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Who uses Advanced Technologies? Evidence from Manufacturing Firms from 38 Countries in 2025

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Joachim Wagner

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Who uses Advanced Technologies?
Evidence from Manufacturing Firms from 38 Countries in 2025 *

Joachim Wagner

Leuphana University Lueneburg, and Kiel Centre for Globalization

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Abstract

The use of advanced technologies like artificial intelligence, robotics, or smart devices will go hand in hand with, among others, higher productivity, higher product quality, more exports and better chances to survive any crisis. Better firms tend to use advanced technologies. Information on firm level determinants of adoption of these technologies, therefore, is important to inform industrial policies. This paper uses firm level data for manufacturing enterprises from 38 countries collected in 2025 to shed further light on this issue by investigating the link between the use of advanced technologies and firm characteristics. 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 use of advanced technologies, firm characteristics and any control variables, we find that firms which use advanced technologies tend to be larger and more innovation orientated, while firm age does not matter.

JEL classification: D22

Keywords: Advanced technologies, firm characteristics, Flash Eurobarometer 559, kernel-regularized least squares (KRLS)

* 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.

Professor Dr. Joachim Wagner
Leuphana University Lueneburg
D-21314 Lüneburg
Germany
e-mail: joachim.wagner@leuphana.de

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 Garcia (2022), Wagner (2007)). Furthermore, the use of these advanced 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 advanced technologies can be expected to be positively related to export activities of firms that use these technologies (Wagner (2025))

The bottom line, then, is that the use of advanced technologies and various dimensions of firm performance tend to be positively related. Good firms more often use advanced technologies. 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 use of todays advanced technologies. This paper contributes to the literature by using firm level data for manufacturing enterprises from 38 countries taken from the Flash Eurobarometer 559 survey conducted early in 2025 to document the use of ten different types of advanced technologies. Furthermore, it looks at the links between firm characteristics and the use of advanced technologies. Applying a new machine-learning estimator, Kernel-Regularized Least Squares (KRLS), which does not impose any restrictive assumptions for the functional form of this relation we find that firms which use more advanced technologies are larger and more innovation-oriented while firm age does not matter.

The rest of the paper is organized as follows. Section 2 introduces the data used and discusses the different advanced technologies and the firm characteristics 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 in 38 countries. The sample used covers 2,064 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 562 (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 six percent or less using *Blockchain, Biotechnology* or *Micro- and nanoelectronics* to 38 percent using *Digital technologies for security, cybersecurity* and 49 percent using *Cloud computing.*

On average, firms use 2.09 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 is 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 investigation of the link between the use of advanced technologies and firm characteristics three characteristics are considered: *firm size* (measured as the number of employees – excluding the owners - at the time of the survey; see question DX3a), *firm age* (measured in years, based on the answer given to question DX2a), and *innovation orientation of a firm* (proxied by the fact 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).

The selection of these firm characteristics is motivated by the large literature on the determinants of the adoption of advanced technologies (and limited by the information available in the survey data at hand here). While a comprehensive survey of this literature is far beyond the scope of this applied note, a short outline might be helpful to motivate the inclusion of the selected characteristics.

Firm size is considered the most robust predictor of advanced technology adoption. Reasons include economies of scale due to often involved high fixed costs and easier access to internal and external financing which is critical given the high sunk costs and uncertain returns of many projects related to the use of advanced technology projects (see Acemoglu, Lelarge and Restrepo (2020)).

Firm age is found to be both positively (due to, e.g., easier access to finance for long established older firms) and negatively (due to the "born digitals" effect that favors the adoption of advanced technologies in younger firms) related to the use of advanced technologies. Therefore, this is an open issue to be investigated in the data at hand.

Innovation orientation of a firm – or how open minded the owners and managers of a firm are with a view to the adoption of new advanced technologies – is proxied here by the introduction of any new products, new production processes, new ways to organize the management, etc. over the last year. Such innovations are often found to be positively related to the adoption of advanced technologies (see, e.g., Babina et al. (2024)).

