Digital transformation and innovation activities: evidence from Spanish firms

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Abstract.
We analyse the relationship between the digital transformation of Spanish manufacturing firms and their innovation activity. We construct a synthetic index of digitalization at the firm level that considers the multi-faceted phenomenon of the digital transformation, and explore the role of digitalization for firm performance in terms of innovation strategies, distinguishing between technological (new products/services and new processes of production) and non-technological (organizational and marketing innovations) outcomes. We use data of Spanish manufacturing firms from the Survey on Business Strategies (ESEE), for the period 2001 to 2017. Our empirical approach is based on the estimation of a knowledge production function in which we explicitly account for the impact of firms' digitalization. We estimate a quadrivariate *probit* model that allows to jointly analyse firms' decisions to implement product, process, organizational and marketing innovations, controlling for unobserved firms' heterogeneity. Our findings show that, aside from product innovation, digitalization is a significant enabler of firms' innovations, particularly in the case of SMEs, and even in the case of non-R&D performers.

Keywords: Digitalization, manufacturing firms, product innovation, process innovation, organizational innovation, marketing innovation, quadrivariate *probit*.

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1. Introduction.

The digitalization of the economy and society is becoming a global reality. Having slowly gathered momentum over the last few decades, the process of digitalization has accelerated rapidly in recent years, though the progress in this transformation varies greatly across firms.

In general, digital technologies are supposed to have disruptive effects on the reorganization of production processes and the functioning of markets, and their effects are spreading across the entire economy and society (Brynjolfsson and McAfee, 2012; Kenney et al., 2015). The use of digital technologies allows firms to source inputs more efficiently, facilitates the development of new products, and leads to changes in management and organizational practices (Añón Higón, 2012; Brynjolfsson and Hitt, 2000). In addition, digitalization has transformed producer-customer relationships, improving customer experiences and multiplying customer feedback on product and processes (Fremont et al. 2019; Von Leipzig et al, 2017). Thus, digital technologies may trigger not only firms' technological innovations, such as product and process innovations, but also non-technological innovations, such as organizational and marketing innovations.

Previous studies have focused on the impact of information and communication technologies (ICT) on the innovation process and the innovative performance of firms (Añón Higón, 2012; Kleis et al., 2012; Hall et al., 2013). In a broader sense, ICTs have significantly changed the knowledge generation process of firms, leading to efficiency gains and changes in firm's organizational structure, so that their use is widely regarded as an enabler of innovation (e.g., Brynjolfsson and Saunders, 2009; Brynjolfsson and McAfee, 2014).

However, by focusing just on ICT, previous studies ignore the fact that digitalization is a complex phenomenon that is poorly captured by a single indicator and that different firms and sectors are affected by digital and automated technologies in diverse ways.[1] To overcome these drawbacks, we follow Calvino *et al.* (2018) and construct a synthetic index of digitalization at the firm level that considers the multi-faceted phenomenon of the digital transformation. The ultimate aim of this study is to analyse the relationship between the digital transformation of the Spanish manufacturing sector and its innovation activity. In particular, the aim of this study is to assess the effects of digitalization on the propensity of Spanish firms to implement different types of innovations. Following the Oslo Manual, we consider four types of innovation outcomes, such as product, process, organizational and marketing innovations (see OECD/Eurostat, Oslo Manual, 2005) and investigate whether our synthetic index of a firm's digitalization increases the probability of introducing these four types of innovations.

We use data from the Spanish Survey on Business Strategies (ESEE) for a sample of Spanish manufacturing firms from 2001 to 2017. The database provides information about the firm's innovation activities as well as distinct features regarding the use of digital technologies that allow us to construct a digitalization index at the firm level, following Añón Higón and Bonvin (2022), based on Calvino et al. (2018).

We analyse the impact of digitalization on firms' propensity to innovate within the widely used knowledge production function framework (Geroski, 1990). This framework proposes a transformation process linking various inputs associated with knowledge accumulation, such as R&D or human capital, to the firms' innovative output. Knowledge production functions have been the workhorse model in understanding the importance of various knowledge sources besides formal R&D. In this study, we explicitly account for

[1] Digitalization is the process of applying digital technologies to economic production activities, which encompasses ICTs, but include also other advanced technologies, such as connectivity and platform technologies (OECD, 2019). See Matt et al. (2022) for a description of the digitalization concept applied to manufacturing industries.

digitalization in the firms' knowledge production processes, in order to provide insights into the relevance of the digital transformation for firms' innovation activities. Within this knowledge production function framework, we estimate a quadrivariate *probit* model that allows us to jointly analyse firms' decisions to introduce four types of innovations, namely, product, process, organizational and marketing innovations, controlling for unobserved firms' heterogeneity. In addition, we distinguish between large and small firms and explore whether the impact of digitalization differs by size groups, and also between firms investing in R&D and those not performing R&D activities, to investigate if the role of digitalization is different between the two groups of firms.

Our findings indicate that digitalization has a positive impact on the decision to implement process, organizational, and marketing innovations, but not product innovations, with a larger impact on process and marketing innovation. As a result, digitalization boosts non-technical innovations, as well as process innovation, but not product innovation. Furthermore, we uncover that there are considerable sunk costs involved with innovation, as past innovation decisions influence current innovation decisions for all types of innovations. In terms of the remaining control variables (such as size, age, internal and external R&D, appropriability, financial profile, export status, market competition, and so on), our findings show that the innovation strategies are quite heterogeneous, indicating the utility of conducting a disaggregate analysis on them. We also find that there are significant disparities in the impact of digitalization and the extent of sunk costs between SMEs and large firms. Finally, we discover that, with the exception of product innovation, digitalization is a key facilitator of innovation even for enterprises that do not do R&D.

Our paper contributes to the literature in various respects: (i) we provide the first empirical evidence based on representative firm-level data on the role of digitalization for firm performance in terms of innovation activities of manufacturing firms; (ii) while previous studies have focused on different indicators of ICTs, we follow Calvino *et al*. (2018) and construct a synthetic index of digitalization at the firm level that considers the multi-faceted phenomenon of the digital transformation; (iii) we distinguish between technological (product and process) and non-technological (organizational and marketing) innovations. We explicitly consider the impact on non-technological innovations, namely, organizational and marketing innovations. This is important because the digitalization could have a heterogeneous effect on both types of innovations and very little is known about this potential heterogeneity; and, (iv) our research further contributes to a better understanding of the relationship between digitalization and innovation across industries and helps to assess the potential benefits and challenges of the digital transformation.

The rest of the paper is organized as follows. Section 2 revises the related literature. Section 3 presents the data and variables used in the empirical analysis. Section 4 describes the conceptual framework of our empirical approach. Section 5 presents and discusses the main results. Finally, Section 6 concludes.

