Advanced Digital Technologies and International Activities: Evidence on EU-27 SMEs

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Abstract

This paper provides evidence on the impact of Advanced Digital Technology (ADT) adoption on firms' trade activities. Using survey data of European small and medium-sized enterprises (SMEs), we estimate static Ordinary Least Squares (OLS), Probit, and Negative Binomial models to assess the relationship between ADT adoption and trade behavior at the firm level. Our findings show that firms utilizing ADTs are more productive, more likely to be exporters, more engaged in Global Value Chains (GVCs), and tend to export to a greater number of destinations. However, not all ADTs have the same impact on trade activities. While adopting Artificial Intelligence (AI) positively correlates with the probability of exporting, it has no significant effect on GVC participation or on the number of export destinations. Furthermore, the effects of an ADT vary by a firm's sector. These results highlight the need for more comprehensive digital transformation strategies that foster international trade, particularly for SMEs that have yet to fully capitalize on ADTs.

Keywords: Advanced Digital Technologies; Artificial Intelligence; exports; GVC participation; export destinations.

Contents

1. Introduction

Advanced Digital Technologies (ADT) like artificial intelligence, cloud computing, the use of robots to automate processes, and big data analytics, are increasingly applied by firms directly or indirectly through the recent and prominent use of large language models. Despite growing adoption, there is a lack of thorough empirical evidence on the causal effect of the use of ADT in Europe as well as its role in firm level labor productivity and exports. In a thorough discussion of AI and international trade, Goldfarb and Trefler (2018, p. 1) claim that "*even to the extent that progress has been made in understanding the impact of AI, we remain largely uninformed about its international dimensions. This is to our great loss*."

Our primary aim is to assess whether digitalization facilitates businesses' trade activities, focusing specifically on Small and Medium-sized Enterprises (SME). Recent studies have explored the impact of artificial intelligence (AI) on firms' export behavior. For example, Zhang (2022) investigates how AI enhances export performance. However, the geographic focus of that study is limited to China. In contrast, this study centers on SMEs within the EU-27. Related research by Wagner (2024) examines the influence of specific ADT on the export activities of manufacturing firms. Although Wagner uses the same dataset used in this paper, his analysis is limited to the effects of specific ADT within the manufacturing sector. This paper broadens the scope by analyzing how ADT, and AI in particular, influences SME's trade behavior across multiple industries within the EU-27. In doing that, we focus on the export decision as well as on the number of the firm's export destinations. As a novelty, we also assess the role that these ADT brings to participate in global value chains (GVCs).

This paper contributes to the literature because it investigates differences in trade activities between small and medium sized enterprises (SMEs) from member countries of the European Union that use or do not use Advanced Digital Technologies. To achieve this, using survey information from the European Commission we will construct an index of ADTs at the firm level, which accounts for the multi-faceted phenomenon of digitalization. Moreover, we will explore the impact of AI and compare it with that of other ADTs. Based on a Google Scholar search for "Flash Eurobarometer 486" performed on August 23, 2024, no empirical research has been done on the effect of ADT using an index that accounts for Big Data, AI, Cloud Computing, Robotics, High Speed Infrastructure and blockchain on firm's trade activities using these data.

More specifically, this study tries to provide answers to two main research questions: (1) Are internationalized firms more productive than non-internationalized firms? In other words, is there an international trade premium? To answer this question, we estimate OLS regression models to determine the extent to which trade status affects labor productivity levels of firms, measured by the log of firm turnover per employee. We compare firms that are engaged in various forms of trade, such as exporting within and outside the EU, participating in global value chains (GVC), and the number of countries to which the firm exports. In addition, we also consider the impact of digitalization and assess the existence of a digitalization premium.

The second research question that we address is: (2) What is the impact of ADT on a firm's decision to export, and to participate in GVCs? Additionally, does ADT have an impact on the number of destinations exported to? To answer these questions, we estimate probit models to analyze the determinants of exporting and GVC participation. The probit models include the digitalization index, and a series of control variables that literature demonstrates to have an impact on trade activities. Marginal effects are computed to assess the impact of each factor on the probability of exporting and GVC participation. Furthermore, we explore the determinants of the number of export destinations using a negative binomial regression model due to the nature of the dependent variable. The results indicate that ADT, alongside other firm characteristics, significantly influences the likelihood of exporting, GVC participation, and the scale of export markets. The adoption of Artificial Intelligence alone is also found to be significant in determining export activities, although its impact varies between sectors. These findings highlight the role of digitalization and advanced technologies in advancing a firm's international trade activities and integration into global value chains.

The rest of the study is organized as follows. Next section reviews the studies assessing the relationship between ADTs and trade. In section 3, we introduce the data used and discuss the characteristics of SMEs that export and/or adopt ADTs. In section 4 we report the results, and the main findings are discussed. Finally, section 5 concludes.

2. Literature Review

The integration of ADT is consistently acknowledged as a source of competitiveness in business operations, impacting a company's inclination and level of involvement in exporting (Añón Higón & Bonvin, 2022, 2024; Fernandes et al., 2019; Kneller & Timmis, 2016). Digital technologies influence export decisions and international market growth by offering additional sales channels, improving knowledge of foreign markets, supporting product customization, and facilitating international marketing strategies. The use of these technologies also improves access to competitor information and strengthens commercial relationships with customers, suppliers, and distributors (Añón Higón & Bonvin, 2024). Additionally, these technologies play a crucial role in global and regional value chains by increasing flexibility and improving supply chain efficiency. Existing empirical literature shows a positive relationship between productivity and export activities, consistent with the self-selection hypothesis at the firm level and at the macro level (Ferencz et al., 2022; Wagner, 2007). By increasing productivity, ADT eventually allows firms to produce goods at lower costs and/or with higher quality, enhancing their competitiveness in international markets.

Furthermore, AI can reduce trade costs by providing accurate and timely predictions about competitors, markets, and customer preferences in foreign markets (Ferencz et al., 2022). Meltzer (2018) further supports this by highlighting AI's ability to improve consumer demand forecasts, enhancing firms' capacity to adapt to market conditions and maintain competitiveness by moderating an appropriate supply of goods and services. The impact of AI on reducing trade costs and boosting productivity is further evidenced in its application within digital platforms like eBay, where AI translation services have increased exports by enabling small businesses to use the platform to reach international customers (Meltzer, 2018). The adoption of other specific ADTs like robotics in Spanish firms further corroborated that it was a significant factor in the commencement of importing and exporting, further leading to increases in export share from total sales (Alguacil et al., 2022).

