovation as new-to-firm and new-to- market reflects their theoretical differences. An additional advantage is that this operationalization measures successful imitation and innovation (Kleinknecht *et al.*, 2002), that is, the output of new product development processes. Although inputs are related to outputs, the link between outputs and firm performance tends to be more direct. The time lag between outputs and performance gains is likely to be shorter than the one between inputs and performance gains. Measuring outputs directly also takes account of differing efficiency levels when transforming inputs into outputs. Nevertheless, the operationalization has weaknesses. Many firms can only provide a rough estimation of sales generated by new products, rather than a precise figure. In addition, perceptions of whether a product is new-to-firm or new-to-market often vary between firms (Kleinknecht *et al.*, 2002).

Although operationalizing imitation and innovation as new-to-firm and new-to-market has limitations, it has both empirical and theoretical value. It enables me to investigate a research question by analyzing a large number of firms in a substantial dataset, which has not previously been realized. In addition, by defining imitation as new-to- firm, I recognize the element of novelty in imitation (Schnaars, 1994; Niosi, 2017). This is consistent with previous studies that consider new-to-firm as imitative innovation (Vinding, 2006; Arora *et al.* 2016).

Dependent variable

In terms of performance, previous theoretical work mainly distinguishes imitation from innovation through their ef- fect on productivity (Nelson and Phelps, 1966; Aghion and Howitt, 2006). Ideally, I would like to use total factor productivity as the dependent variable. However, PITEC does not record the quantities of inputs and outputs. Revenue-based total factor productivity would be a feasible alternative if the variable value-added sales were available. Given that PITEC provides firms' gross sales but not the costs of inputs, I turned to labor productivity, which correlates highly with total factor productivity. Therefore, the dependent variable is “labor productivity,” calculated as the logarithm of sales (in thousands of euros) per employee. This is a revenue-based productivity measure, and therefore can be interpreted as an efficiency measure.

One may argue that using labor productivity to represent total factor productivity is problematic when some industries and firms are more capital intensive than others. To lessen the concern, I used firm FE and control for capital intensity. In addition, I checked the robustness of the main analysis using two alternative measures: gross revenue-based total factor productivity and the difference between the focal and frontier firms’ labor productivity. Both yield results consistent with the main analysis.

Independent variables

The questionnaire asked respondents to break down a firm’s annual sales into three mutually exclusive categories: new-to-market, new-to-firm, and old products. Therefore, the data provide a direct measure of the proportion of sales of new-to-market and new-to-firm products introduced in the 2 years prior to the survey year. I use the term “new product sales” to refer to sales of either new-to-market or new-to-firm products. Among these, imitative sales are of new-to-firm products, and innovative sales are of new-to-market products.

The main independent variable compares the extent of imitation with that of innovation. The variable “share of imitative sales” refers to imitative sales as a share of total new product sales. This is the amount of sales of new-to-firm products divided by the sum of sales of new-to-market and new-to-firm products. The more a firm imitates, the higher this value. The variable enters the regression analysis with a 1-year lag.

Although all firms included in the analysis introduced at least one new product during the survey period, about 30% of the firm-year observations have missing values for the variable “share of imitative sales.” This is because not all firms make new product sales every year. When a firm makes no new product sales in a given year, the value of “share of imitative sales” is missing. I excluded observations with missing values from the regression analysis when using “share of imitative sales” as the independent variable. To confirm that discarding these observations does not bias the results, I used alternative measures as the second specification of the model. I replaced the variable “share of imitative sales” with two variables: “imitative sales” and “innovative sales.” The former is sales of new-to-firm products and the latter is sales of new-to-market products. Both variables are expressed in thousands of euros (with log transformation) and enter the regression equation with a 1-year lag.

Control variables

The production function framework states that labor productivity is determined by knowledge stock, physical stock, and other factors. However, both amounts of inputs and the outcomes of using these inputs affect labor productivity. Therefore, I used "intensity of R&D stock" and "new product sales" to capture knowledge stock; and "intensity of capital stock" and "new process" to approximate physical stock. Using the perpetual inventory method (PIM), I calculated R&D stock using yearly internal R&D expenditure with a constant depreciation rate of 20% (Jäger, 2017). I divided this figure by the number of employees to obtain the "intensity of R&D stock," expressed in logarithmic form. New product introduction has been used to represent firm knowledge (Griffith *et al.*, 2006). Therefore, I used "new product sales," defined as the sum of sales from new-to-firm and new-to-market products, to capture the outcomes of using R&D inputs. The variable "new product sales" is expressed in thousands of euros and with log transformation.

To capture the input dimension of the physical stock, I calculated capital stock based on yearly investment in tangible assets, using the PIM. Since PITEC does not distinguish between types of tangible assets, I used a constant depreciation rate of 13%, which is the average depreciation rate for tangible assets suggested by Jäger (2017).[6] Then I the intensity of capital stock by dividing the capital stock by the number of employees. I used the log of "intensity of capital stock" in the regression analysis. I also included "new process" (a binary) to indicate whether a firm intro- duces a new process in a given year. This variable aims to capture the outcomes of using the tangible assets.

Firm size and age are important determinants of productivity, so I controlled for both. The variable "age" is measured by the log of the number of years since the establishment of the firm. "Size" is measured by the log of the number of employees. I also included the quadratic terms of both variables, "age2" and "size2." Other control variables include

[6] Tangible assets include computing and communications equipment, transport, and other machinery, as well as total non-residential investment and residential structures.

whether a firm belongs to a group of companies (“group”) and whether a firm exports (“export”). Sectoral dummies are based on NACE codes, the statistical classification of economic activities in the European Community.[7]7 All control variables enter the regression equation with a 1-year lag. I present a summary of the variables and their correlation coefficients in Table A1.

Results

Descriptive statistics

Table 1 summarizes the number of firms and observations engaging in imitation and innovation. This shows that dividing firms into imitators or innovators overlooks the possibility that they could do both. Considering one firm as a unit, around 67% of firms both imitated and innovated between 2005 and 2013. Of the 5842 firms in the sample, 25% only imitated during the 9-year period. Pure innovators account for about 8%. After excluding 17,383 firm- year observations with no new product sales, 35,117 observations remain. Around 35% of these cover both imitation and innovation in a given year.

