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Digitalization Intensity and Extensive Margins of Exports in Manufacturing Firms from 27 EU Countries - Evidence from Kernel-Regularized Least Squares Regression

Joachim Wagner [a, *]

[a] *Kiel Centre for Globalization, Leuphana Universität Lüneburg, Lüneburg, Germany*

ABSTRACT

The use of digital technologies like artificial intelligence, robotics, or smart devices can be expected to go hand in hand with higher productivity and lower trade costs, and, therefore, to be positively related to export activities. This paper uses firm level data for manufacturing enterprises from the 27 member countries of the European Union to shed further light on this issue by investigating the link between the digitalization intensity of a firm and extensive margins of exports. We use a new machine-learning based regression method, Kernel-Regularized Least Squares (KRLS), which effectively handles non-linear relationships in models and does not impose any restrictive assumptions for the functional form of the relation between margins of exports, digitalization intensity, and any control variables. We find that firms which use more digital technologies do more often export, do more often export to various destinations all over the world, and do export to more different destinations.

KEYWORDS

Digital Technologies; Exports; Firm Level Data; Flash Eurobarometer 486; Kernel-Regularized Least Squares (KRLS)

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* Corresponding author: Joachim Wagner
E-mail address: joachim.wagner@leuphana.de

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1. Motivation

The use of digital technologies like artificial intelligence, robotics, or smart devices can be expected to go hand in hand with higher productivity (see e.g. Acemoglu, Lelarge and Restrepo (2020), Chen and Volpe Martincus (2022), DeStefano, Kneller and Timmis (2024), Deng, Plümpe and Stegmaier (2024)). According to a large empirical literature that uses firm level data from many different countries productivity and export activities in firms are positively related (Ferencz, López González and Garcia (2022), Wagner (2007)). Furthermore, the use of digital technologies can be expected to lower trade costs (see e.g. Ferencz, López González and Garcia (2022), López González, Sorescu and Kaynak (2023), Meltzer (2018)). Therefore, the use of digital technologies can be expected to be positively related to export activities of firms that use these technologies.

Empirical evidence on the link between the use of selected digitalization strategies and export activities of firms is supporting this view. Wagner (2023) shows that firms who use big data analytics do more often export and export to more destinations than firms that do not use this digital technology. The same big picture is reported in Wagner (2024a) for firms that do or do not use robotics, and in Wagner (2024c) for firms that do or do not use cloud computing.

This paper contributes to the literature by using firm level data for manufacturing enterprises from the 27 member countries of the European Union taken from the Flash Eurobarometer 486 survey conducted early in 2020 to investigate the link between the digitalization intensity of a firm (measured by the number of different digital technologies adopted in a firm) and extensive margins of exports (export participation, exports to various parts of the world, and number of export destinations). The focus, therefore, is not on the role of one single digitalization measure, but on the intensity of use of digital technologies measured by the number of different digitalization technologies applied by a firm.

We use a new machine-learning based regression method, Kernel-Regularized Least Squares (KRLS), which effectively handles non-linear relationships in models and does not impose any restrictive assumptions for the functional form of the relation between margins of exports, digitalization intensity, and any control variables. We find that firms which use more digital technologies do more often export, do more often export to various destinations all over the world, and do export to more different destinations. The estimated digitalization premium for extensive margins of exports is statistically highly significant after controlling for firm size, firm age, patents, and country. Extensive margins of exports and the use of digital technologies are positively related.

The rest of the paper is organized as follows. Section 2 introduces the data used and discusses the export activities that are looked at. Section 3 reports results from the econometric investigation. Section 4 concludes.

2. Data and discussion of variables

The firm level data used in this study are taken from the Flash Eurobarometer 486 survey conducted early in 2020. Note that while the data were collected at the start of the COVID-19 pandemic, information on export activities relates to the year 2019, the year before the pandemic. We use data for firms from the 27 member states of the European Union in 2020 (i.e., firms from the UK are no longer included in the sample). The sample covers 2,355 firms from manufacturing industries (included in NACE section C); unfortunately, no more details on the industry affiliation of the firms are revealed in the data. The numbers of firms by country are reported in the appendix table.