Even though a great deal of the literature concerning ADTs is regarding large companies, ADTs are critical to enhancing the competitiveness and productivity of SMEs. ADTs offer SMEs similar benefits, including automating repetitive tasks, reduction of errors, and the development of new products and services (Hansen & Bøgh, 2021; Del Sarto & Piccaluga, 2021). Despite these advantages, SMEs often face more challenges than large firms in the adoption of these technologies because of their limited resources or expertise. Targeted applications of ADT would allow SMEs to integrate these technologies over time, gradually improving efficiency through predictive analytics. This incremental approach is crucial as AI-driven solutions are expected to become essential to maintain competitiveness in the digital era (Del Sarto & Piccaluga, 2021). Embracing ADT is not just a competitive advantage but ultimately a necessity for SMEs aiming to sustain their market position.

While ADTs benefit productivity, their impact is complex and varies across sectors and firms. Related studies suggest that firms already exhibiting higher levels of efficiency and output benefit more from digitalization as they can integrate digital technologies to optimize existing processes. For instance, in highly digitized sectors investments in digital technologies have been associated with productivity improvements of up to 0.34 percentage points annually (Anderton et al., 2023). Conversely, in less digitized sectors or among firms categorized as 'laggards,' the productivity gains from digitalization are often modest or even negative (Anderton et al., 2023). This suggests that the relationship between digitalization and productivity may be not linear and is influenced by sector-specific factors as well as the extent to which firms can effectively integrate and utilize advanced digital tools. In sectors like manufacturing and construction, which have been slow to adopt digital technologies in the past, the anticipated productivity increases from digitalization have failed to materialize as expected (Aalto University, 2021). This could be due to the initial challenges of implementation and the need for adjustments in business processes to capitalize on digital investments. Despite these challenges, there is evidence—using panel data and similar models as employed in this paper—that adoption of Big Data Analytics and Cloud Computing in manufacturing firms leads to higher productivity, more innovation, and reduced trade costs (Wagner, 2024).

To tackle concerns of endogeneity between productivity and exporting, we follow Bernard and Jensen (1999), who demonstrate that productivity drives exports. While there is a positive correlation between exports and productivity, their research suggests that we can expect productivity boosts given by ADTs to drive export activity, rather than the reverse. This is because exporting does not generally lead to increases in the productivity growth rates of firms. Exporting is further associated with a reallocation of resources from less efficient to more efficient plants within industries (Bernard & Jensen, 1999). Similarly, ADTs could amplify the reallocation of resources towards more efficient firms within industries.

Addressing the endogeneity between different ADTs is challenging. These technologies often complement and work synergistically with one another. For example, AI is frequently paired with cloud computing because AI relies on data processing (Li et al., 2024). Big data also plays a crucial role by feeding AI and ML algorithms the information needed to make predictions (Li et al., 2024). Cloud computing and robotics also go hand in hand, sometimes making it difficult to distinguish between these fields with developments like "cloud robotics" (Saha & Dasgupta, 2018). This constructive collaboration is also evident in our dataset, where significant correlations exist across all ADTs measured. Evidence of these correlations is shown in Figure A.4 in the appendix.

While most of the research analyzing the role of ADT in trade activities has focused on exports, few studies have looked at the role of these technologies in facilitating the participation of firms in GVCs. In terms of GVC participation, Gopalan et al. (2022) provide firm-level evidence from 52 emerging markets, demonstrating that digitalization, particularly high-speed internet and online presence, significantly enhances GVC integration. Analyzing data from 24,839 firms over 12 years, they find that digital adoption facilitates integration into global production networks and benefits financially constrained firms, relevant to SME's. This supports the broader argument that digital infrastructure is important for firms to be good firms, which in turn leads to exporting (Bernard and Jensen, 1999).

To summarize, ADTs enhance firm-level productivity and export activities, thereby boosting global competitiveness. AI and other ADTs improve efficiency and output and reduce production costs by substituting more expensive human labor. Empirical studies consistently demonstrate a positive relationship between productivity gains and increased export activity, facilitated by ADT's ability to lower trade costs through accurate market predictions and demand forecasting. Moreover, ADT-driven tools on digital platforms have expanded export opportunities for businesses. However, the impact of digitalization varies across sectors. Highly digitized industries benefit from AI adoption, while less digitized sectors or lagging businesses face challenges in achieving similar productivity improvements. Nonetheless, McKinsey (2023) projects that AI could contribute an additional $13 trillion to global GDP by 2030, especially in sectors where efficiency and customization are critical, emphasizing AI's potential for economic growth and international trade.

3. Data and descriptive statistics

3.1. Data

The firm level data used in this study is from the Flash Eurobarometer 486 survey conducted in February – May 2020. Although the data was collected at the start of the COVID-19 pandemic, the data on export activities relate to the year 2019 before the pandemic as well as before the United Kingdom's withdrawal from the European Union. We used data of firms from the 27 member states of the European Union in 2020 (including firms from the UK). The sample covers 12,617 firms and 2,362 firms from manufacturing industries (included in NACE section C).

Table 1. Use of ADTs and AI in SMEs

Variable	Mean	SD	Max	Min
ADT	1.409	1.425	7	0
AI	0.072	0.258	1	0
Non AI	1.337	1.316	6	0

Source: Flash Eurobarometer 486, for a sample of 12,617 observations

In the survey, firms were asked in question Q23_1 whether they introduced Artificial Intelligence or Machine Learning (e.g. Bayes Naïve classifying algorithm, Lasso Regression). Firms that answered affirmatively are classified as firms that have adopted AI. The descriptives shown in Table 1, suggest that only 7% of European SMEs had adopted AI by 2019. The same question was asked regarding Cloud Computing, Robotics, Smart Devices, Big Data Analytics, High Speed Infrastructure and Blockchain in questions Q23_2, Q23_3 and so on, respectively. The answers to these questions were then used to construct an ADT Digitalization index, as an unweighted sum of all positive answers. In this sense, a company that introduced AI and Robotics would have a higher score (2) than a firm which only introduced AI (1). The mean value of this variable is 1.409, meaning that on average, SMEs in Europe adopted 1.4 ADTs by 2019 from a potential maximum of seven technologies available. This variable is used to estimate the effect of ADT on labor productivity as well as on a firm's trade activities.

To measure trade activities at the firm level, we use additional questions from the survey. In question Q11_1, firm representatives were asked whether their firm exported any goods. Based on their responses, firms were classified as either exporters or non-exporters. To identify which firm was part of a GVC, column Q9_5 was used, which asked the representative if they were part of a Global Value Chain (or not). Firms were classified as part of a GVC if the response was affirmative. To count the total number of export destinations, questions Q11_2, Q11_3, Q11_4, Q11_5, Q11_6, Q11_7, and Q11_8 were used. These asked the representative if the firm exported to other countries in the EU27, exported to North America, exported to Latin America and the Caribbean, exported to China, exported to Asia-Pacific, and exported to the Middle East and Africa, respectively. A dummy was created for exporters of each region and tallied up for a maximum score of 7 for exporters to all available regions.

