estructura econòmica
ECONOMÍA APLICADA II

Do digitalization spurs SMEs' participation in foreign markets?

by

Dolores Añon Higón

and

Daniel Bonvin

May 2023

Working Papers in Applied Economics

WPAE-2023-2307

ECONOMÍA APLICADA II

VNIVERSITAT DE VALÈNCIA

Departamento de Estructura Económica (Economía Aplicada II), Facultad de Economía, Universitat de València
Avda dels Tarongers, s/n, 46022 – Valencia, Spain
Phone +34 96 382 83 49 / Fax +34 96 382 83 54
http://www.estructuraeconomica.es
e-mail: investigacion.estructura@uv.es

ISSN 2172-3036

Do digitalization spurs SMEs' participation in foreign markets?

Dolores Añón Higón[1]; Daniel Bonvin[2]

ABSTRACT

This study aims to empirically examine the impact of the digital transformation on the participation of small and medium-sized enterprises (SMEs) in export and import activities. In this regard, empirical evidence at the firm level is very limited. Using a representative panel of Spanish SMEs from 2001 to 2014, we contribute to the literature by constructing a multi-dimensional index of digitization at the firm level and estimating a set of dynamic models analyzing the direct and indirect (via total factor productivity) effects of the digital transformation on SMEs' export and import strategies. Overall, our results show that firm decisions to export and import are simultaneously determined. Moreover, the firms' degree of digitalization positively influences the probability to export and import, both directly and indirectly through TFP. The direct effect seems to be larger for exports than for imports, while the opposite seems true for the indirect effect.

Keywords: Exports, Imports, Digital transformation, SMEs, Productivity.

JEL: D22, D24, F14, O33.

[1] *Department of Applied Economics II and ERI-CES, Faculty of Economics, Universitat de València, Avda. Tarongers, s/n, 46022 Valencia (Spain); e-mail:* m.dolores.anon@uv.es. *ORCID*: orcid.org/0000-0003-2468-9490

[2] *Department of Applied Economics II, Faculty of Economics, Universitat de València, Avda. Tarongers, s/n, 46022 Valencia (Spain); e-mail:* dabon@alumni.uv.es.

We acknowledge financial support from Grant ECO2017-86793-R funded by MCIN/AEI/ 10.13039/501100011033 and by "ERDF A way of making Europe", and from Grant PROMETEO/2019/095 funded by Generalitat Valenciana. Usual caveats apply.

1. Introduction

It is widely admitted that the digital transformation represents a fundamental potential source of competitiveness and growth for firms in global markets (OECD, 2019). It is in this context that adequate attention needs to be placed so that these new opportunities provided by digital technologies (DTs) are not only limited to large enterprises. Since small and medium-sized enterprises (SMEs) play a very significant role in the economy (due to their contribution to the generation of jobs and value-added), it is then desirable that they are stimulated into adopting and integrating new DTs more rapidly and efficiently. Moreover, it has been claimed that the adoption and the smart use of DTs may represent the fundamental basis for their survival[3] (Parker and Castelman, 2007).

In recent years, most developed economies have witnessed an expansion in the involvement of DTs in the process of production and distribution of goods and services (Alcácer *et al.*, 2016). While most studies have focused on the role of digitalization, and more specifically of information and communication technologies (ICTs, henceforth) in the production process (Brynjolfsson *et al.*, 2002; Corrado *et al.*, 2017), its role in distribution, and in particular, in trade has received less attention. Moreover, most of these studies use single indicators of the digitalization phenomenon, which are only able to partially capture the degree of penetration of (certain) DTs and struggle to mirror the fast pace at which the digital transformation has unfolded. Hence, they omit the fact that digitalization is a complex phenomenon that is poorly captured by a single indicator and that different firms and sectors

[3] Nevertheless, it has been shown that while large companies have been quick to adopt ICT and other digital technologies, SMEs have had more serious problems with the requirements and challenges of these new technologies (Swamidass, 2003; Parker and Castelman, 2007).

are affected by digital and automated technologies in diverse ways. To overcome these drawbacks, we follow Calvino *et al*. (2018) and construct and 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 analyze the relationship between the digital transformation by SMEs in the Spanish manufacturing sector and their trade activity. More specifically, we explore how digitalization can facilitate trade in SMEs by focusing on the firms' decisions to both export and import.

The impact of digitalization on trade may be direct or indirect throughout efficiency gains. On the one hand, the digital transformation may enhance trade flows by lowering trade costs and barriers associated with the use of DTs (Yushkova, 2014). In this regard, there are various mechanisms through which DTs may lead to the reduction of trade costs. First, digitalization improves the transparency on the markets, which is an essential condition for exchange, and thus lowers the costs of searching, matching, and communicating with different stakeholders across borders (Hagsten, 2015). Second, DTs provide additional channels for commercial relationships, marketing, and sales, allowing firms to reach larger numbers of digitally connected customers globally. On the other hand, DTs enable firms to source their inputs and organize production more efficiently, thereby enhancing productivity (Fernandes *et al*., 2019). Furthermore, advances in digitalization can be exploited to facilitate the outsourcing of non-core activities and to support the integration into the global value chain. These potential benefits from the digital transformation may be even greater for SMEs since it can contribute to reduce the internationalization costs related to their size and the difficulty to commit financial and human resources (Cassetta *et al*., 2020; Hagsten and Kotnik, 2017).

According to the arguments above, we contend that there is a positive relationship between firms' degree of digitalization and the internationalization of SMEs. Certainly, as DTs reduce the costs and the barriers to international trade, such as allowing buyers to easily compare the prices set by different suppliers, we claim that a higher level of digitalization may induce SMEs to export and/or import. Furthermore, digitalization may also indirectly affect trade due to its potential enhancing effect on the firm's productivity (Cardona *et al*., 2013). In this regard, this study aims to gain additional insights into the relationship between digitalization and export and import activities by distinguishing between a direct effect of the digital transformation on trade activities and, on the other hand, an indirect effect through enhanced productivity. In doing so, data from the *Spanish Survey on Business Strategies* (ESEE) for a sample of Spanish manufacturing SMEs from 2000 to 2014 will be used. A distinguishing feature of the database is that it provides information about the firm's export and import activities, as well as for distinct facets of the digital transformation.

Empirical evidence on the role of DTs on trade using micro-level data is scarce, with few exceptions (see Añón Higón and Bonvin, 2022; Añón Higón and Driffield, 2011; Fernandes *et al*., 2019; Hagsten and Kotnik, 2017; Kneller and Timmis, 2016). The contribution of our study to previous literature is manifold. First, in contrast to previous studies, we construct a multi-faceted index of digitalization at the firm level. Second, in addition to the direct effect of digitalization on trade performance, we also analyze the effect of digitalization through enhanced productivity. We do so, by estimating in a first stage a production function in which we endogenize the digitalization index and the trade decision and retrieve the firm's total factor productivity (henceforth, TFP). In a second stage, we study the effect of both digitalization and the estimated TFP on the export and import participation decisions. A positive estimate of the TFP variable in the trade participation equations should be considered as evidence of a positive indirect effect of digitalization through enhanced productivity on exports and/or imports. Second, instead of using a static model, we model foreign market participation as a dynamic process[4]. In this respect, our empirical analysis builds on recent literature (Añón Higón and

[4] Although the model of Hagsten and Kotnik (2017) is dynamic in its specification, they estimate the export participation equation using a pooled probit.

Bonvin, 2022; Brancati *et al*., 2017; Mañez *et al*., 2014) and tackles the issues related to the endogeneity of the lagged dependent variable and to the initial conditions problem. Besides, following Aristei *et al*. (2013) and Elliott *et al*. (2019) we estimate exports and imports equations jointly in order to account for the fact that they are simultaneously determined. Therefore, we account for the contemporaneous correlation between the two internationalization choices. All in all, our results suggest that digitalization has a significant direct and indirect role in the decision to export and import. The direct effect of digitalization seems to be grater for exports than for imports, while the opposite seems true for the indirect effect.

The remainder of the study is organized as follows. The next section reviews the extant literature. We then go on to describe the database and methodological approach, followed by the empirical results obtained. Lastly, we discuss the findings, implications, and limitations of this study.

2. Literature Review

2.1. The link between digital technologies and trade

In this section, we review existing literature on the relationship between DTs and trade for SMEs. Although recent empirical studies have brought new evidence regarding the positive role of digitalization, and more specifically ICT and the internet, for export performance (see, for instance, Añón Higón and Bonvin, 2022; Fernandes *et al*., 2019; Kneller and Timmis, 2016), studies focusing specifically on SMEs are scarce. However, because of their limited resources (Bennett, 1997) which impede their ability to compete (Coviello and Martin, 1999), SMEs may benefit from digitalization in a different way than their larger counterparts. Indeed, entering foreign markets has a high sunk cost, which is expected to be more burdensome for smaller firms and could prevent them from internationalization (Melitz, 2003). The internet, for instance, has been proved to reduce trade barriers for SMEs (Hamill and Gregory, 1997) in being a low-cost medium of internationalization (Kim, 2020) and thus, helping them to overcome distance and entry-related costs (Hagsten and Kotnik, 2017), as well as communication costs (Aspelund and Moen, 2004). According to Mata *et al*. (1995), using ICT could provide firms with a competitive advantage, which is one of the reasons that SMEs adopt these technologies at first (Dholakia and Kshetri, 2004).

Although a large number of studies base their findings on country-level data[5], micro studies with firm-level data are relatively rarer. Despite this, micro studies can be classified into two types: studies that focus on firms of all sizes and others that focus solely on SMEs. Among the former, Kneller and Timmis (2016), using data from UK firms between 2000 and 2005, show that broadband use has a positive causal effect on the probability of exporting business services. Similarly, using data of Chinese firms from 1999 to 2007, Fernandes *et al*. (2019) find a causal and significant impact of the internet deployment on manufacturing exports. Moreover, they show that this took place even before the rise of e-commerce platforms. More recently and for a sample of Spanish manufacturing firms, Añón Higón and Bonvin (2022) find that firms using ICTs, and in particular those that have a website, experience a direct increase in their probability of exporting, but not in their export intensity. Nevertheless, ICTs increase export intensity indirectly via the productivity channel.

Other studies have put the focus on SMEs. For instance, Loane (2005), using a sample of SMEs from Ireland, Canada, New Zealand, and Australia, finds that the internet enables SMEs to trade globally even at an early stage of development. Hagsten and Kotnik (2017) show that, for a sample of SMEs from 12 European countries, basic ICT tools, such as having a website, are more important for entering foreign markets than advanced ICT tools, such as e-

[5] Part of the literature in this field of research uses country-level data and focuses on the macro aspect of the relation between ICT and trade (see for instance, Clarke and Wallsten, 2006; Demirkan *et al*., 2009; Freund and Weinhold, 2002, 2004a; Yushkova, 2014). The macro literature suggests that there is a positive and significant influence of using ICT on trade.

commerce, which play a more crucial role in export intensity. The UK has received ample evidence. Within the early studies, Hamill and Gregory (1997) suggest that the internet is well suited to help SMEs to overcome trade-related barriers, and this even when the Internet was at a very early stage of development. More recently, Mostafa *et al*. (2005) using 5 ICT indicators (resources committed to the internet, internet usage, perceived benefits, web function, and internet experience) find that the Internet helps to improve trade, especially when firm managers have a strong entrepreneurial orientation, which would make them more likely to benefit from the opportunities offered by the Internet. Similarly, Añón Higón and Driffield (2011) identify a positive correlation between the use of ICT by firms and the propensity to export, as well as the export intensity. Morgan-Thomas and Jones (2009) find a strong association between internet use and rapid business internationalization, while Sinkovics et al. (2013) argue that the Internet, if used as a sales channel, should be complemented with other tools, such as advertising or delivery support, in order to increase export performance. Using respectively a sample of UK and Norwegian SMEs, Tseng and Johnsen (2011) and Aspelund and Moen (2004) evidence that the Internet has a greater impact on high-tech SMEs than on their low-tech counterparts. More recently, Jin and Hurd (2018) illustrate that digital platforms, Alibaba in particular, help SMEs to overcome some entry barriers into foreign markets, while Lendle *et al*. (2012) find a similar result for eBay. Finally, as far as Spanish firms are concerned, using the Survey of Business Strategies, Nieto and Fernandez (2005) evidence that there is a positive effect on SMEs' export intensity of selling to other businesses online, while selling to final consumers or having a website do not have a significant effect. Hence, there seems to be a consensus that using digital technologies, and more specifically, internet-related technologies, has a positive effect on the export performance of SMEs and therefore, on their internationalization process.

