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Abstract: The use of robots by firms can be expected to go hand in hand with higher productivity, higher product quality and more product innovation, which should be positively related to export activities. This paper uses firm level data from the Flash Eurobarometer 486 survey conducted in February – May 2020 to investigate the link between the use of robots and export activities in manufacturing enterprises from the 27 member countries of the European Union. Applying standard parametric econometric models and a new machine-learning estimator, Kernel-Regularized Least Squares (KRLS), we find that firms which use robots do more often export, do more often export to various destinations all over the world, and do export to more different destinations. The estimated robots premium for extensive margins of exports is statistically highly significant after controlling for firm size, firm age, patents, and country. Furthermore, the size of this premium can be considered to be large. Extensive margins of exports and the use of robots are positively related.

Keywords: D22, F14

JEL Classification: Robots, exports, firm level data, Flash Eurobarometer 486, kernel-regularized least squares (KRLS)

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Acknowledgement: 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.

1 Motivation

Digital technologies like artificial intelligence, cloud computing, the use of robots to automate processes, or big data analytics, are more and more widely applied by innovative firms. However, comprehensive empirical evidence on the links between the use of digital technologies and various dimensions of firm performance seems to be lacking. A case in point is the role of these technologies for export activities of firms. In their comprehensive discussion of artificial intelligence (AI) and international trade Goldfarb and Trefler (2018, p. 1) state 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." [1]

This note attempts to contribute to closing one of these gaps by looking at differences in extensive margins of exports between manufacturing enterprises from 27 member countries of the European Union that use or do not use robots. We expect these differences to be positive for firms that use robots for three reasons:

First, productivity in firms that use robots can be expected to be higher. Empirical evidence in support of this view is reported by Acemoglu et al. (2020) for firms from France; Koch et al. (2021) and Alguacil et al. (2022) for firms from Spain; Duan et al. (2023) for firms from China; and Deng et al. (2024) for firms from Germany. 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 et al. (2022), p. 12; see Wagner (2007) for a survey of the empirical literature).

Second, the quality of products manufactured with the use of robots can be expected to be higher. DeStefano and Timmis (2021) point out that robots are used to undertake a range of repetitive tasks that require a consistent high-level of accuracy. Robots are often explicitly designed to achieve greater accuracy and can include sensors that allow the machines themselves to identify product defects. This may lead to an increase in the quality of products, and thereby to an increase in competitiveness on international markets.

Third, firms that use robots can be expected to be more often product innovators. Empirical evidence in favor of this view is reported by Alguacil et al. (2022) for firms from Spain and by Deng et al. (2024) for German firms. It can be considered as a stylized fact that product innovation and exports are highly positively linked at the level of the firm.

This note contributes to the literature by looking at differences in exports between manufacturing enterprises from 27 member countries of the European Union that use or do not use robots. In doing so it adds to our understanding of the role of robots in exports by presenting evidence for firms from a large number of countries (instead of looking at firms from one country only). Furthermore, we report results for various extensive margins of exports beyond participation in exporting by looking at exports to seven distinct areas of the world market for goods. It should be pointed out that a new

[1] See Ferencz et al. (2022), Goldfarb and Trefler (2018) and Meltzer (2018) for a discussion of various aspects of the relations between artificial intelligence and international trade and Wagner (2023) for a study on the use of big data analytics and exports of firms from 27 EU countries.

machine-learning estimator, Kernel-Regularized Least Squares (KRLS), is applied as a robustness check besides standard parametric econometric models.

To anticipate the most important result we find that firms which use robots do more often export, do more often export to various destinations all over the world, and do export to more different destinations. The estimated robots premium for exports is statistically highly significant after controlling for firm size, firm age, patents, and country. Furthermore, the size of this premium can be considered to be large. The take-home message, therefore, is that extensive margins of exports and the use of robots 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 in February – May 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); the numbers of firms by country are reported in the appendix table.

In the survey firms were asked in question Q23_3 whether they introduced r*obotics, i.e. robots used to automate processes for example in construction or design etc.* Firms that answered in the affirmative are classified as users of robots. Descriptive evidence is reported in Table 1, showing a share of 20.7 percent of firms with robots.

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.

[Table 1 near here]

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.