3.2. Descriptive Statistics

Due to the recent surge of Artificial Intelligence (AI), a special focus was taken on this emerging technology. The following table provides descriptive statistics for the independent variables used in this paper. AI was adopted by 7.2% of EU27 firms while the average firm was shown to adopt more than one of the seven measured technologies. Furthermore, firms that adopted AI were larger, on average, than firms that had not as shown in Table 12 in the appendix section. It should be noted that the firms in our sample are relatively small, 80% of which have less than 50 employees. This could mean that they are unlikely to have the resources needed to fully take advantage of ADT.

Table 2. Dependent Variables Descriptive Statistics

Variable	Mean	SD	Max	Min
Exports	0.359	0.48	1	0
N# of Destinations	0.72	1.408	7	0
GVC participation	0.096	0.294	1	0

Source: Flash Eurobarometer 486, for a sample of 12,617 observations

Our analysis assesses how ADT influences a company's decision to export, the number of export destinations, and the likelihood of participating in a GVC. Descriptive statistics in Table 2 show that within our sample, 35.9% of firms were found to export, and 9.6% were part of a GVC. The standard deviation of the number of export destinations was high relative to the average, indicating significant variability.

We control for other variables that have been suggested by previous literature (Wagner, 2024). The control variables in our models include the size of the firm, which is measured by the number of employees[1], the number of years it has been operating (age), if it has patent or has applied to a patent/s (patent), if the firm is in a rural area, if it is a family firm, if the firm is part of a cluster or regional association, as well as dummies for sector and country. In the trade equation we also control for labor productivity, which is calculated by dividing total firm turnover per employee[2]. Table 3 shows descriptive evidence for the first seven control variables.

Table 3. Descriptive Statistics of control variables

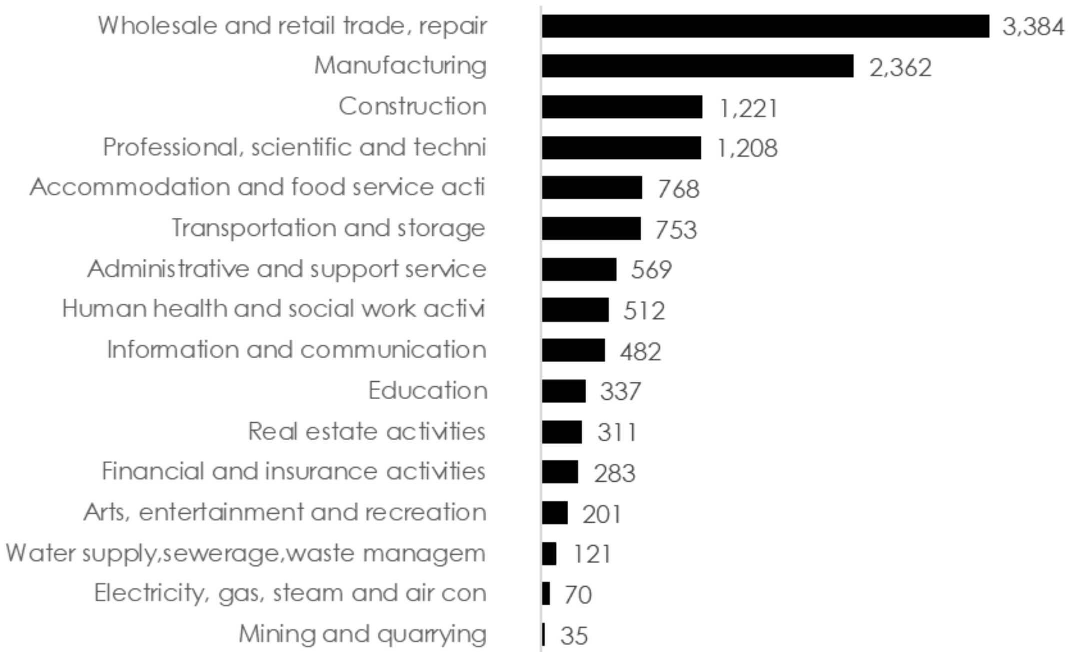
Variable	Mean	SD	Max	Min	N
Size	65.365	294.726	9000	1	12,493
Age	25.659	22.061	171	1	12,294
Patented	0.062	0.24	1	0	12,617
In Rural Area	0.105	0.306	1	0	12,617
Family Owned	0.209	0.407	1	0	12,617
Labor Productivity	380,000	2,040,000	98,400,000	0	7,556
Cluster or Regional Association	0.095	0.293	1	0	12,617

Source: Flash Eurobarometer 486

Figure 1 shows the distribution of observations across sectors. The wholesale and retail trade sector accounts for the largest share of observations. In contrast, the number of firms per country within the EU27 exhibits minor variation, with approximately 500 firms represented per country in figure A.3 in the appendix.

[1] Note that the owner of the firm is not counted in its size. Thus, if a firm representative failed to answer the number of employees in its company or if its sole employee is the company owner, an observation was not recorded. Similarly, representatives that lacked knowledge of the firm founding under the question vq1 in the survey were marked with a "9999". These observations were replaced with missing values.
[2] Thus, if Turnover or firm size was not recorded, labor productivity was not observed.

Figure 1. Number of firms by sector



Source: Flash Eurobarometer 486

In this study we look at various measures of trade activity of firms. The data presented in Table 4 shows that 34.2 percent of SMEs are exporters (65.8 percent only trade domestically). In addition, firms that had adopted an ADT were more likely to have exported, especially in the case of Artificial Intelligence and Machine Learning (AI adopting firms), which boosted the figure up to 54.8%. Most exporters serve one or two destinations, however, there is still a considerable number of firms that export to more (or even all) destinations as shown in Table 4. Interestingly, if a firm adopted AI, and exported to at least to four destinations, they were more likely to export to all.

