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RESEARCH ARTICLE

Digitalization and trade participation of SMEs

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Abstract This study examines the impact of digitalization on the participation of small and medium-sized enterprises (SMEs) in export and import activities. Using data on Spanish manufacturing SMEs from 2001 to 2014, we construct a multidimensional firm-level index of digitalization. We then estimate a set of dynamic models analyzing the direct and indirect (via total factor productivity) effects of digitalization on firms' export and import strategies. We find evidence that firms' digitalization positively influences the probability of exporting and importing, both directly and through productivity. We find that productivity has a stronger impact on SMEs' trade behavior than the direct channel of digitalization. A one standard deviation increase in the digitalization index increases the probability of exporting and importing by 1.5 and 0.8 percentage points, respectively, while the same increase in the logarithm of productivity has a three times greater effect for exporting and nine times greater for importing.

Plain English Summary Digitalization facilitates the access of SMEs to international markets. In this study, we analyze how the use of digital technologies affects Spanish small and medium-sized enterprises (SMEs) in their ability to access foreign markets. We find that digitization can help SMEs to export and import, both directly (by facilitating access to a larger market of customers and suppliers) and by improving their productivity. Interestingly, we also find that productivity has a greater impact on trade decisions than the direct channel of digitalization. It should be noted that not all digital technologies have the same effect on trade participation, and that automation technologies only influence trade through the productivity channel. Based on our findings, policymakers interested in helping SMEs export and integrate into global markets should support their digital transformation.

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1 Introduction

The digital transformation represents a source of competitiveness for firms in global markets. It is in this context that attention needs to be placed so that the opportunities provided by digital technologies (DTs) are not only limited to large firms. Since small and medium-sized enterprises (SMEs) play a significant role in the economy (because of their contribution to employment and value-added), it is then desirable that they adopt and integrate new DTs more rapidly and efficiently. Moreover, the smart use of DTs may represent the fundamental basis for their survival.

Extant studies on the role of DTs in trade base their analysis on single indicators of digitalization (Alguacil et al., 2022; Malgouyres et al., 2021). In this way, they omit the fact that digitalization is a complex phenomenon that is poorly captured by a single indicator, and that DTs are interrelated, with the effect of one technology being enhanced by the use of other. To overcome these drawbacks, we follow Calvino et al. (2018) and construct a synthetic index of digitalization at the firm level that considers this multi-faceted phenomenon. Our ultimate aim is to assess whether digitalization facilitates SMEs' export and import decisions.

While previous studies have focused primarily on exports, recent developments such as the surge in outsourcing and globalization make the study of digitalization on imports increasingly relevant (Rasel, 2017). By leveraging DTs, SMEs can gain access to technological advances and competitively priced and higher-quality intermediates that are not available domestically. This can contribute to the quality of their final products and enhance their competitiveness in global markets. Therefore, it is important to analyze the impact of digitalization on both exports and imports to gain a more comprehensive understanding of how DTs are transforming global trade and reshaping the competitive landscape for SMEs.

DTs can improve trade flows by reducing the costs of searching for, matching with, and communicating with international stakeholders (Hagsten & Kotnik, 2017). Second, DTs provide additional channels for marketing and sales, allowing companies to reach a broader base of customers and suppliers. Moreover, DTs enable firms to source inputs and organize production more efficiently, thus improving their productivity and becoming more competitive (Añón Higón & Bonvin, 2022; Fernandes et al., 2019). Additionally, advances in digitalization can be leveraged to facilitate the outsourcing of non-core activities and support the integration into global value chains (GVCs). These potential benefits may be even greater for SMEs, since DTs may contribute to reduce internationalization costs related to their size and difficulty in committing financial and human resources (Cassetta et al., 2020; Hagsten & Kotnik, 2017).

In line with the above arguments, we assert that firms' digitalization influences their decision to trade directly and indirectly through efficiency gains. Digitalization can induce SMEs to export and/or import by reducing information and trade costs. Moreover, digitalization may also indirectly affect trade due to its potential impact on productivity (Cardona et al., 2013). The analysis of indirect effect requires to consider, first, the link between digitalization and productivity, and second, the link between productivity and trade (Melitz, 2003). Hence, we aim to gain additional insights into the complex relationship between digitalization, productivity and trade. For this purpose, data for a sample of Spanish manufacturing SMEs from 2000 to 2014 from the *Spanish Survey on Business Strategies* (ESEE) is used.

Our study makes several important contributions to the existing literature. First, to the best of our knowledge, we are the first to construct a firm-level multifaceted index of digitalization to examine the role of DTs in facilitating trade. Second, we examine not only the direct impact of digitalization on trade, but also its indirect impact through enhanced productivity. To this end, we estimate in a first stage a production function in which we endogenize the digitalization index, and retrieve the firm's total factor productivity (TFP). In a second stage, we study the effect of both digitalization and TFP on the export and import participation decisions. The estimate of digitalization in the trade participation model provides insight into the direct effect, while that of TFP informs us about the indirect effect. Third, to evaluate the causal impact of digitalization we use a control function approach in a dynamic random effects bivariate probit model, which accounts for the simultaneous determination of export and import decisions.

The paper proceeds as follows. The next section reviews the extant literature. Next, the database and methodology are described, followed by the empirical results. Last, the findings, implications, and limitations of this study are discussed.

2 Related literature

2.1 The link between digital technologies and trade

Recent studies have brought new evidence on the positive role of digitalization, and particularly ICT and the Internet, on exports (Añón Higón & Bonvin, 2022; Fernandes et al., 2019; Kneller & Timmis, 2016). Studies focused specifically on SMEs are scarce. However, SMEs may benefit from digitalization differently from large firms due to their limited resources that impede their ability to compete (Coviello & Martin, 1999). For example, the Internet, being a low-cost means of internationalization, has been shown to reduce trade barriers (Hamill & Gregory, 1997). Therefore, it can help SMEs overcome distance- and entry-related costs in an affordable way (Cassetta et al., 2020; Hagsten & Kotnik, 2017). Further, DTs may provide SMEs with a competitive advantage, which is one of the reasons why they adopt these technologies at first (Dholakia & Ksheti, 2004).

Among the first studies on SMEs,[1] Hamill and Gregory (1997) show that, even at an early stage of development, the Internet helps firms overcome trade-related barriers. Using a sample of SMEs from Ireland, Canada, New Zealand, and Australia, Loane (2005) also finds that the Internet enables small entrepreneurial firms to trade globally. Similarly, Mostafa et al. (2005) show that the Internet helps improve trade, especially when managers have a strong entrepreneurial orientation. Beyond the role of the Internet, Añón Higón and Driffield (2011) observe a positive correlation between the use of ICT by British SMEs and their export performance. According to Hagsten and Kotnik (2017), basic ICT tools such as websites are more effective for accessing foreign markets than advanced ones, such as e-commerce. There is also evidence that digital platforms, such as Alibaba and eBay, are helpful for SMEs trying to enter foreign markets (Jin & Hurd, 2018; Lendle et al., 2016). Finally, regarding Spanish firms, Nieto and Fernández (2005) report that selling online to other businesses increases SMEs' export intensity, while selling to end consumers or having a website has no effect.