2. Related literature.

Digitalization refers to all socio-economic transformations arising from the combination of information, computing, communication, and platform and connectivity technologies in an increasing data availability environment (Brunetti et al., 2020; Vial 2019). Digital technologies have transformed the whole industrial production model, including product design and management, converting manufacturers from producers to system integrators and service providers (Zhou, 2013). When applied to manufacturing industries, digital technologies allow real-time monitoring, remote control devices, machinery production through networking infrastructure, and close linkages between manufacturing and tertiary industries (Matt et al, 2022).[2] Digitalization has changed producer-customer relationships, improving customer experiences and multiplying customer feedback on products and processes (Fremont et al. 2019; Von Leipzig et al. 2017). Stone et al. (2017) and Cenamor et al. (2017) examine how the development of digital platforms for specialized products may be used by manufacturers to gather new information about customers and to increase linkages with them.

Over the past decade, a growing body of empirical literature has emerged analysing the links between the use of ICTs by firms and firms' innovative performance. In these studies, a number of different indicators of ICT and innovation outcomes have been used. Polder et al. (2010) analyse the use of broadband and e-commerce by Dutch firms and find positive effects on product, process, and organizational innovation, both in manufacturing and services, but in particular in service sectors. The work of Spiezia (2011), based on data of eight OECD countries, finds that the use of web facilities, automatic IT links, broadband, website, and e-commerce increases the likelihood of firms to innovate in product, processes, marketing, and organization; however, the use of such ICTs does not seem to favour new-to-the-market product innovation. Analysing UK small-and-medium enterprises, Añón Higón (2012) provides evidence of a positive impact of five indicators of ICTs on firms' propensity to introduce product and process innovations. The work of Galindo-Rueda et al. (2020) finds a positive relationship between the use of advanced technologies, including ICTs, and business practices and firm innovation outcomes in Canadian firms. Niebel et al. (2019) find a significant positive relationship between the use of big-data analytics and product innovation in German firms.

The literature analysing the impact of ICTs has documented how they have significantly transformed the knowledge generation process of firms, leading to efficiency gains and changes

[2] See Matt et al. (2022) for an extensive review of the literature on industrial digitalization and for a discussion on the differences among the concepts of digitalization and "Industry 4.0".

in firm’s organizational structure, so that they are widely regarded as an enabler of innovation (Brynjolfsson and Saunders, 2009; Brynjolfsson and McAfee, 2014). ICTs enable efficiency gains in terms of reducing transaction costs, improving business processes, facilitating coordination with suppliers, and enabling the fragmentation of processes along the value chain and across different locations, and fostering product diversification (Koellinger, 2005). Each of these efficiency gains brings new opportunities for innovation. In particular, all these changes, associated with firms’ digital transformation, may be considered enablers of the introduction of different innovations by manufacturing firms, not only in physical products, but also in production processes, as well as in internal organization within the firm, and in the way to connect and bring their products to their customers (Spiezia, 2011). Thus, firms’ digitalization is expected to increase the probability of firms introducing product, process, organizational, and marketing innovations.

Our study is based on the knowledge production function approach of Geroski (1990), which establishes a transformation process linking the inputs associated with knowledge accumulation to the firms’ innovative output. In this context, we explicitly consider firms’ digitalization as an input into the firms’ knowledge production process and explore its role on the innovative performance of firms. This conceptual framework has already been used by a number of studies to analyse the role of ICTs as an input in the firms’ knowledge production function, such as Añón Higón (2011), Hall et al. (2013), and Polder et al. (2010).

By stressing the role of digitalization on the creation of new knowledge within the firm and its impact on its organizational structure and business model, our study is also linked to other strands in the literature. First, the literature on knowledge management has stressed that digitalization implies an increasing access to document repositories and information-based platforms that facilitate information gathering and allows firms to establish a so-called personal knowledge management system based on digital prototypes (Wilkesmann and Wilkesmann, 2018). Yoo et al. (2010) and Trantopoulos et al. (2017) show that new centralized repositories may improve firms' capabilities to handle heterogeneous and dispersed knowledge, facilitating process innovation in manufacturing. Further, ICTs improve the internal dissemination of information and facilitate firms to harness tacit knowledge, thereby improving the internal organization of the R&D process (Hempell and Zwick, 2008).

Second, our study is also related to the literature dealing with the open innovation paradigm, where a number of studies have also dealt with the impact of digitalization on innovative ecosystems. The works of Frishammar et al. (2019) and Kolloch and Dellermann (2018) state that digitalization has distorted sectoral boundaries in traditional industries, favouring the convergence of their knowledge base and redesigning social and technological networks. Further, the potential of digital platforms for creating industrial value in different manufacturing sectors has been stressed by Müller (2019). The improvement of data exchange and data processing along supply chains and innovation activities implies a reduction in transaction costs and exploitation of economies of scale and scope. Also, within the framework of an open innovation model, the work of Gómez et al. (2017) finds that investment in IT, by reducing identification, assimilation, and utilization costs of external R&D investments, positively affects the production of patents and product innovations in Spanish manufacturing firms.

Third, our work may also be linked to the theory of absorptive capacity, which establishes that firms increasingly depend on their knowledge capabilities to innovate (Cohen and Levinthal, 1990; Zahra and George, 2002). According to this theory, a set of organizational routines and processes used by firms to acquire, assimilate, transform and exploit knowledge help to build dynamic capabilities, which in turn, create new knowledge to be used in other organizational capabilities, such as production or marketing (Zahra and George, 2002). By enabling the creation, dissemination, and use of knowledge, ICTs are key in nurturing and rising firms' knowledge capabilities (Alavi and Leidner, 2001; Sambamurthy and Subramani, 2004; Tanriverdi, 2005). Knowledge capabilities have been positively associated with firms' innovation, but the literature is still scarce (Tippins and Sohi, 2003). The work of Joshi et al. (2010) uses the theory of absorptive capacity to examine how ICTs, by enabling knowledge capabilities, affect firms' innovation outcomes in terms of patents and new products, providing empirical evidence in support of a positive link between the use of ICTs and firms' innovations.

3. Data description.

The data used in this study draws on the Survey on Business Strategies (ESEE, henceforth) for the period 2001-2017. The ESEE is a yearly survey, carried out by the SEPI Foundation, which is representative (by industry and size) of the manufacturing sector in Spain. The sampling design of the ESEE is as follows. No firms with employees below 10 are included in the survey. Firms with 10–200 employees (SMEs) are randomly included, being about 5 percent of the population of firms within this size range in 1990. All firms with more than 200 workers (large firms) are invited to contribute to the survey, with a participation of about 70 percent in 1990. To minimize attrition in the initial sample, important efforts are undertaken. Thus, annually new firms are incorporated with the same criterion of the base year to preserve the sample representativeness across time.