Table 4. Number of Destinations Exported to by Firm

	Total Firms			AI adopting firms		
Number of Destinations	**Freq**	**Percent**	**Cum. Percent**	**Freq**	**Percent**	**Cum. Percent**
0	8,306	65.83	65.83	410	45.25	45.25
1	2,388	18.93	84.76	207	22.85	68.1
2	860	6.82	91.57	105	11.59	79.69
3	343	2.72	94.29	51	5.63	85.32
4	222	1.76	96.05	38	4.19	89.51
5	150	1.19	97.24	30	3.31	92.83
6	132	1.05	98.29	20	2.21	95.03
7	216	1.71	100	45	4.97	100

Source: Flash Eurobarometer 486

As descriptive evidence in Table 5 shows, digitalized firms outperformed non-digitalized firms across all measurable metrics. They were more likely to export (35.9% vs 46.5%), exported to more countries, had higher rates of exporting outside Europe (including Russia) and are more likely to be part of a Global Value Chain (GVC). They were also more likely to file or have filed a patent. Additionally, these firms had higher average turnovers, greater labor productivity, and larger employee counts. One possible explanation outside of ADT’s influence is that digitalized firms were more established, having operated slightly longer and being on a regional association, as digitalized firms were also older, even if only by a small margin. Descriptive evidence is shown in Table 5.

Table 5. Digitalized vs. Non-Digitalized Firms

Variable	Total Firms	Digitalized firms
Firms	12,617	4,959
Exports	35.9%	46.5%
Avg. International Destinations	0.7	1.1
Export Outside Europe*	11.4%	19.3%
Part of a Global Value Chain	9.6%	16.1%
Patent	6.2%	11.0%
Avg. Turnover	EUR 6,679,618	EUR 9,956,873
Avg. Employees	65.4	109.2
Firm Age	25.7	27.7
Productivity	380,337	385,990
Adopted AI/ML	7.2%	17.1%
Digitalization Index	1.41	2.89
In a rural Area	10.5%	8.7%
Part of a Cluster or Regional Association	9.5%	15.4%

Notes: Digitalized firms are defined as firms that adopted two or more Advanced Digital Technologies, including AI, Blockchain, Cloud Computing, Robotics, High Speed Infrastructure, big data, and smart devices. Productivity defined as Turnout divided by Employees
Source: own calculations based on Flash Eurobarometer 486

4. Methodology

4.1. Trade and ADT premium.

In this section, we follow the methodology of Bernard and Jensen (1995, 1999) to compute the "*export premium*," which is defined as the ceteris paribus percentage difference of labor productivity between exporters and non-exporters. We extend this analysis to include participation in Global Value Chains (GVCs) and the number of export destinations. In addition, we examine differences between firms that do and do not use Advanced Digital Technologies (ADT) to investigate the existence and magnitude of an "ADT productivity premium."

To estimate the productivity premium, we use a model where the dependent variable is labor productivity, and the main independent variable represents the type of trade activity (exports, GVC participation, or the number of export destinations). The model also includes the ADT variable as well as other controls. The model is estimated using Ordinary Least Squares (OLS) with robust standard errors, appropriate for estimating productivity as a continuous variable. Formally, the model is represented as:

$$Ln\, LP_i = \alpha + \beta Trade_i + \gamma ADT_i + \theta Control_i + \epsilon_i \quad (1)$$

Where i is the index of each firm, LP is Labor Productivity, $Trade$ represents the main independent variable for international trade premium (Exports, GVC participation and number of export destinations), ADT stands for Advanced Digital technologies, and its coefficient allows to test the existence of a "digital premium" and $\boldsymbol{\epsilon}$ is the error term. $Control_i$ is a vector that includes the control variables previously mentioned. Finally, the exporter premium is computed from the estimated coefficient ß as 100(exp(ß)-1). This shows the average percentage difference between exporters and non-exporters when controlling for the characteristics included in the vector Control. The ADT premium is computed as the estimated average marginal effects of the ADT index.

4.2. The facilitating role of ADT in the decision to trade.

To assess the relationship between ADT adoption and trade participation we follow Añón Higón and Bonvin (2022). We first estimate the decision to export, and secondly, we estimate the decision to participate in GVCs as well as the decision to export to a region outside Europe, including Russia. The probit model that explains the extensive margin or decision to trade is represented by equation (1). For the decision to export, the dependent variable is a dummy variable that takes the value of 1 if it is an exporter firm and 0 otherwise. We use the same framework to estimate the determinants of GVC participation and exporting outside Europe where each dependent variable is also a dummy (1 = yes, 0 = no). The probit model is adequate given the discreet and binary variable to be estimated. Formally,

$$\Pr(Export|GVC|Far = 1)_i = \Phi(\alpha + \beta ADT_i + c\; Control_i + \epsilon_i) \quad (2)$$

Were i is the index for each firm, $Exports$, $GVC\ and\ Far$ are the binary variables discussed above, indicating whether firm i exports, is part of a GVC, or exports outside Europe. $\Phi\,(.)$ is the cumulative distribution function of the standard normal distribution. ADT represents the ADT index, $Control$ represents the control variable vector, including Labor productivity and ϵ is the error term. These factors are evidenced to influence the decision to engage in foreign sales and exports: firm size (Añón Higón & Driffield, 2011), firm age and previous export knowledge (Calof & Viviers, 1995), patenting and innovation (Brancati et al., 2018), rural location (Hagsten & Kotnik, 2017), family ownership (Pascucci et al.,2021), labor productivity (Lukiewska, 2022), and membership of a cluster or regional association (Resbeut, & Gugler, 2016). Mañez et al. (2004) further supports that that the size, age of the firm, labor productivity, and patenting propensity are significant and positive influences on the decision to export.

4.3 Number of export destinations

In what follows, we are interested in assessing the extent to which ADTs allow firms to access a larger number of destinations. To assess this, we use equation (3). In this case, the number of export destinations is the dependent variable in a negative Binomial regression. This model is appropriate given the count nature of the dependent variable which treats the count of destinations exported to as discrete described in Table 4, ranging from 0 (non-exporter) to 7 (exporter to seven regions). Formally,

$$\mathrm{E}(Destinations_i \mid ADT_i, Control_i) = \exp\left(\alpha + \beta ADT_i + c\ Control_i + \epsilon_i\right) \tag{3}$$

Where *i* is the index for each firm, *Destinations* is the outcome variable of interest, *ADT* is the ADT index, *Control* is the vector of control variables, and ϵ is the error term. Each model will have a single different dependent variable to analyze each effect while keeping the same controls. The controls of the first model are the size and age of firm in its logged form as well as if the firm is in a rural area, part of a cluster, is owned by a family and has a patent application.

In all models, fixed effects for country of origin and for the sector of the firm are controlled with a full set of dummy variables. Robust standard errors are also applied to all models to account for heteroskedasticity. The significance and intensity of the trade coefficients in equation (1) will determine the trade premium effect. Similarly, the significance and size of the marginal effects of ADT in equation (2) and (3) will determine the effect of ADTs on trade activities. The controls for the equation (2) and (3) are the same as those in equation (1), with the addition of labor productivity.