However, most of the above literature focuses on exports and overlooks the importance of digitalization for imports. Certainly, imports can also be facilitated by more extensive use of DTs, as the cost of imports can be reduced through lower communication and coordination costs (Jungmittag and Welfens, 2009). Hence, thanks to digitalization, information can circulate more rapidly, allowing buyers and sellers to find each other at lower costs. This is, at least partly, responsible for what we commonly refer to as the death of distance, for both imports and exports (see Freund and Weinhold, 2004b; Demirkan *et al.*, 2009). In this regard, digital technologies are replacing face-to-face interactions with, for instance, interactions by phone or email (Dettmer, 2014).

Few studies analyze the impact of digitalization on imports. Using a panel of 49 countries between 2000 and 2013, Nath and Liu (2017) provide evidence that the development of ICT facilitates imports of financial services, insurance services, other business services, royalty and license fees, and telecommunication services. Similarly, Ozcan (2018), for a sample of countries trading with Turkey between 2000 and 2014, shows a positive effect of ICT development on both exports and imports volumes, the effect being larger for imports. More lately, and at a micro-level, a couple of studies have shifted the focus away from ICT and analyzed the role of the adoption of automated technologies, mainly robots, on imports. For example, Stapleton and Webb (2020) find a positive effect of robot adoption by Spanish firms on their imports from low-income countries over the period 1990 to 2016. This effect is mainly caused by firms starting to import from low-income countries as a result of automation. However, the effect of adopting robots for firms that were already importing from low-income countries before robot adoption is to shift some of their imports away from low-income countries towards high-income countries. The conclusions of Alguacil-Marí *et al.* (2020) are quite similar. Using a sample of Spanish manufacturing firms between 1994 and 2014, they show that the adoption of robots helps firms to start importing and exporting, and increases the value and weight of imports in total sales. Likewise, they also evidence an eventual shift from low labor costs countries to higher labor costs countries, ensuring greater quality and technology of inputs. Overall, these studies suggest that digitalization and automation have a positive effect on imports. Nevertheless, these studies do not take into account that the decision to export and import are determined simultaneously (Aristei *et al*., 2013; Elliott *et al*., 2019).

2.2. The link between digital technologies and productivity

Knowing the cost-reducing nature of digitalization, we also expect it to have a productivity-enhancing effect. Hence, we argue that digitalization affects trade directly, but indirectly too through the enhancement of productivity. The analysis of the indirect impact of digitalization on exports and imports through productivity gains thus relates this study to a constantly expanding literature on the role of digital and automated technologies on firm productivity. The arguments by which DTs are said to have strong positive effects on productivity are diverse (Syverson, 2011). Digitalization endows firms to source their inputs and organize production more efficiently, and it facilitates changes in management and organization practices (Arvanitis and Loukis, 2009; Bloom *et al*. 2014). Hence, it is argued that ICT, and other digital and automated technologies, are key enablers of innovation and technical change, and thus, foster productivity gains (Brynjolfsson and Saunders, 2010; Jovanovic and Rousseau, 2005). Yet, the empirical evidence, particularly at the firm level, is rather mixed.

When it comes to the empirical evidence, early studies found limited evidence of the positive impact of ICT on productivity (for an overview, see Cardona *et al*., 2013). For instance, Loveman (1994) finds no evidence of IT having a significant effect on productivity based on firm-level data from the US and Western Europe between 1978 and 1984. Berndt and Morrison (1995) and Brynjolfsson (1996), both using data from the US between 1968 and 1986, and 1987 and 1991 respectively, reach similar conclusions and show no significant effect of ICT on productivity.

In turn, as technology diffused and adoption rates increased, the number of firm-level studies finding a positive significant effect on productivity increased. Brynjolfsson and Hitt (2003), using data from 527 US firms from 1987 to 1994, show that computerization has a positive impact on productivity in the long term but not in the short term. O'Mahony and Vecchi (2003) also conclude a long-term impact of ICT on TFP using industry panel data from the US and UK between 1976 and 2000. Hempell (2005), with firm-level data from Germany over the 1994-1999 period, evidences a positive impact of ICT on the productivity of firms in the service sector. Commander *et al.* (2011), using firm-level data from manufacturing firms in Brazil and India, also find a strong and positive association between ICT capital and productivity.

More recently, the productivity slowdown has sparked renewed interest in the role of DTs, albeit again with mixed results. Using US firm-level data from 1977 to 2007, Acemoglu *et al.* (2014) find that the intensity of IT has no effect on manufacturing productivity, except in the computer-producing industry. According to DeStefano *et al.* (2018), broadband has a causal effect on firm size but not on productivity in UK establishments in the early 2000s. In contrast, Bartelsman *et al.* (2019) find a positive relationship between the share of broadband-connected employees and productivity for a sample of European firms from 2002 to 2010. Similarly, Gal *et al.* (2019) show a strong relationship between the adoption of DTs in a sector and productivity gains at the firm level for a large sample of OECD firms.

In contrast to previous literature, we propose that digitalization endogenously affects TFP. By opting for an endogenous process in the dynamics of TFP, as proposed by Doraszelski and Jaumandreu (2013) for R&D, we account for uncertainties linked to the success of the digitalization process, which might explain the heterogeneous results obtained in previous studies. Further contributions to the literature discussed above are made. First, we use a multi-dimensional digitalization index, which includes 13 dimensions of the digital transformation along the lines of the taxonomy presented in Calvino *et al.* (2018). This allows us to better capture the degree of digitalization than including separate dummies that only consider, for example, the use of the internet or the presence of e-commerce. We also differ from previous studies in that we consider both the direct and indirect effect, through TFP, of digitalization on trade. In addition, we also examine the interdependent relationship between imports and exports. To do so, we estimate the decision to export and import simultaneously within a dynamic random-effects model based on recent literature (Brancati *et al.*, 2017; Elliot *et al.*, 2019) and attempt to control for the potential endogeneity of digitization.

3. Methodology

To analyze the role of the digital transformation as a trade facilitator for SMEs, we estimate a model that considers the impact of digitalization on the *extensive margin* of both exporting and importing, i.e., the propensity to export (import) or the probability to participate in foreign markets though export (import). More specifically, this model is based on the model proposed by Roberts and Tybout (1997). According to this model, firms decide to export (import) when current and expected revenues exceed current costs and any sunk cost the firm faces in accessing foreign markets. Therefore, to model the SMEs propensity to export (import), we assume that firm *i* decides to export (import) in period *t* if the expected present value of profits from exporting (importing), EXP_{it}^* (IMP_{it}^*), is positive. Formally,

$$\begin{cases} EXP_{it}^* = \alpha_i^{exp} + \delta^1 DIG_{it} + \gamma^1 TFP_{it-1} + \beta^1 X_{it-1} + \eta^1 EXP_{it-1} + \theta^1 IMP_{it-1} + d_j + d_t + \varepsilon_{it}^1 \\ IMP_{it}^* = \alpha_i^{imp} + \delta^2 DIG_{it} + \gamma^2 TFP_{it-1} + \beta^2 X_{it-1} + \eta^2 IMP_{it-1} + \theta^2 EXP_{it-1} + d_j + d_t + \varepsilon_{it}^2 \end{cases} \quad (1)$$

Where EXP_{it}^* (IMP_{it}^*) is a latent variable that represents the unobserved profitability of engaging in exports (imports), which in turn depends on the firm's digital transformation (DIG_{it}), the lagged TFP (in logs), which controls for the indirect effect of digitalization on export (import) via the productivity channel (TFP_{it-1}), and a vector of other lagged observable explanatory variables represented by X_{it-1}. Moreover, both α_i represent the time-constant unobserved firm-specific effect, while d_j denotes industry fixed effects at the two-digit level, and d_t is a set of time effects. Finally, EXP_{it-1} and IMP_{it-1} are dummies accounting for previous (realized) export (import) experience and are included to capture sunk-entry costs. The effect of other time- and firm-specific unobservable determinants are summarized in the idiosyncratic error terms, ε_{it}.

However, instead of observing the latent variable, EXP_{it}^* (IMP_{it}^*), we only observe a binary variable, EXP_{it} (IMP_{it}), which indicates the sign of the latent variable and states whether firm i engages in exporting (importing) in year t or not. Hence, the observed binary variable and its underlying latent counterpart are related according to:

$$EXP_{it} = \begin{cases} 1, & EXP_{it}^* \geq 0 \\ 0, & EXP_{it}^* < 0 \end{cases} \tag{2}$$

$$IMP_{it} = \begin{cases} 1, & IMP_{it}^* \geq 0 \\ 0, & IMP_{it}^* < 0 \end{cases} \tag{3}$$

It is also important to emphasize that η in equation (1) is the parameter of persistence of the dependent variable induced by the existence of sunk costs. If η is positive and significant, it implies that SMEs that export (import) in t-1 are more likely to export (import) in t than if they do not export (import) in $t-1$. However, to estimate η consistently, it is necessary to account for both unobserved heterogeneity[6] and the initial conditions problem. Indeed, the first observation of EXP_{it} (IMP_{it}) is correlated with both the unobserved heterogeneity term α_i (Heckman, 1981) and all the future realizations of EXP_{it} (IMP_{it}). This entails that EXP_{it-1} (IMP_{it-1}) is correlated with the unobserved firm-specific time-invariant effects, α_i, and this will yield inconsistent estimates, unless the initial condition is accounted for. To address this issue, we follow Wooldridge (2005) who suggests making assumptions about the distribution of the unobserved effects conditional on observed covariates and adopting a conditional maximum likelihood approach (Chamberlain, 1982; Semykina, 2018). Therefore, we assume that the unobserved firm-specific term in the export equation can be modeled as follows:

$$\alpha_i^{exp} = \delta_1^{exp}\overline{q_i} + \delta_2^{exp}EXP_{i0} + u_i^{exp} \tag{4}$$

Or in the case of importing:

$$\alpha_i^{imp} = \delta_1^{imp}\overline{q_i} + \delta_2^{imp}IMP_{i0} + u_i^{imp} \tag{5}$$

Where $\overline{q_i}$ is a vector including the Mundlak-Chamberlain means (Chamberlain, 1982; Mundlak, 1978). In other words, it represents the within-means of the control variables that are likely to be correlated with α_i. In this regard, we follow Semykina (2018) and assume in the baseline specification that the unobserved individual effects are only correlated with the firm's internal and external financial constraints. In the present context, the time means can be interpreted as measures of the firm's financial stability, which can also be viewed as proxies for unobserved firm-specific characteristics (e.g., management quality). As a robustness check, we

[6] To control for unobserved firm heterogeneity, both fixed-effects and random-effect specification can be used. However, since the model is nonlinear, the standard fixed effect panel method would produce inconsistent estimators (Semykina, 2018).

also consider a specification that includes the within-means of all exogenous variables included in X. On the other hand, EXP_{i0} (IMP_{i0}) represents the initial conditions, and both u_i's are the unobserved time-invariant heterogeneity terms, which are assumed to be independent of the initial conditions, the explanatory variables, and the respective idiosyncratic error term (ε_{it}).