However, previous studies have overlooked the importance of digitalization for imports. By reducing communication and coordination costs, DTs can also facilitate imports (Jungmittag & Welfens, 2009). Thanks to digitalization, information can circulate faster, making it easier for buyers and suppliers to connect. Yet, few studies have examined the impact of digitalization on imports. Exceptions include Nath and Liu (2017), who use data for 49 countries to find that ICT enables the import of services, including financial, insurance and telecommunications. Ozcan (2018) shows, for a sample of countries trading with Turkey, that ICT influences both exports and imports, with the effect being more pronounced for imports. Along similar lines, Malgouyres et al. (2021) find that broadband diffusion increases French firms' imports by about 25%. More recently, a few studies have shifted the focus away from ICTs and examined the impact of automated technologies, primarily robots. For example, Alguacil et al. (2022) show that robot adoption helps Spanish firms to start importing and exporting and leads to an increase in the value and share of imports in total sales. However, the above studies do not consider that export and import decisions are determined simultaneously (Elliott et al., 2019).

2.2 The link between digital technologies, productivity and trade

The analysis of the indirect impact of digitalization on trade via TFP draws on two strands of literature. First, we contribute to the literature on the role of DTs in shaping productivity. Second, we add to the existing literature on productivity and trade (Melitz, 2003). By bringing these two strands together, this study aims to deepen our understanding of the complex relationships between digitalization, productivity, and trade.

First, the arguments by which DTs enhance productivity are diverse. Digitalization endows firms to source inputs and organize production more efficiently, and facilitates changes in management and organizational practices (Bloom et al., 2014). Yet, the

[1] Studies that focus on firms of all sizes have also shown that DTs enhance export performance. See Kneller and Timmis (2016) and Fernandes et al. (2019) for the causal impact of the Internet, and Añón Higón and Bonvin (2022) for ICTs.

empirical evidence at the firm level is mixed. Early studies focused on ICT found scant support that DTs improve productivity (Cardona et al., 2013). For example, Berndt and Morrison (1995) and Brynjolfsson (1996), both using data from the US before the nineties, find no evidence that IT increases firms' productivity. As DTs spread and adoption rates increased, the number of studies showing a positive impact on productivity grew. For instance, Brynjolfsson and Hitt (2003) show that computerization increases productivity in US firms in the long term but not in the short term. Hempell (2005) for German firms, and Commander et al. (2011) for firms in Brazil and India, also find a strong positive association between ICT and productivity.

More recently, the productivity slowdown has sparked new interest in the subject, albeit again with mixed results. Using US firm-level data from 1977 to 2007, Acemoglu et al. (2014) find that the IT intensity does not affect 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 firms in the early 2000s. In contrast, Bartelsman et al. (2019) point to a positive relationship between the share of broadband-connected employees and productivity for European firms. Likewise, Gal et al. (2019) evidence a strong relationship between DT adoption in an industry and productivity gains in a sample of OECD firms.

In contrast to previous studies, we propose that digitalization endogenously affects TFP. By opting for an endogenous process, as proposed by Doraszelski and Jaumandreu (2013) for R&D, we account for uncertainties linked to the success of digitalization, which might explain the heterogeneous results previously obtained.

This study also adds to the literature on productivity and international trade by examining the indirect effect of digitalization on trade through firm productivity. Previous research has established that relatively more productive firms are more likely to export, a phenomenon known as self-selection into exporting (Bernard & Jensen, 1999). This observation forms the basis of Melitz's (2003) theoretical model, which shows that only firms with productivity above a certain threshold level are able to overcome the sunk costs of exporting and enter foreign markets. Similarly, there is evidence of self-selection into importing, with only the most productive firms importing intermediates due to the fixed costs involved (Kasahara & Lapham, 2013). By analyzing the indirect effect of digitalization on trade, this study contributes to a deeper understanding of how these self-selection mechanisms shape the productivity of SMEs engaged in international trade.

3 Methodology

To assess the role of digitalization as a trade facilitator, we follow previous literature on modelling firm's trade status (Roberts & Tybout, 1997).[2] Particularly, we use a dynamic probit model to evaluate the impact of digitalization and other determinants on a firm's decision to export (E) and import (I). The probit model is appropriate because the dependent variables, i.e., trade participation decisions, are dichotomous. Moreover, using a dynamic model allows us to account for the presence of sunk costs of accessing foreign markets, which are a source of "true state dependence" in export/import decisions (Roberts & Tybout, 1997). Formally,

$$\begin{cases} E_{it} = 1\left[\beta_E DIG_{it} + \gamma_E TFP_{it-1} + \eta_E E_{it-1} + \theta_E I_{it-1} + x'_{it-1}\psi_E + d_j^E + d_t^E + \alpha_i^E + \varepsilon_{it}^E > 0\right] \\ I_{it} = 1\left[\beta_I DIG_{it} + \gamma_I TFP_{it-1} + \eta_I I_{it-1} + \theta_I E_{it-1} + x'_{it-1}\psi_I + d_j^I + d_t^I + \alpha_i^I + \varepsilon_{it}^I > 0\right] \end{cases} \quad (1)$$

where i denotes firms, t years, and 1[.] is an indicator function that takes the value of one when firm exports (imports) at time t and zero otherwise. DIG_{it} is the firm's degree of digitalization capturing the

[2] Since SMEs are underrepresented in international trade, we focus on how DTs can help SMEs access foreign markets. In the online appendix, we also explore how the intensive margin can be affected by digitalization.

direct impact of DTs on the decision to trade, while TFP_{it-1} controls for the indirect effect via the productivity channel. E_{it-1} and I_{it-1} denote previous export and import experience and capture true state dependence and cross-state dependence. We control for other observed trade determinants (x_{it-1}), industry fixed effects (d_j), and time effects (d_t). Finally, α_i is the unobserved firm-specific effect, and ε_{it} is the respective error term.

