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**Abstract:** The use of advanced technologies like artificial intelligence, robotics, or smart devices will go 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 for manufacturing enterprises from the 27 member countries of the European Union collected in 2025 to shed further light on this issue by investigating the link between the use of advanced technologies and extensive margins of exports. 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 margins of exports, use of advanced technologies, and any control variables, we find that firms which use more advanced technologies do more often export and do export to more different destinations.

**Keywords:** Advanced technologies, exports, firm level data, Flash Eurobarometer 559, kernel-regularized least squares (KRLS)

**JEL Classification:** D22, F14

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**Acknowledgement:** The firm level data used in this study are taken from the Flash Eurobarometer 559 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

The use of advanced technologies like artificial intelligence, cloud computing, or robotics 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 Oliván García (2022), Wagner (2007)). Furthermore, the use of these advanced technologies can be expected to lower trade costs (see e.g. Ferencz, López González and Oliván García (2022), López González, Sorescu and Kaynak (2023), Meltzer (2018)). Therefore, the use of advanced 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 digital technologies and export activities of firms is supporting this view. Wagner (2025) uses firm level data for manufacturing enterprises from the 27 member countries of the European Union collected in 2020 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, do more often export to various destinations all over the world, and do export to more different destinations.

Evidence reported in the literature, however, is based on firm level data that are several years old. For example, the data used in Wagner (2025) were collected at the beginning of 2020 – before the Corona pandemic hit the world, and in a time when artificial intelligence models like ChatGPT or Google Gemini were not available at your fingertips on the laptops but were considered science fiction (if thought of at all).

A fresh look at recent data can help to learn more on the links between the use of todays advanced technologies and the export activities of firms. 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 559 survey conducted early in 2025 to investigate the link between the advanced technologies intensity of a firm (measured by the number of different advanced technologies adopted in a firm) and extensive margins of exports (export participation and number of export destinations). Furthermore, it looks at the role of each of 10 different advanced technologies in this link.

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 margins of exports, use of advanced technologies, and any control variables, we find that firms which use more advanced technologies do more often export 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, innovations, and country. Extensive margins of exports and the use of advanced 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 559 survey conducted between February and April 2025. Note that information on export activities relates to the year 2024. We use data for firms from the 27 member states of the European Union in 2025. The sample covers 1,587 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 Q14 which of the following digital technologies, if any, they have adopted to date: *Artificial intelligence*, e.g. machine learning, Large Language Models.; *Cloud computing*, i.e. storing and processing files or data on remote servers hosted on the internet and big data analytics; *Robotics*, i.e. robots used to automate processes for example in construction or design, etc.; *Internet of Things,* e.g. smart sensors; *Digital technologies for security, cybersecurity; Blockchain; Biotechnology,* e.g. genomics, gene therapy, biofuel; *Micro- and nanoelectronics and photonics; Advanced material,* e.g. polymers; *Clean and resource-efficient technologies.* Firms that answered in the affirmative are classified as users of the respective advanced technology. Descriptive evidence is reported in the upper panel of Table 1.

[Table 1 near here]

Wile 429 (or about a quarter of all firms) did not use any of these technologies, the share of users of the other advanced technologies varies widely – from five percent or less using *Blockchain, Biotechnology* or *Micro- and nanoelectronics* to 37 percent using *Digital technologies for security, cybersecurity* and 49 percent using *Cloud computing.*

On average, firms use 2.04 different advanced technologies. As documented in Table 2 most adopters of advanced technologies apply between one and three different technologies, while the share of "power users" that apply six or more tiny. This information is used to construct an index of *Advanced technology intensity* of a firm that takes on values from zero (for firms without the application of any advanced technology) to ten (for firms that use all ten technologies mentioned). The number of firms and the share in all firms in the sample for each value of advanced technology intensity is listed in Table 2.

[Table 2 near here]

In the empirical study we look at two measures of export activity of firms:[1]

First, firms were asked in question Q8_1 whether they exported any goods (or not) in 2024. Firms are classified as exporters or non-exporters based thereon. Descriptive evidence is reported in Table 1, showing a share of 57.0 percent of exporters.

Second, firms were asked in questions Q8_2 to Q8_8 whether they exported goods in 2024 to the following destinations: Other EU countries; other European countries outside the EU (e.g UK, Russia); North America; Latin America and the Caribbean; China; rest of Asia and the Pacific; Middle East and Africa. 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

[1] Note that both 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.

export destinations is reported in Table 3. Not surprisingly, most exporters serve one or two destinations only, but there are some firms that export to more (or even all) destinations.

[Table 3 near here]

In the empirical investigation of the link between the digitalization intensity of firms and extensive margins of exports we control for three firm characteristics that are known to be linked with exports: firm age (measured in years, based on the answer given to question DX2a), firm size (measured as the number of employees – excluding the owners - at the time of the survey; see question DX3a), and whether the firms has introduced any kind of innovation (e.g., new product, new production process, new organization of management, etc.) over the last 12 months or not (see question Q12-9).[2] Descriptive statistics are reported in the bottom panel 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. Advanced technology premia for export activities

To test for the difference in the extensive margins of exports mentioned in section 2 between firms with various intensities in the use of advanced technologies, 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.