Finally, we substitute equations (4) and (5) into (1) to obtain the final model:

$$\begin{cases} EXP_{it}^{*} = \delta^{1}DIG_{it} + \gamma^{1}TFP_{it-1} + \beta^{1}X_{it-1} + \eta^{1}EXP_{it-1} + \theta^{1}IMP_{it-1} + d_j + d_t \\ \qquad + \delta_1^{exp}\overline{q_i} + \delta_2^{exp}EXP_{i0} + u_i^{exp} + \varepsilon_{it}^{1} \\ IMP_{it}^{*} = \delta^{2}DIG_{it} + \gamma^{2}TFP_{it-1} + \beta^{2}X_{it-1} + \eta^{2}IMP_{it-1} + \theta^{2}EXP_{it-1} + d_j + d_t \\ \qquad + \delta_1^{imp}\overline{q_i} + \delta_2^{imp}IMP_{i0} + u_i^{imp} + \varepsilon_{it}^{2} \end{cases} \tag{6}$$

Although the two equations displayed above look like seemingly unrelated regression equations, it is important to note that they are in fact correlated via the error terms, as the lagged dependent variable in the first equation is part of the explanatory variables in the second, and vice versa (Elliott *et al.*, 2019). The Conditional Mixed Process (CMP) framework implemented by Roodman (2011) allows us to combine both the export and import propensity equations and estimate them jointly. Thus, ε_{it}^{1} and ε_{it}^{2} are the error terms of each equation with $\rho = Corr(\varepsilon_{it}^{1}, \varepsilon_{it}^{2})$. If ρ is significantly different from zero, then EXP_{it}^{*} and IMP_{it}^{*} are two interdependent processes, and a joint estimation is more efficient than estimating two separate probit models.

3.1. Modeling the indirect effect of digitalization through total factor productivity

To analyze the indirect effect that digitization may play on the trade strategies of SMEs, we need first to estimate TFP. Thus, to see whether digitization enhances firms' productivity, we estimate a production function that takes into account the possible effect of digitalization on the productivity process. Thus, firm-level TFP is estimated for SMEs in each two-digit industry from the following Cobb-Douglas production function (see Añón Higón and Bonvin, 2022):

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + \omega_{it} + e_{it} \qquad (7)$$

where we denote the logarithm of real gross output, labor, non-ICT physical capital, ICT capital, and materials as y_{it}, l_{it}, $k_{it}^{NIT}, k_{it}^{IT}$, and m_{it}, respectively. In addition, ω_{it} is the firm's productivity, which is assumed to be observable by the firm but not by the analyst; and e_{it} is the error term[7]. Labor and materials are assumed to be freely variable inputs, while both types of capital are regarded as fixed factors.

A crucial assumption in the estimation is the specification of the Markov process for productivity, in which productivity at time $t+1$ consists of expected productivity given a firm's information set, and an innovation term, ξ_{it+1}, which is assumed uncorrelated with the state variables. Following Doraszeski and Jaumandreu (2013) and De Loecker (2013), we propose an endogenous (first-order) Markov process, in which we allow the digitalization index and the trade status (i.e., whether the firm exports or imports) to impact future productivity:

$$\omega_{it+1} = g(\omega_{it}, DIG_{it}, TRADE_{it}) + \xi_{it+1} \qquad (8)$$

Where g(.) is an unknown function. By using an endogenous productivity process, we control for potential learning effects. In this way, we account for the potential role that both firm's experience in digitization and trade may play in shaping future productivity.

[7] The estimated errors are robust to heteroscedasticity and autocorrelation.

The discussion now turns to the estimation process. The estimation of equation (7) with OLS will result in biased and inconsistent estimates because the firm's choice of inputs, especially variable inputs, depends on the firm's productivity, ω_{it} (which is observed by the firm but not by the econometrician). To address this endogeneity problem and consistently estimate the parameters in (7), we use the control function approach pioneered by Olley and Pakes (1996). More specifically, we apply the GMM estimation proposed by Wooldridge (2009)[8]. In doing so, we assume that the demand for intermediate inputs is a function of firms' ICT and non-ICT capital, as well as productivity. Moreover, such demand for intermediates is monotonic and strictly increasing in productivity, and, under certain conditions, it can be inverted to obtain: $\omega_{it} = m_t^{-1}(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) = h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it})$. Then, substituting into (7) we get the first equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) + e_{it} \qquad (9)$$

Since h_t (.) is an unknown function, which we proxy by a third-degree polynomial in its arguments, this results in the coefficients of capital and materials being non-identified in (9). Hence, the identification of these coefficients requires an additional equation that deals with the law of motion of productivity (Wooldridge, 2009). Therefore, as stated above, we introduce the assumption that productivity evolves according to an endogenous first-order Markov process as described by (8).

[8] The method distinguishes between state variables, in our case both types of capital, and flexible variables, here labor and materials. The realization of the state variables in period *t* is decided based on the information in *t*-1, and thus they are not affected by the productivity shock arriving *t*, while flexible variables are determined in response to the shock.

Considering that $\omega_{it} = h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it})$, equation (8) can be rewritten as $\omega_{it} = f(h_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}), DIG_{it-1}) + \xi_{it} = g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}) + \xi_{it}$; and plugging this expression into (7) we obtain the second equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}) + u_{it} \quad (10)$$

Where g_t (.) is an unknown function proxied by a third-degree polynomial in its arguments, and where $u_{it} = \xi_{it} + e_{it}$ is a composed error term.

Following Wooldridge (2009), equations (9) and (10) are jointly estimated by GMM using the appropriate instruments[9] for each of the 10 industries considered. As a result, we obtain industry-specific output elasticity estimates as well as firm-specific TFP estimates obtained as residuals. Table 1 reports the estimates of the production function (7) for each industry considered for the sample of SMEs. The results show that the output elasticity of ICT-capital is significant for all industries, except for the transport equipment industry, and it ranges from 0.006 in the metals and metal products industry to 0.045 in the electrical goods sector.

<Insert Table 1 here>

Following previous studies, once the estimated TFP is obtained as a residual for each of the two-digit industries, we winsorize the resulting distribution at the 1st and 99th percentiles to control for the impact of outliers. Then, TFP is included as a regressor in the export (import)

[9] We follow Doraszelski and Jaumandreu (2013) and De Loecker (2013) and do not account for sample selection by modelling a firm's exit decision.

participation equations. Finally, it should be noticed that for digitization to have an indirect effect through TFP on export (import) performance, two conditions should be met. First, the digitalization index should have a significant effect on productivity; and, second, the coefficient of TFP in the export (import) participation equation should be positive and significant. Then, a positive and significant estimate for the TFP variable in the export (import) propensity equation should be considered as evidence of a positive indirect effect accruing from firms' digital transformation to export (import) participation through enhanced productivity.

To check the first condition, we consider a linear specification of the endogenous Markov process described by equation (8):

$$\omega_{it} = \beta_1 \omega_{it-1} + \beta_2 DIG_{it-1} + \beta_2 TRADE_{it-1} + \gamma' z_{it-1} + \alpha_{jt} + \alpha_i + \epsilon_{it} \qquad (11)$$

Where the firm's TFP (ω_{it}) is a function of its lag value (ω_{it-1}), the *Digital* index (DIG_{it-1}), and the trade status ($TRADE_{it-1}$). In addition, we control for other factors that may influence the evolution of productivity including a vector of observed firm characteristics[10] (z_{it-1}), sector-year dummies (α_{jt}), and firm fixed effects (α_i). We interpret positive and significant estimates of β_2 as evidence of enhancing TFP effects from digitalization. Equation (11) is estimated by the two-step system-GMM estimator for dynamic models (Arellano and Bover, 1995; Blundell and Bond, 1998), which enables us to deal with both unobserved heterogeneity and the endogeneity bias.

3.2. Additional explanatory variables.

[10] We control also for firm's size and age.

We include in the vector X_{it-1} of equation (6) additional variables that previous literature has considered to influence the decision to engage in trade activities (Añón Higón and Bonvin, 2022; Brancati *et al*., 2017; Mañez *et al*., 2014, 2020). First, we control for the firm's market power, as measured by markups (Mañez *et al*., 2020), relative to the average markup in the industry. The markup is defined as the ratio of firms' output price (P_{it}) to marginal cost (MC_{it}). While the theory predicts that exporters may charge higher markups than non-exporters due to their productivity premium, if they face tougher competition abroad than at home, they will have to reduce markups to remain competitive there or they may choose to rely on dynamic pricing strategies, charging lower prices to build up a customer base. As a result, the average firm markup, conditional on physical productivity, might be lower for SMEs exporters than for non-exporters. To obtain firms' markups we use the methodology proposed by De Loecker and Warzynski (2012). This methodology does not require any assumptions on the shape of the demand faced by firms or on how firms compete. The only assumptions required are that: i) there is at least one variable factor of production, and, ii) firms are cost minimizers. Hence, from the first order condition of the cost minimization with respect to the variable input, one can compute the firm's markup (μ). Here we use intermediate inputs as the variable factor of production, given that labor in Spain may be subject to more rigidities. Hence, following De Loecker and Warzynski (2012), the estimate of the firm's markup can be obtained as the ratio between the output elasticity of the intermediate inputs (β_m), obtained from the estimation of equation (7), and the cost share of intermediate inputs relative to total sales $\left(\frac{P_{it}^m M_{it}}{P_{it} Q_{it}}\right)$. More specifically,

$$\mu_{it} = \frac{\beta m}{\left(\frac{P_{it}^m M_{it}}{P_{it} Q_{it}}\right)} \qquad (12)$$

Second, we control for the firm's internal and external finance. Numerous studies have addressed the role that financial factors and liquidity play in internationalization activities, especially in the export decision. All in all, results from the literature using different variables (and approaches) to measure internal and external financial resources show that firms with liquidity constraints have greater difficulty in starting to export (see Wagner, 2014) and are less likely to import intermediate goods (Nucci *et al*., 2020). In this study, we use a multivariate financial index that captures both internal and external finance, respectively (see Bellone *et al.*, 2010). First, to reflect firms' accessibility to internal funds we use the cash flow-to-assets ratio and the profitability ratio, measured by net profit after sales, as variables for the internal finance index. Both, a higher cash flow ratio and higher profitability may imply that firms have lower internal financial constraints[11]. Second, we use the cost of new long-term debt (Máñez *et al*., 2014) and the total volume of new long-term debt to measure firms' accessibility to external funds. The cost is obtained as the weighted average of the unit cost of debts that the firm has borrowed in a given year from both banks and other long-term lenders. It is generally assumed that the higher the interest payment the firms can afford, the lower the external financial constraints they face. In addition, new long-term debt refers to long-term loans obtained from banks and other long-term lenders in a given year. Positive values of this variable would correspond to firms that have access to a higher volume of external debt and, therefore face fewer financial constraints.

Following Bellone *et al*. (2010), for each variable representing both internal and external finance, we scale each firm/year observation for the corresponding two-digit sector average and assign to it a number corresponding to the quintiles of the distribution in which it falls[12]. The resulting value for each of the variables (a number between one and five) is then collapsed into two indices, one for internal and one for external finance, using a simple sum.