We include in x_{it-1} variables considered to influence the decision to trade. First, we control for the firm's internal and external financial resources. Firms with liquidity constraints have greater difficulty in exporting (Wagner, 2014), and are less likely to import intermediate goods (Nucci et al., 2021). In this study, we follow Añón Higón and Bonvin (2022) and use a multivariate financial index to capture internal and external financial resources. Second, we control for market power, as measured by firm's markups relative to the average markup in the industry. 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 or they may choose to rely on dynamic pricing strategies, charging lower prices to build up a customer base (Mañez et al., 2020). As a result, the firm's average markup, conditional on productivity, might be lower for SMEs exporters than for non-exporters. Furthermore, we control for the firm's age, firm's size, R&D, human capital, foreign capital participation, appropriability conditions, firm's business cycle (measured by the firm's assessment of whether the demand in its main market is recessive or expansive), and the number of market competitors.[3]

To estimate (1) consistently we need to account for unobserved heterogeneity. To that end, we adopt a RE model, which treats α_i as a random term that follows a normal distribution. The alternative to the RE would be to use a fixed effect (FE) specification, in which each α_i is treated as a parameter to be estimated. However, standard FE versions of non-linear models are prone to the incidental parameter problem, which can result in biased estimates, particularly if the model is dynamic (Roberts & Tybout, 1997). Hence, we use a RE probit model, which is an established approach for binary outcomes with panel data and has been widely used in studies examining the determinants of trade participation (Añón & Bonvin, 2022; Brancati et al., 2018; Elliot et al., 2019; Mañez et al., 2020). However, the RE model assumes that α_i and the covariates are uncorrelated, which may be an unrealistic assumption. Hence, a concern in the estimation of Eq. (1) is the potential correlation between the unobserved heterogeneity terms, α_i's, and the covariates, as well as the bias due to the initial conditions problem (Heckman, 1981). To simultaneously deal with these issues, we follow Wooldridge (2005), who draws from Mundlak (1978) and Chamberlain (1982). Thus, we model the distribution of α_i conditional on the initial conditions (i.e., first observation of E_{i0} and I_{i0}) and the means over time of the covariates ($\overline{q_i}$), such that:

$$\alpha_i^E = \delta_2^E E_{i0} + \delta_1^E \overline{q_i} + u_i^E \tag{2}$$

$$\alpha_i^I = \delta_2^I I_{i0} + \delta_1^I \overline{q_i} + u_i^I \tag{3}$$

where u_i are normally distributed and independent of the initial conditions, the covariates, and the ε_{it}'s. The vector $\overline{q_i}$ contains the within-means of the covariates that are likely to be correlated with α_i. Here, we follow Semykina (2018) and assume in the baseline specification that the α_i*'s* are only correlated with the firm's internal and external financial variables.[4] As a robustness check, we will consider a specification including all the within-means of x.

We substitute (2) and (3) into (1) to obtain the final model:

$$\begin{cases} E_{it} = 1[\beta_E DIG_{it} + \gamma_E TFP_{it-1} + \eta_E E_{it-1} + \theta_E I_{it-1} + x_{it-1}{}' \psi_E \\ \quad + d_j^E + d_t^E + \delta_1^E \overline{q} + \delta_2^E E_0 + u_i^E + \varepsilon_{it}^E > 0] \\ I_{it} = 1[\beta_I DIG_{it} + \gamma_I TFP_{it-1} + \eta_I I_{it-1} + \theta_I E_{it-1} + x_{it-1}{}' \psi_I \\ \quad + d_j^I + d_t^I + \delta_1^I \overline{q} + \delta_2^I I_0 + u_i^I + \varepsilon_{it}^I > 0] \end{cases} \tag{4}$$

[3] See Appendix for how the markup is obtained and Table 8 for variable definitions.

[4] Semykina's (2018) approach differs from Wooldridge (2005) in that, instead of using the within means of all time varying variables in x, it takes only the time means of a subset of variables (q) that are theoretically more likely to be correlated with α_i. Here, we assume that the within means of the financial variables measure the firm's financial stability and proxy for unobserved firm-specific characteristics (e.g., management quality).

where ε_{it}^{E} and ε_{it}^{I} are the error terms of each equation with $\rho = Corr\left(\varepsilon_{it}^{E}, \varepsilon_{it}^{I}\right)$. Previous studies have shown that exporting and importing are not independent decisions, but rather tend to be made simultaneously (Exposito & Sanchis-Llopis, 2020). Thus, we jointly estimate both trade decisions jointly using the conditional recursive mixed process (CMP) approach (Roodman, 2011), allowing for correlated error terms. Such correlations are likely if there are complementarities between exporting and importing, or in case there are unobserved factors that affect simultaneously both decisions (e.g., management practices, foreign contacts). Thus, if ρ differs significantly from zero, then exporting and importing are two interdependent decisions, and a joint estimation is more efficient than estimating two separate probit models.

Another concern that arises with the above model is that DIG may be endogenous relative to the trade strategies. To address this issue, we treat the potential endogeneity of DIG as an omitted variable problem and employ a control function (CF) method[5] (Wooldridge, 2015). The CF entails taking the residuals from a reduced-form model of the digitalization index, and including them as a covariate in Eq. (4). The instruments that we use are the industry regulatory index in communications drawn from the OECD NMR database[6] and, the average value of the digitalization index for firms (excluding the focal firm) in the same year, industry, region and R&D status as the focal firm. We expect that regulation of communication services is negatively correlated with the diffusion of DTs among firms, while digitalization of peer-firms leads to a reduction in the cost of adopting DTs that positively affects the digital transformation of the focal firm. However, we argue that both instruments do not affect the firm's trade participation decisions in period t, other than by being correlated with DIG. Hence, we first estimate a reduced form equation for the digitalization index based on a fixed effect model and calculate the residuals of this equation. In this regression, the instruments must be significant to be valid. The statistical significance of the residual in the second step allows checking for the existence of an endogeneity problem for DIG (Rivers-Vuong endogeneity test). If this is the case, including the residual would correct for the bias.

3.1 Modeling the indirect effect of digitalization

To analyze the indirect effect of digitalization, we first need to estimate the TFP. For that, we assume a Cobb–Douglas production function:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + \omega_{it} + e_{it} \tag{5}$$

where y_{it}, l_{it}, k_{it}^{NIT}, k_{it}^{IT}, and m_{it}, stand for the firm's i logarithm of output, labor, non-ICT capital, ICT capital, and materials. The productivity is denoted by ω_{it}, and e_{it} is the error term.

In line with Doraszelski and Jaumandreu (2013), we model the dynamics of productivity as an endogenous Markov process that depends on DIG and a random shock:

$$\omega_{it} = g\left(\omega_{it-1}, DIG_{it-1}\right) + \xi_{it} \tag{6}$$

where $g(.)$ is an unknown function, and ξ_{it} is a random shock.

The estimation of Eq. (5) by ordinary least squares (OLS) causes biased and inconsistent estimates because the firm's choice of (variable) inputs depends on productivity, ω_{it} (that is only observed by the firm). To address this problem, we apply the GMM-based semi-parametric control function estimator by Wooldridge (2009) for each of the 10 industries. As a result, we obtain industry-specific output elasticity and firm-specific TFP estimates, obtained as residuals. More details on the estimation can be found in the online Appendix, including the elasticity estimates for each industry.

Once TFP is obtained,[7] it is included as a regressor in Eq. (1). Finally, for digitalization to have an indirect effect through TFP on the export (import) participation equation, two conditions should be met. First, DIG should have a significant impact on TFP; and, second, the coefficient of TFP in the export (import) equation should be significantly positive in support of the self-selection into trade hypothesis. To check the first condition, we consider a linear specification of Eq. (6):

[5] See Añón Higón & Bonvin (2022) for recent applications of the CF approach.