The ESEE provides information about firms' strategies. The questionnaire covers information on: the firm's activity, products and manufacturing processes, customers and suppliers, costs and prices, markets, technological activities, foreign trade; and, accounting data. Yet, some of the questions relative to the digital transformation, in particular, online trade and training in ICT appear since 2000 and 2001, respectively, which is why our period of analysis starts in 2001.

The initial sample consists of an unbalanced panel corresponding to firms observed at least for two consecutive periods from 2001 to 2017. We drop out firm that do not provide information on the relevant variables used in the analysis. Hence, after this process, we end up with a sample of 6,609 observations corresponding to 1,708 firms. Below we explain how we measure the main variables of interest (See Table A1 in the appendix for the complete list description of the variables we use in this study).

Dependent variable: Innovation decisions

To analyse the impact of digitalization on innovation activities we distinguish between technological and non-technological innovation decisions. More specifically, technological innovations refer to product and process innovation. Product innovation is a dummy variable that takes the value of 1 if the firm responds that has *introduced new or significantly improved products or services* in the current year and 0 otherwise. On the other hand, the variable process innovation is a dummy variable that takes the value of 1 if the firm responds that has *introduced new or significantly improved processes* and 0 otherwise. With respect to non-technological innovation, we consider organizational and marketing innovation decisions. Thus, organizational innovation is a dummy variable that takes the value of 1 if the firm responds that has *introduced a new organizational method* and 0 otherwise. Marketing innovation is defined as a dummy variable that takes the value of 1 if the firm responds that has *introduced a marketing innovation* and 0 otherwise.

The Digitalization Index

The primary indicator of digitalization at the firm level employed in this study follows Añón Higón and Bonvin (2022) and is based on the study by Calvino et al. (2018), which has been modified according to the data available in the ESEE. This index was created with the understanding that digital transformation is a multifaceted process that cannot be represented with a single indicator. To build this multi-faceted index we use different dimensions of the digital transformation process. The dimensions considered are: 1) technological components, measured by ICT capital, computer programming services, and the implementation of software programs hired or developed by the firm; 2) digital-related human capital, measured by personnel training in software and information technology; 3) automation, proxied by the use of robots, computer-aided design, and flexible systems; and, 4) how digitalization changes the way firms interact, measured by the use of LAN, the ownership of an internet domain and webpage, and the use of different modalities of e-commerce, such as B2B, B2C, and e-buying. In total, the synthetic index collapses information on 13 variables that contain relevant information relative to the digital transformation of Spanish manufacturing firms. In Table A2 of the appendix, we compare the dimensions and variables we use to those of Calvino *et al.* (2018).

The process for constructing the digitalization index is as follows. First, monetary variables (ICT investment and training expenses) are capitalized, and their value relative to the industry-year mean is classified by the decile of the distribution to which they belong. After that, the result is rescaled in the [0-1] range. Categorical variables (robot use, CAD, flexible systems, and LAN) that are only available every four years are first extrapolated and then normalized in the [0-1] interval. The remaining categorical variables are left unchanged. As a result, we have 13 variables with values ranging from 0 to 1. Finally, to obtain an overall index, we combine the information of these variables as an unweighted sum. The result is then normalized in the [0-1] interval. Higher values imply a larger degree of digitalization.

Determinants of Innovation Performance: The choice of Independent Variables

We follow previous literature concerning the determinants of innovation, beyond the degree of a firm's digitalization. These variables can be related to both the characteristics of the firm, including variables that relate to the firm's internal capabilities, and to the firm's environment.

The following explores in more detail these variables conditional on the information facilitated by the dataset.

First, we control for *firm size*. The relationship between *firm size* and innovation decisions has been extensively researched since the seminal work of Schumpeter (1942). Large firms, according to the Schumpeterian arguments, are better placed to develop and exploit new technologies as a result of larger availability of resources, better appropriability conditions, and greater ability to benefit from scale economies. Alternatively, small firms, assuming they hold more flexible structures, may be more innovative in their responses to changes in customers' needs and environmental conditions (Rogers, 2004). However, the debate on the role of firm size is still ongoing as empirical studies have reached mixed conclusions. There are studies that find a positive relationship between size and innovation (Cohen and Klepper, 1996), while others are unable to confirm this positive relationship. For instance, Acs and Audretsch (1988) find that small firms have an innovative advantage in highly innovative industries and in highly competitive markets. In addition, studies generally find that size has a more positive association with process than with product innovation (Cohen and Levin, 1989).

We also account for the firm's *age*. In theory, a positive relationship may be expected because years of experience may capture "learning by doing" effects. However, if younger firms are more proactive, flexible, and aggressive, the opposite is expected. There are also mixed findings, while Balasubramanian and Lee (2008) find that younger firms are more likely to innovate, Harris *et al*. (2003) find no significant effect. Additionally, we control for *human capital*, which is measured by the share of qualified personnel (Freel and Robson, 2004). Among the firm's internal innovation capabilities, we include whether the firm invests in *internal R&D*, and/or acquires *external R&D*. As Mairesse and Mohnen (2010) claim, efforts in developing internal R&D competencies constitute the most often reported determinant of innovation outcomes. More recent studies confirm that internal R&D increases the probability to innovate (Conte and Vivarelli, 2014). Similarly, previous research has shown that R&D outsourcing practices enhance innovation performance (e.g., Laursen and Salter, 2006).

In addition, we control for *group* membership, to allow for the possibility of intra-firm spillovers (Oakey *et al.*, 1980), and for whether the firm is *foreign-owned*. Some arguments suggest a positive impact (foreign ownership may imply greater financial resources or access to more advanced knowledge and technology), whereas a product life cycle perspective implies that R&D and innovative activities are performed close to home markets. Previous empirical studies have found that foreign-owned firms are more likely to introduce new products and processes (Sadowski and Sadowski-Rasters, 2006; Frenz and Ietto-Gillies, 2007). There are, however, some exceptions that show that foreign ownership has a negative association with innovation (Love and Roper, 1999; Bishop and Wiseman, 1999).

We account also for whether the firm *exports.* There is a large body of literature on the relationship between exporting and innovation activities. Though the direction of causality is still debated, there are arguments that suggest that the involvement in exporting will broaden the firm's geographical network and get access to a richer source of knowledge, expertise, and technology that is not available in the home market (Lachenmaier and Wößmann, 2006). There is empirical evidence that suggests that firms that export are more likely to innovate (Baldwin *et al.*, 2001). In line with Lerner (2009) and Raymond et al. (2010) we include a proxy for the *appropriability* conditions since they are assumed to spur the introduction of innovations by allowing firms to receive the returns of their innovation activities.