Furthermore, we control for the firm's age, R&D propensity, size (measured by the number of employees), human capital, foreign capital participation, appropriability conditions,

[11] While a higher cash flow ratio is usually regarded a sign of financial health, there are studies that suggest that firms may be forced to be liquid because they are unable to access external resources (Almeida *et al*., 2014).
[12] Sectoral averages are subtracted to account for industry-specific differences in financial variables.

firm's business cycle (measured by the firm's assessment of whether the demand in its main market is recessive or expansive), and the firm's number of market competitors[13]. To deal with the potential simultaneity bias, all explanatory variables enter with one lag in the model specification.

3.3. Control Function Approach

As the last specification, we use a control function (CF) approach[14]. The aim is to tackle more appropriately the potential endogeneity concerning the Digital index, treating the issue as an omitted variable problem (Wooldridge, 2015). The advantage of this approach to our context is that it can be applied to non-linear models. The CF that we propose to use is the residual of a regression of digitalization on the second lag of the Digitalization index and the industry regulatory index in communications drawn from the OECD NMR database[15]. We expect that regulation in communication services to be negatively correlated with the diffusion of DTs among firms, but we argue that both the regulation index and early digitalization not do not affect the firm's trade participation decisions in period *t*, other than by being correlated with the Digital index in period *t*. Particularly, the CF method consists of two stages. First, we estimate a reduced form equation for the digitalization index based on a fixed effect model and calculate the residuals of this equation[16]. In this regression, the instruments must be significant to be valid. In the second step, the residual is added to both equations in (6) to filter out the factors that might cause correlation between the digitalization index and the error term (Newey, 1987, Blundell and Powell, 2004). The statistical significance of the residual allows checking

[13] Table A1 in the Appendix presents the definition of variables.
[14] For a recent application of the CF approach see García-Vega and Huergo (2019).
[15] The index on the regulatory environment of communications (telecom and post) quantifies information on *ex-ante* anti-competitive restrictions in the market, measured by the extent of entry barriers, the degree of vertical integration and market conduct.
[16] Although for ease of exposition the results of the first-stage fixed effect regression are not shown, the effect of the second lag of the digitalization index is significantly positive, while the regulation index is significantly negative.

for the existence of an endogeneity problem for the digitalization index (Rivers-Vuong endogeneity test). If this is the case, the inclusion of the residual would correct for the bias. Note that we also use the CMP approach in this specification and estimate both equations jointly.

4. Data and Descriptive Statistics

4.1 Data

The data used in this study have been drawn from the Survey on Business Strategies (ESEE, henceforth) for the period 2001-2014. The ESSE is an annual panel database, carried out since 1990, sponsored by the Spanish Ministry of Industry, Tourism and Trade and, administered by the SEPI Foundation. It is worth noticing that the ESEE is representative of Spanish manufacturing firms classified by two-digit manufacturing industries of the NACE-Rev.1 and size categories. In particular, the ESEE provides information about firms' strategies, i.e., decisions firms take regarding their competition. 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 sampling procedure of the ESEE is as follows. Firms with less than 10 employees were initially excluded from the survey. Firms employing between 10 and 200 workers were randomly sampled, holding about 5% of the population in 1990. All firms with more than 200 employees were surveyed on a census basis, obtaining a participation rate of around 70% in 1990. Important efforts have been made to minimize attrition and to annually incorporate new firms with the same sampling criteria as in the base year. Hence, the sample of firms remains representative over time.

Our initial sample consists of an unbalanced panel of about 25,056 observations corresponding to firms observed at least two consecutive periods from 2001 to 2014. From this initial sample, to analyze the impact of the digital transformation on the export and import strategies of SMEs, we sample out large firms and those firms that fail to supply relevant information in any given year. After cleansing the data, we end up with a sample of 12,783 observations corresponding to 1,814 small and medium-sized firms.

Regarding our variables of interest, the ESEE provides information about whether the firm exports (imports). For the firm's export status, we use the following question: "*Indicate whether the firm, either directly or through other firms from the same group, has exported during this year (including exports to the European Union)*". Similarly, for the import status, we use the question: "*Indicate whether the firm, either directly or through other firms from the same group, has imported during this year (including imports from the European Union)*".

4.1.1 The Digitalization Index

The key indicator of digitalization at the firm level used in this study is based on the work of Calvino *et al*. (2018), adapted according to the availability of data in the ESEE. This index is conceived under the consideration that the digital transformation is a complex phenomenon that can hardly be captured by a single indicator, and that firms and sectors are affected by digital technologies in a heterogeneous way.

To create this index, we use several dimensions of the digital transformation that aim to represent the extent of digitalization of firms in Spain. The dimensions considered are: i) the technological components (proxied by ICT capital, computer programming services, and the implementation of software programs either hired or developed by the focal firm); ii) the digital-related human capital (proxied by personnel training in software and information technology); iii) the extent of automation (proxied by the use of robots, computer-aided design and flexible systems); iv) the way digitalization changes how firms interact with their stakeholders (measured by the use of LAN, the ownership of an internet domain and webpage, and the use of different modalities of e-commerce: b2b, b2c, and e-buying). In total, the synthetic index collapses information on 13 variables that measured in different ways contain relevant information relative to the digital transformation. In Table A2 of the appendix, we compare the dimensions and variables we use to those of Calvino *et al*. (2018). We will also analyze distinctively the role of automation from other DTs, which we will refer as ICTs. Hence, the automation index will capture the use of robots, computer-aided design and flexible systems, or in other words the automation component in the Digitalization index of Calvino et al. (2018).

The procedure to build the overall digitalization index can be summarized as follows. First, variables in monetary units (ICT investment and training costs) are capitalized and their relative value with respect to the industry-year mean is classified according to the decile of the distribution to which they belong. The result is then rescaled in the [0-1] range. Categorical variables available only every 4 years (use of robots, CAD, flexible systems and LAN), are first extrapolated and then normalized in the [0-1] interval. The rest of the categorical variables are not transformed. As a result, we end up with 13 variables ranging from 0 to 1. Finally, to obtain a synthetic index, we combine the information of these variables as an unweighted sum. The result is subsequently normalized in the [0-1] interval. Values close to 0 imply that the firm in that particular period is very little digitalized, while values close to 1 suggest a high degree of digitalization in the dimensions considered.

<Insert Figure 1 here>

In Figure 1, we show the digital transformation of manufacturing firms in Spain over the period 2001 to 2014 using the synthetic digitalization index. According to the left panel of

Figure 1, we observe that firms in Spain have undergone a process of digital transformation, which was much faster at the beginning of the 21 century and that slowdown later on as a result of the 2008 financial crisis. Moreover, the degree of digitalization varies significantly according to firm size, with SMEs (firms with less than 200 employees) being less digitalized than large firms.

<Insert Figure 2 here>

Figure 2 shows the digital transformation by industry from 2001 to 2014. All sectors have endured a process of digitalization, which for some industries, such as agricultural and industrial machinery, and transport equipment has been remarkable. By 2014, the most digitalized industries are transport equipment, agricultural and industrial machinery, and the electrical goods sectors. In contrast, textiles, timber and furniture, and food, beverages, and tobacco are among the least digitalized industries. This is in line with the taxonomy presented by Calvino *et al*. (2018) at the industry level.

4.2 Descriptive Statistics

Table 2 shows the percentage of observations in the overall sample of SMEs contained in each category according to the export and import activities of the firm. We notice that the percentage of observations corresponding to SMEs that export over the period 2001-2014 is about 60%; while those that do not export equals 40%. Similar percentages are obtained when considering non-importers and importers.

<Insert Table 2 here>

In Table 3, descriptive statistics for the variables of interest are presented, including the export and import propensity, the digitalization index, and variables that reflect the structural characteristics of the firms of the sample. Here, we first compare the SMEs that export in a given period with a sub-sample of SMEs that do not export, for which we can obtain an estimate of TFP. Exporters are on average larger, more productive, more innovative, with more human capital, and with a higher stake of foreign ownership. More interestingly, we see that exporters are more digitalized on average than non-exporters. Furthermore, exporting SMEs have a lower relative markup than non-exporters. This may be because exporting SMEs may face a tougher competitive environment in foreign markets than their peers serving only the domestic market, therefore they have to charge lower markups in order to remain competitive relative to the more efficient foreign competitors. Second, we compare importers to non-importers on the same characteristics. Similar to exporters, firms that import are, on average, more digitalized, larger, more productive, more innovative, with more human capital, with a higher stake of foreign ownership, and with lower mark-ups.

<Insert Table 3 here>

5. Results

We now turn to assess the direct and indirect impact of digitization on the export and import decision of SMEs. We will consider the direct effect attributed to the use of DTs, once we control for the indirect impact via TFP. As stated above, two conditions must be met for the existence of the indirect effect. First, the digital index must have a positive significant effect on TFP. Second, the coefficient of TFP in the export and import participation equations should be positive and significant. Therefore, the initial step for the analysis of the indirect effect is the endogenous Markov process presented in equation (11). The results of estimating this equation by system-GMM are presented in Table 4. We present the tests of Arellano and Bond (1991) for serial correlation in the error terms. Although the hypothesis of no second-order autocorrelation is rejected, the Arellano-Bond AR(3) test indicates the absence of third-order autocorrelation in the error term. Hence, we use third or higher lags as instrumental variables. All the specifications provide suitable results for the Hansen test of overidentifying restrictions and the validity of the instruments.

First, column (1) of Table 4 displays the results of the estimation of equation (11), excluding the vector of observed firm characteristics as controls. The results show that the coefficient of the digital index is positive and significant, which supports the assumption that digitization enhances future TFP. In column (2) we control also for the vector of observed firm characteristics. Here, digitalization positively and significantly enhances TFP. Finally, we use the growth rate of TFP as a dependent variable as a robustness check in column (3). Overall, the results displayed in Table 4 show that digitalization has a positive and significant impact on TFP and TFP growth, hence the first condition for the presence of the indirect effect is satisfied. This implies that, if we find evidence of a positive effect of TFP on exports and/or imports, we can conclude an indirect effect of digitalization on trade via TFP. Then, the estimation of the system of equations in (6) will provide the final proof.

<Insert Table 4 here>

Table 5 provides the estimation results of the export and import decision under different specifications of the system of equations in (6). Results are presented as average marginal effects (AME, henceforth). The potential interdependency between export and import participation is ignored in the first specification (columns 1 and 2), Thus, this specification is estimated as two separates RE dynamic probit models with the Wooldridge (2005) approach. The interdependence between both strategic decisions is considered in the second specification (columns 3 and 4), but the potential endogeneity of the digitalization index is ignored. This second specification is estimated as a RE dynamic bivariate probit model. As expected, the results of this specification confirm that the export and import strategies are not independent. The statistically significant estimated correlation coefficient for the error terms (ρ-value = 0.391) demonstrated this. This explains why a bivariate model, rather than two separate probit models, was chosen as the correct specification for each trading decision.

Finally, in the third specification (columns 5 and 6 in Table 5), an instrumental-variable control function (CF) approach is adopted to account for the potential endogeneity of the digital index to explain the decisions to export and import. 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 at the two-digit CNAE level to capture different technological opportunities and other unobserved factors 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 instruments (the second lag of the Digital index and the industry regulatory index in communications) and the rest of exogenous variables in a fixed effect model. Although, for ease of exposition, the estimates of the first-stage regression are not shown, the coefficient of the second lag of the digitalization index is significantly positive and the regulation index is significantly negative, as expected. However, the residual from this first-stage is not significant in the export and import participation equations, suggesting that the digital index does not suffer from endogeneity.