[6] 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.

[7] We winsorize the resulting distribution of TFP at the 1st and 99th percentiles to control for the impact of outliers.

$$\omega_{it} = \beta_1\omega_{it-1} + \beta_2 DIG_{it-1} + \gamma' z_{it-1} + \alpha_{jt} + \alpha_i + \epsilon_{it} \quad (7)$$

where TFP (ω_{it}) is a function of its lag value (ω_{it-1}) and the digitalization index (DIG_{it-1}). We also control for other observed firm characteristics[8] that may influence the evolution of TFP (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 (7) is estimated by the two-step system-GMM estimator (Blundell & Bond, 1998).

4 Data and Descriptive Statistics

4.1 Data

The data is drawn from the *Survey on Business Strategies* (ESEE). The ESSE is an annual survey, carried out since 1990, sponsored by the Spanish Ministry of Industry, Tourism and Trade, and administered by the SEPI Foundation. The sample in the survey is representative at the industry-level of the population of Spanish manufacturing firms with more than 10 employees.[9] The questionnaire provides rich information on the firm's activity, including export and import activities. Yet, some of the questions concerning DTs, specifically online trade and training in ICT, appear as early as 2000 and 2001, respectively, which is why our analysis begins in 2001.

Our initial sample consists of an unbalanced panel of 25,056 observations corresponding to firms observed at least two consecutive periods between 2001 and 2014. From this sample we drop large firms and firms that cannot supply relevant information. After that, we end up with a sample of 12,783 observations corresponding to 1,814 SMEs.

4.2 The Digitalization Index

The firm level index of digitalization is based on the work of Calvino et al. (2018) at sector level. This index is conceived under the consideration that digitalization is a complex phenomenon that can hardly be captured by a single indicator. Moreover, DTs are interrelated, with the impact of one technology being enhanced by the use of another. Hence, the effectiveness of DTs should be assessed considering them as a whole and not individually.

To create this index, we use several dimensions that aim to represent the extent of digitalization of Spanish firms in the period of analysis. These dimensions are: i) the technological components (proxied by ICT capital, computer programming services, and the implementation of software programs either hired or developed by the firm); ii) the digital-related human capital (proxied by personnel training in software and information technology); iii) the extent of automation (measured by the use of robots, computer-aided design, flexible systems, and LAN); iv) the way digitalization changes how firms interact with their stakeholders (measured by 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 components that, measured in different ways, contain relevant information of the digital transformation. In Table 9 of the Appendix, we compare the variables we use to those of Calvino et al. (2018). We also analyze distinctively the role of automation from other DTs, referred here as ICTs. Hence, we construct an automation index that captures the extent of automation, measured by dimension iv) of the general index. The rest of dimensions will be part of the ICT index.

The procedure for building the overall index can be summarized as follows. First, variables in monetary units (ICT investment and training costs) are capitalized and their relative value 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

[8] We control for firm's size, trade status, foreign ownership and age.

[9] The ESEE sampling design has a two-tier structure, combining a comprehensive sample of firms with more than 200 employees with a stratified sample of firms with 10-200 employees. Since 1990, special efforts have been made to ensure the representativeness of the sample. Because of this sampling procedure, in the empirical analysis we define SMEs as firms with less than 200 employees, instead of using the usual threshold of 250 employees. For detailed information on the ESEE, see https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp.

Table 1 Observations in the sample by trade activity

	All firms	Non-Exporters	Exporters	Non-Importers	Importers
Size class	Observations	Observations	Observations	Observations	Observations
SME	12,783	5,067	7,716	5,107	7,676
%	100%	39.64%	60.36%	39.95%	60.05%

size class is defined in terms of the average number of employees: 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

normalized in the [0–1] interval. Values close to 0 imply that the firm in that period is little digitalized, while values close to 1 suggest a high degree of digitalization.

In Fig. 1, we show the digitalization of manufacturing firms in Spain from 2001 to 2014 using the digitalization index. According to the left panel of Fig. 1, firms have undergone a process of digitalization, which was much faster at the beginning of the 21 century and that slowdown later on because of the 2008 financial crisis. The degree of digitalization varies according to firm size, with SMEs being less digitalized than large firms.

Figure 2 plots 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. Textiles, timber and furniture, and food, beverages, and tobacco are the least digitalized. This is in line with the taxonomy presented by Calvino et al. (2018).

4.3 Descriptive Statistics

Table 1 shows the percentage of observations contained in each category according to the export and import status. The percentage of observations corresponding to SMEs that export is approximately 60%, while those that do not export equals 40%. Similar percentages are obtained for importers and non-importers.

Descriptive statistics are presented in Table 2. We first compare SMEs that export with non-exporters. Exporters are on average larger, more productive, more innovative, have more human capital, and a larger stake of foreign ownership. More interestingly, exporters are also more digitalized than non-exporters. Moreover, SMEs that export have a lower relative markup than those that do not. This may be because exporters may face a tougher competitive environment in foreign markets than their peers serving only the domestic market, requiring them to bear lower markups to remain competitive relative to the more efficient foreign competitors. Similar to exporters, importers are, on average, more digitalized, larger, more productive, more innovative, with more human capital, a higher stake of foreign ownership, and lower mark-ups.

5 Results

We now turn to assess the direct and indirect impact of digitalization on trade decisions. 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, DIG must have a positive impact on TFP. Second, the coefficient of TFP in the trade participation equations should be positive and significant. Therefore, the initial step for the analysis of the indirect effect is the estimation of Eq. (7). The results of estimating this dynamic equation by system-GMM are presented in Table 3. All the specifications provide suitable results for the Hansen test of overidentifying restrictions[10] (testing for instruments validity) and for the non-serial correlation of the error terms.[11] Overall, and in line with recent studies (Bartelsman

[10] The null hypothesis of the Hansen test is that all overidentifying restrictions are jointly valid.

[11] The optimal lag length of the dependent variable is selected until no serial correlation is achieved in residuals. For the disturbances to be not serially correlated, there should be evidence of significant negative first order serial correlation and no evidence of second order serial correlation in the differenced residuals. Hence, according to the Arellano-Bond test for serial correlation presented in Table 3, all models show evidence of significant first-order serial correlation in differenced residuals, and none show evidence of second-order serial correlation in the differenced residuals, suggesting the overall consistency of our estimates (Arellano & Bond, 1991).