In the survey firms were asked in question Q23 which of the following digital technologies, if any, they have adopted to date: *Artificial intelligence*, e.g. machine learning or technologies identifying objects or persons, etc.; *Cloud computing*, i.e. storing and processing files or data on remote servers hosted on the internet; *Robotics*, i.e. robots used to automate processes for example in construction or design, etc.; *Smart devices*, e.g. smart sensors, smart thermostats, etc.; *Big data analytics,* e.g. data mining and predictive analysis; *High speed infrastructure*;

Blockchain. Firms that answered in the affirmative are classified as users of the respective digital technology. Descriptive evidence is reported in the upper panel of Table 1.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Artificial intelligence (Dummy; 1 = yes)	0.0811	0.2731	0	1
Cloud computing (Dummy; 1 = yes)	0.4480	0.4974	0	1
Robotics (Dummy; 1 = yes)	0.2068	0.4051	0	1
Smart devices (Dummy; 1 = yes)	0.3299	0.4703	0	1
Big data analytics (Dummy; 1 = yes)	0.1380	0.3450	0	1
High speed infrastructure (Dummy; 1 = yes)	0.3053	0.4606	0	1
Blockchain (Dummy; 1 = yes)	0.0386	0.1928	0	1
Digitalization intensity (Index; 0 – 7)	1.5478	1.5218	0	1
Exporter (Dummy; 1 = yes)	0.645	0,478	0	1
Export Destination (Dummy-Variables; 1 = yes)				
EU-countries	0.618	0,486	0	1
Other Europe	0.292	0.455	0	1
North America	0.157	0.364	0	1
Latin America	0.099	0.298	0	1
China	0.109	0.311	0	1
Other Asia	0.138	0.345	0	1
Middle East, Africa	0.132	0.339	0	1
Number of Export Destinations	1.544	1.857	0	7
Firm Age (years)	29.03	23.43	0	170
No. of Employees	91.63	269.11	1	5000
Patent (Dummy; 1 = yes)	0.120	0.325	0	1
No. of Firms in Sample	2,355		0	1

Source: Own calculation based on data from Flash Eurobarometer 486; for details, see text.

While 738 (or about a third of all firms) did not use any of the technologies, the share of users of the other digital technologies varies widely – from less than 4 percent using *Blockchain* and 8 percent using *Artificial intelligence*[1] to 32 percent using *High speed infrastructure* and 45 percent using *Cloud computing*.

On average, firms use 1.55 different digital technologies. As documented in Table 2 most digitalized firms apply only one or two different technologies, while the share of "power users" that apply six or seven is tiny. This information is used to construct an index of *Digitalization intensity* of a firm that takes on values from zero (for firms without the application of any digital technology) to seven (for firms that use all seven technologies mentioned). The number of firms and the share in all firms in the sample for each value of digitalization intensity is listed in Table 2.

Table 2. Share of Firms by Digitalization Intensity.

Digitalization Intensity	Number of Firms	Percent
0	738	31.34
1	618	26.24
2	421	17.88
3	294	12.48
4	160	6.79
5	87	3.69
6	31	1.32
7	6	0.25
Total	2,355	100.0

Source: Own calculation based on data from Flash Eurobarometer 486; see text for details.

1 Note that at the time of the survey early in 2020 the now popular Large Language Models like ChatGPPT and Google Gemini were not yet available.

In the empirical study, we look at various measures of export activity of firms:[2]

First, firms were asked in question Q11_1 whether they exported any goods (or not) in 2019. Firms are classified as exporters or non-exporters based thereon. Descriptive evidence is reported in Table 1, showing a share of 64.5 percent of exporters.

Second, firms were asked in questions Q11_2 to Q11_8 whether they exported goods in 2019 to the following destinations: Other EU countries; other European countries outside the EU (including Russia); North America; Latin America; China; other countries from Asia and the Pacific; countries from the Middle East and Africa. Descriptive evidence is reported in Table 1, showing that 61.8 percent of firms exported to countries from the EU, while 29.2 percent exported to other European countries. The other destinations follow with shares between some 10 percent and about 16 percent. Exporters to each destination are investigated separately.

Third, from the evidence reported for exports to the seven destinations mentioned for each exporting firm the number of different destinations exported to is calculated. The share of firms by number of export destinations is reported in Table 3. Not surprisingly, most exporters serve one or two destinations only, but there are quite some firms that export to more (or even all) destinations.

Table 3. Share of Firms by Number of Export Destinations.

Number of Export Destinations	Number of Firms	Percent
0	835	35.46
1	700	29.72
2	338	14.35
3	150	6.37
4	100	4.25
5	73	3.10
6	68	2.89
7	91	3.86
Total	2,355	100.0

Source: Own calculation based on data from Flash Eurobarometer 486.

In the empirical investigation of the link between the digitalization intensity of firms and exports we control for three firm characteristics that are known to be positively linked with exports: firm age (measured in years, based on the answer given to question Q1), firm size (measured as the number of employees – excluding the owners - at the time of the survey; see question Q2A), and whether the firms have a patent or a patent application pending (see question Q9_6).[3] Descriptive statistics are again reported in Table 1.

Furthermore, in the empirical investigations, the country of origin of the firms is controlled for by including a full set of country dummy variables.