In what follows, and after ruling potential reverse causality problem between the digital index and trade participation decisions, we proceed to discuss in detail our estimation results on the main variables of interest based on columns 3 and 4. Concerning the main variable of interest, the digitalization index, we notice that it has a direct positive significant effect on the probability to export and import. To be more specific, the marginal effect implies that an increase of the digitalization index by 10% raises the corresponding probability to export by almost 0.9 percentage points, holding all other variables constant. Hence, digitalization appears to facilitate the internationalization of SMEs by reducing transaction costs, for instance, those related to marketing or entry-related cost, which allow SMEs to engage in foreign sales. Similarly, concerning imports, an increase of 10% of the digitalization index appears to increase the probability to import by about 0.5 percentage points. In this regard, the results suggest that digitalization directly facilitates trade in Spanish manufacturing SMEs, although the effect seems to be large for exports than for imports.

Concerning the indirect effect (through TFP enhancement) that digitalization may play in trade activities, the results in Table 5 provide also support. TFP has both a significant effect on the export and import propensity. Therefore, our results support the argument that digitalization enhances the probability to participate in exports and imports not only through a direct channel but also through productivity gains (the indirect TFP channel). Hence, TFP appears as significant and positive in the export and import equation. Particularly, the marginal effects show that an increase of 10% in TFP raises the export probability by 0.4, while import probability by 0.8 percentage points.

<Insert Table 5 here>

As expected from previous studies (Elliot *et al*., 2019), past export and import experiences stand as important determinants of actual export and import propensities, respectively. This suggests that there are important sunk costs into internationalization. In other words, once a firm has paid the sunk costs of being global, it is easier to pursue its export or import activities in the next period. Indeed, everything else being equal, SMEs exporting in period *t-1* vis-à-vis non-exporters, are about 16 percentage points more likely to continue exporting in period *t*. Similarly, SMEs importing in period *t-1* are 19 percentage points more likely to import in period *t* with respect to non-importers in *t-1*. Moreover, we show that previous import experience also has a positive effect on export participation and vice-versa. Importing firms have access to a greater variety and better quality of intermediate inputs allowing them to improve their productivity and break into export markets (Kasahara and Rodrigue, 2008). Firms that import in period *t-1* are 3.3 percentage points more likely to export in period *t* with respect to non-importers in *t-1*, whereas previous export experience raises the probability of importing in period *t* by 5.1 percentage points.

In terms of the rest of the control variables, the results displayed in Table 5 show that, ceteris paribus, small firms with lower relative markups have a higher probability to participate in exporting and importing. Additionally, concerning export propensity, human capital, appropriability conditions, and firm size have also a positive and significant effect, whereas R&D, foreign ownership, firm size and an expansive market demand appear as positive and significant in the import equation. Despite not being reported, the initial condition appears positive and significant in all the specifications. The rest of the firm-level controls do not seem to affect the decision of SMEs to enter into foreign markets.

5.1.Robustness Analysis

In this section, we perform some robustness tests to check if the results we have obtained are robust to some different specifications of the model. The results are displayed in Table 6 where, for clarity reasons, we present only the average marginal effects of the digital index variable and that of the TFP[17].

[17] Although all specifications include the same controls as in Table 5, for ease of exposition only the results for the variables of interest are presented. Full results are available from the authors on request.

As discussed above, in previous specifications the unobserved firm-specific effect has been modeled using only the individual time means of the internal and external financial variables. While such restrictions may help to avoid the multicollinearity problem, they can also cause biases (Semykina, 2018). As a first robustness check, we include all the within-means of the control variables for the different specifications of our model to avoid potential biases. Having a look at the results in column (1) of Table 6, we perceive that digitalization still has a positive and significant effect on export participation. This effect is to raise the probability to export by roughly 0.9 percentage points for an increase of 10% of the digital index. TFP remains also significant, confirming the indirect effect. Moving to the second column, the results show similar results than in Table 5. Indeed, we have evidence of both a direct and indirect effect of digitalization on import propensity. However, the direct effect is of a lower magnitude, i.e., raising the digital index by 10% increases the probability of importing by only 0.4 percentage points.

Second, we follow Mañez *et al*. (2020) and model the unobserved firm's heterogeneity terms, α_i, conditional on the pre-sample mean of the dependent variable, as follows:

$$\alpha_i^{exp} = \delta_o^{exp} + \delta_r^{exp}\overline{EXP_{i98-99}} + u_i^{exp}$$

$$\alpha_i^{imp} = \delta_o^{imp} + \delta_r^{imp}\overline{EXP_{i98-99}} + u_i^{imp}$$

The pre-sample mean $EXP_{i98\text{-}99}$ ($IMP_{i98\text{-}99}$) is calculated as the within-firm mean of *EXP* (*IMP*) for pre-sample years. As the dynamic nature of equation (1) implies that the period of analysis covers 2002-2014, we use the pre-sample period 1998-1999. Results are reported in columns (3) and (4), and despite the loss in observations, both the digital index and TFP remain positive and significant in explaining both the decision to export and import.

<Insert Table 6 here>

Our last robustness check deals with a concern related to the fact that TFP in the trade equations is an estimated regressor, which could render the standard errors inaccurate and therefore affect inference. To address this problem, we report block bootstrapped standard errors with the firm as the block unit and based on 250 replications. The results are presented in columns (5) and (6) and are very similar to the baseline specification. Indeed, in column (5), we notice that digitalization and TFP have a positive and significant effect on export participation. Concerning import participation, in column (6), results show that both digitalization and TFP also have a positive and significant effect on the decision to import.

The effect of digitalization on export and import propensity appears to be confirmed by the robustness checks we have performed. We also have evidence of a positive and significant effect of TFP. Overall, our results indicate that digitalization facilitates both exports and imports, both directly and indirectly through TFP enhancement.

5.2. Sensitivity Analysis

At this stage, we have shown that digitalization has a significant and positive direct effect on the export and import participation of Spanish manufacturing SMEs, as well as an indirect effect through the TFP channel. Now, our purpose is to examine which firms and industries benefit most from digitalization. Previous studies have shown that the relationship between DTs and firm performance is heterogeneous, with some firms or industries being more successful in exploiting DTs than others (DeStefano *et al*., 2018).

Thus, considering that the take-up of DTs and automation varies widely across industries, we first perform the analysis distinguishing between firms belonging to high- and low-digitalized industries according to the classification by Calvino *et al*. (2018) (see Table

A.3). In principle, it is unclear whether the trade effect of digitalization is greater for firms in low-digitized industries or vice-versa. While firms in low-digitized industries have more to gain from the adoption of DTs, the digital transformation may be more effective when many firms in an industry use DTs intensively because of the potential for knowledge spillovers (Laursen and Meliciani, 2010).

<Insert Table 7 here>

The trade impact of the Digital index and TFP in low-digitalized industries (columns 1 and 2) and in high-digitalized industries (columns 3 and 4) is displayed in Table 7. The results suggest that DTs in low-digitalized industries both directly facilities the entry into foreign markets and have an indirect effect through productivity gains. The direct effect implies that a 10% increase of the digital index boosts the probability of exporting by 6.3 percentage points, while raises the probability of importing by 7.4 percentage points. However, digitalization does not appear to influence the export decision in high-digitized industries, and only affects imports indirectly through TFP. In sectors with a high degree of digitization, the use of DTs is not a distinctive feature that enhances firms' likelihood of exporting. In contrast, it is precisely in more digitally disadvantaged sectors where SMEs can gain more from the use of DTs, both directly and indirectly through TFP gains.

Secondly, DTs have been linked to the fragmentation of the global value chain (GVC) and the decision to offshore and outsource as they reduce the transaction and adjustment costs of moving some activities outside the firm (Abramosky and Griffith, 2006; Rasel, 2012). At the same time, SMEs are under-represented in GVCs, and DTs may open up new avenues for them to play a more active role (Sasidharan and Reddy, 2021). Given that the integration in GVCs varies greatly across industries, we perform the analysis distinguishing between firms in sectors that are low- and highly-integrated in GVCs (see Table A.3). In this case, the classification on GVC participation is based on the OECD "GVC forward linkage" indicator at industry level for Spain for the year 2000, which is expressed as the share of domestically produced inputs used in third countries' exports.

The trade impact of the digital index and TFP in industries with low-participation (columns 5 and 6) and in high-participation in GVCs (columns 7 and 8) is displayed in Table 7. The results show that in low-GVC integrated sectors, digitization exerts a direct and indirect impact on exports, while digitization increases the probability to import just through the productivity effect. In the case of industries with high participation in GVCs, digitization directly increases the probability to export, but there is no indirect effect through productivity. In contrast, digitization has a direct and indirect impact on imports.

Finally, while both automation and ICTs will bring productivity gains to the firm, it seems plausible that the direct effect of these technologies on trade may be different. Although both are derived from the same technologies, they potentially have quite different implications for the international division of labor and trade activities. On the one hand, automation technologies -including robots and CAD- are more likely to reduce the number of tasks and may accelerate the substitution of humans by machines, and thus, they are likely to induce "reshoring" of some tasks previously outsourced. On the other hand, ICTs, particularly communication technologies (Baldwin, 2016), help to overcome physical distance, reduce matching and coordination costs, and thus, are likely to encourage fragmentation of the production processes. To assess this, we estimate the system of equations (6) distinguishing two dimensions within the digital index: the automation index, and the ICT index. The results, presented in Table 8, show that while the ICT index appears positive in explaining both the export and import participation decisions, the automation index does not play a significant direct role. Nevertheless, the productivity effect of both ICT and automation leads to a higher probability to import and export. The results for the effect of ICT and automation and imports are in line with previous studies that suggest that digitization, and automation, did not cause reshoring in Spanish firms (see Alguacil-Marí *et al*., 2020; Stapleton and Webb, 2020).

Conclusion

Digital technologies have been considered to exert an important role in facilitating trade because of their potential to reduce transaction costs and improve communications between buyers and sellers, but also owing to their ability to enhance firms' efficiency. Thus, DTs may help SMEs to overcome the barriers they face to enter into foreign markets. In this study we analyze both the direct and indirect effect (via productivity) of the digital transformation on both the export and import participation of SMEs. In contrast to previous studies that use a single indicator of the digitalization phenomenon, we use a synthetic index of digitalization at the firm level that considers the multi-faceted phenomenon of the digital transformation. Then, we study both the direct effect of digitalization on the import and export participation decisions, as well as the indirect effect through enhanced productivity. To unravel the indirect effect, we consider an endogenous Markov process for the dynamics of TFP.

Our main empirical strategy consists of estimating a dynamic RE bivariate probit model that models the decision to export and import simultaneously. An important feature of the model is that we consider previous import activity when examining the determinants of firms' decision to export and vice-versa. We use a sample from the ESEE database of manufacturing SMEs in Spain observed between 2001 and 2014. Our findings suggest that the degree of digitalization in SMEs exerts a direct positive effect on the decision to trade. Moreover, import and export participation increases with digitalization also through productivity enhancements (i.e., the indirect TFP channel). In addition, the direct effect seems to be larger for exports than for imports, while the opposite seems true for the indirect effect.

Our results provide important insights to managers of SMEs. By investing in the process of digitalization, SMEs may improve their likelihood to enter into foreign markets and become more efficient, which reinforces the effect of digitalization upon export and import participation. From a policy perspective, our findings highlight that efforts should be placed in fostering the adoption and efficient use of DTs by SMEs. As the results suggest, this will increase the export base in Spain, which has been shown to be small. Thus, our results point to a need for policy makers to provide not just the necessary digital infrastructure but also, to offer incentives, well in the form of subsidies or tax breaks, in order to promote the adoption and efficient use of digital technologies.

Nevertheless, our study is not without limitations, which provide interesting avenues for future research. For instance, we have no information on new technologies that are part of the Industry 4.0, such as 3D printing, cloud computing, artificial intelligence, or blockchain. The availability of data on these technologies will allow for a more comprehensive state of the real digital transformation and how it affects trade activities. Further, data on the firms' export destination and origin of imports might allow us to test the hypothesis of the effect of digitalization on the *death of distance*. Still, caution should be used regarding the generalizability of these results, and therefore, many questions regarding policy implications are still open.