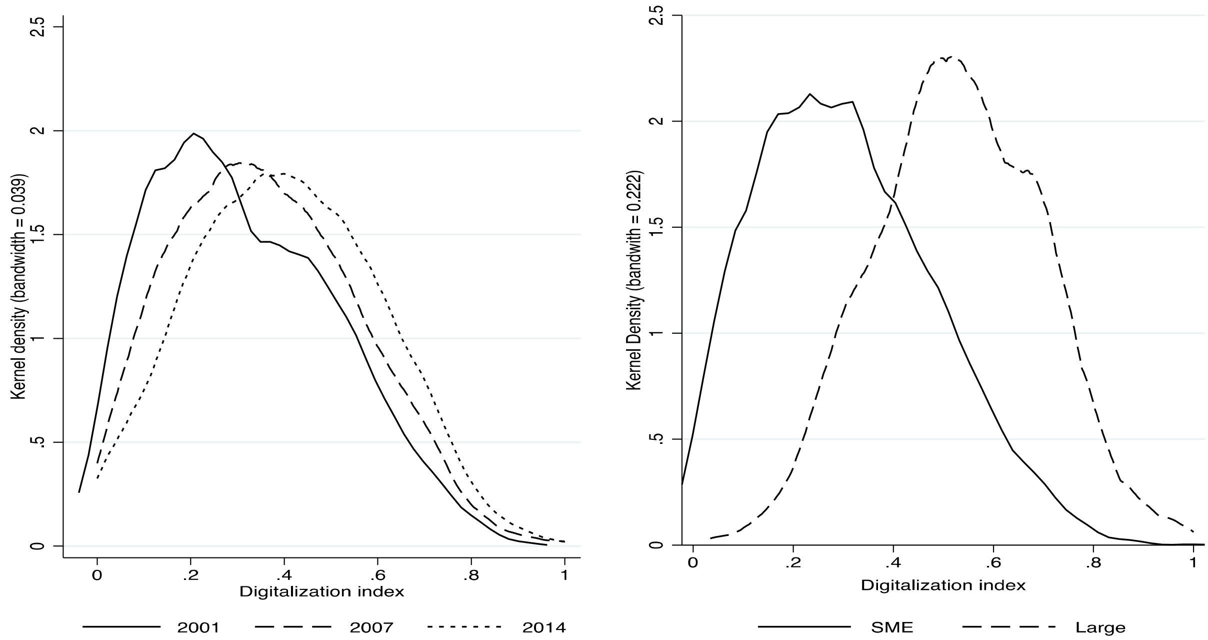

Fig. 1 The digital transformation in the Spanish manufacturing sector. *Source*: ESEE survey and own' elaboration

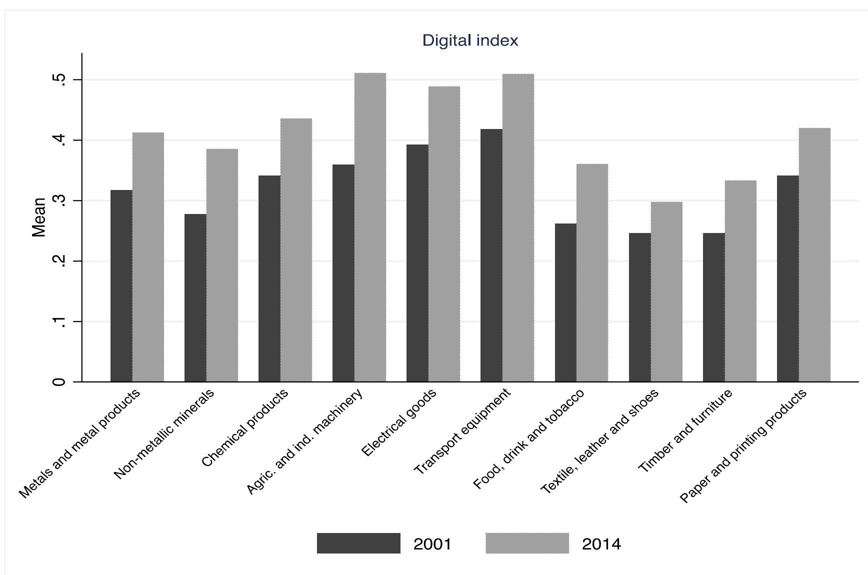

Fig. 2 The digital transformation by industry (2001–2014). *Source*: ESEE survey and own' elaboration

et al., 2019; Gal et al., 2019), we find that digitalization, measured by the overall index or by the ICT and automation dimensions, 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 impact of TFP on exports (imports), we can conclude an indirect effect of digitalization on trade via TFP. Then, the estimation of the system of equations in (4) will provide the final proof.

We continue the analysis by estimating the trade decisions under different specifications. The results

Table 2 Descriptive statistics for exporters, non-exporters, importers and non-importers

	All		Exporters		Non-exporters		Importers		Non-importers	
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d
Export propensity	0.60	-	1.00	-	0.00	-	0.81	-	0.30	-
Import propensity	0.60	-	0.80	-	0.29	-	1.00	-	0.00	-
DIG	0.33	0.17	0.38	0.17	0.25	0.15	0.38	0.17	0.26	0.16
TFP*	3.68	1.07	3.77	1.06	3.66	1.00	3.81	1.08	3.62	0.96
Markup	1.10	0.61	0.99	0.32	1.25	0.85	0.97	0.31	1.28	0.84
R&D propensity	0.26	-	0.37	-	0.09	-	0.38	-	0.09	-
Human capital	0.12	0.13	0.14	0.14	0.08	0.12	0.14	0.14	0.09	0.12
Age	29.47	20.60	32.02	21.31	25.57	18.82	32.00	21.67	25.65	18.24
Size	56.39	55.24	71.74	60.22	33.06	35.78	73.65	61.47	30.49	29.12
Foreign capital	0.09	-	0.14	-	0.02	-	0.15	-	0.01	-
Appropriability	0.03	-	0.04	-	0.01	-	0.04	-	0.01	-
Recessive market	0.33	-	0.32	-	0.34	-	0.33	-	0.33	-
Expansive market	0.19	-	0.21	-	0.15	-	0.21	-	0.16	-
Competitors	0.20	-	0.20	-	0.21	-	0.21	-	0.19	-
External FC	4.11	3.33	4.26	3.43	3.88	3.16	4.30	3.44	3.83	3.14
Internal FC	6.05	2.43	6.21	2.40	5.80	2.45	6.19	2.41	5.84	2.45
Observations	12,782		7,716		5,067		7,676		5,107	

Source: Authors' calculations with data from ESEE 2001–2014

s.d. stands for standard deviation. The sample is SMEs observed at least for two consecutive years and for which an estimate of TFP can be obtained. * variables in logs

presented in Table 4 are the average marginal effects (AME). Although not reported, all specifications control also for sector and time dummies. The potential interdependence between export and import participation is ignored in columns 1 and 2. Thus, this specification is estimated using the Wooldridge (2005) approach as two independents RE dynamic probit models. The interdependence between both decisions is considered in columns 3 and 4, but the potential endogeneity of the digitalization index is ignored. This specification is estimated as a bivariate RE dynamic probit model. The statistically significant estimated correlation coefficient for the error terms confirms that the two decisions are not independent. Hence, a bivariate model is preferred.