For model (3), a column was calculated by counting the number of international destinations exported to. These destinations include North America, Latin America and the Caribbean, China, Asia Pacific, the Middle East and Africa, and EU countries outside the EU. A Negative Binomial Regression was chosen to manage the substantial number of firms that did not export at all with the same controls used in the probit model. A Negative Binomial was used over a Poisson Distribution because of its lower AIC and BIC relative to the alternative. Because most manufacturing firms are exporters (63.9% compared to 35.9% of total firms), each model was also applied solely to firms in the manufacturing sector for comparison. The results can be found in the Appendix section in Tables A.2, A.3 and A.4.

5. Results

5.1. Trade and ADT premium

The results of the Ordinary Least Squares (OLS) estimation with robust standard errors for equation (1) are presented in Table 6. The regression results indicate that exporting firms (column (1)), particularly those exporting within the EU27, and SMEs participating in Global Value Chains (column (2)), exhibit significantly higher labor productivity compared to non-exporters. Specifically, exporting to EU27 countries and being part of a GVC are associated with productivity increases of 37.6% (column (5)) and 22.1% (column (2)), respectively. Additionally, digitalization, measured by the ADT index, has a positive and significant effect on firm productivity across the total sample, as expected from previous literature. However, this positive effect is not observed in the manufacturing sector, as shown in the results of Table A.2 in the Appendix. Among the control variables, firm size, firms located in a rural area and, surprisingly, filing for patents is negatively and significantly associated with productivity in our SME sample. In contrast, firm age and belonging to a business group are positively associated with firms' labor productivity.

Table 6. The international trade premium

Dependent Variables: Labor Productivity (Turnover/ Employees)
Method: Ordinary Least Squares

Variable	**(1) Productivity**	**(2) Productivity**	**(4) Productivity**	**(5) Productivity**
Exports	0.400***			
	(0.042)			
Part of a GVC		0.221***		
		(0.061)		
N# of destinations			0.096***	
			(0.016)	
ADT	0.068***	0.079***	0.070***	0.066***
	(0.015)	(0.015)	(0.015)	(0.015)
Size	-0.216***	-0.206***	-0.213***	-0.218***
	(0.015)	(0.015)	(0.015)	(0.015)
Age	0.151***	0.148***	0.142***	0.152***
	(0.026)	(0.026)	(0.026)	(0.026)
Rural Area	-0.091*	-0.087	-0.089*	-0.090*
	(0.053)	(0.053)	(0.053)	(0.053)
Group	0.311***	0.294***	0.299***	0.306***
	(0.071)	(0.072)	(0.072)	(0.072)
Family-firm	0.026	0.032	0.029	0.018
	(0.047)	(0.047)	(0.047)	(0.047)
Patents	-0.177**	-0.119	-0.194**	-0.193**
	(0.078)	(0.078)	(0.080)	(0.081)
Exports to EU27				0.376***
				(0.044)
Exports to other EU				0.185***
				(0.061)
Exports to N America				0.095
				(0.100)
Exports to LAC				-0.080
				(0.132)
Exports to China				-0.020
				(0.120)
Exports to Asia-Pac.				-0.139
				(0.107)
Exports to MEA				0.005
				(0.105)
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
R^2	0.204	0.196	0.199	0.205
Observations	7414	7414	7414	7414
LL	-1.38e+04	-1.38e+04	-1.38e+04	-1.38e+04

Notes: robust standard errors in parenthesis. All specifications include sector and country dummies. * p<005, **p<001, *** p<0001

5.2. Impact of ADT on trade activities

As we can expect from previous contributions, the results of estimating the probit model described by equation (2) are shown in Table 7. The results are presented in average marginal effects and show that digitalization and productivity positively influence the likelihood of exporting in European SMEs (see column (1)). This effect is seen for all sectors of the economy, as well as within the manufacturing sector (see Table A.3 in Appendix). An increase of one point in the ADT index is associated with a 3.7% increase in the probability of exporting (column 1) and with a 1.7% increase in the probability of being part of a GVC (column 3). When distinguishing between AI and other ADTs (columns (2) and (4)), we find that AI has an overall significant effect on exports, but no significant effect in explaining GVC participation. As shown in Table A.3 in the Appendix, AI is insignificant too for the firm exporting decision within the manufacturing sector. This suggests variance between sectors where some firms benefit more from digitalization than others. Furthermore, ADTs other than AI have a strong and significant impact on a firm's decision to export. This could be attributed to the early stage of AI adoption in 2019, when the survey was conducted, and the fact that AI often requires support from other ADTs and skilled personnel to be fully effective. Additionally, as noted in the literature review, many firms—especially smaller ones—may not yet have fully developed their AI capabilities. This is consistent with the fact that 65.5% of the firms in our sample that adopted AI have fewer than 50 employees, as shown in Table A.1.

Table 7. Impact of ADT on SMEs trade activities

Dependent Variables: Exports (Dummy; 1 = yes), part of GVC (Dummy; 1 = yes)
Method: Probit

Variable	(1) Export	(2) Export	(3) GVC	(4) GVC
ADT	0.037***		0.017***	
	(0.004)		(0.002)	
AI/LM		0.044**		0.016
		(0.019)		(0.011)
Other ADT		0.036***		0.018***
		(0.004)		(0.003)
Productivity	0.031***	0.031***	0.009***	0.009***
	(0.004)	(0.004)	(0.002)	(0.002)
Size	0.040***	0.040***	0.020***	0.020***
	(0.004)	(0.004)	(0.002)	(0.002)
Age	-0.017**	-0.016**	-0.014***	-0.014***
	(0.007)	(0.007)	(0.004)	(0.004)
Rural Area	0.007	0.007	-0.010	-0.010
	(0.017)	(0.017)	(0.011)	(0.011)
Group	0.070***	0.070***	0.121***	0.121***
	(0.017)	(0.017)	(0.009)	(0.009)
Family-firm	0.033***	0.033***	0.030***	0.030***
	(0.012)	(0.012)	(0.008)	(0.008)
Patents	0.217***	0.217***	0.066***	0.066***
	(0.021)	(0.021)	(0.011)	(0.011)
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	7414	7414	7363	7363

Notes: Marginal effects. robust standard errors in parenthesis. Standard errors in parenthesis. All specifications include sector and country dummies. * p<005, **p<001, *** p<0001

5.3. Impact of ADT on the number of export destinations

In this section, we delve into the relationship between digitalization and the number of export destinations. To do so, we provide the results in terms of average marginal effects, resulting from the estimation of equation (3). Table 8 presents the results of the Negative Binomial model examining the impact of ADT on the number of export destinations. The results show that ADTs, particularly those non-related to AI (column (2)) are associated with a larger number of export destinations. Besides digitalization, productivity is also positively associated with exporting to more destinations. These results hold when we focus exclusively on the manufacturing sector (see Table A.3 in the Appendix). Moreover, the results show that AI has a negative correlation with the number of destinations exported to within the manufacturing sector, albeit insignificant. This suggests the variability and struggles that some sectors and firms may have at deploying AI or ML models due to a lack of tools or expertise.