References

Abramovsky, L., and Griffith, R. (2006), Outsourcing and offshoring of business services: How important is ICT? *Journal of the European Economic Association*, 4(2-3): 594-601.

Acemoglu, D., Dorn, D., Hanson, G. H., and Price, B. (2014), Return of the Solow paradox? IT, productivity, and employment in US manufacturing. *American Economic Review*, 104(5): 394-99.

Alcácer, J., Cantwell, J., and Piscitello, L. (2016), Internationalization in the information age: A new era for places, firms, and international business networks? *Journal of International Business Studies*, 47(5): 499-512.

Alguacil Marí, M. T., Lo Turco, A., and Martínez-Zarzoso, I. (2020), What is so special about robots and trade? (No. 410). Cege Discussion Papers.

Almeida, H., Campello, M., Cunha, I., and Weisbach, M. S. (2014), Corporate liquidity management: A conceptual framework and survey. *Annual Review of Financial Economics*, 6(1), 135-162.

Añón Higón, D., and Bonvin, D. (2022), Information and communication technologies and firms' export performance. *Industrial and Corporate Change*.

Añón Higón, D., and Driffield, N. (2011), Exporting and innovation performance: Analysis of the annual Small Business Survey in the UK. *International Small Business Journal*, 29(1): 4-24.

Arellano, M., and Bond, S. (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2): 277-297.

Arellano, M., and Bover, O. (1995), Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1): 29-51.

Aristei, D., Castellani, D., and Franco, C. (2013), Firms' exporting and importing activities: is there a two-way relationship? *Review of World Economics*, 149(1): 55-84.

Arvanitis, S., and Loukis, E. N. (2009), Information and communication technologies, human capital, workplace organization and labour productivity: A comparative study based on firm-level data for Greece and Switzerland. *Information Economics and Policy*, 21(1): 43-61.

Aspelund, A., and Moen, Ø. (2004), Internationalization of small high-tech firms: the role of information technology. *Journal of Euromarketing*, 13(2-3): 85-105.

Baldwin, R. (2016), The World Trade Organization and the future of multilateralism. *Journal of Economic Perspectives*, 30(1): 95-116.

Bartelsman, E. J., Falk, M., Hagsten, E., and Polder, M. (2019), Productivity, technological innovations and broadband connectivity: firm-level evidence for ten European countries. *Eurasian Business Review*, 9(1): 25-48.

Bellone, F., Musso, P., Nesta, L., and Schiavo, S. (2010), Financial constraints and firm export behaviour. *The World Economy*, 33(3): 347-373.

Bennett, R. (1997), Export marketing and the Internet: Experiences of Web site use and perceptions of export barriers among UK businesses. *International Marketing Review*, 14(5): 324-344.

Berndt, E. R., and Morrison, C. J. (1995), High-tech capital formation and economic performance in US manufacturing industries An exploratory analysis. *Journal of econometrics*, 65(1): 9-43.

Bloom, N., Lemos, R., Sadun, R., Scur, D., and Van Reenen, J. (2014), JEEA-FBBVA Lecture 2013: The new empirical economics of management. *Journal of the European Economic Association*, 12(4): 835-876.

Blundell, R., and Bond, S. (1998), Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1): 115-143.

Blundell, R. W., and Powell, J. L. (2004), Endogeneity in semiparametric binary response models. *The Review of Economic Studies*, 71(3): 655-679.

Brancati, R., Marrocu, E., Romagnoli, M., and Usai, S. (2017), Innovation activities and learning processes in the crisis: evidence from Italian export in manufacturing and services. *Industrial and Corporate Change*, 27(1): 107-130.

Brynjolfsson, E. (1996), The contribution of information technology to consumer welfare. *Information Systems Research*, 7(3): 281-300.

Brynjolfsson, E., and Hitt, L. M. (2003), Computing productivity: Firm-level evidence. *Review of economics and statistics*, 85(4): 793-808.

Brynjolfsson, E., Hitt, L. M., and Yang, S. (2002), Intangible assets: computers and organizational capital. *Brookings Papers on Economic Activity*, 2002(1): 137–198.

Brynjolfsson, E., and Saunders, A. (2010), Wired for Innovation: How Information Technology Is Reshaping the Economy. *MIT Press*, Cambridge, MA.

Calvino, F., Criscuolo, C., Marcolin, L., and Squicciarini, M. (2018), A taxonomy of digital intensive sectors. *OECD Science, Technology and Industry Working Papers*, No. 2018/14. OECD Publishing, Paris.

Cardona, M., Kretschmer, T., and Strobel, T. (2013), ICT and productivity: conclusions from the empirical literature. *Information Economics and Policy*, 25(3): 109-125.

Cassetta, E., Monarca, U., Dileo, I., Di Berardino, C., and Pini, M. (2020), The relationship between digital technologies and internationalisation. Evidence from Italian SMEs. *Industry and Innovation*, *27*(4), 311-339.

Chamberlain, G. (1982), Multivariate Regression Models for Panel Data. *Journal of Econometrics*, 1: 5-46.

Clarke, G. R., and Wallsten, S. J. (2006), Has the internet increased trade? Developed and developing country evidence. *Economic Inquiry*, 44(3): 465-484.

Commander, S., Harrison, R., and Menezes-Filho, N. (2011), ICT and productivity in developing countries: New firm-level evidence from Brazil and India. *Review of Economics and Statistics*, 93(2): 528-541.

Corrado, C., Haskel, J., and Jona-Lasinio, C., (2017), Knowledge spillovers, ICT and productivity growth*. Oxford Bulletin of Economics and Statistics*, 79(4): 592-618.

Coviello, N. E., and Martin, K. A. M. (1999), Internationalization of service SMEs: an integrated perspective from the engineering consulting sector. *Journal of International Marketing*, 7(4): 42-66.

De Loecker, J. (2013), Detecting learning by exporting. *American Economic Journal: Microeconomics*, 5(3): 1-21.

De Loecker, J., and Warzynski, F. (2012), Markups and firm-level export status. *American economic review*, 102(6): 2437-71.

Demirkan, H., Goul, M., Kauffman, R. J., and Weber, D. M. (2009), Does distance matter? The influence of ICT on bilateral trade flows. *In Proceedings of the Second Annual SIG GlobDev Workshop* (Vol. 14).

DeStefano, T., Kneller, R., and Timmis, J. (2018), Broadband infrastructure, ICT use and firm performance: Evidence for UK firms. *Journal of Economic Behavior & Organization*, 155: 110-139.

Dettmer, B. (2014), International service transactions: Is time a trade barrier in a connected world? *International Economic Journal*, 28(2): 225-254.

Dholakia, R. R., and Kshetri, N. (2004), Factors impacting the adoption of the Internet among SMEs. *Small Business Economics*, 23(4): 311-322.

Doraszelski, U., and Jaumandreu, J. (2013), R&D and productivity: Estimating endogenous productivity. *Review of Economic Studies*, 80(4): 1338-1383.

Elliott, R. J., Horsewood, N. J., and Zhang, L. (2019), Importing exporters and exporting importers: A study of the decision of Chinese firms to engage in international trade. *Review of International Economics*, 27(1): 240-266.

Fernandes, A. M., Mattoo, A., Nguyen, H., and Schiffbauer, M. (2019), The internet and Chinese exports in the pre-ali baba era. *Journal of Development Economics*, 138: 57-76.

Freund, C., and Weinhold, D. (2002), The Internet and International Trade in Services. *American Economic Review*, 92(2): 236-240.

Freund, C., and Weinhold, D. (2004a), The effect of the Internet on international trade. *Journal of International Economics*, 62(1): 171-189.

Freund, C. L., and Weinhold, D. (2004b), An Empirical Investigation of the Internet and International Trade: The Case of Bolivia. *Revista Latinoamericana de Desarrollo Económico*, 2: 33-55.

Gal, P., Nicoletti, G., Renault, T., Sorbe, S., and Timiliotis, C. (2019), Digitalisation and productivity: In search of the holy grail–Firm-level empirical evidence from EU countries. *OECD Economics Department Working Papers* (1533).

García-Vega, M., and Huergo, E. (2019), The role of international and domestic R&D outsourcing for firm innovation. *Journal of Economic Behavior and Organization*, 157: 775-792.

Hagsten, E. (2015), Distributed access to linked microdata: The example of ICT and exports. *Applied Economics Letters*, 22(7): 576-580.

Hagsten, E., and Kotnik, P. (2017), ICT as facilitator of internationalization in small and medium-sized firms. *Small Business Economics*, 48(2): 431-446.

Hamill, J., and Gregory, K. (1997), Internet marketing in the internationalization of UK SMEs. *Journal of marketing Management*, 13(1-3): 9-28.

Heckman, J. J. (1981), Heterogeneity and state dependence. *Studies in Labor Markets*, 31: 91-140.

Hempell, T. (2005), Does experience matter? Innovations and the productivity of information and communication technologies in German services. *Economics of Innovation and New Technology*, 14(4): 277-303.

Jin, H., and Hurd, F. (2018), Exploring the impact of digital platforms on SME internationalization: New Zealand SMEs use of the Alibaba platform for Chinese market entry. *Journal of Asia-Pacific Business*, 19(2): 72-95.

Jungmittag, A., and Welfens, P. J. (2009), Liberalization of EU telecommunications and trade: theory, gravity equation analysis and policy implications. *International Economics and Economic Policy*, 6(1): 23-39.

Jovanovic, B., and Rousseau, P. L. (2005), General purpose technologies. In Handbook of economic growth (Vol. 1: 1181-1224). Elsevier.

Kasahara, H., and Rodrigue, J. (2008), Does the use of imported intermediates increase productivity? Plant-level evidence. *Journal of Development Economics*, 87(1): 106-118.

Kim, D. (2020), Internet and SMEs' internationalization: The role of platform and website. *Journal of International Management*, 26(1).

Kneller, R., and Timmis, J. (2016), ICT and Exporting: The Effects of Broadband on the Extensive Margin of Business Service Exports. *Review of International Economics*, 24(4): 757-796.

Laursen, K., & Meliciani, V. (2010), The role of ICT knowledge flows for international market share dynamics. *Research Policy*, 39(5): 687-697.

Lendle, A., Olarreaga, M., Schropp, S., and Vezina, P.L. (2012), There goes gravity: how eBay reduces trade costs. *CEPR discussion article 9094*.

Loane, S. (2005), The role of the internet in the 40nternationalization of small and medium sized companies. *Journal of International Entrepreneurship*, 3(4): 263-277.

Loveman, G. W. (1994), An assessment of the productivity impact of information technologies. *Information technology and the corporation of the 1990s: Research studies*, 84: 110.

Mañez, J.A., Rochina, M.E., Sanchis, J.A., and Vicente, O. (2014), Financial Constraints and R&D and Exporting Strategies for Spanish Manufacturing Firms. *Industrial and Corporate Change*, 23(6): 1563-1594.

Mañez, J. A., Rochina-Barrachina, M. E., and Sanchis, J. A. (2020), Foreign sourcing and exporting. *The World Economy*, 43(5): 1151-1187.

Mata, F. J., Fuerst, W. L., and Barney, J. B. (1995), Information technology and sustained competitive advantage: A resource-based analysis. *MIS quarterly*, 487-505.

Melitz, M. J. (2003), The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6): 1695-1725.

Morgan-Thomas, A., and Jones, M. V. (2009), Post-entry internationalization dynamics: differences between SMEs in the development speed of their international sales. *International Small Business Journal*, 27(1): 71-97.