< Insert Table 1 about here>

Table 2 summarizes the mean values of firms’ labor productivity. I first ranked observations by labor productivity for firms in the same industry in the same year. I then divided them into quintiles by labor productivity. I further classified them into groups of imitators or innovators using a threshold of 0.5 for “share of imitative sales,” since a value of 0.5 implies that firms generate the same value of sales from imitative and innovative products.

The distribution of “share of imitative sales” shows a concentration of firms with the value 0.5. I take this as evidence that these firms consider imitation and innovation as equally important. In any case, no strong theoretical arguments are available to classify such firms as imitators or innovators. Therefore, I classified observations as imitation when the share of imitative sales is greater than 0.5 and innovation when the share of imitative sales is less than 0.5. Accordingly, 18,826 of the 35,117 observations concern imitators and 12,434 concern innovators. I excluded 3857 observations from Table 2, because they have equal shares of imitative and innovative sales.

[7] PITEC has provided two-digit NACE codes from NACE rev.2 since year 2008.

< Insert Table 2 about here>

Table 2, column 1, shows that when classifying all observations in the imitation or the innovation group (regard- less of their level of labor productivity), the equality of the mean values of labor productivity in the two groups can- not be rejected. When comparing the mean values of labor productivity by quintile, observations in the imitation group show higher labor productivity than those in the lower four quintiles of the innovation group. The difference is statistically significant. In the highest quintile, observations in the imitation group, on average, show lower labor productivity than those in the innovation group. However, the difference is not statistically significant. The results of the preliminary data analysis are consistent with my expectations.

Regression analysis

Table 3 presents the regression estimations for labor productivity, using “share of imitative sales” as the independent variable. The number of observations falls to 32,107, because 14,369 observations show no new product sales during the year. As shown in Table 3, Models (1) and (2) are pooled OLS regressions (OLS) and panel regressions with FE, respectively. Both of them estimate the effect for average firms. The coefficient of “share of imitative sales” is positive and significant in the OLS estimation; however, the coefficient in the FE estimation is not significant. This suggests that most of the differences in labor productivity due to “share of imitative sales” are between individual firms. When an average firm focuses on imitation rather than innovation, this does not affect its labor productivity. This further confirms the need to use quantile regression with firm FE to clarify whether focusing on imitation or innovation affects non-average firms differently.

< Insert Table 3 about here>

In Table 3, Model (3) shows the results of FE panel quantile regressions at selected quantiles. The estimated coefficient of “share of imitative sales” is positive and significant at the 10th quantile. At the 25th quantile, the coefficient is positive but not significant. At the 50th quantile, the coefficient becomes negative and remains non-significant. At the 75th and 90th quantiles, the coefficients of "share of imitative sales" are negative and significant. I interpret a negative coefficient of "share of imitative sales" as showing that the effect of imitation on productivity is smaller than that of innovation. This is because "share of imitative sales" is the ratio of imitative sales to total new product sales. The magnitudes of the coefficients (i.e. absolute value of the coefficients) are larger at the 10th and 90th quantiles, and smaller at the 25th, 50th, and 75th quantiles. The equality of the five coefficients, estimated at selected quantiles, is rejected at the conventional level of significance.

Overall, the results suggest that for firms further from the productivity frontier, imitation increases productivity more than innovation does. The more the firm imitates, the stronger the effect. The further the firm is from the frontier, the more beneficial any given level of imitation. For firms close to the frontier, imitation increases productivity less than innovation does. The more the firm imitates rather than innovates, the smaller the productivity effect. The closer the firm is to the frontier, the stronger the negative effect of focusing on imitation rather than innovation. The empirical evidence conforms my expectations.

Most of the control variables are significant. Their coefficients are consistent with the literature. The coefficients of "new product sales" are positive and significant in all three models. Whether due to imitation or innovation, new product sales relate positively to productivity. The coefficients of "new process" suggest that for firms in lower quantiles, investing in process innovation improves productivity. This positive effect diminishes as firms become more productive. In higher quantiles, the coefficients of process innovation are negative and not significant. This suggests that process innovation improves the productivity of laggards more than that of firms close to the frontier. The coefficients for "intensity of R&D stock" and "intensity of capital stock" are positive and significant across all quantiles.

< Insert Table 4 about here>

I present the results of the second specification (using imitative and innovative sales as the independent variables) in Table 4. The control variables are the same as in the previous estimation, except that I drop "new product sales," which is a linear combination of "imitative sales" and "innovative sales." The estimated coefficients of "imitative sales" and "innovative sales" in the OLS and FE models are positive and significant. For an average firm, the effects of imitation and innovation are similar. The equality between the coefficients of imitative and innovative sales cannot be rejected in either the OLS or the FE model.

The estimated coefficients of “imitative sales” in Model (6) are positive and significant, except at the 90th quantile. The equality of the five coefficients, estimated at the selected quantiles, is rejected at the conventional level of significance. The size of the coefficient falls as companies become more productive. When sales from imitative products increase by 1%, the 10th conditional quantile of productivity increases by 0.004%, other variables remaining constant. However, the same increase in imitative sales generates a 0.003% increase in the 25th conditional quantile and only a 0.002% increase in the conditional median of productivity. This suggests that imitation improves laggards’ productivity more than leaders. The further from the frontier, the stronger the effect of imitation, controlling for the extent of innovation.

The coefficients of “innovative sales” are significant at the 25th, 50th, 75th, and 90th quantiles. The positive effect increases as companies become more productive. The equality of the five coefficients, estimated at the selected quantiles, is rejected at the conventional level of significance. This suggests that innovation increases the productivity of less productive firms less strongly. For more productive firms, the productivity effect of innovation is stronger.

The differences between the estimated coefficients of “imitative sales” and “innovative sales” are statistically significant at the 10th, 25th, and 90th quantiles. The differences are only marginally significant at the 50th quantile and not significant at the 75th quantile. This suggests that for an average firm, the effects of imitation and innovation are similar. However, imitation and innovation enhance the productivity of firms at the lower or upper end of the productivity spectrum differently. When further from the frontier, imitation increases productivity more than innovation; when close to the frontier, innovation increases productivity more than imitation. Thus, the results in Tables 3 and 4 are consistent.