We also consider some environmental variables which are expected to affect firms' propensity to innovate. We control for the role of *competition* as a determinant of innovation activities (Cohen and Levin, 1989; Levin *et al.*, 1985; Scherer, 1970). Another feature contributing to the decision to innovate is the growth of demand (Schmookler, 1966). In this regard, we control for whether the market is in recession. We expect that a *recessive demand* discourages engaging in innovation activities. Extensive is also the literature studying the importance of *financial resources* (Hewitt-Dundas, 2006). Particularly, studies of SMEs consistently stress that the lack of finance is one of the most important constraints to innovation (Vossen, 1998). Further, *government funding* can also be regarded as contributing to, or augmenting, the firm's resource base and could be therefore anticipated as a positive impact on the decision to innovate. In Table 1 we report the descriptive statistics for the variable used in this study.

[Table 1 here around here]

4. Conceptual approach.

The aim of this study is to gauge the importance of firms' digitalization in determining the decision to innovate. To do so, we estimate the now standard knowledge production function (Geroski, 1990), in which one of the inputs is the digitalization index. In this study, we consider four types of innovation strategies, indexed by *j*, namely product, process, organizational, and marketing innovation decisions. In general terms, one can write the knowledge production function for enterprise *i* as follows:

$$I_{it}^{*} = \alpha DIG_{it} + \gamma I_{ijt-1} + \beta X_{it-1} + d_s + d_t + \varepsilon_{it} \quad (1)$$

The latent variable in equation (1), the propensity to innovate, I_{it}^{*}, is not observed. In this case, we only observe whether a firm had introduced a certain type of innovation or not, i.e., whether the firm has introduced a product, process, organizational, or marketing innovation, such that:

$$I_{it} = \begin{cases} 1 & if\ I_{it}^{*} > 0 \\ 0 & if\ I_{it}^{*} \leq 0 \end{cases} \quad (2)$$

In order to reflect the fact that in practice firms consider simultaneously the decision to engage in different innovation strategies, we use a multivariate *probi*t model. In this way, the four equations' disturbances, ε_{it}, for the product, process, organizational or marketing innovation, are assumed to be independent over time and to follow a multivariate normal distribution. Therefore, besides the estimation of the parameters for the explanatory variables, the multivariate *probit* model incorporates the estimation of correlation coefficients of the error terms. Not considering these correlations, might cause biased and inconsistent parameter estimates due to the relationship among the different innovation types (Greene, 2003). To model the four innovation decisions, we use a quadrivariate *probit* specification as follows,

$$
\begin{aligned}
Prod._{it} &= \begin{cases} 1 & if\ \alpha^{pd} DIG_{it} + \gamma^{pd} Prod._{it-1} + \beta^{pd} X_{it-1} + d_s^{pd} + d_t^{pd} + \varepsilon_{it}^{pd} > 0 \\ 0 & otherwise \end{cases} \\
Proc._{it} &= \begin{cases} 1 & if\ \alpha^{pc} DIG_{it} + \gamma^{pc} Proc._{it-1} + \beta^{pc} X_{it-1} + d_s^{pc} + d_t^{pc} + \varepsilon_{it}^{pc} > 0 \\ 0 & otherwise \end{cases} \\
Org._{it} &= \begin{cases} 1 & if\ \alpha^{o} DIG_{it} + \gamma^{o} Org._{it-1} + \beta^{o} X_{it-1} + d_s^{o} + d_t^{o} + \varepsilon_{it}^{or} > 0 \\ 0 & otherwise \end{cases} \\
Mark._{it} &= \begin{cases} 1 & if\ \alpha^{m} DIG_{it} + \gamma^{m} Mark._{it-1} + \beta^{m} X_{it-1} + d_s^{m} + d_t^{m} + \varepsilon_{it}^{m} > 0 \\ 0 & otherwise \end{cases}
\end{aligned}
\qquad (3)
$$

Following Ganter and Hecker (2013), the estimates of the system of equations in (3) are obtained by simulated likelihood estimation using the Stata command cmp written by Roodman (2011).

A central test of the hypothesis that digitalization (*DIG*) has an impact on the likelihood of firms' innovating will be determined by the empirical significance and sign of the vector of parameters α^k (for k = product, process, organizational or marketing innovation). In choosing the likely determinants of the propensity to innovate, in addition to the digitalization index, we include the previously realized innovation strategy captured by $Prod._{it-1}$, $Proc._{it-1}$, $Org._{it-1}$ and $Mark._{it-1}$, and a vector of lagged observable variables (X_{it-1}) that have been shown to be important in the traditional and modern literature on innovation performance. To deal with the potential simultaneity bias, these explanatory variables enter with one lag in the model specification. We control also for sector fixed effects at the two-digit level, represented by d_s, and a set of time fixed effects, denoted by d_t.

Nevertheless, there may be firm unobserved factors that affect the firm's innovation decisions, including managerial skills and the ability of the personnel in the R&D department. For this reason, we assume that the error term ε_{it} in each innovation decision in (3) has two components, a permanent firm-specific effect (η_i) and a transitory component (υ_{it}). Thus, $\varepsilon_{it} = \eta_i + \upsilon_{it}$. In the estimation of Equation (3), we control for correlated unobserved firms' heterogeneity using the correlated random-effects approach developed by Wooldridge (2005) in combination with Blundell et al. (1999; 2002). Accordingly, we model the distribution of the firm's unobserved effect, conditional on the pre-sample mean of the dependent variable ($\overline{I_{\iota 0}}$), as follows:

$$\eta_i = \eta_0 + \eta_1 \overline{I_{\iota 0}} + a_i \tag{4}$$

The specification in equation (4) gives rise to a new unobserved heterogeneity term a_i in each of the equations in (3) that is assumed to be distributed as $N(0, \sigma_a^2)$ and uncorrelated with the explanatory variables, and the error terms in (3). Thus, $\overline{I_{\iota 0}}$ is added as an additional regressor in each equation in the specification (3). The pre-sample mean is calculated as the within-firm mean of I_i for pre-sample years. As the information in the survey about non-technical observations has been available since 2007, we use as the pre-sample period the year 2006. Further, as the explanatory variables in (3) are lagged one period, we carry out the estimation for the period 2008–17. Table 1 provides descriptive statistics of the main variables of interest.