Finally, in columns 5 and 6, a CF approach is adopted to account for the potential endogeneity of DIG. Before examining the results, note that to avoid further simultaneity problems, the rest of covariates are lagged one period. The first step of the CF approach consists of regressing DIG on the instruments and the rest of exogenous variables in a FE model. Although, for brevity, the estimates of the first-stage regression are not shown,[12] the coefficient of the mean digitalization index of peer-firms is significantly positive and the regulation index is significantly negative, as expected. However, the residual from this first-stage is not significant in the trade participation equations, suggesting that DIG does not suffer from endogeneity.

Next, and after ruling out the reverse causality problem between DIG and trade participation decisions, we discuss the results from columns 3 and 4. Digitalization exerts a positive impact on the export and import probability.[13] Increasing the index by 10 percentage points (p.p.) raises the probability of exporting by 0.9 p.p., holding all other variables constant. Hence, digitalization facilitates the internationalization of SMEs by reducing transaction costs.

[12] They are available upon request.

[13] We also test whether the relationship between DIG and propensity to trade is nonlinear and whether it changes over time. Our results suggest that the relationship is linear and increases over time. Results are available upon request.

Table 3 The effect of the Digital Index on TFP

Dependent variable:	TFP (1)	TFP (2)	TFP (3)	TFP (4)	TFP growth (5)
DIG_{t-1}	0.075*** (0.026)	0.132*** (0.042)		0.082** (0.041)	0.082** (0.041)
$Automation_{t-1}$			0.037** (0.015)		
ICT_{t-1}			0.099** (0.049)		
AR1 (p-value)	0.000	0.000	0.000	0.000	0.000
AR2 (p-value)	0.283	0.794	0.708	0.712	0.712
Hansen-J (p-value)	0.152	0.351	0.443	0.396	0.396
Controls	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9058	9058	9058	9049	9049
No. firms	1487	1487	1487	1486	1486
No. of instruments	68	111	145	214	214

The dependent variable in columns (1) to (4) is the log of TFP, whereas in (5) it is the difference of the log of TFP from *t*-1 to *t*. All specifications include the first and second lag of TFP. Firm controls include employment, firm's age, trade status and foreign ownership. All controls are included with one-period lag. Estimates are obtained through the two-step system GMM estimator with robust standard errors corrected for finite sample bias (Windmeijer, 2005). AR1 and AR2 values report the p-values of the tests for first and second order serial correlation in the differenced residuals, respectively. In column (1) DIG is considered exogenous, while in the rest it is considered endogenous. The Hansen test of over-identification is under the null hypothesis that all of the instruments are valid. We use levels of TFP, DIG, Automation, ICT, trade status and employment dated (*t*-3) to (*t*-6) as instruments in the difference equation, and differences dated (*t*-2) as instruments in the levels equation, as well as age, foreign ownership, industry dummies and year dummies. Year FE only enter in the equation in levels. * Significant at 10%, ** significant at 5%, *** significant at 1%

Similarly, concerning imports, a 10-percentage point increase of DIG increases the probability of importing by about 0.5 p.p. These result support earlier findings that DTs are positively related to export (Añón Higón & Bonvin, 2022; Hagsten & Kotnik, 2017) and import activities (see, e.g., Ozcan, 2018; Alguacil et al., 2022). Therefore, digitalization directly facilitates foreign trade of SMEs, although this effect appears larger for exports than for imports. This may suggest that digitalization may be more effective in facilitating access to new customers rather than suppliers.

The results in Table 4 also support the indirect effect of digitalization (via TFP). Consistent with the self-selection hypothesis (Melitz, 2003), TFP influences trade behavior, as a 10% increase of TFP raises the probability of exporting and importing by 0.4 and 0.8 p.p., respectively. This is in line with previous studies that found that more productive firms are more likely to export (Añón Higón & Bonvin, 2022; Mañez et al., 2020) and import (Muûls & Pisu, 2009), respectively. Thus, digitalization spurs participating in foreign markets not only through a direct channel, but also through productivity gains. However, to compare the relative size of their effects, we need to consider that DIG and prior productivity are measured on different scales. To address this issue, we calculate the impact of a one standard deviation change in each variable. Our findings show that a one standard deviation (0.17) increase in DIG leads to a 1.5 p.p. and 0.8 p.p. increase in the propensity to export and import, respectively. In contrast, a one standard deviation increase in log TFP results in a much larger increase of 4.1 p.p. and 7.5 p.p. in the probability of exporting and importing, respectively. These results suggest that TFP has a stronger impact on export and import behavior than DIG.

Past export and import experiences stand as important determinants of current export and import propensities (Elliott et al., 2019). This evidences the importance of sunk costs in internationalization (Kasahara & Lapham, 2013; Roberts & Tybout, 1997). Once a

Table 4 The effect of digitalization on SMEs trade. Marginal effects

	RE Probit		RE Biprobit		RE Biprobit & CF	
Dependent var	Export	Import	Export	Import	Export	Import
	(1)	(2)	(3)	(4)	(5)	(6)
DIG_t	0.107***	0.059**	0.090***	0.049**	0.100***	0.075**
	(0.025)	(0.027)	(0.021)	(0.025)	(0.030)	(0.033)
TFP_{t-1}	0.045**	0.085***	0.038**	0.075***	0.038**	0.076***
	(0.018)	(0.023)	(0.015)	(0.020)	(0.015)	(0.020)
$Export_{t-1}$	0.198***	0.050***	0.163***	0.051***	0.162***	0.050***
	(0.012)	(0.008)	(0.013)	(0.008)	(0.013)	(0.009)
$Import_{t-1}$	0.035***	0.205***	0.033***	0.185***	0.033***	0.184***
	(0.008)	(0.012)	(0.007)	(0.013)	(0.007)	(0.013)
Relative $Markup_{t-1}$	-0.028***	-0.075***	-0.023***	-0.068***	-0.023***	-0.068***
	(0.010)	(0.015)	(0.009)	(0.013)	(0.009)	(0.013)
$R\&D_{t-1}$	0.013	0.023**	0.010	0.022**	0.010	0.021**
	(0.009)	(0.010)	(0.008)	(0.009)	(0.008)	(0.009)
Human $Capital_{t-1}$	0.047*	0.038	0.040*	0.034	0.038	0.029
	(0.028)	(0.028)	(0.023)	(0.025)	(0.024)	(0.025)
Age_{t-1}	0.005	0.002	0.004	0.002	0.004	0.001
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
$Size_{t-1}$	0.246**	0.554***	0.196**	0.494***	0.188**	0.472***
	(0.097)	(0.106)	(0.082)	(0.095)	(0.084)	(0.097)
Foreign $Capital_{t-1}$	0.019	0.040**	0.016	0.036**	0.016	0.036**
	(0.017)	(0.017)	(0.014)	(0.015)	(0.014)	(0.015)
Recessive $Market_{t-1}$	-0.003	-0.007	-0.003	-0.005	-0.003	-0.006
	(0.007)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)
Expansive $Market_{t-1}$	0.007	0.015*	0.006	0.013*	0.006	0.013*
	(0.008)	(0.009)	(0.007)	(0.008)	(0.007)	(0.008)
$Competitors_{t-1}$	-0.013	0.004	-0.011	0.004	-0.011	0.004
	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)	(0.008)
$Appropriability_{t-1}$	0.052**	0.008	0.044**	0.007	0.044**	0.007
	(0.022)	(0.018)	(0.018)	(0.016)	(0.018)	(0.016)
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	0.001	-0.000	0.001	-0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Rho			0.391***	0.391***	0.389***	0.389***
			(0.062)	(0.062)	(0.062)	(0.062)
Residual[a]					-0.022	-0.055
					(0.042)	(0.047)
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Initial Condition	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak Means	Yes	Yes	Yes	Yes	Yes	Yes
IV Control Function					Yes	Yes
Observations	9,182	9,145	9,143	9,143	9,143	9,143
Log-Likelihood	-1,558.25	-2,035.87	-3,568.35	-3,568.35	-3,567.55	-3,567.55