Robustness check

Due to data availability, the study uses sales per employee as a proxy of labor productivity, aiming to capture the concept of total factor productivity. The measurement is relatively crude. To ensure my results are robust, I used two alternative dependent variables. First, I replaced labor productivity (i.e. sales per employee) by a proxy of gross revenue-based total factor productivity, for both specifications of the main analysis. The proxy is the residual obtained by regressing (gross) sales on capital stock and the number of employees.

Except for replacing labor productivity by the proxy of gross revenue-based total factor productivity, the other variables remained the same as in the main analysis. Table 5, Panel A, presents the regression results with share of imitative sales as the independent variable. The coefficients of share of imitative sales are positive when estimating at the 10th and 25th quantiles. They become negative at the 75th and 90th quantiles. Except for the 50th quantile, the coefficients are significant. The estimated coefficients are larger at the 10th and 90th quantiles than at the 25th and 75th quantiles. The equality of the five coefficients, estimated at selected quantiles, is rejected at the conventional level of significance.

< Insert Table 5 about here>

Table 5, Panel B, shows the results with imitative and innovative sales as independent variables. Although the coefficients of imitative sales are similar for all firms, the coefficient of innovative sales increases with productivity. The equality of the five coefficients, estimated at the 10th, 25th, 50th, 75th, and 90th quantiles, is rejected at the conventional level of significance. The productivity effect of innovation increases as companies become more productive. Innovation is more important than imitation for firms close to the frontier. Overall, the evidence from this robustness check is consistent with the main analysis.

In the second set of robustness checks, I replaced labor productivity by the variable "closeness," which is the ratio between the focal firm's labor productivity and that of the frontier firm. The variable "closeness" ranges between zero and one. The larger the value, the closer a firm is to the frontier. I transformed the measure of relative labor productivity using the logit function to exclude frontier firms. This slightly reduces the number of observations. The regression equations and control variables are the same as in the main analysis.

As shown in Table 6, Panel A, the coefficients of share of imitative sales follow the expected pattern. The estimated coefficients are positive for the lower quantiles and negative for the upper quantiles. I interpret a positive coef- ficient as showing that imitation moves firms closer to the frontier than innovation does. The effect is larger at the 10th and 90th quantiles than at the 25th, 50th, and 75th quantiles. Table 6, Panel B, presents the results using imitative and innovative sales as independent variables. The effect of imitation falls and that of innovation increases as productivity increases. The results of the second set of robustness check are also consistent with the main analysis.

< Insert Table 6 about here>

Search costs as the mechanism

I argue that search costs drive the association between imitation, innovation, and productivity. If this is the case, then choosing between imitation and innovation is more critical for firms with high search costs, and that the differences between how imitation and innovation enhance productivity would intensify. When firms have low search costs, the choice is less important. The effect of imitation and innovation on productivity would be similar. That is to say, if we divide the sample into two groups according to their search costs, the productivity effect of imitation and innovation would vary for the subsample of firms with high search costs, depending on these firms' ranking in the conditional productivity distribution. For the subsample of firms with low search costs, the variation would weaken or even disappear.

One way to test the mechanism is to leverage firm location. I consider that firms located in a cluster are likely to find imitation easier, because many potential targets are at hand. Holding other variables constant, when focal firms invest a similar amount of resources to find a target in a geographic area, their chance of finding a target to imitate is higher when the density of firms in that area is higher.[8] Therefore, I argue that firms located in a cluster have lower search costs, due to the concentration of firms within a geographic area.

Firms located inside the science park are often considered as a cluster of firms. PITEC has information on whether a firm is located in a science park. Firms in certain industries are more likely to be located in a science park than firms in other industries. Of the 44 industries, 10 have no firms located in a science park. Therefore, I excluded firms in these 10 industries. Using the reduced sample, I divided firms into two subsamples, according to whether or not they are located in a science park.[9] Then, I ran

[8] What matters is the density rather than the number of firms. Search costs are not necessarily lower when a larger number of firms are distributed more widely.

[9] Data on whether firms are located in a science park are available from 2007. I assume that the variable on- or off-park is stable from 2006 to 2007. The subsample division is based on the lagged variable of the location, as some firms move to or from a science park between 2007 and 2013.

the FE panel quantile regression for each subsample, with the same set of control variables as in the main analysis.

< Insert Table 7 about here>

Table 7 compares the results of the subsample of firms located in a science park (on-park firms) and outside a science park (off-park firms).[10] The number of observations of on-park firms is 1888. As expected, the coefficients of “share of imitative sales” are not significant in all five estimated quantiles, due to low search costs. The regression results for the 27,943 observations of off-park firms are consistent with expectations. Due to high search costs, the effect of imitation and innovation on productivity varies along the distribution. The coefficients of “share of imitative sales” change signs from positive to negative as firms become more productive. They are negative and significant at the 75th and 90th quantiles. For firms closer to the frontier, innovation has a larger effect on productivity than imitation.

Although the results of the subsample analysis are consistent with the idea that search costs are the mechanism, the analysis is not without limitations. Studies have discussed the issue of firms self-selecting to enter science parks, for example in Spain (Montoro-Sánchez et al., 2011; Vásquez-Urriago et al., 2014; Vásquez-Urriago et al., 2016). This raises the concern that on-park firms tend to be more innovative and productive than off-park firms. In other words, off-park firms are likely to be more imitative and less productive. If off-park firms are mainly laggards, the inclusion of mostly imitative, unproductive firms in the off-park subsample would bias the results against my expectation. Nevertheless, the estimated coefficients are still significant and of the expected sign.

Conclusion

This study investigates the dynamics underlying the notion that “laggards imitate and leaders innovate.” The empirical evidence demonstrates that both imitation and innovation contribute to productivity, but that their effects vary. Quantile regression analyses show that, as firms become more productive, the effect of imitation on productivity decreases while the effect of innovation increases. Consequently, for

[10] The complete regression results are not presented in the article but available upon request.

laggards, imitation improves productivity more than innovation does. For leaders, innovation enhances productivity more than imitation. These variations in the relative effectiveness of imitation and innovation explain why laggards tend to imitate, and leaders innovate. I also argue theoretically, and provide empirical evidence, that search costs are the mechanism explaining variations in the relative importance of imitation and innovation.