5. Empirical results.

In this section, we provide empirical evidence of the impact of digitalization on the decision to engage in innovation strategies (product, process, organizational, and marketing innovation). Table 2 provides the estimation results of the four innovation decisions, as stated in the system of equations in (3). Results are presented as average marginal effects (AME, henceforth). The potential interdependency between the four innovation strategies is considered, and the estimated correlation coefficients for the error terms appear positive and statistically significant. This implies that a multivariate model that considers the four decisions jointly, rather than separated binary discrete models, is the correct specification for the four innovation decisions. Moreover, the correlation coefficients show that the highest degree of interdependency is between marketing innovation and organizational innovation (see Carboni & Russu, 2018), followed by process and organizational innovation; while the lowest is between product innovation and organizational innovation.

Second, an instrumental-variable control function (CF) approach is adopted to account for the potential endogeneity of the digital index to explain the decisions to innovate. Before examining the results, it is important to note that to avoid further simultaneity problems, all the independent variables are lagged one period. Although not reported, all specifications control also for sector dummies to capture different technological opportunities varying across industries and a set of time dummies capturing business cycle effects. The first step of the CF approach consists of regressing the digital index on the instrument (the average digitalization index by firms in the same industry, region, size band, and R&D status) and the rest of the exogenous variables in a fixed effects model. Although to ease the exposition, the estimates of the first-step regression are not shown, the coefficient of the instrument is significantly positive, as expected. In the main equation, the residual from this first-step appears significant in the process and marketing innovation equations (columns 2 and 4), while it is not significant in the product and organizational innovation participation (columns 1 and 3).

[Table 2 around here]

In what follows, we proceed to discuss in detail our estimation results on the main variable of interest, i.e., the digitalization index. Digitalization exerts a positive impact on the decision to innovate in process, organizational, and marketing, but not in product. The effect is larger for process and marketing innovation. To be more specific, the marginal effect implies that an increase of the digitalization index by 1% raises the corresponding probability to introduce a process innovation by almost 0.26 percentage points, holding all other variables constant. Furthermore, a 1% increase in digitalization raises the probability to introduce a marketing innovation and organizational innovation by 0.21 and 0.14 percentage points, respectively. Therefore, digitalization acts as an enhancer of non-technical innovations, and also process innovation, but not product innovation.

Past innovation decisions, as expected, are important determinants of current innovation decisions. This suggests that there are significant sunk costs associated with innovation. In other words, once a firm has paid the sunk costs of innovation, it is easier to pursue this strategy in the next period. In terms of the remaining control variables, their coefficients also differ appreciably across the equations. This shows that the innovation strategies are quite heterogeneous, and hence the disaggregate innovation-decision analysis is appropriate. For example, we find that size has a positive effect on the decision to introduce a product, process, and organizational innovation. Internal R&D also influences positively the decision to do product and process innovation, as well as the decision to do marketing innovation. On the other hand, external R&D only affects product and marketing innovations. The export status is positively related to technological innovations. In contrast, firms' appropriability positively influences the decision to engage in non-technological innovations. Financial health helps to explain the decision to do process innovation, whereas the degree of competition and the fact of obtaining public funding for innovation affect positively the decision to do organizational innovation. On the other hand, the age of the firm and being in a recessive market have a negative impact on the decision to do process and organizational innovation, while being part of a group affects negatively the decision to do marketing innovation.

Sensitivity Analysis

At this point, we have demonstrated that digitalization has a significant and positive effect on Spanish manufacturing firms' innovation decisions. Our goal now is to determine which firms benefit the most from digitalization. Thus, we perform the analysis for SMEs and large firms, respectively. A priori, it is unclear whether the impact of digitalization should be greater for smaller or larger firms. On the one hand, small firms may benefit more from digitalization. SMEs can use basic digital technologies to rapidly introduce innovations, most likely in terms of process or organizational, at a relatively low cost, overcoming some of the sunk costs of the innovation process. However, the use of more advanced digital and automated technologies may require high adjustment costs, which may be feasible only for larger firms.

The results presented in Table 3 show that digitalization has a positive impact on the decision of SMEs to introduce process, organizational, and marketing innovations, but not product innovations. However, in the case of large firms, digitalization only affects the decision to engage in process and marketing innovation. There are also interesting differences between SMEs and large firms relative to the size of sunk costs and correlation coefficients. Large firms exhibit larger sunk costs of innovating than SMEs, which leads to higher innovation persistence. Moreover, for SMEs the strongest complementarity between innovation strategies is found for marketing and organizational innovation; for SMEs, the strongest complementarity is between process and organizational innovation, followed by product and process innovation.

[Table 3 around here]

Finally, we assess how digitalization affects the decision to innovate for both R&D performers and non-R&D firms. The aim here is to see how digitalization facilitates innovation even in the absence of internal R&D. To do so, we divide the sample into firms that perform internal R&D and firms that never perform internal R&D during the period sample. The results are presented in Table 4. For firms with inhouse R&D spending, digitalization increases the probability to introduce process and marketing innovation but is not significant for enhancing product or organizational innovation. For firm not engaged in internal R&D activities, digitalization increases the propensity to introduce process, organizational, and marketing innovation. Therefore, even for firms without R&D activities, digitalization proves to be a significant facilitator for innovation, except for product innovation. These results are partly in line with Barge-Gil et al. (2011), who document that for non-performer R&D firms, activities such as technology forecasting, design, use of advanced technologies and training are key factors explaining product and process innovations. In the case of product innovation, our results show that investing in R&D, mainly internally but also through outsourcing is key to increasing the probability to introduce product innovations into the market.

[Table 4 around here]

6. Conclusions.

The digitalization of the economy is spreading out worldwide. After progressively gaining traction over the last few decades, the digitalization process has accelerated in recent years, while the pace of change differs widely amongst companies. Digital technologies are expected to disrupt the restructuring of production processes and the functioning of markets in general, and their effects are extending throughout the economy and society.

The main goal of this study is to assess the relationship between the digital transformation of the Spanish manufacturing sector and its innovation activities. We are particularly interested in how digitalization affects the likelihood of Spanish companies to implement various types of innovations. We have examined whether firm's digitalization intensity boosts the possibility of introducing four categories of innovations, namely product, process, organizational, and marketing innovations, in accordance with the Oslo Manual (see OECD/Eurostat, Oslo Manual, 2005). We acknowledge that the digitalization process is complex as it comprises various indicators, and different firms and sectors are affected by digital and automated technologies in diverse ways. Thus, in this work, following Añón Higón and Bonvin (2022), we have built a synthetic index of digitalization at the company level based on Calvino et al. (2018) approach, which accounts for the multi-faceted phenomenon of the digital transformation.