Here we look at differences between firms with various intensities of the use of advanced technologies listed above (instead of differences between exporters and non-exporters) and are interested in the existence and size of an advanced technologies 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

$$\text{Export activity}_i = f\,[\text{Use of advanced technology}_{i,}\ \text{Control}_i] \qquad [1]$$

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), Use of advanced technology is the value of the variable listed in the first panel of Table 1, and Control is a vector of control variables (that consists of measures of firm age, firm size, and innovations, and dummy variables for countries). The advanced technology premium is computed as the estimated average marginal effects of the variable that indicates the respective use of advanced technologies.

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

[2] 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.

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 (2026).

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 (2026)). 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.

In a first step we measure the use of advanced technologies by the index of advanced technology intensity that takes on values between 0 and 10 (see the discussion in section 2 and Table 2). Results for an application of KRLS to the models for both extensive margins of exports are reported in Table 4.

[Table 4 near here]

The big picture that is shown is crystal clear. Higher values of the index go hand in hand with higher probabilities of export participation, and with exporting to a larger number of destinations. Each estimated premium is statistically highly significant ceteris paribus after controlling for firm age, firm size, innovations, and country of origin of the firms.

To shed more light on the relation between the use of advanced technologies and extensive margins of exports in a second step the empirical models were estimated with variables that control for the use of each of the ten technologies (listed in the first panel of Table 1) separately. Results are reported in Table 5.

[Table 5 near here]

From column 1 of Table 5 it can be concluded that five of the ten technologies are not related with export participation – the estimated average marginal effects can not be considered to be statistically significantly different from zero at a usual level. This holds for the seldom used *Blockchain, Biotechnology*, and *Micro and -nanoelectronics,* but also for the more commonly used *Internet of things* and *Clean technologies.* The overall positive relation between the use of advanced technologies and export participation is driven by the other five technologies, i.e. *Artificial intelligence, Cloud computing, Robotics, Digital technology for security*, and *Advanced materials.*

Results reported in column 2 of Table 5 indicate the positive link between the use of advance technologies and the number of different markets served by exporters is mainly driven by using *Robotics* and the *Internet of things*. The estimated average marginal effects of all other advanced technologies are not statistically significantly different from zero at a conventional level.

## 4. Concluding remarks

This study finds that manufacturing firms from 27 EU member countries that use advanced technologies more intensively in 2025 are more often exporters and do export to a larger number of destinations.

Does this study imply that to be successful in export markets, firms should use advanced technologies? Or that using advanced technologies will help the firms to be successful as an exporter? Can the results that are reported here for the use of different technologies hint to especially important technologies (e.g. Robotics)? 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 advanced technologies, or whether it is the effect of using advanced 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 advanced technologies or not over time (in both directions). 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 |
|---|---|---|---|---|
| Artificial intelligence (Dummy; 1 = yes) | 0.1890 | 0.3917 | 0 | 1 |
| Cloud computing (Dummy; 1 = yes) | 0.4908 | 0.5000 | 0 | 1 |
| Robotics (Dummy; 1 = yes) | 0.2281 | 0.4197 | 0 | 1 |
| Internet of things (Dummy; 1 = yes) | 0.2602 | 0.4389 | 0 | 1 |
| Digital tech. for security (Dummy; 1 = yes) | 0.3743 | 0.4841 | 0 | 1 |
| Blockchain (Dummy; 1 = yes) | 0.0359 | 0.1861 | 0 | 1 |
| Biotechnology (Dummy; 1 = yes) | 0.0504 | 0.2189 | 0 | 1 |
| Micro- and nanoelectronics (Dummy; 1 = yes) | 0.0491 | 0.2162 | 0 | 1 |
| Advanced materials (Dummy; 1 = yes) | 0.1361 | 0.3430 | 0 | 1 |
| Clean technologies (Dummy; 1 = yes) | 0.2299 | 0.4210 | 0 | 1 |
| Advanced technology intensity (Index; 0 – 10) | 2.0441 | 1.8705 | 0 | 10 |
| Exporter (Dummy; 1 = yes) | 0.570 | 0.495 | 0 | 1 |
| Number of Export Destinations | 1.307 | 1.621 | 0 | 7 |
| Firm Age (years) | 33.54 | 32.65 | 0 | 325 |
| No. of Employees | 136.53 | 460.67 | 1 | 11457 |
| Innovations (Dummy; 1 = yes) | 0.674 | 0.469 | 0 | 1 |
| No. of Firms in Sample | 1,587 | | | |

Source: Own calculation based on data from Flash Eurobarometer 559; for details, see text.