[2] To the best of my knowledge (based on a Google Scholar search for "Flash Eurobarometer 486" performed on January 20, 2024) the data used in this note have not been used to investigate the links between exports and the use of robots before. 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.

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 2. 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 2 near here]

In the empirical investigation of the link between the use of robots 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 has 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 Testing for robots premium in export activities

To test for the difference in the types of export activities listed in section 2 between firms that do and do not use robots, 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. This premium is computed from a regression of log labour productivity on the current export status dummy and a set of control variables:

$$(1)\ \ln LP_i = a + ß\ Export_i + c\ Control_i + e_i$$

where i is the index of the firm, LP is labour productivity, Export is a dummy variable for current export status (1 if the firm exports, 0 else), Control is a vector of control variables, and e is an error term. The exporter premium, computed from the estimated coefficient ß as 100(exp(ß)-1), shows the average percentage difference between exporters and non-exporters controlling for the characteristics included in the vector Control (see Wagner (2007) for a more complete exposition of this method).

Here we look at differences between firms that do and that do not use robots (instead of differences between exporters and non-exporters) and are interested in the existence and size of a robots premium in export activities (instead of an exporter premium in various forms of firm performance like

[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.

productivity). For export activities that are measured by dummy variables (the decision to export or not, and the decision to export to one of the seven export destinations listed in section 2) the empirical model is estimated by Probit instead. Therefore, (1) becomes (2)

$$(2)\ \text{Indicator}_i = a + ß\ \text{Robots}_i + c\ \text{Control}_i + e_i$$

where i is the index of the firm, Indicator is a dummy variable for the use or not of a type of export activity, Robots is a dummy variable for the use of robots by the firm (1 if the firm uses it, 0 else), Control is a vector of control variables (that consists of measures of firm age, firm size, and patents, and dummy variables for countries), and e is an error term. The robots premium is computed as the estimated average marginal effects of the robots dummy variable.

For the number of export destinations, (1) becomes (3)

$$(3)\ \text{Number}_i = a + ß\ \text{Robots}_i + c\ \text{Control}_i + e_i$$

where i is the index of the firm, number is the number of export destinations, Robots is a dummy variable for the use of robots by the firm (1 if the firm uses it, 0 else), Control is a vector of control variables (that consists of measures of firm age, firm size, and patents, and dummy variables for countries), and e is an error term. The robots premium is the estimated coefficient ß; it shows the average difference between firms that use and do not use robots, controlling for firm age, firm size, patents, and country of origin of the firm.

3.1 Results from standard parametric models

In a first step, the empirical models outlined above are estimated using standard parametric econometric models with Probit or OLS. Results are reported in the first columns of tables 3 - 5.

The big picture that is shown is crystal clear: Firms that use robots are more often exporters. This is in line with results from papers that use firm level data from Spain (Koch et al. (2021); Alguacil et al. (2022)), China (Zhang et al. (2023)) and Germany (Deng et al. (2024)). Furthermore, firms with robots do more often export to any of the seven different destinations, and do export to a larger number of destinations. Each estimated robots premium is statistically highly significant ceteris paribus after controlling for firm age, firm size, patents, and country of origin of the firms.[4] Furthermore, the size of this premium can be considered to be large – the estimated marginal effects reported in the first columns of Table 3 and Table 4 are in the order of magnitude of 7 to 21 percent, and from Table 5 we see that the average difference in the number of destinations exported to is 0.5 in favour of firms that use robots (with an average value of 1.544 destinations for all firms).

[Tables 3 – 5 near here]

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

3.2 Results from Kernel-Regularized Lest Squares (KRLS) models

In the standard parametric models used in section 3.1 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. In a robustness check of the results from the standard parametric models, 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 et al. (2017), and used to estimate empirical models for margins of trade for the first time in Wagner (2024)[5].

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 (see Wagner (2024)). For any details the reader is referred to the original papers by Hainmueller and Hazlett (2014) and Fernwerda et al. (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 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 et al. (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 et al. (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 et al. (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 et al.2017: 11). These estimates can be used to examine the heterogeneity of the marginal effects.

[5] The only other application of KRLS in economics is Minviel and Ben Bouheni (2022), a study of the impact of research and development on economic growth with macro data.

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 the second to fifth columns of tables 3 - 5.