We analyse the impact of digitalization on firms' propensity to innovate within the widely used knowledge production function framework (Geroski, 1990), using data from a sample of Spanish manufacturing firms from the Spanish Survey on Business Strategies (ESEE) from 2001 to 2017. We use this approach to explicitly account for digitalization in firms' knowledge production processes, in order to get insights into the relevance of the digital transformation for firms' innovation activities. We develop a quadrivariate *probit* model that allows us to examine firms' decisions to introduce four types of innovations (product, process, organisational, and marketing innovations) while controlling for unobserved firm heterogeneity. Furthermore, we distinguish between large and small firms to see if the impact of digitalization varies by size, as well as between firms that spend in R&D and those that do not, to see if the role of digitalization differs between these two categories of companies.

We have found that digitalization has a positive impact on the decision to implement process, organizational, and marketing innovations, but not product innovations, being this impact larger for process and marketing innovation. After controlling for sunk costs and many other variables (such as size, age, internal and external R&D, appropriability, financial profile, export status, market competition, etc.) we find that digitalization enhances non-technical innovations, as well as process innovation, but not product innovation. We also confirm that these four innovation choices are interconnected, notwithstanding their diversity.

Furthermore, when comparing large and small businesses, we find that digitalization influences SMEs' decisions to implement process, organizational, and marketing innovations, but not product innovations. In the case of large companies, however, digitalization has only an impact on the decision to invest in process and marketing innovation. Furthermore, large companies have higher sunk costs of innovation than SMEs, resulting in greater innovation persistence. Finally, we look at how digitalization influences R&D and non-R&D performers' decisions to innovate. Digitalization enhances the likelihood of introducing process and marketing innovation in companies with in-house R&D spending, but it has little effect on product or organisational innovation. Digitalization enhances the likelihood of non-R&D performers introducing process, organisational, and marketing innovation. Therefore, except for product innovation, digitalization shows to be a substantial facilitator of innovation even for organisations without R&D investments.

Our findings provide crucial insights for managers, particularly in SMEs that do not do R&D and are generally characterised by limited engagement in innovative activities and a lack of digitalization. Investing in digitalization can help SMEs increase their probability of innovating. Furthermore, digitalization may serve as an alternative means to conduct innovative activities among non-R&D enterprises, which are typically SMEs.

In terms of policy recommendations, the findings of this study can assist policy makers to better design measures to boost the competitiveness of Spanish firms through innovation. Our findings suggest that governments should not only provide the required digital infrastructure, but also give incentives, such as subsidies or tax breaks, to encourage adoption and thereby drive the digital transformation of Spanish businesses. This is particularly important for SMEs with considerable financial constraints, especially if the goal is to push the innovation process. Investment in digital infrastructure, on the other hand, may be ineffective if businesses lack the digital skills required to effectively employ digital technologies. Therefore, training initiatives should be also in place.

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Appendix.

Table A1. Variables definition.

Product innovation	Dummy = 1 if the firm declares to have obtained product innovations (products completely new or with such important modifications that make them different to those being produced before), and 0 otherwise.
Process innovation	Dummy = 1 if the firm declares to have introduced any modification important in the productive and/or distribution processes referring to: introduction of new machinery and equipment, introduction of new techniques and/or methods and introduction of new software programmes linked to industrial processes, and 0 otherwise.
Organizational innovation	Dummy = 1 if the firm declares to have introduced new organizational methods referring to: new firm practices in the organization of labour (in the routines or in the allocation of responsibilities), new methods of management of the external relations with other firms or public institutions (providers, clients, other), and 0 otherwise.
Marketing innovation	Dummy = 1 if the firm declares to have introduced commercialization innovations referring to: significant modifications in the design or packaging of its products, new methods in using the sales-channels, news methods in the promotion of its products, new methods in setting prices for its products, and 0 otherwise.
Digitalization index	Index than ranges from 0 to 1, and that covers different dimension of the digital transformation, including technological components, personnel training in software and information technology, automation, and how digitalization changes how firms interact (see Añón and Bonvin, 2022).
Size	The logarithm of the number of employees
Age	The logarithm of the age of the firm.
Human capital	Percentage of employees with a three-year degree.
Internal R&D	Dummy = 1 if the firm conducts internal R&D activities, and 0 otherwise.
External R&D	Dummy = 1 if the firm conducts external R&D activities, and 0 otherwise.
Export	Dummy = 1 if the firm exports, and 0 otherwise.
Foreign capital	Dummy = 1 if the firm has foreign capital participation, and 0 otherwise.
Financial score	Financial score including both internal and external financial constraints (see Mañez & Vicente, 2021). The higher the value the better the financial health of the firm (i.e., less the financially constrained).
Recessive market	Dummy = 1 if the firm faces a recessive market demand, and 0 otherwise.
Appropriability	Dummy = 1 if the firm has registered patents either in Spain or abroad and/or utility models, and 0 otherwise.
CR4	It is an indicator of the concentration degree in the main market of the firm, measured as the market-share of the four largest companies of that market. If in the main market there are no companies with a significant share, a value of zero has been assigned to the shares of the four main competitors.

Group	Dummy = 1 if the firm is part of a group of companies, and 0 otherwise.
Public funding	Dummy = 1 if the firm declares that has received funding for innovation activities from the (estate or regional) administration, and 0 otherwise.

Table A2. Digitalization Index. Comparing Calvino et al. (2018) with this study.

Calvino et al. (2018) At the 2-digit industry level	**This study** At firm level
1. Technological components: - Investment in ICT equipment - Purchases of ICT services - Purchases of ICT services - Purchases of ICT goods	**1. Technological components:** - ICT capital - Computer programming services - Implementation of software programs
2. The extent of automation: - Robot stock	**2. The extent of automation:** - Use of robots - Use of computer-aided design - Use of flexible systems - Use of LAN
3. Digital-related human capital: - ICT specialists as a share of total employment	**3. Digital-related human capital** - Personnel training in software and information technology
4. Interactions with stakeholders: - Share of turnover from online sales	**4. Interactions with stakeholders:** - - Ownership of an internet domain - Ownership of a webpage - Business to business e-commerce - Business to consumer e-commerce - E-buying

Table 1. Descriptive statistics.

Variables	Mean	s.d.	Min.	Max.
Product innovation	0.169	0.375	0	1
Process innovation	0.319	0.466	0	1
Organizational innovation	0.197	0.398	0	1
Marketing innovation	0.177	0.382	0	1
Digitalization index	0.384	0.203	0	1
Employment (in logs)	3.993	1.394	0	9.6
Age (in logs)	3.375	0.575	1.1	5.2
Human capital	0.079	0.108	0	1
Internal R&D	0.291	0.454	0	1
External R&D	0.227	0.419	0	1
Exports	0.668	0.471	0	1
Foreign capital	0.141	0.348	0	1
Financial score	4.930	1.525	1	10
Recessive market	0.370	0.483	0	1
Appropriability	0.067	0.250	0	1
CR4	0.287	0.361	0	1
Group	0.348	0.476	0	1
Government funding	0.124	0.330	0	1

Note: s.d. stands for standard deviation.
Source: ESEE

Table 2. The innovation decisions and digitalization. All firms.