The study goes beyond measuring average effect, using the technique of quantile regression, which offers a more complete picture of how the effect of imitation and innovation on productivity varies along the productivity distribution. Unlike most previous studies, which either imply that *not innovating* means *imitating* or assume a linear relationship between the effect of imitation and innovation, I measure and test the effect of imitation on labor productivity without such assumptions. In addition, providing empirical evidence from a large number of firms helps fill the gap between the rich theoretical discussion of the relationship between imitation, innovation, and productivity, and limited empiricism on the topic.

Despite these contributions to the literature, the study has its limitation. The distinction between imitation and in- novation is fuzzy and lacks consensus (Niosi, 2017). I consider imitation as new-to-firm and innovation as new-to- market, emphasizing their differences in terms of degree of novelty and existence of a target. I assume that firms need to identify a target to imitate before they develop new-to-firm products. This assumption does not necessarily hold in all situations. For example, it is possible for two firms to conduct independent R&D and obtain similar results. According to my operationalization, the firm launching the product first is the innovator and the other is the imitator. In this particular case, my empirical operationalization is inadequate, because it fails to capture situations when firms introduce new-to-firm products without first identifying a target. That is, using new-to-firm and new-to- market to approximate imitation and innovation does not capture the full complexity of innovation and imitation strategies. This needs to be borne in mind when interpreting the results.

Although it identifies the different effects of imitation and innovation on productivity, this study does not suggest the causality between imitation, innovation, and productivity. My goal is to explain the notion that laggards imitate and leaders innovate, rather than searching for causality. Moreover, using a firm's location inside or outside a science park to test the proposed mechanism—search costs—is not ideal.

On-park firms are likely to differ from off-park firms in additional ways. It is also possible that firms self-select into the science park, so I do not clearly identify the causality between location and productivity. This provides opportunities for further research to test the proposed mechanism.

Both imitation and innovation can occur in various business activities, such as product introduction, process improvement, organizational structure, and marketing approaches (OECD and Eurostat, 2005; Lieberman and Asaba, 2006). This study focuses on the effects of imitation and innovation on productivity in terms of launching new products. It ignores other potential effects of other forms of imitation and innovation, such as developing new processes or managerial practices.

Due to its use of data from a single country, my study cannot explore how economic, social, and cultural conditions influence the association between imitation, innovation, and productivity. For example, the strength of the appropriability regime matters. When firms can protect their intellectual property effectively, they are more likely to benefit from innovation, all else being equal. Income distribution is another factor to explore. When a country has mostly low-income consumers, an inexpensive imitative product with limited features is more likely to appeal to them than an expensive innovative product with the latest features. Meanwhile, from a cultural perspective, imitation has negative connotations in some societies. Thus, the reputation of imitative firms is likely to suffer.

The long-term effects of imitation may influence its benefits for laggards. Focusing on "low-hanging fruit" might prevent laggards from moving toward the frontier. However, laggards may learn from their imitation. It would be interesting to explore whether imitation enables laggards to innovate in the future, or whether it confines them to imitation. Further analysis of how the characteristics and type of imitation affect the move from imitation to innovation would also be interesting (Liao, 2017).

This study has several implications for public policy. It might be appropriate to promote imitation as well as innovation. Imitation is less complex than innovation and can be considered as a low-hanging fruit. Previous studies show that firms lagging behind the frontier often use a strategy of imitation (Kim, 2001; Lee and Lim, 2001; Kim *et al.*, 2004; Kale and Little, 2007; Ouyang, 2010). Indigenous firms often source knowledge from advanced foreign multinational firms to improve their productivity (Alfaro and Chen, 2018). Laggards are often at a disadvantage in the innovation process, especially due to their limited financial resources and lack of qualified personnel. Imitation could enable laggards to improve their productivity more economically—in terms of time and resources—and, per- haps, to prepare for innovation in the future.

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References

Acemoglu, D., P. Aghion and F. Zilibotti (2006), ‘Distance to frontier, selection, and economic growth,’ *Journal of European Economic Association*, 4(1), 37–74.

Agénor, P. R. and H. T. Dinh (2013), ‘Public policy and industrial transformation in the process of development’, *Policy Research Paper 6405*, World Bank: Washington, DC.

Aghion, P., C. Harris, P. Howitt and J. Vickers (2001), ‘Competition, imitation and growth with step-by-step innovation,’ *The Review of Economic Studies*, ł8(3), 467–492.

Aghion, P. and P. Howitt (2006), ‘Joseph Schumpeter lecture appropriate growth policy: a unifying framework,’ *Journal of the European Economic Association*, 4(2–3), 269–314.

Alfaro, L. and M. X. Chen (2018), ‘Selection and market reallocation: productivity gains from multinational production,’ *American Economic Journal: Economic Policy*, 10(2), 1–38.

Amable, B., L. Demmou and I. Ledezma (2010), ‘Product market regulation, innovation, and distance to frontier,’ *Industrial and Corporate Change*, 19(1), 117–159.

Arora, A., W. M. Cohen and J. P. Walsh (2016), ‘The acquisition and commercialization of invention in American manufacturing: in- cidence and impact,’ *Research Policy*, 45(6), 1113–1128.

Arvanitis, S. and F. Seliger (2014), ‘Imitation versus innovation: what makes the difference?,’ KOF Working Papers 367, KOF Swiss Economic Institute: Zurich.

Bartelsman, E., S. Dobbelaere and B. Peters (2015), ‘Allocation of human capital and innovation at the frontier: firm-level evidence on Germany and the Netherlands,’ *Industrial and Corporate Change*, 24(5), 875–949.

Becker, S. W. and T. L. Whisler (1967), ‘The innovative organization: a selective view of current theory and research,’ *The Journal of Business*, 40(4), 462–469.

Benhabib, J., J. Perla and C. Tonetti (2014), ‘Catch-up and fall-back through innovation and imitation,’ *Journal of Economic Growth*, 19(1), 1–35.

Bianchini, S., G. Pellegrino and F. Tamagni (2014), ‘Innovation strategies and firm growth: new longitudinal evidence from Spanish firms,’ Technical report. Laboratory of Economics and Management (LEM), Sant’Anna School of Advanced Studies: Pisa, Italy.