We report marginal effects at sample means and standard errors clustered at the firm level in parenthesis. 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. Specifications in (5) and (6) include the residual from a first step of an IV control function (CF) approach in which the regulation index and the average (excluding the firm) of the digital index by year, industry, region and R&D status are used as instruments for DIG. * Significant at 10%, ** significant at 5%, *** significant at 1%. [a] Rivers and Vuong (1988) endogeneity test firm has paid the sunk costs of being global, it becomes easier to continue with trade. Additionally, previous import experience matters for export participation and vice-versa. Previous studies have also highlighted the complementarity effects between import and export activities, with learning effects from importing allowing firms to access new export markets (Kasahara & Rodrigue, 2008). Conversely, firms can benefit from foreign networks and connections through exporting, which will help them locate and engage with foreign suppliers. It should be noted that our results differ slightly from those of Elliott et al. (2019), as we find evidence of complementarity effects between import and export decisions, with each activity enhancing the other.

In terms of the remaining covariates, larger SMEs and those with lower relative markups have a higher probability of exporting and importing. Human capital and appropriability conditions are positively correlated with the probability of exporting, whereas R&D, foreign ownership, and an expansive market demand appear positively correlated with the import decision. Despite not being reported, the initial condition appears positive and significant in all the specifications. The rest of controls do not seem to affect the decision of SMEs to access foreign markets.

5.1 Robustness Analysis

In this section, we run some robustness checks.[14] The results are presented in Table 5, where, for clarity, we show only the AMEs of DIG and TFP.[15] As a first robustness check (columns 1 and 2), we follow Wooldridge (2005) and model the unobserved heterogeneity terms, α_i's, including the time means of all variables contained in the x vector.[16] Second (columns 2 and 3), we follow Mañez et al. (2020), and model the distribution of α_i, conditional on the pre-sample mean of the dependent variable, instead of using the within means. Here, the pre-sample means are calculated as the within-firm mean of export and import propensity for pre-sample years, which in our case correspond to the period 1998–1999. The third robustness check deals with the fact that TFP is an estimated regressor, which could render the standard errors inaccurate and affect inference. To address this problem, we report bootstrapped standard errors (see columns 5 and 6). The fourth check uses instead of the leave-one-out mean instrument in the first-step of the CF approach, the second lag of the dependent variable together with the regulatory index in communications.[17] The results of the second-stage are presented in columns 7 and 8. In this case too, the first-stage residual is not significant in the trade equations, corroborating that DIG does not suffer from endogeneity. For the final check we estimate in columns 9 and 10 two static linear probability FE models to control for unobserved firm characteristics not fully captured by the Wooldridge (2005) approach and that can simultaneously affect the probability of using DTs and accessing foreign markets. However, linear probability models have the disadvantage that the estimated probabilities are not restricted to the interval [0–1].[18] Overall, the results of the above checks were broadly consistent with the baseline estimates, except for the FE model where the direct impact of digitalization on imports became insignificant.

5.2 Different subsamples of firms

At this point, we have shown that digitalization has a direct and indirect impact on the export and import participation of SMEs. Now, our goal is to assess 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 varies widely across industries, we first perform the analysis distinguishing between firms in high- and low-digitalized industries following the classification by Calvino et al. (2018) (see Table 10). In principle, it is unclear

14 In the online Appendix we also show the results of estimating two independent static FE logit models.

15 Full results are available from the authors on request.

16 To avoid a multicollinearity problem, the α_i's have been previously modeled using only the time means of the internal and external financial variables (Semykina, 2018). However, this may cause biases.

17 The estimates of the first-step regression, although not shown, reveal that the coefficients of the second lag of DIG and the regulation index have the expected sign and are significant.

18 Moreover, this specification ignores the role of sunk costs by estimating a static model and that export and import are interdependent decisions.

Table 5 Robustness checks

	Wooldridge (2005)		Mañez et al. (2020)		Bootstrapped s.e		Alternative IV		OLS FE	
Dependent var	Export	Import	Export	Import	Export	Import	Export	Import	Export	Import
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DIG_t	0.087***	0.044*	0.108***	0.106***	0.090***	0.049*	0.071***	0.076**	0.092***	0.052
	(0.021)	(0.025)	(0.028)	(0.041)	(0.022)	(0.027)	(0.027)	(0.033)	(0.029)	(0.034)
TFP_{t-1}	0.035**	0.065***	0.094***	0.140***	0.038**	0.075***	0.029*	0.081***	0.062**	0.088***
	(0.016)	(0.021)	(0.025)	(0.033)	(0.018)	(0.021)	(0.015)	(0.021)	(0.026)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial condition	Yes	Yes			Yes	Yes	Yes	Yes		
Mundlak means (All)	Yes	Yes								
Pre-sample mean $_{(98/99)}$			Yes	Yes						
Bootstrapped s.e					Yes	Yes	Yes	Yes		
Firm FE									Yes	Yes
Observations	9,143	9,143	7,321	7,321	9,143	9,143	8,322	8,322	9,183	9,182
Log-Likelihood	-3,546.95	-3,546.95	-3,417.36	-3,417.36	-3,567.62	-3,567.62	-3,214.88	-3,214.88	2,157.44	-782.15

We report marginal effects at sample means of the variables of interest. All specifications include the same control variables as in Table 4 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 bootstrapped standard errors in parentheses (250 replications), while in the rest of specifications we report standard errors clustered at the firm level. Specifications in (7) and (8) include the residual from a first step of an IV control function approach in which the regulation index and the second lag of DIG are used as instruments for the Digital index in *t*. In (9) and (10) we estimate two independent static linear probability FE models. * Significant at 10%, ** significant at 5%, *** significant at 1%