	Product innovation	Process innovation	Organizational innovation	Marketing innovation
Digitalization index	0.044	0.258***	0.136***	0.208***
	(0.028)	(0.036)	(0.032)	(0.029)
$Size_{t-1}$	0.007*	0.017***	0.015***	0.000
	(0.004)	(0.006)	(0.005)	(0.005)
Age_{t-1}	-0.001	-0.024***	-0.023***	-0.009
	(0.007)	(0.009)	(0.008)	(0.007)
Human $capital_{t-1}$	0.049	-0.006	0.040	0.008
	(0.034)	(0.049)	(0.042)	(0.038)
Internal $R\&D_{t-1}$	0.059***	0.058***	0.020	0.021*
	(0.010)	(0.014)	(0.012)	(0.011)
External $R\&D_{t-1}$	0.022**	0.019	-0.001	0.026**
	(0.010)	(0.015)	(0.013)	(0.012)
$Export_{t-1}$	0.046***	0.024*	0.005	-0.003
	(0.011)	(0.013)	(0.012)	(0.011)
Foreign $capital_{t-1}$	-0.004	0.002	0.003	-0.011
	(0.011)	(0.015)	(0.013)	(0.012)
Financial $score_{t-1}$	0.001	0.007**	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Recessive $market_{t-1}$	-0.003	-0.021*	-0.019**	0.008
	(0.008)	(0.011)	(0.009)	(0.009)
$Appropriability_{t-1}$	0.010	-0.006	0.031*	0.041***
	(0.013)	(0.020)	(0.016)	(0.014)
$CR4_{t-1}$	0.014	-0.004	0.029**	-0.000
	(0.011)	(0.014)	(0.012)	(0.011)
$Group_{t-1}$	-0.007	0.007	-0.003	-0.022**
	(0.009)	(0.012)	(0.011)	(0.010)

Public funding$_{t-1}$	-0.006	0.026	0.032**	-0.005
	(0.011)	(0.017)	(0.014)	(0.013)
Prod.$_{t-1}$	0.193***			
	(0.007)			
Proc.$_{t-1}$		0.295***		
		(0.008)		
Org.$_{t-1}$			0.257***	
			(0.007)	
Mark.$_{t-1}$				0.243***
				(0.007)
Pre-sample	YES	YES	YES	YES
Time dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Prod.$_0$	0.068***			
	(0.008)			
Proc.$_0$		0.048***		
		(0.010)		
Org.$_0$			0.044***	
			(0.009)	
Mark.$_0$				0.053***
				(0.008)
Residual	-0.008	-0.229***	-0.108	-0.189***
	(0.063)	(0.085)	(0.074)	(0.068)
ρ_{12}	0.367***			
	(0.038)			
ρ_{13}	0.259***			
	(0.039)			
ρ_{14}	0.381***			
	(0.040)			
ρ_{23}	0.487***			
	(0.034)			
ρ_{24}	0.345***			
	(0.036)			
ρ_{34}	0.615***			
	(0.039)			
N. observations	5616			

Notes:
1. Standard errors are in parenthesis.
2. *, ** and ***, mean statistically significant at the 10%, 5% and 1% levels of significance, respectively.

Table 3. The innovation decisions and digitalization. SMEs vs large firms.

	SMEs				Large			
	Product innovation	**Process innovation**	**Organizational innovation**	**Marketing innovation**	**Product innovation**	**Process innovation**	**Organizational innovation**	**Marketing innovation**
Digitalization index	0.021	0.272***	0.144***	0.210***	0.118	0.254***	0.110	0.142*
	(0.028)	(0.040)	(0.034)	(0.031)	(0.084)	(0.089)	(0.087)	(0.080)
$Size_{t-1}$	0.001	0.023***	0.009	-0.000	0.002	0.025	0.050***	0.031**
	(0.005)	(0.008)	(0.006)	(0.006)	(0.015)	(0.018)	(0.016)	(0.014)
Age_{t-1}	0.002	-0.018*	-0.019**	-0.006	-0.019	-0.038*	-0.031	-0.006
	(0.007)	(0.010)	(0.009)	(0.008)	(0.020)	(0.021)	(0.020)	(0.018)
Human $capital_{t-1}$	0.035	0.033	0.048	0.025	0.096	-0.046	0.036	-0.040
	(0.037)	(0.058)	(0.048)	(0.045)	(0.087)	(0.098)	(0.092)	(0.084)
Internal $R\&D_{t-1}$	0.052***	0.026	0.023*	0.013	0.077***	0.154***	0.017	0.038
	(0.010)	(0.017)	(0.014)	(0.013)	(0.029)	(0.029)	(0.030)	(0.028)
External $R\&D_{t-1}$	0.032***	0.047***	0.006	0.035***	-0.009	-0.035	0.002	0.021
	(0.010)	(0.018)	(0.015)	(0.013)	(0.026)	(0.029)	(0.027)	(0.025)
$Export_{t-1}$	0.044***	0.014	0.004	-0.003	0.019	0.093*	-0.003	-0.010
	(0.011)	(0.014)	(0.012)	(0.011)	(0.051)	(0.049)	(0.051)	(0.044)
Foreign $capital_{t-1}$	-0.011	0.016	0.013	-0.033*	0.005	-0.025	-0.005	0.020
	(0.013)	(0.020)	(0.017)	(0.017)	(0.024)	(0.026)	(0.024)	(0.023)
Financial $score_{t-1}$	0.001	0.007*	0.003	0.001	0.006	0.007	-0.002	-0.004
	(0.003)	(0.004)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)	(0.007)
Recessive $market_{t-1}$	-0.005	-0.024**	-0.026***	0.007	-0.000	-0.013	0.009	0.014
	(0.008)	(0.012)	(0.010)	(0.009)	(0.024)	(0.026)	(0.024)	(0.022)
$Appropriability_{t-1}$	0.005	0.008	0.019	0.049***	0.024	-0.024	0.031	0.041
	(0.015)	(0.026)	(0.021)	(0.018)	(0.030)	(0.034)	(0.032)	(0.028)
$CR4_{t-1}$	0.008	-0.007	0.018	0.008	0.037	-0.007	0.062*	-0.043
	(0.011)	(0.016)	(0.013)	(0.012)	(0.032)	(0.033)	(0.033)	(0.030)
$Group_{t-1}$	-0.001	-0.007	-0.008	-0.025**	-0.012	0.060**	0.021	0.008
	(0.009)	(0.014)	(0.011)	(0.011)	(0.028)	(0.029)	(0.028)	(0.026)
Public $funding_{,t-1}$	-0.019	0.019	0.018	-0.015	0.018	0.024	0.057**	0.022
	(0.012)	(0.022)	(0.018)	(0.016)	(0.027)	(0.030)	(0.028)	(0.025)
$Prod._{t-1}$	0.155***				0.326***			
	(0.008)				(0.017)			