Mostafa, R. H., Wheeler, C., and Jones, M. V. (2005), Entrepreneurial orientation, commitment to the Internet and export performance in small and medium sized exporting firms. *Journal of international Entrepreneurship*, 3(4): 291-302.

Mundlak, Y. (1978), On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society*, 46(1): 69-85.

Nath, H. K., and Liu, L. (2017), Information and communications technology (ICT) and services trade. *Information Economics and Policy*, 41: 81-87.

Newey, W. K. (1987), Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, 36(3): 231-250.

Nieto, M. J., and Fernández, Z. (2005), The role of information technology in corporate strategy of small and medium enterprises. *Journal of International Entrepreneurship*, 3(4): 251-262.

Nucci, F., Pietrovito, F., and Pozzolo, A. F. (2020), Imports and credit rationing: A firm-level investigation. *The World Economy*.

OECD (2019), "Editorial: Making digital transformation work for growth and well-being", in Going Digital: Shaping Policies, Improving Lives, OECD Publishing, Paris.

Olley S., and Pakes A. (1996), The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64: 1263-1298.

O'Mahony, M., and Vecchi, M. (2003), Is there an ICT impact on TFP? A heterogeneous dynamic panel approach. *NIESR Discussion Paper*, 219.

Ozcan, B. (2018), Information and communications technology (ICT) and international trade: evidence from Turkey. *Eurasian Economic Review*, 8(1): 93-113.

Parker, C., and Castleman, T. (2007), Why should small firms adopt eBusiness? A framework for understanding the SME eBusiness context. In *ACIS 2007: Proceedings of the 18th Australasian Conference on Information Systems*, 497-507. University of Southern Queensland.

Rasel, F. (2012), Offshoring and ICT–Evidence for German Manufacturing and Service Firms. *ZEW-Centre for European Economic Research Discussion Paper*, (12-087).

Rivers, D., and Vuong, Q. H. (1988), Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics*, 39(3): 347-366.

Roberts, M., and Tybout, J. (1997), The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs. *American Economic Review*, 87(4): 545-564.

Roodman, D. (2011), Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, 11(2): 159-206.

Sasidharan, S., and Reddy, K. (2021), The Role of Digitalisation in Shaping India's Global Value Chain Participation.

Semykina, A. (2018), Self-employment among women: Do children matter more than we previously thought? *Journal of Applied Econometrics*, 33(3): 416-434.

Sinkovics, N., Sinkovics, R. R., and Jean, R. J. (2013), The internet as an alternative path to internationalization? *International Marketing Review*, 30(2): 130-155.

Stapleton, K., and Webb, M. (2020), Automation, trade and multinational activity. Micro evidence from Spain. University of Oxford.

Swamidass, P. M. (2003), Modeling the adoption rates of manufacturing technology innovations by small US manufacturers: a longitudinal investigation. *Research Policy*, 32(3): 351-366.

Syverson, C. (2011), What determines productivity*? Journal of Economic Literature*, 49(2): 326-65.

Tseng, K., and Johnsen, R.E. (2011), Internationalisation and the internet in UK manufacturing SMEs. *Journal of Small Business and Enterprise Development*, 18(3): 571-593.

Wagner, J. (2014), Credit constraints and exports: A survey of empirical studies using firm-level data. *Industrial and Corporate Change*, 23(6): 1477–1492.

Windmeijer, F. (2005), A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1): 25-51.

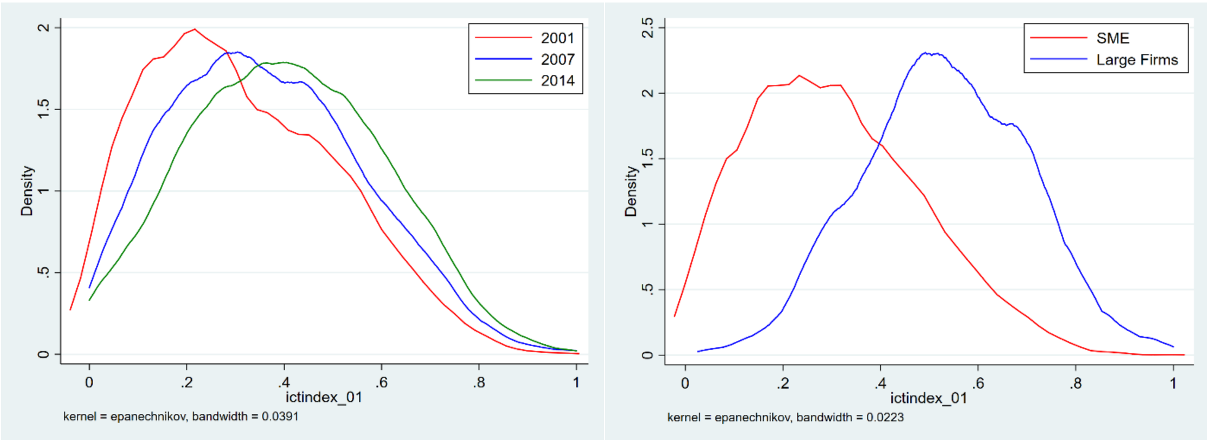
Wooldridge, J. M. (2005), Simple Solutions to the Initial Conditions Problem for Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity. *Journal of Applied Econometrics*, 20: 39-54.

Wooldridge, J. M. (2009), On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, 104(3): 112-114.

Wooldridge, J. M. (2015), Control function methods in applied econometrics. *Journal of Human Resources*, 50(2): 420-445.

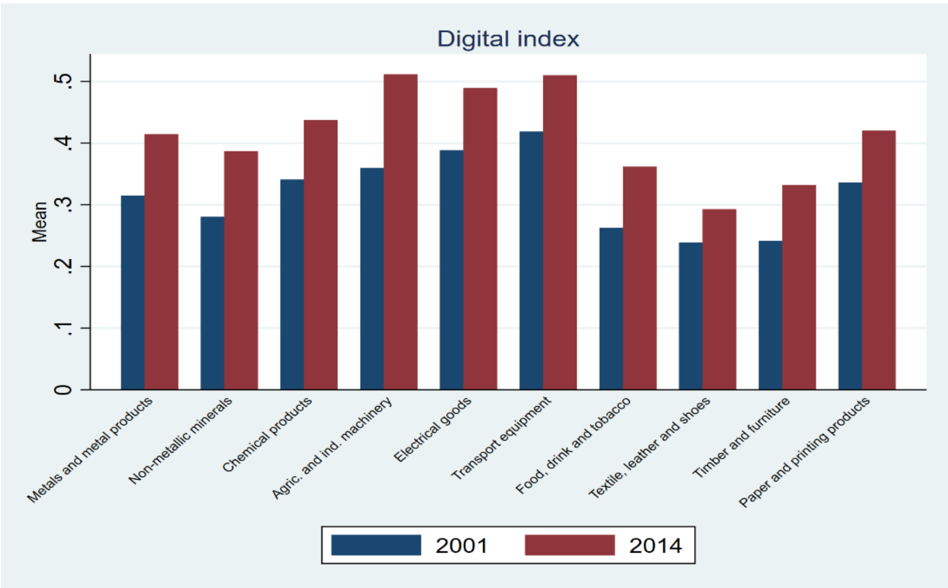
Yushkova, E. (2014), Impact of ICT on trade in different technology groups: analysis and implications. *International Economics and Economic Policy*, 11(1-2): 165-177.

Figure 1: the digital transformation in the Spanish manufacturing sector



Source: ESEE survey and own' elaboration.

Figure 2: the digital transformation by industry (2001-2014)



Source: ESEE survey and own' elaboration.

Table 1: Results of the estimation of the production function for SMEs

Industry	l	k^{NIT}	k^{IT}	m	Obs.
1. Metals and metal products	0.233***	0.055***	0.006**	0.688***	1734
	(0.011)	(0.009)	(0.003)	(0.016)	
2. Non-metallic minerals	0.212***	0.045***	0.014***	0.728***	798
	(0.015)	(0.014)	(0.005)	(0.025)	
3. Chemical products	0.237***	0.049***	0.009***	0.717***	1334
	(0.012)	(0.011)	(0.003)	(0.021)	
4. Agric. And ind. Machinery	0.202***	0.039***	0.023***	0.700***	765
	(0.015)	(0.015)	(0.006)	(0.022)	
5. Electrical goods	0.222***	0.072***	0.045***	0.634***	695
	(0.014)	(0.016)	(0.006)	(0.031)	
6. Transport equipment	0.202***	0.082***	0.005	0.744***	542
	(0.019)	(0.017)	(0.008)	(0.028)	
7. Food, drink and tobacco	0.106***	0.080***	0.014***	0.714***	1695
	(0.008)	(0.009)	(0.003)	(0.023)	
8. Textile, leather and shoes	0.362***	0.080***	0.012**	0.450***	1213
	(0.016)	(0.017)	(0.006)	(0.039)	
9. Timber and furniture	0.230***	0.031***	0.019***	0.679***	1116
	(0.011)	(0.010)	(0.004)	(0.022)	
10. Paper and printing products	0.275***	0.122***	0.010**	0.460***	1012
	(0.013)	(0.016)	(0.005)	(0.056)	

Notes: Estimates of the input coefficients from equation (7) are shown for different industries using the GMM estimation proposed by Wooldridge (2009). The dependent variable is the log of gross output. Each row represents a separate regression. Robust standard errors are reported in parenthesis. *** denotes level of significance at 1%, ** at 5%, * at 10%.

Table 2: The effect of the Digital Index on TFP

Dependent variable:	TFP	TFP	TFP growth
	(1)	(2)	(3)
TFP_{t-1}	0.559***	0.492***	-0.508***
	(0.093)	(0.093)	(0.093)
Digital $Index_{t-1}$	0.113***	0.080**	0.080**
	(0.040)	(0.038)	(0.038)
Age_{t-1}		0.561***	0.561***
		(0.190)	(0.190)
$Size_{t-1}$		0.642***	0.642***
		(0.227)	(0.227)
Trade $Participation_{t-1}$	0.028	0.018	0.018
	(0.025)	(0.024)	(0.024)
Foreign $ownership_{t-1}$		0.003	0.003
		(0.013)	(0.013)
AR(2) [p-value]	0.000	0.000	0.000
AR(3) [p-value]	0.243	0.250	0.250
Hansen test[p-value]	70.20	170.53	170.53
Industry-Year FE	Y	Y	Y
Observations	10,893	10,886	10,886
Firms	1,698	1,698	1,698
No. of instruments	262	313	313

Notes: The dependent variable in (1) and (2) is the log of TFP; while in (3) is the difference in the log of TFP from *t*-1 to *t*. All explanatory variables are included with one-period lag. All specifications include industry-year dummies. Estimates are obtained through the two-step system GMM estimator with robust finite sample bias corrected standard errors (Windmeijer, 2005).
We use levels of TFP, the digital index, size, trade status dated (*t*-4) to (*t*-7) as instruments in the difference equation, and differences dated (*t*-3) as instruments in the levels equation, as well as age, foreign ownership and industry-year dummies. [*] Significant at 10%, [**] significant at 5%, [***] significant at 1%.

Table 3: Observations in the sample by export activity

	All firms	Non-Exporters	Exporters	Non-Importers	Importers
Size class	Observations	Observations	Observations	Observations	Observations
SME	12,783	5,067	7,716	5,109	7,676
%	100%	39.64%	60.36%	39.95%	60.05%

Note: size class is defined in terms of the average number of employees of the firm: SME (< 200 employees). The sample is firms that are at least observed for two consecutive years and for which an estimate of TFP can be obtained.