Table 6 Sensitivity Analysis: Digitalization and GVC participation by sector

	Low-Digitalized		High-Digitalized		Low GVC integrated		High GVC integrated	
Dependent var	Export	Import	Export	Import	Export	Import	Export	Import
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DIG_t	0.085***	0.052	0.079**	0.050	0.115***	0.028	0.076***	0.069**
	(0.025)	(0.034)	(0.037)	(0.035)	(0.038)	(0.039)	(0.025)	(0.031)
TFP_{t-1}	0.046***	0.070**	0.022	0.085***	0.055**	0.058**	0.008	0.108***
	(0.016)	(0.028)	(0.029)	(0.030)	(0.023)	(0.027)	(0.020)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial condition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,624	5,127	3,519	3,519	3,524	3,524	5,619	5,619
Log-Likelihood	-2,096.69	-2,096.69	-1,425.81	-1,425.81	-1,474.03	-1,473.03	-2,048.27	-2,048.27

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 and standard errors clustered at the firm level in parenthesis. All specifications include the same control variables as in Table 4 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%

whether the trade effect of digitalization is greater for firms in low-digitized industries or vice versa. While firms in low-digitalized industries have more to gain from 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 & Meliciani, 2010).

The trade impact of DIG and TFP in low-digitalized industries (columns 1 and 2) and high-digitalized industries (columns 3 and 4) is displayed in Table 6. Digitalization in low-digitalized industries directly facilitates exports and has an indirect effect on both exports and imports via productivity. However, in high-digitalized industries, digitalization only affects exports directly but not via TFP. In contrast, the decision to import is only indirectly affected by digitalization through TFP. While firms in highly digitalized industries still appear to benefit from the use of DTs, 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.

Second, DTs have been linked to the fragmentation of the GVC and the decision to offshore and outsource as they reduce the transaction and adjustment costs of moving some activities outside the firm (Rasel, 2017). 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 (Gopalan et al., 2022). Given that the integration in GVCs varies across industries, we perform the analysis distinguishing between firms in sectors that are low- and highly integrated into GVCs (see Table 10). Here, the classification on GVC participation is based on the OECD "GVC forward linkage" indicator at the 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 DIG and TFP in industries with low-participation (columns 5 and 6) and with high-participation in GVCs (columns 7 and 8) is displayed in Table 6. The results show that in low-GVC integrated sectors, digitalization exerts a direct and indirect impact on exports, while digitalization increases the probability of importing just through the productivity channel. In industries with high participation in GVCs, digitalization directly increases the probability of exporting, but there is no indirect effect through TFP. In contrast, digitalization has a direct and indirect impact on import participation.

5.3 ICTs and automation technologies.

Finally, while both automation and ICTs may bring productivity gains to the firm, it seems plausible that the effect of these technologies on trade may be different. They potentially have different implications for the international division of labor and trade activities. Automation technologies -including robots- are more likely to reduce the number of tasks and may

Table 7 Sensitivity Analysis: ICTs vs. Automation

Dependent var	Export (1)	Import (2)
ICT_t	0.086***	0.054**
	(0.020)	(0.022)
$Automation_t$	0.012	0.002
	(0.010)	(0.012)
TFP_{t-1}	0.038**	0.075***
	(0.015)	(0.020)
Controls	*Yes*	*Yes*
Initial condition	*Yes*	*Yes*
Mundlak means	*Yes*	*Yes*
Observations	9,143	9,143
Log-Likelihood	-3,566.00	-3,566.00

We report marginal effects of the variables of interest and standard errors clustered at the firm level in parenthesis. All specifications include the same controls as in Table 4 together with industry and year dummies. All specifications include the initial condition and the within-means of internal and external finance. * Significant at 10%, ** significant at 5%, *** significant at 1%

accelerate the substitution of humans for machines, and thus, they are likely to induce the reshoring of some tasks previously outsourced. In contrast, ICTs, particularly communication technologies, help to overcome physical distance, reduce matching and coordination costs, and thus, are likely to encourage fragmentation of the production processes (Baldwin, 2016), leading to more trade. To assess this, we estimate model (1) distinguishing two dimensions of the digitalization index: the automation index, and the ICT index. The results presented in Table 7 are in line with the above arguments. We show that, while ICT influences both export and import participation decisions, the automation index has no direct impact. Nevertheless, the productivity effect of both ICT and automation leads to a higher probability of importing and exporting.

6 Conclusion

Digital technologies are 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 overcome the barriers they face to enter foreign markets. In this study, we analyze both the direct and indirect effect (via productivity) of digitalization on both the export and import participation decisions of SMEs. In contrast to previous studies that use a single indicator of the digitalization phenomenon, we use a synthetic index 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 comprises 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 firm's 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 digitalization exerts a direct positive impact on the decision to take part in foreign markets, both through exports and imports. Moreover, firms' participation in imports and exports increases with digitalization through the indirect TFP channel. However, TFP has a stronger impact on export and import behavior than the direct channel of digitalization. In addition, the direct effect seems to be larger for exports than for imports, while the opposite seems to be true for the indirect effect. This means that the same percentage increase in digitalization has, on average, a greater increase in the probability of exporting than importing. Conversely, the same percentage increase in TFP increases the probability of importing more than exporting.

Our results provide important insights to managers. By investing in digitalization, SMEs can improve their access to foreign markets and become more efficient, which reinforces the impact of digitalization on their export and import participation. Additionally, the costs associated with leveraging DTs are likely to be lower compared to other trade-enhancing strategies, e.g., R&D activities (Barrios et al., 2003). From a policy perspective, our findings highlight that efforts should be made to support the adoption of DTs by SMEs as a way to promote trade. Policymakers can play a key role in supporting the adoption of DTs by SMEs by providing the necessary digital infrastructure and offering incentives to encourage their use. These initiatives can as a result help SMEs to integrate into GVCs and increase their export base.

Our study is not without limitations, which offer interesting avenues for future research. For example, we do not have information on new technologies that are part of Industry 4.0, such as 3D printing, cloud computing, artificial intelligence or blockchain. Data on these technologies will allow for a more comprehensive state of the current digital transformation and whether they have contributed to accelerate or slowdown globalization. In addition, data on the destination of companies' exports and the origin of imports could allow us to test the hypothesis of the effect of digitalization on the *death of distance*, i.e., on the ability of companies to source and serve more distant markets. Finally, although this study has focused on the manufacturing industry, data on the service sector could allow us to assess the impact of digitalization on the rapid increase in cross-border trade in services.

Appendix

Table 8 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
DIG	Digitalization index, which ranges from 0 to 1 (see methodological section)
TFP	The logarithm of TFP (see Online Appendix)
Relative Markup	Firm's markup relative to the average markup of the industry (see Online Appendix)
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	Firm's access to internal funds (see Añón Higón & Bonvin, 2022)
Internal Finance	Firm's access to external funds (see Añón Higón & Bonvin, 2022)

Table 9 Digitalization Index by Dimensions. Comparing Calvino et al. (2018) with this study

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

Author's elaboration

Table 10 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	✓			✓

"*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

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