3. Digitalization premia for export activities

To test for the difference in the types of export activities listed in section 2 between firms with various intensities of digitalization, and to document the size of these differences, an empirical approach is applied that modifies a standard approach used in hundreds of empirical investigations on the differences between exporters and non-exporters that has been introduced by Bernard and Jensen (1995, 1999). Studies of this type use data for firms to compute the so-called exporter premium, defined as the ceteris paribus percentage difference of a firm characteristic - e.g. labour productivity - between exporters and non-exporters.

[2] Note that all measures looked at here refer to extensive margins of exports; information on intensive margins (share of exports in total sales) are not available in the data used.

[3] Given that these variables are included as control variables only, we do not discuss them in detail here. Suffice it to say that numerous empirical studies show a positive link between these firm characteristics and export performance.

Here we look at differences between firms with various values of the digitalization index defined above (instead of differences between exporters and non-exporters) and are interested in the existence and size of a digitalization intensity premium in export activities (instead of an exporter premium in various forms of firm performance like productivity). The empirical model used can be written in general as

$$Export\ activity_i = f[Digitalization\ intensity_i, Control_i] \quad (1)$$

Where i is the index of the firm, Export activity is a variable for the type of export activity (listed in the second panel of Table 1), Digitalization intensity is the value of the digitalization index, and Control is a vector of control variables (that consists of measures of firm age, firm size, and patents, and dummy variables for countries). The digitalization premium is computed as the estimated average marginal effects of the digitalization intensity variable.

In standard parametric models the firm characteristics that explain the export margins enter the empirical model in linear form. This functional form which is used in hundreds of empirical studies for margins of exports, however, is rather restrictive. If any non-linear relationships (like quadratic terms or higher order polynomials, or interaction terms) do matter and if they are ignored in the specification of the empirical model this leads to biased results. Researchers, however, can never be sure that all possible relevant non-linear relationships are taken care of in their chosen specifications. Therefore, this note uses the Kernel-Regularized Least Squares (KRLS) estimator to deal with this issue. KRLS is a machine learning method that learns the functional form from the data. It has been introduced in Hainmueller and Hazlett (2014) and Ferwerda, Hainmueller and Hazlett (2017), and used to estimate empirical models for margins of trade for the first time in Wagner (2024).

While a comprehensive discussion of the Kernel-Regularized Least Squares (KRLS) estimator is far beyond the scope of this applied note, a short outline of some of the important features and characteristics might help to understand why this estimator can be considered as an extremely helpful addition to the box of tools of empirical trade economists (se Wagner (2024b)). For any details the reader is referred to the original papers by Hainmueller and Hazlett (2014) and Fernwerda, Hainmueller and Hazlett (2017).

The main contribution of the KRLS estimator is that it allows the researcher to estimate regression-type models without making any assumption regarding the functional form (or doing a specification search to find the best fitting functional form). As detailed in Hainmueller and Hazlett (2014) the method constructs a flexible hypothesis space using kernels as radial basis functions and then finds the best-fitting surface in this space by minimizing a complexity-penalized least squares problem. Ferwerda, Hainmueller and Hazlett (2017) point out that the KRLS method can be thought of in the "similarity-based view" in two stages. In the first stage, it fits functions using kernels, based on the assumption that there is useful information embedded in how similar a given observation is to other observations in the dataset. In the second stage, it utilizes regularization, which gives preference to simpler functions (see Ferwerda, Hainmueller and Hazlett (2017), p.3).

KRLS works well both with continuous outcomes and with binary outcomes. It is easy to apply in Stata using the krls program provided in Ferwerda, Hainmueller and Hazlett (2017). Instead of doing a tedious specification search that does not guarantee a successful result, users simply pass the outcome variable and the matrix of covariates to the KRLS estimator which then learns the target function from the data. As shown in Hainmueller and Hazlett (2014), the KRLS estimator has desirable statistical properties, including unbiasedness, consistency, and asymptotic normality under mild regularity conditions. An additional advantage of KRLS is that it provides closed-form estimates of the pointwise derivatives that characterize the marginal effect of each covariate at each data point in the covariate space (see Ferwerda, Hainmueller and Hazlett (2017), p. 11).

Therefore, KRLS is suitable to estimate empirical models when the correct functional form is not known for sure – which is usually the case because we do not know which polynomials or interaction terms matter for correctly modelling the relation between the covariates and the outcome variable.

Results for an application of KRLS to the models for margins of exports are reported in Table 4.

Table 4. Digitalization Intensity and Extensive Margins of Exports: Estimated Average Marginal Effects from Kernel-Regularized Least Squares.