Table 8. Impact of ADT on Number of Destinations Exported to

Dependent Variable: Number of Destinations Exported to (1-7)
Method: Negative Binomial

Variable	(1) N# of Destinations b/se	(2) N# of Destinations b/se
ADT	0.130***	
	(0.012)	
AI/LM		0.038
		(0.056)
Other ADT		0.141***
		(0.015)
Productivity	0.087***	0.086***
	(0.016)	(0.016)
Size	0.128***	0.128***
	(0.013)	(0.013)
Age	-0.014	-0.014
	(0.024)	(0.024)
Rural Area	0.025	0.027
	(0.056)	(0.056)
Group	0.269***	0.269***
	(0.047)	(0.047)
Family-firm	0.140***	0.139***
	(0.039)	(0.039)
Patents	0.535***	0.537***
	(0.048)	(0.048)
Sector FE	Yes	Yes
Country FE	Yes	Yes
Observations	7414	7414

Notes: Marginal effects. Robust standard errors in parenthesis.
All specifications include sector and country dummies. * p<005, **p<001, *** p<0001

Finally, we provide results that try to assess the role of ADT facilitating firms' entry into more distant destinations, due to ADT's ability to reduce information costs. ADT was significant in determining if a firm exported to destinations outside Europe with an association of a 2.3% increase. A firm adopting AI alone, however, was not significant on a firm's decision to export outside Europe. This is at odds with Table 4 which paints a picture that AI is responsible for exporting activity to distant and further regions. Other forms of ADT excluding AI demonstrate a significant and positive impact on exports to distant destinations, associated with a 2.4% increase.

Table 9. The Impact of ADT on Distant Destinations

Dependent Variable: Exports Outside Europe (Dummy; 1 = yes)
Method: Probit

Variable	**(1) Exports to Distant Destinations** b/se	**(2) Exports to Distant Destinations** b/se
ADT	0.023***	
	(0.002)	
AI / ML		0.009
		(0.012)
Non-AI ADT		0.024***
		(0.003)
Size	0.020***	0.020***
	(0.002)	(0.002)
Productivity	0.011***	0.011***
	(0.003)	(0.003)
Age	0.005	0.005
	(0.005)	(0.005)
Rural Area	0.014	0.015
	(0.011)	(0.011)
Group	0.052***	0.052***
	(0.010)	(0.010)
Family-firm	0.019**	0.018**
	(0.008)	(0.008)
Patents	0.107***	0.108***
	(0.011)	(0.011)
Country FE	Yes	Yes
Sector FE	Yes	Yes
Observations	7414	7414

Notes: Marginal effects. Robust standard errors in parenthesis Standard errors in parenthesis. All specifications include country dummies. * p<005, **p<001, *** p<0001

6. Conclusion

We have examined the relationship between digitalization, productivity, and trade activities for a sample of European SMEs. In particular, we have examined how ADTs influence a firm's decision to export, their probability of participating in GVCs, and the number of destinations exported. Using a comprehensive dataset from the European Commission, our analysis shows that digitalization and trade activities are associated with a productivity premium. Moreover, we find that ADTs are significantly correlated with a firm's probability of exporting and an increased likelihood of exporting to more markets. This holds across all sectors of the economy, including the manufacturing sector which is the most exposed to international trade. The relationship remains highly significant after controlling for productivity and firm characteristics, such as size, age, patenting activities, etc., as well as industry and country fixed effects. The impact of AI on export activities presents a more nuanced picture. While AI indeed has a positive influence on the export decision in the overall sample, it lacks a statistically significant effect within the manufacturing sector. AI further shows a negative, though insignificant, association with the number of export destinations in this sector.

These findings have interesting implications for policy and management. To promote export activities, it may be more effective to encourage broader digitalization initiatives beyond just AI, particularly for SMEs with 50 employees or fewer. Because AI often benefits from technologies like cloud computing and Big Data Analytics, which are often used to train models, AI may require certain infrastructure, including other ADTs, to be fully effective. Because AI is still in its infancy, smaller firms may lack the expertise to capitalize on its potential fully.

Finally, our study has limitations. Using total factor productivity (TFP) as a control variable would provide a more accurate measure of firm performance compared to labor productivity. Furthermore, the potential endogeneity between digitalization variables such as AI, Big Data, and cloud computing also deserves further exploration. Firms may have also adopted these technologies with the expectation of future export benefits that are not shown in our panel data. Longitudinal data that covers several years would provide more conclusive evidence. Furthermore, the dataset was gathered before the explosive interest in AI tools such as ChatGPT. A recent survey would provide more relevant results. Addressing these limitations in future research would give a more convincing assessment of the dynamic between digitalization and export activities.

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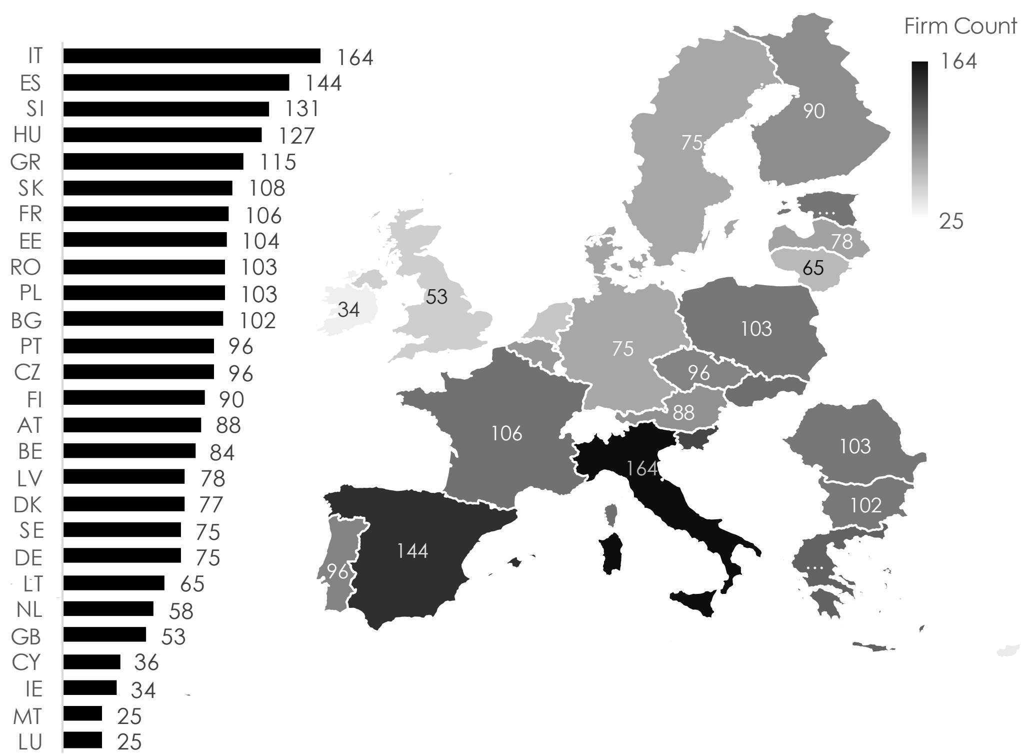
Appendix