The big picture that is shown is again crystal clear, and it is identical to the one shown by the standard parametric models: Firms that use robots are more often exporters, do more often export to any of the different destinations, and do export to a larger number of destinations. Each estimated robots premium is statistically highly significant ceteris paribus after controlling for firm age, firm size, patents, and country of origin of the firms.[6] Furthermore, the size of this premium can again be considered to be large, although the estimated average marginal effects tend to be smaller here than in the standard parametric models. The difference in the size of the average marginal effects can be explained by the fact that the parametric model in column 1 imposes a restrictive functional form in the shape of the estimated relationships, while KRLS estimated this relationship without imposing a functional form.

An additional advantage of KRLS compared to the parametric models used in the original estimation 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). The last three columns of tables 3 - 5 report the marginal effects estimated by KRLS at the 1st quartile, at the median, and at the 3rd quartile. We can clearly see the heterogeneity in the marginal effects. The estimated marginal effects differ widely over the quartiles and tend to increase for all variables considered here. This shows the nonlinearity and heterogeneity of the relationship between the covariates and the share of exports in total sales.

4 Concluding remarks

This study finds that manufacturing firms from 27 EU member countries that use robots are more often exporters than firms that do not use robots. This is in line with results from papers that use firm level data from Spain (Koch et al. (2021); Alguacil et al. (2022)), China (Zhang et al. (2023)) and Germany (Deng et al. (2024)). Furthermore, firms with robots do more often export to any of the seven different destinations, and do export to a larger number of destinations. The robots premium is large for all types of export activities.

Does this study imply that in order to be successful in export markets, firms should use robots? Or that using robots 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 robots, or whether it is the effect of using robots. 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

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

years and that include a sufficiently large number of firms that switch the status between using robots or not over time (in both directions). While we have some evidence for both positive effects of the introduction of robots on exports and for self-selection of exporters into the use of robots from the few empirical studies that use longitudinal data (see Koch et al. (2021), Alguacil et al. (2022), Deng et al. (2024)), the jury is still out to find a generally accepted answer.

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Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Robots (Dummy; 1 = yes)	0.2068	0.404	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)	0.12	0.325	0	1
No. of Firms in Sample	2,355			

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

Table 2: 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	3.1
6	68	2.89
7	91	3.86
Total	2,355	100

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

Table 3: Empirical results, Part I: Export participation

Method	Probit Average marginal effects	KRLS Average marginal effect	P25	P50	P75
Robots	0.208	0.1627	0.1215	0.1721	0.2201
(Dummy; 1 = yes)	(0.000)	(0.000)			
Firm age	0.0012	0.0013	-0.000031	0.0007	0.0028
(years)	(0.007)	(0.009)			
Firm size	0.00032	0.00074	0.00059	0.00074	0.0009
(Number of employees)	(0.000)	(0.000)			
Patent	0.1953	0.1753	0.1031	0.1801	0.2457
(Dummy; 1 = yes)	(0.000)	(0.000)			
26 country dummies	included	included			
Number of cases	2,355	2,355			

Note: Probit reports average marginal effects from a model estimated by ML Probit. KRLS reports average marginal effects and marginal effects at the 25th, 50th and 75th percentile estimated by kernel-based regularized least squares. P-values are reported in parentheses. For details, see text.