Biggart, N. W. and M. F. Guillén (1999), ‘Developing difference: social organization and the rise of the auto industries of South Korea, Taiwan, Spain, and Argentina,’ *American Sociological Review*, ł4(5), 722–747.

Blumenthal, T. (1976), ‘Japan’s technology strategy,’ *Journal of Development*, 3, 245–255.

Canay, I. A. (2011), ‘A simple approach to quantile regression for panel data,’ *The Econometrics Journal*, 14(3), 368–386.

Cappelli, R., D. Czarnitzki and K. Kraft (2014), ‘Sources of spillovers for imitation and innovation,’ *Research Policy*, 43(1), 115–120.

Chang, S., H. Kim, J. Songand K. Lee (2015), ‘Imitation to innovation: late movers’ catch-up strategy and technological leadership change,’ *Columbia Business School Research Paper 15–51*. Columbia Business School: New York, NY.

Coad, A. (2011), ‘Appropriate business strategy for leaders and laggards,’ *Industrial and Corporate Change*, 20(4), 1049–1079.

Coad, A. and R. Rao (2008),‘Innovation and firm growth in high-tech sectors: a quantile regression approach,’ *Research Policy*, 37(4), 633–648.

Coad, A., A. Segarra and M. Teruel (2016), ‘Innovation and firm growth: does firm age play a role?,’ *Research Policy*, 45(2), 387–400.

Crépon, B., E. Duguet and J. Mairesse (1998), ‘Research, innovation and productivity: an econometric analysis at the firm level,’ *Economics of Innovation and New Technology*, 7(2), 115–158.

Fast Company (2017), ‘Most Innovative Companies 2017,’ https://www.fastcompany.com/most-innovative-companies/2017.

Gerschenkron, A. (1962), *Economic Backwardness in Historical Perspective: A Book of Essays*. Harvard University Press: Cambridge, MA.

Griffith, R., E. Huergo, J. Mairesse and B. Peters (2006), 'Innovation and productivity across four European countries,' *Oxford Review of Economic Policy*, 22(4), 483–498.

Griliches, Z. (1986), 'Productivity, R&D, and basic research at the firm level in the 1970's,' *American Economic Review*, 76(1), 141–154.

Guo, L., M. Y. Zhang, M. Dodgson and C. Hong (2015), 'Has Huawei achieved catch-up with forerunners? Overall vs. core techno- logical capability,' *Academy of Management Proceedings*, 2015(1), 14201.

Hall, B. H. and J. Mairesse (1995), 'Exploring the relationship between R&D and productivity in French manufacturing firms,' *Journal of Econometrics*, ł5(1), 263–293.

Hall, B. H., F. Lotti and J. Mairesse (2009), 'Innovation and productivity in SMEs: empirical evidence for Italy,' *Small Business Economics*, 33(1), 13–33.

Hobday, M. (1995), 'East Asian latecomer firms: learning the technology of electronics,' World Development, 23(7), 1171–1193.

Jäger, K. (2017), 'EU KLEMS Growth and Productivity Accounts 2017 Release, Statistical Module: Description of Methodology and General Notes,' http://www.euklems.net/.

Kale, D. and S. Little (2007), 'From imitation to innovation: the evolution of R&D capabilities and learning processes in the Indian pharmaceutical industry,' *Technology Analysis & Strategic Management*, 19(5), 589–609.

Kim, L. (1997), 'The dynamics of Samsung's technological learning in semiconductors,' *California Management Review*, 39(3), 86–100.

Kim, L. (2001), 'The dynamics of technological learning in industrialisation,' *International Social Science Journal*, 53(168), 297–308. Kim, W., Y. Shi and M. Gregory (2004), 'Transition from imitation to innovation: lessons from a Korean multinational corporation,'*International Journal of Business*, 9(4), 329–346.

Kleinknecht, A., K. Van Montfort and E. Brouwer (2002), 'The non-trivial choice between innovation indicators,' *Economics of Innovation and New Technology*, 11(2), 109–121.

Knight, K. E. (1967), 'A descriptive model of the intra-firm innovation process,' *The Journal of Business*, 40(4), 478–496.

Köhler, C., W. Sofka and C. Grimpe (2012), 'Selective search, sectoral patterns, and the impact on product innovation performance,' *Research Policy*, 41(8), 1344–1356.

König, M. D., J. Lorenz and F. Zilibotti (2016), 'Innovation vs. imitation and the evolution of productivity distributions,' *Theoretical Economics*, 11(3), 1053–1102.

Laursen, K. and A. Salter (2006), 'Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms,' *Strategic Management Journal*, 27(2), 131–150.

Lee, K. and C. Lim (2001), 'Technological regimes, catching-up and leapfrogging: findings from the Korean industries,' *Research Policy*, 30(3), 459–483.

Liao, C. T. (2017), 'Product imitation and skill upgrading: firm level evidence from developing countries,' *Academy of Management Proceedings*, 2017(1), 11050.

Lieberman, M. and S. Asaba (2006), 'Why do firms imitate each other?,' *Academy of Management Review*, 31(2), 366–385.

Madsen, J. B., M. R. Islam and J. B. Ang (2010), 'Catching up to the technology frontier: the dichotomy between innovation and imitation,' *Canadian Journal of Economics*, 43(4), 1389–1411.

Mahmood, I. P. and C. Rufin (2005), 'Government's dilemma: the role of government in imitation and innovation,' *Academy of Management Review*, 30(2), 338–360.

Mansfield, E. (1963), 'Size of firm, market structure, and innovation,' *Journal of Political Economy*, 71(6), 556–576.

MIT Technology Review (2015), '50 Smartest Companies 2015,' https://www.technologyreview.com/lists/companies/2015/#xiaomi.

Montoro-Sánchez, A., M. Ortiz-de-Urbina-Criado and E. M. Mora-Valent´ın (2011), 'Effects of knowledge spillovers on innovation and collaboration in science and technology parks,' *Journal of Knowledge Management*, 15(6), 948–970.

Montresor, S. and A. Vezzani (2015), 'The production function of top R&D investors: accounting for size and sector heterogeneity with quantile estimations,' *Research Policy*, 44(2), 381–393.

