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Intensity of Artificial Intelligence Use and the Intensive Margin of Exports: Evidence from Firms in 12 Euro Area Countries in 2025

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Intensity of Artificial Intelligence Use and the Intensive Margin of Exports: Evidence from Firms in 12 Euro Area Countries in 2025*

Abstract

The use of artificial intelligence (AI) goes hand in hand with higher productivity, higher product quality, and lower trade costs. Therefore, it can be expected to be positively related to export activities. This paper uses firm level data from 12 member countries of the Euro Area collected in 2025 to shed further light on this issue by investigating the link between the intensity of use of AI and the intensive margins of exports measured as the percentage share of exports in total sales. Applying a new machine-learning estimator, Kernel-Regularized Least Squares (KRLS), which does not impose any restrictive assumptions for the functional form of the relation between margin of exports, the intensity of use of AI and any control variables, we find that firms which use AI more intensively do export a higher share of total sales. AI intensity and export intensity are positively related.

JEL classification

D22, F14

Keywords

artificial intelligence, exports, firm level data, SAFE Data, kernel-regularized least squares (KRLS)

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* The firm level data used in this study are taken from the *Survey on the access to finance of enterprises*, 2025 Q4 (SAFE Data) by the European Commission and European Central Bank. Link to public use data: https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/data.en.html. Stata code used to generate the empirical results reported in this note is available from the author.

1. Motivation

The use of artificial intelligence (AI) 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 (2025), 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 AI 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, its use 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 digital technologies and export activities of firms is supporting this view. Wagner (2026a) uses firm level data for manufacturing enterprises from the 27 member countries of the European Union from the Flash Eurobarometer 559 collected in 2025 to investigate the link between the use of digital technologies and extensive margins of exports. He finds that firms which use more digital technologies do more often export and do export to more different destinations.

While this points to a positive link between the use of AI and extensive margins of exports comparable evidence for the relation between AI use and the intensive margin of exports – the share of exports in total sales of a firm – is lacking. This paper contributes to the literature by using firm level data from 12 member countries of the Euro Area collected in 2025 in the *Survey on the access to finance of enterprises*, 2025 Q4 (SAFE Data) by the European Commission and European Central Bank to investigate the link between the intensity of use of AI in a firm and the share of exports in its total sales.

Applying a new machine-learning estimator, Kernel-Regularized Least Squares (KRLS), which does not impose any restrictive assumptions for the functional form of the relation between export intensity, intensity of use of AI, and any control variables, we find that firms which use AI more intensively do export a larger share of their total sales.

The rest of the paper is organized as follows. Section 2 introduces the data used. 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 *Survey on the access to finance of enterprises*, 2025 Q4 (SAFE Data) by the European Commission and European Central Bank. The public use data used cover information on 4,324 firms from 12 Euro Area countries with 1 to 249 employees. Firms are active in industry, construction, trade and services. The countries covered and the numbers of firms by country are reported in the appendix table. A comprehensive descriptive analysis of the results from the survey can be found in Ferrando et al. (2026). Note that the paper by Ferrando et al. (2026) does not cover any discussion of the export activities of firms.

In the survey firms were asked in question D7 “What percentage of your company’s total turnover in 2024 is accounted for by exports of goods or services?”. This variable is the information on the intensive margin of exports used in this paper. Table 1 reports the share of exports in total sales by broad categories; a table with detailed results by percentage is available on request. More than half of all firms in the sample did not export at all, and about one fifth of the firms did only export 1 to 10 percent.

[Table 1 near here]

In question QA1_2025Q4 firms were asked about the use of artificial intelligence (AI) technologies (including predictive tools such as text mining, voice and image recognition, machine learning and generative tools like chatbots and text/image generation, or robotic process automation). Table 2 reports the answers by the four intensity categories used in the survey. While about one third of all firms in the sample do not currently use AI technologies and 30 percent use it very infrequently or experimentally only, the share of firms that report a moderate use is about one quarter and firms with a significant use are rare with about 7 percent. The intensity of AI use is measured in this study by an index from 1 to 4 according to the four categories mentioned.