Export margin	Digitalzation (Index; 0-7)	Firm Age (Years)	Firm Size (Number Employees)	Patent (Dummy; 1 = yes)
Participation	0.0581	0.0014	0.00069	0.1498
	[0.000]	[0.006]	[0.000]	[0.000]
EU countries	0.0579	0.0014	0.00071	0.1486
	[0.000]	[0.007]	[0.000]	[0.000]
Other Europe	0.0450	0.0022	0.00040	0.1797
	[0.000]	[0.000]	[0.000]	[0.000]
North America	0.0265	0.0011	0.00022	0.1557
	[0.000]	[0.000]	[0.000]	[0.000]
Latin America	0.0184	0.00088	0.00025	0.1130
	[0.000]	[0.001]	[0.000]	[0.000]
China	0.0213	0.0010	0.00019	0.0949
	[0.000]	[0.000]	[0.000]	[0.000]
Other Asia	0.0239	0.0014	0.00031	0.1191
	[0.000]	[0.001]	[0.000]	[0.000]
Middle East/Africa	0.0262	0.0012	0.00026	0.1248
	[0.000]	[0.002]	[0.000]	[0.000]
Number of Destinations	0.1501	0.0086	0.0011	0.7027
	[0.000]	[0.000]	[0.000]	[0.000]

Note: All models include a complete set of country dummies; p-values are reported in parentheses. For details, see text.

The big picture that is shown is crystal clear.[4] Higher values of the digitalization index go hand in hand with higher probabilities of export participation, exporting to each of the seven export destinations, and with exporting to a larger number of destinations. This is in line with theory and empirical findings from earlier studies (summarized in the introductory section above). The use of digital technologies like artificial intelligence, robotics, or smart devices can be expected to go hand in hand with higher productivity. According to a large empirical literature that uses firm level data from many different countries productivity and export activities in firms are positively related. Furthermore, the use of digital technologies can be expected to lower trade costs. Therefore, the use of digital technologies can be expected to be positively related to export activities of firms that use these technologies. Each estimated premium is statistically highly significant ceteris paribus after controlling for firm age, firm size, patents, and country of origin of the firms.[5]

4. Concluding remarks

This study finds that manufacturing firms from 27 EU member countries that use digital technologies more intensively are more often exporters, do more often export to any of the seven different destinations looked at here, and do export to a larger number of destinations.

Does this study imply that in order to be successful in export markets, firms should use digital technologies? Or that using digital technologies will help the firms to be successful as an exporter? This is an open question (that is asked the same way when the exporter premium is discussed; see Wagner (2007)) because we do not know whether this premium is due to self-selection of exporting firms into the use of digital technologies, or whether it

[4] Note that the same big picture is revealed when standard regression methods (Probit and OLS) are applied that impose restrictions on the functional form of the models used in estimations. Results are not reported here to economize on space, but are available on request from the author.

[5] Note that all control variables have the expected positive sign and all are highly significant statistically.

is the effect of using digital technologies. This issue cannot be investigated with the cross-section data at hand. To answer this important question longitudinal data for firms are needed that cover several years and that include a sufficiently large number of firms that switch the status between using various digital technologies or not over time (in both directions). The jury is still out to find a generally accepted answer.

Another open question that should be investigated with firm-level longitudinal data is the role of the intensity of use of any particular digital technology. The data at hand only tell us which digital technology a firm use – but not how intensively it is used. How many robots does a firm use? How much money is spent for cloud computing? Etc.

That said, it is not possible to derive any sound policy recommendations based on the findings reported here. Better firm-level longitudinal data are needed that can be used to reveal causal relationships between the use of digital technologies and dimensions of firm performance, including margins of exports.

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Data Availability Statement

The firm level data used in this study are taken from the Flash Eurobarometer 486 and can be downloaded free of charge after registration at http://www.gesis/eurobarometer. Stata code used to generate the empirical results reported in this note is available from the author.

Conflict of interest

The author claims that the manuscript is completely original. The author also declares no conflict of interest.

Appendix

A1. Number of Firms by Country.

Country	Number of Firms	Percent
Austria	86	3.65
Belgium	81	3.44
Bulgaria	97	4.12
Cyprus	33	1.40
Czech Republic	94	3.99
Germany	74	3.14
Denmark	75	3.18
Estonia	99	4.20
Spain	137	5.82
Finland	88	3.74
France	101	4.29
Greece	111	4.71
Croatia	136	5.77
Hungary	117	4.97
Ireland	30	1.27
Italy	149	6.33
Lithuania	64	2.72
Luxembourg	25	1.06
Latvia	75	3.18

Malta	21	0.89
Netherlands	55	2.34
Poland	101	4.29
Portugal	93	3.95
Romania	102	4.33
Sweden	75	3.18
Slovenia	130	5.52
Slovakia	106	4.50
Total	2,355	100.0

Source: Own calculations based on data from Flash Eurobarometer 486.

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