Table 4: Empirical results, Part II: Export participation by destination country

Method	Probit Average marginal effects	KRLS Average marginal effect	P25	P50	P75
EU countries					
Robots	0.202	0.1646	0.1212	0.165	0.2221
(Dummy; 1 = yes)	(0.000)	(0.000)			
Firm age	0.0014	0.0013	-0.00023	0.0012	0.0027
(years)	(0.003)	(0.006)			
Firm size	0.00034	0.0007	0.00057	0.00071	0.00081
(Number of employees)	(0.000)	(0.000)			
Patent	0.2081	0.1726	0.0981	0.1739	0.2479
(Dummy; 1 = yes)	(=.000)	(0.000)			
Other Europe					
Robots	0.1391	0.1142	0.0785	0.1164	0.1496
(Dummy; 1 = yes)	(0.000)	(0.000)			
Firm age	0.0019	0.002	0.0012	0.0019	0.0028
(years)	(0.000)	(0.000)			
Firm size	0.00017	0.00056	0.00044	0.00057	0.0007
(Number of employees)	(0.000)	(0.000)			
Patent	0.2201	0.2059	0.1419	0.2124	0.261
(Dummy; 1 = yes)	(0.000)	(0.000)			
North America					
Robots	0.1303	0.1029	0.0697	0.1031	0.1281
(Dummy; 1 = yes)	(0.000)	(0.000)			
Firm age	0.001	0.001	0.00047	0.00089	0.0016
(years)	(0.000)	(0.000)			
Firm size	0.000079	0.00025	0.0002	0.00025	0.00028
(Number of employees)	(0.000)	(0.000)			
Patent	0.1739	0.1633	0.1201	0.1691	0.2021
(Dummy; 1 = yes)	(0.000)	(0.000)			
Latin America					
Robots	0.0744	0.0617	0.0346	0.0565	0.0849
(Dummy; 1 = yes)	(0.000)	(0.001)			
Firm age	0.00071	0.0008	0.0002	0.00055	0.0013
(years)	(0.002)	(0.001)			
Firm size	0.000073	0.00025	0.00019	0.00023	0.00028
(Number of employees)	(0.000)	(0.000)			
Patent	0.108	0.1186	0.0615	0,1260	0.16
(Dummy; 1 = yes)	(0.000)	(0.000)			

Method	Probit Average marginal effects	KRLS Average marginal effect	P25	P50	P75
China					
Robots	0.1037	0.0745	0.0504	0.0682	0.0961
(Dummy; 1 = yes)	(0.000)	(0.000)			
Firm age	0.00096	0.00087	0.00036	0.00084	0.0013
(years)	(0.000)	(0.000)			
Firm size	0.000084	0.00022	0.00016	0.00021	0.00027
(Number of employees)	(0.000)	(0.000)			
Patent	0.1061	0.108	0.0753	0.0993	0.1436
(Dummy; 1 = yes)	(0.000)	(0.000)			
Other Asia					
Robots	0.0902	0.0736	0.0327	0.0706	0.1113
(Dummy; 1 = yes)	(0.000)	(0.001)			
Firm age	0.0011	0.00091	0.000082	0.00076	0.0018
(years)	(0.000)	(0.003)			
Firm size	0.00011	0.00037	0.00026	0.00035	0.00043
(Number of employees)	80.000)	(0.000)			
Patent	0.1438	0.1334	0.0862	0,1287	0.1663
(Dummy; 1 = yes)	(0.000)	(0.000)			
Middle East, Africa					
Robots	0.0786	0.0696	0.0307	0.0561	0.1027
(Dummy; 1 = yes)	(0.000)	(0.001)			
Firm age	0.0011	0.00097	0.000052	0.00078	0.0016
(years)	(0.000)	(0.002)			
Firm size	0.000087	0.00037	0.0003	0.00037	0.00044
(Number of employees)	(0.000)	(0.000)			
Patent	0.1442	0.1465	0.0947	0.1481	0.1916
(Dummy; 1 = yes)	(0.000)	(0.000)			
Number of cases	2355	2355			

Note: Probit reports average marginal effects from a model estimated by ML Probit. KRLS reports average marginal effects and marginal effects at the 25th, 50th and 75th percentile estimated by kernel-based regularized least squares. P-values are reported in parentheses. All models include a set of country dummies. For details, see text.

Table 5: Empirical results, Part III: Number of export destinations

Method	OLS Regression coefficient	KRLS Average marginal effect	P25	P50	P75
Robots	0.5041	0.3738	0.2513	0.3971	0.4726
(Dummy; 1 = yes)	(0.000)	(0.001)			
Firm age	0.0104	0.0084	0.0054	0.0087	0.0119
(years)	(0.000)	(0.000)			
Firm size	0.00072	0.0011	0.00095	0.0011	0.0014
(Number of employees)	(0.002)	(0.000)			
Patent	0.9297	0.8077	0.5946	0.834	1.0436
(Dummy; 1 = yes)	(0.000)	(0.000)			
26 country dummies	included	included			
Number of cases	1520	1520			

Note: OLS reports the estimated regression coefficients from a linear model. KRLS reports average marginal effects and marginal effects at the 25th, 50th and 75th percentile estimated by kernel-based regularized least squares. P-values are reported in parentheses. For details, see text.

Appendix

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.