Nelson, R. R. and E. S. Phelps (1966), 'Investment in humans, technological diffusion, and economic growth,' *The American Economic Review*, 56(1/2), 69–75.

Nicoletti, G. and S. Scarpetta (2003), 'Regulation, productivity and growth: OECD evidence,' *Economic Policy*, 18(36), 9–72.

Niosi, J. (2017), 'Imitation and innovation new biologics, biosimilars and biobetters,' *Technology Analysis and Strategic Management*, 29(3), 251–262.

OECD and Eurostat (2005), *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data*. OECD: Paris. Ouyang, H. S. (2010), 'Imitator-to-innovator S curve and chasms,' *Thunderbird International Business Review*, 52(1), 31–44.

Parisi, M. L., F. Schiantarelli and A. Sembenelli (2006), 'Productivity, innovation and R&D: micro evidence for Italy,' *European Economic Review*, 50(8), 2037–2061.

Pierce, J. L. and A. L. Delbecq (1977), 'Organization structure, individual attitudes and innovation,' *Academy of Management Review*, 2(1), 27–37.

Raustiala, K. and C. J. Sprigaman (2012), *The Knockoff Economy*. Oxford University Press: Oxford, UK.

Santi, C. and P. Santoleri (2017), 'Exploring the link between innovation and growth in Chilean firms,' *Small Business Economics*, 49(2), 445–467.

Schnaars, P. S. (1994), *Managing Imitation Strategies: How Later Entrants Seize Markets from Pioneers*. The Free Press: New York, NY.

Teece, D. J. (1986), 'Profiting from technological innovation: implications for integration, collaboration, licensing and public policy,' *Research Policy*, 15(6), 285–305.

The Economist (2016), 'China's Mobile Internet: WeChat's World,' https://www.economist.com/news/business/21703428-chinas-wechat-shows-way-social-medias-future-wechats-world.

Triguero, A., L. Moreno-Monde´jar and M. A. Davia (2016), 'Leaders and laggards in environmental innovation: an empirical analysis of SMEs in Europe,' *Business Strategy and the Environment*, 25(1), 28–39.

Vandenbussche, J., P. Aghion and C. Meghir (2006), 'Growth, distance to frontier and composition of human capital,' *Journal of Economic Growth*, 11(2), 97–127

Vásquez-Urriago, Á. R., A. Barge-Gil and A. M. Rico (2016), 'Science and technology parks and cooperation for innovation: empiric- al evidence from Spain,' *Research Policy*, 45(1), 137–147.

Vásquez-Urriago, Á. R., A. Barge-Gil, A. M. Rico and E. Paraskevopoulou (2014), 'The impact of science and technology parks on firms' product innovation: empirical evidence from Spain,' *Journal of Evolutionary Economics*, 24(4), 835–873.

Vega-Jurado, J., A. Gutiérrez-Gracia, I. Fernández-de-Lucio and L. Manjarrés-Henríquez (2008), 'The effect of external and internal factors on firms' product innovation,' *Research Policy*, 37(4), 616–632.

Vinding, A. L. (2006), ‘Absorptive capacity and innovative performance: a human capital approach,’ *Economics of Innovation and New Technology*, 15(4–5), 507–517.

Yasar, M., C. H. Nelson and R. Rejesus (2006), ‘Productivity and exporting status of manufacturing firms: evidence from quantile regressions,’ *Review of World Economics*, 142(4), 675–694.

Zhang, L. and K. M. Park (2014), ‘What are good R&D investment strategies for leaders and followers?,’ *Technology Analysis and Strategic Management*, 26(8), 909–925.

Tables

Table 1. Firms engaging in imitation and innovation

	Imitation only[a]	%	Imitation and innovation[b]	%	Innovation only[c]	%	Total
Number of firms	1455[d]	25	3930	67	457	8	5842
Number of firm-year observations	14,572	41	12,119	35	8426	24	35,117[e]

[a]"Imitation only" refers to the situation in which all new product sales are from new-to-firm products.

[b]"Imitation and innovation" refers to the situation in which new products sales come from both new-to-firm and new-to-market products.

[c]"Innovation only" refers to the situation in which all new products sales are from new-to-market products.

[d]There are 1455 firms with only new-to-firm sales and no new-to-market sales during the entire survey period from 2005 to 2013.

[e]Among the total 52,500 firm-year observations, there are 17,383 firm-year observations without any new product sales.

Table 2. Mean values of firms' labor productivity

Observation type[a]	Overall	Quintiles by labor productivity[b]				
		Lowest	Second	Middle	Fourth	Highest
Imitation	243,724	68,708	111,131	159,391	232,894	627,734
Innovation	239,141	59,525	100,913	144,504	216,980	648,642
Difference[c]	4583	9183*	10,219*	14,886*	15,914*	−20,909

[a]This table dichotomizes observations into imitation or innovation, using the threshold of share of imitative sales equal to 0.5. An observation is included in the imitation group when the share of imitative sales is greater than 0.5. When the share is less than 0.5, the observation is classified as innovation. Observations with a share of imitative sales equal to 0.5 are excluded.

[b]Observations are ranked by labor productivity within the group of the same industry and year. Then they are divided into quintiles.

[c]The equality of mean labor productivity is tested using *t*-tests. Except for the overall sample and the highest quintiles, the equality of means is rejected at *P*-value = 0.000.

*$P < 0.001$.