Proc.$_{t-1}$		0.271***				0.358***		
		(0.009)				(0.016)		
Org.$_{t-1}$			0.220***				0.378***	
			(0.009)				(0.013)	
Mark.$_{t-1}$				0.218***				0.323***
				(0.008)				(0.015)
Pre-sample	YES	YES	YES	YES	YES	YES	YES	YES
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES	YES	YES	YES
Residual	-0.032	-0.215**	-0.099	-0.186***	0.099	-0.312	-0.087	-0.071
	(0.063)	(0.085)	(0.074)	(0.068)	(0.185)	(0.196)	(0.189)	(0.175)
ρ_{12}	0.335***				0.503***			
	(0.046)				(0.075)			
ρ_{13}	0.247***				0.295***			
	(0.048)				(0.071)			
ρ_{14}	0.378***				0.377***			
	(0.048)				(0.076)			
ρ_{23}	0.483***				0.547***			
	(0.040)				(0.070)			
ρ_{24}	0.308***				0.478***			
	(0.042)				(0.077)			
ρ_{34}	0.665***				0.493***			
	(0.047)				(0.074)			
N. observations	4441				1175			

Notes:
1. Standard errors are in parenthesis.
2. *, ** and ***, mean statistically significant at the 10%, 5% and 1% levels of significance, respectively.

Table 4. The innovation decisions and digitalization. R&D vs Non-R&D firms.

	With internal R&D				Non-R&D performers			
	Product innovation	**Process innovation**	**Organizational innovation**	**Marketing innovation**	**Product innovation**	**Process innovation**	**Organizational innovation**	**Marketing innovation**
Digitalization index	0.050	0.232***	0.091	0.209***	0.005	0.269***	0.147***	0.184***
	(0.056)	(0.060)	(0.057)	(0.053)	(0.024)	(0.044)	(0.035)	(0.033)
$Size_{t-1}$	0.006	0.021**	0.023**	0.005	0.003	0.012	0.007	-0.002
	(0.009)	(0.009)	(0.009)	(0.008)	(0.004)	(0.008)	(0.006)	(0.005)
Age_{t-1}	-0.007	-0.015	-0.038***	-0.010	0.007	-0.035***	-0.010	-0.010
	(0.013)	(0.015)	(0.014)	(0.013)	(0.006)	(0.012)	(0.009)	(0.009)
Human $capital_{t-1}$	0.067	0.007	0.053	-0.008	0.027	-0.026	-0.000	0.025
	(0.065)	(0.075)	(0.068)	(0.064)	(0.032)	(0.067)	(0.053)	(0.048)
Internal $R\&D_{t-1}$	0.074***	0.041**	0.004	0.017				
	(0.020)	(0.020)	(0.019)	(0.018)				
External $R\&D_{t-1}$	0.033*	0.027	0.013	0.036**	0.019	-0.012	-0.041	0.021
	(0.018)	(0.020)	(0.018)	(0.017)	(0.013)	(0.033)	(0.027)	(0.025)
$Export_{t-1}$	0.043	0.018	-0.017	-0.006	0.015**	0.013	0.002	-0.010
	(0.029)	(0.028)	(0.028)	(0.026)	(0.008)	(0.014)	(0.011)	(0.010)
Foreign $capital_{t-1}$	-0.010	-0.013	-0.007	-0.019	0.011	0.025	0.018	-0.006
	(0.019)	(0.021)	(0.020)	(0.019)	(0.012)	(0.024)	(0.018)	(0.019)
Financial $score_{t-1}$	-0.003	0.005	0.004	-0.000	0.004*	0.009**	-0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)	(0.004)	(0.003)	(0.003)
Recessive $market_{t-1}$	-0.020	-0.007	-0.016	0.018	0.008	-0.029**	-0.016	0.004
	(0.017)	(0.018)	(0.017)	(0.015)	(0.007)	(0.013)	(0.010)	(0.009)
$Appropriability_{t-1}$	0.027	-0.031	0.034	0.040*	0.001	0.081*	0.029	0.082***
	(0.022)	(0.026)	(0.023)	(0.021)	(0.021)	(0.047)	(0.037)	(0.031)
$CR4_{t-1}$	0.054**	0.007	0.040*	-0.010	-0.024**	-0.011	0.013	0.009
	(0.021)	(0.023)	(0.021)	(0.020)	(0.011)	(0.018)	(0.014)	(0.013)
$Group_{t-1}$	-0.004	0.033*	0.014	-0.017	-0.006	-0.014	-0.020	-0.026**
	(0.017)	(0.019)	(0.017)	(0.016)	(0.009)	(0.017)	(0.013)	(0.013)

Public funding $_{t-1}$	-0.004	0.024	0.037*	-0.005		0.185		
	(0.019)	(0.021)	(0.019)	(0.018)		(0.191)		
Prod. $_{t-1}$	0.320***				0.083***			
	(0.012)				(0.009)			
Proc. $_{t-1}$		0.372***				0.220***		
		(0.011)				(0.011)		
Org. $_{t-1}$			0.351***				0.172***	
			(0.010)				(0.010)	
Mark. $_{t-1}$				0.326***				0.173***
				(0.011)				(0.009)
Pre-sample	YES	YES	YES	YES	YES	YES	YES	YES
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES	YES	YES	YES
Residual	0.085	-0.273**	-0.193	-0.164	-0.045	-0.159	0.023	-0.208***
	(0.123)	(0.136)	(0.124)	(0.116)	(0.055)	(0.107)	(0.085)	(0.079)
ρ_{12}	0.346***				0.502***			
	(0.045)				(0.085)			
ρ_{13}	0.244***				0.337***			
	(0.046)				(0.080)			
ρ_{14}	0.317***				0.626***			
	(0.047)				(0.086)			
ρ_{23}	0.468***				0.522***			
	(0.045)				(0.055)			
ρ_{24}	0.335***				0.344***			
	(0.047)				(0.058)			
ρ_{34}	0.587***				0.687***			
	(0.050)				(0.067)			
N. observations	2558				3058			

Notes:
1. Standard errors are in parenthesis.
2. *, ** and ***, mean statistically significant at the 10%, 5% and 1% levels of significance, respectively.