**Table 2: Share of Firms by Advanced Technology Intensity**

| Advanced Technology Intensity | Number of Firms | Percent |
|---|---|---|
| 0 | 429 | 27.03 |
| 1 | 268 | 16.89 |
| 2 | 314 | 19.79 |
| 3 | 271 | 17.08 |
| 4 | 142 | 8.95 |
| 5 | 76 | 4.79 |
| 6 | 46 | 2.90 |
| 7 | 25 | 1.58 |
| 8 | 10 | 0.63 |
| 9 | 4 | 0.25 |
| 10 | 2 | 0.13 |
| Total | 1,587 | 100.0 |

Source: Own calculation based on data from Flash Eurobarometer 559; see text for details.

**Table 3: Share of Firms by Number of Export Destinations**

| Number of Export Destinations | Number of Firms | Percent |
|---|---|---|
| 0 | 682 | 42.97 |
| 1 | 352 | 22.18 |
| 2 | 272 | 17,14 |
| 3 | 118 | 7.44 |
| 4 | 72 | 4.54 |
| 5 | 38 | 2.39 |
| 6 | 25 | 1.58 |
| 7 | 28 | 1.76 |
| Total | 1,587 | 100.0 |

Source: Own calculation based on data from Flash Eurobarometer 559.

**Table 4: Advanced Technology Intensity and Extensive Margins of Exports: Estimated Average Marginal Effects from Kernel-Regularized Least Squares**

| Export margin | Advanced Technology Intensity (Index; 0 – 10) | Firm Age (Years) | Firm Size (Number of Employees) | Innovations (Dummy; 1 = yes) |
|---|---|---|---|---|
| Participation | 0.0295 | 0.0004 | 0.000082 | 0.0721 |
| (Dummy; 1 = yes) | [0.000] | [0.218] | [0.001] | [0.009] |
| No. of firms | 1,587 | | | |
| Number of | 0.0654 | 0.0048 | 0.0011 | 0.2011 |
| Destinations (Index; 1 – 7) | [0.001] | [0.001] | [0.000] | [0.101] |
| No. of firms | 905 | | | |

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

**Table 5: Advanced Technologies and Extensive Margins of Exports: Estimated Average Marginal Effects from Kernel-Regularized Least Squares**

| | Export Participation (Dummy; 1 = yes) | Number of Export Destinations (Index; 1 – 7) |
|---|---|---|
| Artificial intelligence (Dummy; 1 = yes) | 0.049 | -0.085 |
| | [0.064] | [0.390] |
| Cloud computing (Dummy; 1 = yes)1 | 0.037 | 0.124 |
| | [0.093] | [0.157] |
| Robotics (Dummy; 1 = yes) | 0.079 | 0.222 |
| | [0.002] | [0.017] |
| Internet of things (Dummy; 1 = yes) | -0.021 | 0.180 |
| | [0.386] | [0.066] |
| Digital tech. for security (Dummy; 1 = yes) | 0.065 | 0.066 |
| | [0.004] | [0.453] |
| Blockchain (Dummy; 1 = yes) | -0.060 | 0.047 |
| | [0.193] | [0.792] |
| Biotechnology (Dummy; 1 = yes) | -0.040 | -0.033 |
| | [0.334] | [0.853] |
| Micro- and nanoelectronics (Dummy; 1 = yes) | -0.017 | 0.252 |
| | [0.687] | [0.114] |
| Advanced materials (Dummy; 1 = yes) | 0.070 | 0.007 |
| | [0.021] | [0.951] |
| Clean technologies (Dummy; 1 = yes) | 0.039 | 0.065 |
| | [0.125] | [0.503] |
| Firm size (Number of employees) | 0.00005 | 0.0005 |
| | [0.002] | [0.000] |
| Firm age (years) | 0.00045 | 0.0047 |
| | [0.126] | [0.000] |
| Innovations (Dummy; 1 = yes) | 0.051 | 0.1651 |
| | [0.023] | [0.082] |
| Number of Firms | 1,587 | 905 |

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

## Appendix

**Number of Firms by Country**

| Country | Number of Firms | Percent |
|---|---|---|
| Austria | 45 | 2.84 |
| Belgium | 53 | 3.34 |
| Bulgaria | 48 | 3.02 |
| Cyprus | 26 | 1.64 |
| Czech Republic | 60 | 3.78 |
| Germany | 77 | 4.85 |
| Denmark | 109 | 6.87 |
| Estonia | 67 | 4.22 |
| Spain | 59 | 3.72 |
| Finland | 83 | 5.23 |
| France | 59 | 3.72 |
| Greece | 62 | 3.91 |
| Croatia | 62 | 3.91 |
| Hungary | 57 | 3.59 |
| Ireland | 49 | 3.09 |
| Italy | 66 | 4.16 |
| Lithuania | 46 | 2.90 |
| Luxembourg | 24 | 1.51 |
| Latvia | 60 | 3.78 |
| Malta | 26 | 1.64 |
| Netherlands | 53 | 3.34 |
| Poland | 56 | 3.53 |
| Portugal | 50 | 3.15 |
| Romania | 56 | 3.53 |
| Sweden | 69 | 4.35 |
| Slovenia | 48 | 3.02 |
| Slovakia | 69 | 4.35 |
| Total | 1,587 | 100.0 |

Source: Own calculations based on data from Flash Eurobarometer 559.