Table 3. Estimations for labor productivity using share of imitative shares

Dependent variable: labor productivity (in log form)							
Model	(1)	(2)	(3) Panel quantile regression (fixed effects)				
	OLS	FE	q10	q25	q50	q75	q90
Independent variables							
Share of imitative sales	0.023*	−0.004	0.015*	0.007	−0.001	−0.011**	−0.020**
	(0.009)[a]	(0.009)[a]	(0.007)[b]	(0.004)	(0.002)	(0.004)	(0.006)
New product sales	0.141***	0.021***	0.016***	0.017***	0.018***	0.020***	0.025***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
New process	−0.039***	0.012	0.031***	0.015***	0.010***	0.003	−0.004
	(0.009)	(0.008)	(0.007)	(0.003)	(0.002)	(0.004)	(0.006)
Intensity of R&D stock	0.006***	0.018	0.011***	0.014***	0.018***	0.021***	0.024***
	(0.002)	(0.009)	(0.001)	0.000	0.000	0.000	(0.001)
Intensity of capital stock	0.061***	0.009	0.001	0.006***	0.009***	0.012***	0.016***
	(0.002)	(0.006)	(0.001)	(0.001)	0.000	(0.001)	(0.001)
Age	0.335***	1.107	1.365***	1.210***	1.101***	1.014***	0.860***
	(0.063)	(0.568)	(0.045)	(0.024)	(0.013)	(0.023)	(0.052)
Age2	−0.034***	−0.229	−0.262***	−0.242***	−0.227***	−0.217***	−0.197***
	(0.009)	(0.138)	(0.006)	(0.003)	(0.002)	(0.003)	(0.008)
Export	0.140***	0.015	0.020***	0.013***	0.013***	0.005	−0.008
	(0.009)	(0.008)	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)
Group	0.317***	0.03	0.001	0.020***	0.027***	0.038***	0.045***
	(0.009)	(0.016)	(0.007)	(0.003)	(0.002)	(0.003)	(0.006)
Size	−0.025	−0.074	0.067***	−0.013*	−0.070***	−0.122***	−0.213***
	(0.014)	(0.064)	(0.012)	(0.006)	(0.003)	(0.006)	(0.011)
Size2	−0.010***	−0.004	−0.016***	−0.009***	−0.004***	0.001	0.009***
	(0.001)	(0.007)	(0.001)	(0.001)	0.000	(0.001)	(0.001)
Constant	2.601***	3.770***	2.822***	3.381***	3.781***	4.142***	4.728***
	(0.126)	(0.446)	(0.077)	(0.041)	(0.022)	(0.040)	(0.088)
Year effects	Yes	Yes			Yes		
Industry effects	Yes	No			No		
R-squared[c]	0.469	0.895	0.418	0.440	0.430	0.386	0.334
N	32,107	32,107			32,107		

Standard errors are within parentheses.

[a]Robust standard errors are estimated for OLS and FE.

[b]Standard errors for panel quantile regression are obtained using 1000 bootstrap replications.

[c]*R*-squared reported for FE model is the adjusted *r*-squared and for the model of panel quantile regression is the pseudo *r*-squared.

*$P < 0.05$.

**$P < 0.01$.

***$P < 0.001$.

Table 4. Estimations for labor productivity using imitative and innovative sales

Dependent variable: labor productivity (in log form)							
Model	(4)	(5)	(6) Panel quantile regression (fixed effects)				
	OLS	FE	q10	q25	q50	q75	q90
Independent variables							
Imitative sales	0.017***	0.003***	0.004***	0.003***	0.002***	0.002***	0.001
	(0.001)[a]	(0.001)[a]	(0.001)[b]	(0.000)	(0.000)	(0.000)	(0.001)
Innovative sales	0.015***	0.002**	0.001	0.001**	0.001***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
New process	−0.039***	0.005	0.029***	0.015***	0.006*	−0.004	−0.01
	(0.008)	(0.006)	(0.006)	(0.003)	(0.002)	(0.003)	(0.005)
Intensity of R&D stock	0.009***	0.021**	0.017***	0.020***	0.022***	0.023***	0.025***
	(0.001)	(0.007)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Intensity of capital stock	0.067***	0.017**	0.011***	0.015***	0.017***	0.019***	0.022***
	(0.002)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.121*	1.014**	1.236***	1.112***	1.013***	0.892***	0.792***
	(0.056)	(0.322)	(0.048)	(0.021)	(0.019)	(0.027)	(0.039)
Age2	−0.005	−0.208**	−0.235***	−0.220***	−0.207***	−0.192***	−0.180***
	(0.008)	(0.079)	(0.007)	(0.003)	(0.003)	(0.004)	(0.006)
Export	0.176***	0.018*	0.029***	0.017***	0.013***	0.009**	−0.010*
	(0.008)	(0.007)	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
Group	0.367***	0.02	−0.021***	0.005	0.018***	0.031***	0.057***
	(0.009)	(0.014)	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)
Size	0.119***	0.051	0.217***	0.117***	0.050***	−0.012*	−0.115***
	(0.012)	(0.048)	(0.011)	(0.006)	(0.004)	(0.006)	(0.010)
Size2	−0.014***	−0.014**	−0.029***	−0.019***	−0.013***	−0.008***	0.001
	(0.001)	(0.005)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Constant	3.199***	3.525***	2.469***	3.050***	3.508***	4.029***	4.622***
	(0.108)	(0.293)	(0.081)	(0.037)	(0.034)	(0.045)	(0.064)
Year effects	Yes	Yes			Yes		
Industry effects	Yes	No			No		
R-squared[c]	0.395	0.857	0.340	0.360	0.349	0.310	0.266
N	46,476	46,476			46,476		

Standard errors are within parentheses.

[a]Robust standard errors are estimated for OLS and FE.

[b]Standard errors for panel quantile regression are obtained using 1000 bootstrap replications.

[c]*R*-squared reported for FE model is the adjusted *r*-squared and for the model of panel quantile regression is the pseudo *r*-squared.

*$P < 0.05$.

**$P < 0.01$.

***$P < 0.001$.

Table 5. Estimations for gross revenue-based total factor productivity (in log form)

Panel A							
Model	(7)	(8)	(9) Panel quantile regression (fixed effects)				
	OLS	FE	q10	q25	q50	q75	q90
Share of imitative sales	0.008	−0.001	0.009*	0.004*	0.000	−0.005*	−0.008*
	(0.006)[a]	(0.005)[a]	(0.004)[b]	(0.002)	(0.001)	(0.002)	(0.003)
R-squared[c]	0.257	0.856	0.404	0.432	0.418	0.352	0.271
N	32,107	32,107			32,107		

Panel B							
Model	(10)	(11)	(12) Panel quantile regression (fixed effects)				
	OLS	FE	q10	q25	q50	q75	q90
Imitative sales	0.008***	0.001**	0.001**	0.001***	0.001***	0.001***	0.001***
	(0.001)[a]	(0.000)[a]	(0.000)[b]	(0.000)	(0.000)	(0.000)	(0.000)
Innovative sales	0.008***	0.001*	0.000	0.000	0.001***	0.001***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared[c]	0.185	0.852	0.404	0.419	0.393	0.320	0.233
N	46,476	46,476			46,476		

Standard errors are within parentheses. The entire set of control variables, as in the main analysis, is included in all estimations but not reported in detail.