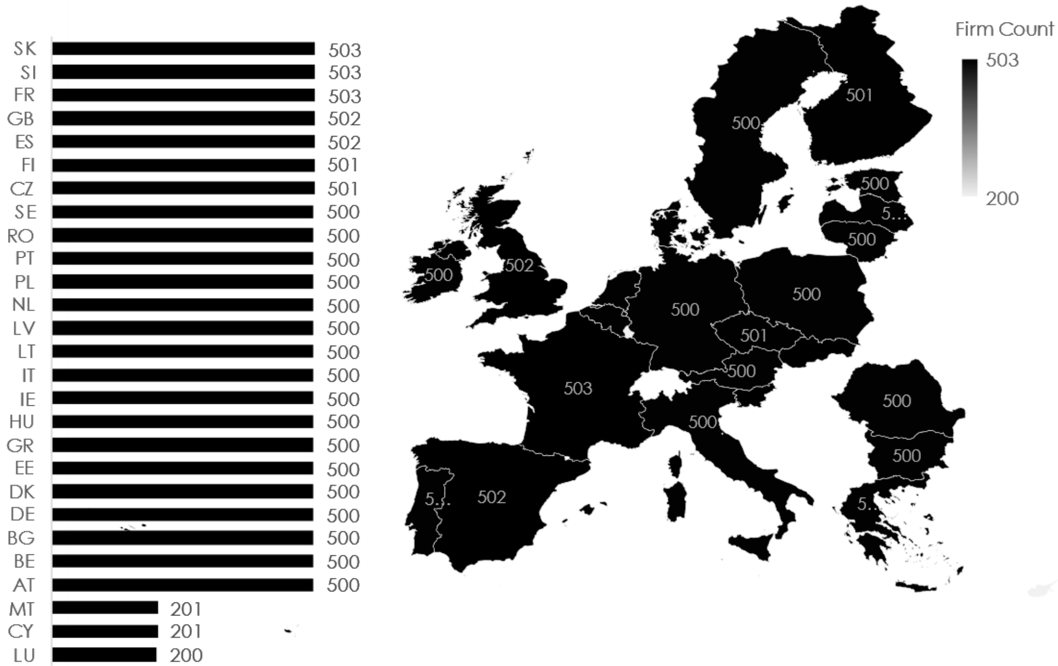
Figure A.1. Ratio of exporting firms by sector

Figure A.2. Manufacturing firms per country



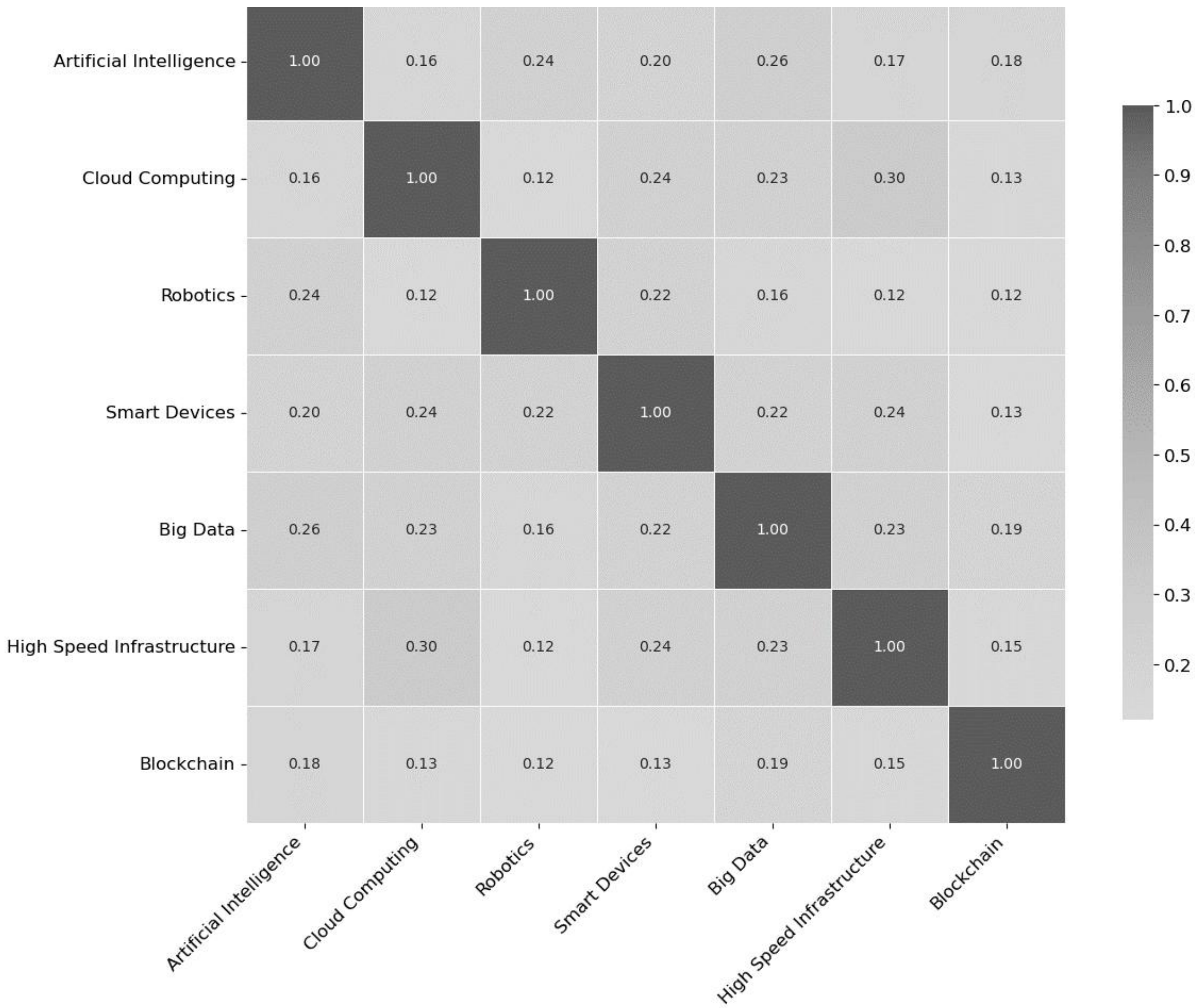
Source: Flash Eurobarometer 486

Figure A.3. Number of Firms by Country (all sectors)