Table 4: Descriptive statistics for exporters and non-exporters

	Exporters		Non-exporters		Importers		Non-importers	
	Mean	**s.d.**	**Mean**	**s.d.**	**Mean**	**s.d.**	**Mean**	**s.d.**
Export propensity	1.00	0.00	0.00	0.00	0.81	0.39	0.30	0.46
Import propensity	0.80	0.40	0.29	0.45	1.00	0.00	0.00	0.00
Digitalization index	0.38	0.17	0.25	0.15	0.38	0.17	0.26	0.16
TFP*	3.77	1.06	3.66	1.00	3.81	1.08	3.62	0.96
Markup	0.99	0.32	1.25	0.85	0.97	0.31º	1.28	0.84
R&D propensity	0.37	0.48	0.09	0.28	0.38	0.48	0.09	0.28
Human capital	0.14	0.14	0.08	0.12	0.14	0.14	0.09	0.12
Age	32.02	21.31	25.57	18.82	32.00	21.67	25.65	18.24
Size	71.74	60.22	33.06	35.78	73.65	61.47	30.49	29.12
Foreign capital	0.14	0.35	0.02	0.14	0.15	0.35	0.01	0.12
Appropriability	0.04	0.20	0.01	0.11	0.04	0.20	0.01	0.11
Recessive market	0.32	0.47	0.34	0.47	0.33	0.47	0.33	0.47
Expansive market	0.21	0.41	0.15	0.36	0.21	0.41	0.16	0.36
Market competitors	0.20	0.40	0.21	0.41	0.21	0.41	0.19	0.39
External FC	4.26	3.43	3.88	3.16	4.30	3.44	3.83	3.14
Internal FC	6.21	2.40	5.80	2.45	6.19	2.41	5.84	2.45
Observations	7,716		5,067		7,676		5,107	

Source: ESEE 2001-2014.

Notes: s.d. stands for standard deviation. The sample is small and medium-sized firms (with less than 200 employees) that are at least observed for two consecutive years and for which an estimate of TFP can be obtained. * variables in logs.

Table 5: The effect of digitalization on SMEs trade. Marginal effects

	RE Probit		RE Biprobit		RE Biprobit & CF	
	Export	Import	Export	Import	Export	Import
	(1)	(2)	(3)	(4)	(5)	(6)
Digital Index	0.107***	0.059**	0.090***	0.049**	0.072***	0.077**
	(0.025)	(0.027)	(0.020)	(0.023)	(0.026)	(0.031)
TFP_{t-1}	0.045**	0.089***	0.038**	0.079***	0.029*	0.085***
	(0.018)	(0.023)	(0.016)	(0.020)	(0.016)	(0.021)
Export status $_{t-1}$	0.198***	0.050***	0.163***	0.051***	0.188***	0.051***
	(0.012)	(0.008)	(0.011)	(0.008)	(0.011)	(0.009)
Import status $_{t-1}$	0.035***	0.205***	0.033***	0.185***	0.033***	0.197***
	(0.008)	(0.012)	(0.007)	(0.011)	(0.007)	(0.011)
Relative Markup $_{t-1}$	-0.028***	-0.075***	-0.023***	-0.068***	-0.022**	-0.067***
	(0.010)	(0.015)	(0.009)	(0.011)	(0.009)	(0.012)
R&D $_{t-1}$	0.013	0.023**	0.010	0.022**	0.009	0.020**
	(0.009)	(0.010)	(0.007)	(0.009)	(0.008)	(0.009)
Human Capital $_{t-1}$	0.047*	0.037	0.040*	0.033	0.048**	0.027
	(0.028)	(0.028)	(0.024)	(0.029)	(0.024)	(0.030)
Age $_{t-1}$	0.005	0.002	0.004	0.002	0.006	-0.000
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Size $_{t-1}$	0.244**	0.546***	0.194***	0.488***	0.182**	0.453***
	(0.098)	(0.106)	(0.074)	(0.096)	(0.075)	(0.100)
Foreign Capital $_{t-1}$	0.019	0.040**	0.015	0.035**	0.019	0.035**
	(0.017)	(0.017)	(0.012)	(0.016)	(0.013)	(0.016)
Recessive Market $_{t-1}$	-0.003	-0.007	-0.003	-0.005	-0.003	-0.008
	(0.007)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)
Expansive Market $_{t-1}$	0.007	0.015*	0.006	0.013*	0.004	0.009
	(0.008)	(0.009)	(0.007)	(0.008)	(0.007)	(0.009)
Competitors $_{t-1}$	-0.013	0.004	-0.011	0.004	-0.006	0.008
	(0.009)	(0.009)	(0.007)	(0.009)	(0.008)	(0.010)
Appropriability $_{t-1}$	0.052**	0.008	0.044**	0.008	0.042**	-0.003
	(0.022)	(0.018)	(0.018)	(0.020)	(0.019)	(0.020)
External Finance $_{t-1}$	-0.000	0.001	-0.000	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Internal Finance $_{t-1}$	-0.000	0.000	-0.000	0.000	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Rho			0.391***	0.391***	0.363***	0.363***
			(0.061)	(0.061)	(0.063)	(0.063)
Residual[a]					0.012	-0.055
					(0.041)	(0.048)
Time & Industry FE	Y	Y	Y	Y	Y	Y
Initial Condition	Y	Y	Y	Y	Y	Y
Mundlak Means	Y	Y	Y	Y	Y	Y
IV Control Function					Y	Y
Observations	9,182	9,145	9,143	9,143	8,322	8,322
Log-Likelihood	-1,558.22	-2,035.12	-3,567.62	-3,567.62	-3,214.14	-3,214.14

Notes: We report marginal effects at sample means. All specifications include industry and year dummies. All specifications include the initial condition and the within-means of internal and external finance, which appear statistically significant. * Significant at 10%, ** significant at 5%, *** significant at 1%. [a] Rivers-Vuong (1988) endogeneity test.

Table 6: Robustness checks

Dependent var.	Wooldridge (2005) Export (1)	Wooldridge (2005) Import (2)	Mañez et *al*. (2020) Export (3)	Mañez et *al*. (2020) Import (4)	Bootstrapped s.e. Export (5)	Bootstrapped s.e. Import (6)
Digital Index	0.088***	0.044*	0.108***	0.105***	0.090***	0.049*
	(0.021)	(0.024)	(0.025)	(0.031)	(0.022)	(0.027)
TFP_{t-1}	0.035**	0.068***	0.095***	0.145***	0.038**	0.079***
	(0.017)	(0.020)	(0.021)	(0.028)	(0.018)	(0.021)
Rest of controls	Y	Y	Y	Y	Y	Y
Initial Condition	Y	Y			Y	Y
Mundlak Means (All)	Y	Y				
Pre-sample Mean $_{(98/99)}$			Y	Y		
Bootstrap 250 reps					Y	Y
Observations	9,143	9,143	7,317	7,317	9,143	9,143
Log-Likelihood	-3546.43	-3546.43	-3416.01	-3416.01	-3567.62	-3567.62

Notes: We report marginal effects at sample means of the variables of interest. All specifications include the same control variables as in Table 5 together with industry and year dummies. Specifications in (1), (2), (5) and (6) include the initial condition and the within-means of internal and external finance, which appear statistically significant. Those are replaced by the pre-sample mean of the dependent variable in (3) and (4). In (5) and (6) we report block bootstrapped standard errors (s.e.) at firm level in parentheses (250 replications). * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 7: Sensitivity Analysis: Digitalization and GVC participation by sector

	Low-Digitalized Export (1)	Low-Digitalized Import (2)	High-Digitalized Export (3)	High-Digitalized Import (4)	Low GVC integrated Export (5)	Low GVC integrated Import (6)	High GVC integrated Export (7)	High GVC integrated Import (8)
Digital Index	0.063**	0.074*	0.060	0.080	0.115***	0.028	0.076***	0.069**
	(0.028)	(0.039)	(0.051)	(0.052)	(0.035)	(0.040)	(0.024)	(0.029)
TFP_{t-1}	0.037**	0.080***	0.016	0.100***	0.056**	0.057**	0.008	0.116***
	(0.018)	(0.027)	(0.030)	(0.033)	(0.025)	(0.029)	(0.022)	(0.029)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Initial condition	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak means	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5127	5127	3195	3195	3524	3524	5619	5619
Log-Likelihood					-1473.99	-1473.99	-2047.13	-2047.13

Notes: The classification on digitalization is based on Calvino et al. (2018). The classification on GVC-integration is based on the GVC forward linkage indicator provided by the OECD for Spain. We report marginal effects at sample means of the variables of interest. All specifications include the same control variables as in Table 5 together with industry and year dummies. All specifications include the initial condition and the within-means of internal and external finance, which appear statistically significant. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 8: Sensitivity Analysis: ICTs vs. Automation

	Export (1)	Import (2)
ICT index	0.086***	0.054**
	(0.019)	(0.022)
Automation index	0.012	0.002
	(0.011)	(0.012)
TFP_{t-1}	0.038**	0.079***
	(0.016)	(0.020)
Rest of controls	Y	Y
Initial condition	Y	Y
Mundlak means	Y	Y
Observations	9,143	9,143
Log-Likelihood		

Notes: We report marginal effects at sample means of the variables of interest. All specifications include the same control variables as in Table 5 together with industry and year dummies. All specifications include the initial condition and the within-means of internal and external finance, which appear statistically significant. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A1: Description of the variables

Variable	**Description**
Export propensity	Dummy=1 if the firm exports; =0 otherwise.
Import propensity	Dummy=1 if the firm imports; =0 otherwise.
Digital index	Index than ranges from 0 to 1 (see methodological section).
TFP	The logarithm of the total factor productivity is estimated as in the methodology section.
Relative Markup	The ratio of *P/MC* of the firm relative to the average markup of the industry. Obtained as in De Loecker and Warzynski (2012)
R&D	Dummy=1 if the firm conducts R&D activities; =0 otherwise.
Human capital	% of employees with a degree.
Age	The logarithm of the age of the firm.
Size	The number of employees.
Foreign capital	Dummy=1 if the firm has foreign capital participation; =0 otherwise.
Appropriability	Dummy=1 if the firm has registered patents either in Spain or abroad, and/or utility models; =0 otherwise.
Recessive market	Dummy= 1 if the firm faces a recessive market demand; =0 otherwise.
Expansive market	Dummy= 1 if the firm faces an expansive market demand; =0 otherwise.
Competitors	Dummy= 1 if the number of competitors reported by the firm is less than 10; =0 otherwise.

External Finance	It reflects the firm's access to internal funds and it is obtained as explained in the methodology section.
Internal Finance	It reflects the firm's access to external funds and it is obtained as explained in the methodology section.

Table A2: Digitalization Index by Dimensions

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

Table A3: Division by industries

Industries	**High digitalized**	**Low digitalized**	**High integrated in GVCs**	**Low integrated in GVCs**
1. Metals and metal products		✓	✓	
2. Non-metallic minerals		✓		✓
3. Chemical products		✓	✓	
4. Agric. and ind. machinery	✓		✓	
5. Electrical goods	✓		✓	
6. Transport equipment	✓		✓	
7. Food, drink, and tobacco		✓	✓	
8. Textile, leather, and shoes		✓		✓
9. Timber and furniture	✓			✓
10. Paper and printing products	✓			✓

Note: "*High digitalized*" identifies sectors classified in terms of digital intensity as High and Medium-high in Calvino *et al.* (2018), while "*Low digitalized*" refers to sectors classified as Low and Medium-low. "*High integrated in GVCs*" identifies sectors that have a GVC forward linkage index (based on *EXGR_DVAFXSH* for Spanish industries in the year 2000) above the average of all manufacturing sectors. "*Low integrated in GVCs*" refers to sectors that have a GVC forward linkage index below the average.