Descriptive statistics on these firm characteristics are reported in the bottom panel of 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.Firm characteristics and use of advanced technologies

To test for the link between the firm characteristics mentioned in section 2 and the use of advanced technologies, and to document the direction and the size of this link, empirical models are used that can be written in general as

[1] $\text{Advanced technology}_i = f\,[\text{Firm characteristics}_i,\ \text{Control}_i]$

where i is the index of the firm, *Advanced technology* is a dummy variable for the respective type of technology (listed in the first panel of Table 1) or the value of the index of advanced technology intensity, *Firm characteristics* is a vector including measures of firm size, firm age, and innovations (listed in the second panel of Table 1), and *Control* is a vector of dummy variables for the 38 countries. The link between a firm characteristic and technology use is computed as the estimated average marginal effect of this characteristic.

In standard parametric models the variables that explain the use of advanced technologies enter the empirical model in linear form. This functional form, 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 (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 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 look at the use of each of the ten advanced technologies separately. In a second step we investigate the link between the firm characteristic and the index of advanced technology intensity. Results for KRLS regressions are reported in Table 3.

[Table 3 near here]

The big picture that is shown is crystal clear. In line with findings from the lliterature the average marginal effect of firm size and innovation is positive – larger and more innovation-oriented firms are more often users of advanced technologies. Firm age, on the other hand, does not matter at all here (except for the use of digital technology for security).

The last three columns of table 3 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. This shows the nonlinearity and heterogeneity of the relationship between the covariates and the use of advanced technologies.

4. Concluding remarks

This study finds that manufacturing firms from 38 countries that use advanced technologies in 2025 are larger and more innovation oriented than non-users, while firm age does not matter here.

Does this study imply that industrial policy measures that intend to support the application of advanced technologies should focus on larger and more innovation-oriented firms? Or that using advanced technologies will help firms to grow and become more innovation-oriented? This is an open question because we do not know whether the larger size and the higher innovation-orientation of firms that use advanced technologies is due to self-selection of these 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)	0.1933	0.3950	0	1
Cloud computing (Dummy; 1 = yes)1	0.4889	0.5000	0	1
Robotics (Dummy; 1 = yes)	0.2326	0.4226	0	1
Internet of things (Dummy; 1 = yes)	0.2660	0.4420	0	1
Digital tech. for security (Dummy; 1 = yes)	0.3765	0.4841	0	1
Blockchain (Dummy; 1 = yes)	0.0392	0.1942	0	1
Biotechnology (Dummy; 1 = yes)	0.0470	0.2117	0	1
Micro- and nanoelectronics (Dummy; 1 = yes)	0.0586	0.2250	0	1
Advanced materials (Dummy; 1 = yes)	0.1541	0.3611	0	1
Clean technologies (Dummy; 1 = yes)	0.2374	0.4256	0	1
Advanced technology intensity (Index; 0 – 10)	2.0935	1.9580	0	10
Firm Age (years)	33.90	31.44	0	325
No. of Employees	150.92	668.81	1	15,000
Innovations (Dummy; 1 = yes)	0.6778	0.4674	0	1
No. of Firms in Sample	2,064			

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	562	27.23
1	367	17.78
2	375	18.17
3	327	15.84
4	185	8.96
5	112	5.43
6	65	3.15
7	46	2.23
8	16	0.78
9	7	0.34
10	2	0.10
Total	2,064	100.0

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

Table 3: Firm characteristics and use of advanced technologies –

Results from Kernel-Regularized Lest Squares Regressions

Technology		Firm size	Firm age	Innovations
Artificial intelligence				
	AME	0.00007	-9.3e-6	0.0999
	p	0.000	0.974	0.000
	P25	0.000035	-0.00061	0.03158
	P50	0.000069	-0.000091	0.08456
	P75	0.00009	0.00056	0.16476
Cloud computing				
	AME	0.00004	0.000369	0.115
	p	0.000	0.111	0.000
	P25	0.000032	0.000113	0.0769
	P50	0.000042	0.000405	0.1084
	P75	0.000048	0.000627	0.1524
Robotics				
	AME	0.000165	0.000512	0.1144
	p	0.000	0.112	0.000
	P25	0.000095	-0.00041	0.04191
	P50	0.000173	0.00027	0.1027
	P75	0.000208	0.001471	0.1828