Source: Flash Eurobarometer 486

Figure A.4. Phi Correlation Heatmap for ADTs



Source: Flash Eurobarometer 486

Table A.1. AI adopters per Size Category

Employees	Total Firms	Firms that adopt AI	% of Total Firms	% of Total AI adopting Firms
1 - 9	6,862	333	54.9%	37.3%
10 - 49	3,159	251	25.3%	28.1%
50 - 249	1,831	187	14.7%	21.0%
250 or more	641	121	5.1%	13.6%
Total	**12,493**	**892**	**100.0%**	**100.0%**

Source: Flash Eurobarometer 486

Table A.2. International Trade Premium in Manufacturing

Dependent Variables: Labor Productivity (Turnout / Employees) Method: Ordinary Least Squares					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Variable	**Productivity**	**Productivity**	**Productivity**	**Productivity**	**Productivity**
	b/se	b/se	b/se	b/se	b/se
Exports	0.538***				
	(0.110)				
Part of a GVC			0.074		
			(0.104)		
N# of Destinations				0.101***	
				(0.034)	
ADT	0.013	0.022	0.027	0.013	0.004
	(0.031)	(0.032)	(0.032)	(0.031)	(0.030)
Size	-0.204***	-0.177***	-0.164***	-0.195***	-0.215***
	(0.035)	(0.034)	(0.033)	(0.036)	(0.036)
Age	0.028	0.026	0.034	0.016	0.022
	(0.065)	(0.065)	(0.066)	(0.064)	(0.063)
Rural Area	0.143	0.134	0.133	0.144	0.159
	(0.099)	(0.101)	(0.102)	(0.101)	(0.100)
Part of a National or international Enterprise Group	0.398***	0.431***	0.442***	0.396***	0.378***
	(0.124)	(0.128)	(0.131)	(0.129)	(0.128)
Business Owned by a Family	-0.134	-0.120	-0.117	-0.129	-0.153
	(0.109)	(0.109)	(0.109)	(0.109)	(0.108)
Has Patents	-0.141	-0.140	-0.117	-0.198	-0.186
	(0.126)	(0.128)	(0.125)	(0.134)	(0.134)
Exports outside all of Europe and Russia		0.224**			
		(0.105)			
Exports to EU27					0.504***
					(0.105)
Exports to Europe					0.393***
					(0.095)
Exports to North America					0.005
					(0.131)
Exports to Latin America and					-0.092

Caribbean					
					(0.206)
Exports to China					-0.018
					(0.174)
Exports to Asia-Pacific					-0.255*
					(0.152)
Exports to Middle East and Africa					0.115
					(0.164)
Constant	12.043***	12.163***	12.163***	12.173***	12.138***
	(0.306)	(0.310)	(0.311)	(0.310)	(0.306)
Country FE	Yes	Yes	Yes	Yes	Yes
R2	.1963419	.1818177	.1793502	.1879248	.208009
Observations	1465.000	1465.000	1465.000	1465.000	1465.000
LL	-2696.244	-2709.364	-2711.570	-2703.876	-2685.532
AIC					

Notes: Robust standard errors in parenthesis.
All specifications include country dummies. * p<005, **p<001, *** p<0001

Table A.3. The Impact of ADT on Trade Activities in the Manufacturing sector

Dependent Variables: Exports (Dummy;1=yes), GVC (Dummy; 1=yes), Number of Destinations (1-7)
Method: Probit (Export/GVC) & Negative Binomial (N# Destinations)

	Export	**Export**	**GVC**	**GVC**	**N# Destinations**	**N# Destinations**
	b/se	b/se	b/se	b/se	b/se	b/se
ADT	0.031***		0.024***		0.145***	
	(0.008)		(0.006)		(0.031)	
AI/LM		0.005		0.047*		-0.183
		(0.043)		(0.029)		(0.131)
Non-AI ADT		0.033***		0.021***		0.183***
		(0.009)		(0.007)		(0.036)
Productivity	0.034***	0.034***	0.008	0.008	0.150***	0.148***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.054)	(0.053)
Firm Size	0.081***	0.081***	0.033***	0.033***	0.383***	0.379***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.039)	(0.039)
Age of firm	0.013	0.013	-0.007	-0.007	0.141**	0.145**
	(0.016)	(0.016)	(0.012)	(0.012)	(0.071)	(0.070)
Rural Area	-0.025	-0.026	-0.015	-0.014	-0.158	-0.166

	(0.030)	(0.030)	(0.025)	(0.025)	(0.123)	(0.123)
Part of a National or international Enterprise Group	0.135***	0.135***	0.148***	0.147***	0.382***	0.388***
	(0.038)	(0.038)	(0.022)	(0.022)	(0.105)	(0.104)
Business Owned by a Family	0.035	0.035	0.008	0.008	0.140	0.138
	(0.025)	(0.025)	(0.020)	(0.020)	(0.102)	(0.101)
Has Patents	0.084**	0.084**	0.052**	0.054**	0.516***	0.515***
	(0.038)	(0.038)	(0.023)	(0.023)	(0.116)	(0.116)
Observations	1465	1465	1360	1360	1465	1465

Notes: Marginal Effects. Robust standard errors in parenthesis. X is short for Exports.
All specifications include sector and country dummies. * p<005, **p<001, *** p<0001

Table A.4. The impact of ADT on Distant Destinations in Manufacturing

	(1) N# Distant Destinations b/se	(2) N# Distant Destinations b/se
ADT	0.029***	
	(0.007)	
AI/ML		-0.059
		(0.036)
Non- AI ADT		0.038***
		(0.008)
Firm Size	0.067***	0.066***
	(0.007)	(0.007)
Productivity	0.017**	0.017**
	(0.007)	(0.007)
Firm Age	0.028*	0.029**
	(0.015)	(0.015)
Firm in a Rural Area	-0.009	-0.012
	(0.029)	(0.029)
Part of Cluster or Assoc.	0.086***	0.087***
	(0.028)	(0.028)
Family Owned	0.015	0.014
	(0.023)	(0.023)
Applied to Patent	0.097***	0.096***
	(0.029)	(0.029)
Country	Yes	Yes
Observations	1451	1451

Notes: Marginal Effects. Robust standard errors in parenthesis.
All specifications include sector and country dummies. * p<005, **p<001, *** p<0001