[Table 2 near here]

In the empirical investigation of the link between the intensity of AI use in firms and the intensive margin of exports we control for three firm characteristics that are known to be linked with exports: Firm size (measured in three broad categories; see Table 3), sector (see Table 4) and firm age (measured in years by four broad categories; see Table 5).[1]

[Tables 3 -5 near here]

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

[1] 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 link between these firm characteristics and export performance.

3. Artificial intelligence use and intensive margin of exports

To investigate the link between the intensity of artificial intelligence use and the intensive margin of exports in the firms we use an empirical model

[1] Export intensity_i = f [Intensity of AI use_i , Control_i]

where i is the index of the firm, Export intensity is the share of exports in total sales (in percentage), Intensity of AI use is the value of the index defined in Table 2, and Control is a vector of control variables that consists of measures of firm size and firm age, dummy variables for sectors, and dummy variables for countries (see Table 3 to Table 5 and the appendix table).

In standard parametric models the firm characteristics that explain the export margin 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 (2026b).

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 (2026b)). 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 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 empirical model for the intensive margin of exports are reported in Table 6.[2]

[Table 6 near here]

The big picture that is shown is crystal clear. Higher values of the index of AI use intensity go hand in hand with higher export intensity both on average and for all percentiles of the marginal effect. The estimated average marginal effect is statistically highly significant ceteris paribus after controlling for firm age, firm size, sector, and country of origin of the firms.

4. Concluding remarks

This study finds that firms from 12 euro area countries that use AI technologies more intensively in 2025 export a larger share of their total sales. This complements the findings on a positive link between the intensity of use of advanced technologies and the extensive margins of exports for manufacturing firms from 27 EU member countries reported in Wagner (2026a).

Does this study imply that to be successful in export markets, firms should use AI technologies? Or that using AI chnologies will help the firms to be successful as an

[2] A table with the complete results for all control variables is available from the author on request.

exporter? This is an open question (that is asked the same way when the exporter productivity premium is discussed; see Wagner (2007)) because we do not know whether this result is due to self-selection of exporting firms into the more intensive use of AI technologies, or whether it is the effect of using AI technologies more intensively.

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 intensity of the use of AI over time. The jury is still out to find a generally accepted answer.

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Table 1: Share of exports in total sales (broad categories)

Share of exports percentage)	Share of firms in sample (percent)
No exports	53.5
1 to 10	19.5
11 to 50	14.0
51 to 100	13.0

Note: Detailed results by percentage share are available on request

Table 2: Intensity of AI use in firms

Category	Share of firms in sample (percent)
Not currently in use	35.57
Very infrequent use or use in pilot projects/ experimentally	30.34
Moderate use	26.78
Significant use	7.31

Note: Coded as index with values from 1 to 4

Table 3: Firm size (broad categories)

Category	Share of firms in sample (percent)
1 to 9 employees	42.21
10 to 49 employees	33.44
50 to 249 employees	24.35

Note: Coded as index with values from 1 to 3

Table 4: Sector

Sector	Share of firms in sample (percent)
Industry	24,21
Construction	13.92
Trade	22,22
Services	39.64

Table 5: Firm age (broad categories)

Category	Share of firms in sample (percent)
Less than 2 years	0.83
2 years or more, but less than 5 years	1.73
5 years or more, but less than 10 years	6.45
10 years or more	90.98

Note: Coded as index with values from 1 to 4

Table 6: Empirical results for the intensive margins of exports

Method	KRLS Average marginal effect	P25	P50	P75
Intensity of AI use (Index, 1 to 4)	1.580 (0.000)	0.029	1.715	3-011
Control variables	included			
Country dummies	included			
Number of cases	4,324			

Note: 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. A table with complete results for all control variables is available from the author on request.

Appendix: Number of firms in the sample by country

Country	Number of firms	Share (percent)
Austria	297	6.87
Belgium	231	5.34
Finland	172	3.98
France	542	12.53
Germany	450	10.41
Greece	302	6.98
Ireland	225	5.20
Italy	643	14.87
Netherlands	358	8.28
Portugal	298	6.89
Slovakia	201	4.65
Spain	605	13.99
All countries	4,324	