Internet of things				
	AME	0.000094	0.00248	0.0986
	p	0.000	0.361	0.000
	P25	0.000072	-0.000296	0.0644
	P50	0.000084	0.000371	0.0947
	P75	0.000114	0.000729	0.1286
Digital technology for security				
	AME	0.00075	0.00095	0.1488
	p	0.000	0.000	0.000
	P25	0.000058	0.000665	0.1006
	P50	0.000077	0.000957	0.1536
	P75	0.000093	0.001409	0.2093
Blockchain				
	AME	3.2e-07	3.3e-06	0.000594
	p	0.000	0.181	0.053
	P25	2.4e-07	8.8e-07	0.000455
	P50	3.0e-07	3.0e-06	0.00059
	P75	3.7e-07	5.6e-06	0.000695
Biotechnology				
	AME	5.0e-06	-0.000028	0.0151
	p	0.106	0.734	0.073
	P25	2.8e-06	-0.0001	0.00915
	P50	4.4e-06	-0.000032	0.0143
	P75	6.4e-06	0.000058	0.0205

Micro- and nanoelectronics			
AME	2.1e-07	3.0e-07	0.0012
p	0.001	0.931	0.002
P25	1.3e-07	-1.6e-06	0.00094
P50	1.9e-07	6.4e-08	0.00110
P75	2.9e-07	2.2e-06	0.00149
Advanced materials			
AME	0.000021	-0.000038	0.0863
p	0.032	0.846	0.000
P25	0.00001	-0.00026	0.0556
P50	0.000017	-0.00013	0.0888
P75	0.000029	0.00016	0.1144
Clean technologies			
AME	0.000047	0.000387	0.11127
p	0.001	0.130	0.000
P25	0.000027	-0.000055	0.0621
P50	0.000048	0.000412	0.0997
P75	0.000068	0.000844	0.1736
Advanced technology untensity			
AME	0.000936	0.0031	0.9599
p	0.000	0.036	0.000
P25	0.000624	-0.000642	0.5069
P50	0.000944	0.003858	0.9344
P75	0.001217	0.008007	1.3826

Note: AME is the average marginal effect estimated by Kernel-Regularized Least Squares (KRLS), p is the prob-value; P25, P50 and P75 are the marginal effects at the 25th, 50th, and 75th percentile estimated by KRLS. All samples include 2,064 firms. For details, see text.

Appendix: Number of Firms by Country

Country	Number of Firms	Percent
Albania	33	1.60
Austria	45	2.18
Belgium	53	2,57
Bulgaria	49	2.37
Canada	63	3.05
Switzerland	57	2.76
Cyprus	26	126
Czech Republic	60	2.91
Germany	78	3.78
Denmark	110	5,33
Estonia	67	3.25
Spain	59	2.86
Finland	83	4.02
France	61	2.96
Great Britain	49	2.37
Greece	62	3.00
Croatia	62	3.00
Hungary	58	2.81
Ireland	49	2.37
Italy	66	3.20
Japan	40	1.94
Lithuania	46	2.23
Luxembourg	24	1.16
Latvia	60	2.91
Montenegro	23	1.11
North Macedonia	31	1.50
Malta	32	1.55
Netherlands	53	2.57
Norway	60	2.91
Poland	56	2.71
Portugal	50	2.42
Romania	56	2.71
Serbia	34	1.65
Sweden	71	3.44
Slovenia	48	2.33
Slovakia	70	3.39
Türkiye	41	1.99
United States	79	3.83
Total	2.064	100.0

Source: Own calculations based on data from Flash Eurobarometer 559

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Leuphana Universität Lüneburg
Institut für Volkswirtschaftslehre
Postfach 2440
D-21314 Lüneburg
Tel.: ++49 4131 677 2321
email: christina.korf@leuphana.de
www.leuphana.de/institute/ivwl/working-papers.html