[a]Robust standard errors are estimated for OLS and FE.

[b]Standard errors for panel quantile regression are obtained using 1000 bootstrap replications.

[c]R-squared reported for FE model is the adjusted r-squared and for the model of panel quantile regression is the pseudo r-squared.

*$P < 0.05$.

**$P < 0.01$.

***$P < 0.001$.

Table 6. Estimations for closeness to the frontier

Panel A							
Model	(13)	(14)	(15) Panel quantile regression (fixed effects)				
	OLS	FE	q10	q25	q50	q75	q90
Share of imitative sales	0.029*	0.000	0.043*	0.021*	−0.014	−0.030**	−0.037**
	(0.014)[a]	(0.020)[a]	(0.018)[b]	(0.010)	(0.008)	(0.010)	(0.013)
R-squared[c]	0.520	0.707	0.412	0.461	0.503	0.505	0.485
N[d]	31,922	31,922			31,922		

Panel B							
Model	(16)	(17)	(18) Panel quantile regression (fixed effects)				
	OLS	FE	q10	q25	q50	q75	q90
Imitative sales	0.021***	0.007***	0.008***	0.006***	0.005***	0.005***	0.004***
	(0.001)[a]	(0.002)[a]	(0.001)[b]	(0.001)	(0.001)	(0.001)	(0.001)
Innovative sales	0.018***	0.005**	0.003	0.002	0.004***	0.005***	0.007***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
R-squared[c]	0.482	0.697	0.331	0.367	0.409	0.418	0.396
N[e]	46,199	46,199			46,199		

Standard errors are within parentheses. The entire set of control variables, as in the main analysis, is included in all estimations but not reported in detail.

[a]Robust standard errors are estimated for OLS and FE.

[b]Standard errors for panel quantile regression are obtained using 1000 bootstrap replications.

[c]*R*-squared reported for FE model is the adjusted *r*-squared and for the model of panel quantile regression is the pseudo *r*-squared.

[d]The number of observations is reduced from 32,107 to 31,922, due to the exclusion of the frontier firms.

[e]The number of observations is reduced from 46,476 to 46,199, due to the exclusion of the frontier firms.

*$P < 0.05$.

**$P < 0.01$.

***$P < 0.001$.

Table 7. Summary of regression estimations of labor productivity by firm location

Dependent variable: labor productivity (in log form)					
	Panel quantile regression (fixed effects)				
	q10	q25	q50	q75	q90
Independent variable[a]: share of imitative sales					
On-park firms (N = 1888)[c]	0.028	0.016	0.003	0.003	0.012
	(0.041)[b]	(0.019)	(0.012)	(0.022)	(0.038)
Off-park firms (N = 27,943)[c]	0.011	0.006	−0.001	−0.012**	−0.016*
	(0.008)[b]	(0.004)	(0.003)	(0.004)	(0.007)

Standard errors are within parentheses.

[a]This table presents only the estimated coefficients of share of imitative sales. The entire set of control variables and year dummies are included as the main analysis, but not reported in detail.

[b]Standard errors for panel quantile regression are obtained using 1000 bootstrap replications.

[c]Due to excluding industries without any firms located in the science park, the total number of firms reduces from 32,107 to 29,831.

*$P < 0.05$.

**$P < 0.01$.

***$P < 0.001$.

Appendix

Table A1. Descriptive statistics and correlation coefficients

	Variable	Mean	Std. dev.	Min	Max	Pairwise correlation												
						1	2	3	4	5	6	7	8	9	10	11	12	13
1	Labor productivity$_t$ (€, 000, log)	4.94	0.94	0.02	11.76													
2	Share of imitative sales$_{t-1}$	0.59	0.41	0.00	1.00	0.04												
3	New product sales$_{t-1}$ (€, 000, log)	5.09	3.93	0.00	16.03	0.25	−0.01											
4	Imitative sales$_{t-1}$ (€, 000, log)	3.74	3.93	0.00	15.72	0.20	0.69	0.76										
5	Innovative sales$_{t-1}$ (€, 000, log)	2.87	3.77	0.00	15.91	0.14	−0.76	0.62	0.17									
6	New process$_{t-1}$	0.61	0.49	0.00	1.00	0.11	0.00	0.30	0.24	0.20								
7	Intensity of R&D stock$_{t-1}$ (€, log)	8.33	3.37	0.00	15.60	−0.01	−0.15	0.16	0.08	0.19	0.08							
8	Intensity of capital stock$_{t-1}$ (€, log)	10.05	2.12	0.00	18.67	0.25	−0.02	0.10	0.07	0.08	0.16	0.12						
9	Age$_{t-1}$ (no. of years)	3.24	0.56	0.00	5.75	0.23	0.05	0.15	0.14	0.08	0.08	−0.14	0.04					
10	Age2$_{t-1}$ (age-squared)	10.83	3.73	0.00	33.09	0.23	0.05	0.15	0.14	0.08	0.08	−0.13	0.05	0.99				
11	Export$_{t-1}$	0.48	0.50	0.00	1.00	0.25	0.00	0.21	0.17	0.15	0.09	0.12	0.08	0.21	0.21			
12	Group$_{t-1}$	0.39	0.49	0.00	1.00	0.30	0.01	0.21	0.18	0.14	0.10	−0.08	0.11	0.13	0.14	0.11		
13	Size$_{t-1}$ (no. of employees)	4.06	1.53	0.69	10.63	0.24	0.03	0.33	0.28	0.22	0.20	−0.27	0.07	0.39	0.39	0.16	0.49	
14	Size2$_{t-1}$ (size-squared)	18.83	14.07	0.48	113.08	0.21	0.02	0.31	0.26	0.22	0.17	−0.26	0.07	0.35	0.36	0.12	0.48	0.97

Except for the variable "share of imitative sales," with 32,107 observations, all other variables have 46,476 observations.