

Use of Advanced Technologies and Extensive  
Margins of Exports in Manufacturing Firms from 27  
EU Countries in 2025

---

by  
Joachim Wagner

University of Lüneburg  
Working Paper Series in Economics

**No. 438**

January 2026

[www.leuphana.de/institute/ivwl/working-papers.html](http://www.leuphana.de/institute/ivwl/working-papers.html)

ISSN 1860 - 5508

# Use of Advanced Technologies and Extensive Margins of Exports in Manufacturing Firms from 27 EU Countries in 2025 \*

**Joachim Wagner**

Leuphana University Lüneburg, and Kiel Centre for Globalization

**[This version: January 6, 2026]**

## 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.

**JEL classification:** D22, F14

**Keywords:** Advanced technologies, exports, firm level data, 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 Lüneburg  
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.

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 today's 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]

While 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:<sup>1</sup>

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 Carribean; 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 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]

---

<sup>1</sup> 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.

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).<sup>2</sup> 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

---

<sup>2</sup> 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.

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

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

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 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 (see 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.

## References

- Acemoglu, Daron, Claire Lelarge and Pascual Restrepo (2020). Competing with Robots: Firm-Level Evidence from France. *American Economic Review Papers and Proceedings* 110, 383-388.
- Bernard, Andrew B. and J. Bradford Jensen (1995). Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987. *Brookings Papers on Economic Activity: Microeconomics* 67-119.
- Bernard, Andrew B. and J. Bradford Jensen (1999). Exceptional exporter performance: cause, effect, or both? *Journal of International Economics* 47 (1), 1-25.
- Chen, Maggie and Christian Volpe Martincus (2022). Digital Technologies and Globalization: A Survey of Research and Policy Applications. *IDB Inter-American Development Bank Discussion Paper No. IDB-DP-00933*.
- Deng, Liucun, Verena Plümpe and Jens Stegmaier (2024). Robot Adoption at German Plants. *Journal of Economics and Statistics* 244 (3), 201-235.

- DeStefano, Timothy, Richard Kneller and Jonathan Timmis (2025). Cloud Computing and Firm Growth. *Review of Economics and Statistics* 107 (6), 1538-1651.
- Ferencz, Janos, Javier López González and Irene Oliván García (2022). Artificial Intelligence and International Trade: Some Preliminary Implications. *OECD Trade Policy Paper* 260.
- Ferwerda, Jeremy, Jens Hainmueller and Chad J. Hazlett (2017). Kernel-Based Regularized Least Squares in R (KRLS) and Stata (krls). *Journal of Statistical Software* 79 (3), 1-26.
- Hainmueller, Jens and Chad Hazlett (2014). Kernel Regularized Least Squares: Reducing Misspecification Bias with a Flexible and Interpretable Machine Learning Approach. *Political Analysis* 22, 143-168.
- López González, Javier, Silvia Sorescu and Pinar Kaynak (2023). Of Bytes and Trade: Quantifying the Impact of Digitalization on Trade. *OECD Trade Policy Paper* 273.
- Meltzer, Joshua P. (2018). The impact of artificial intelligence on international trade. *Center for Technology Innovation at Brookings*.
- Wagner, Joachim (2007). Exports and Productivity: A survey of the evidence from firm level data. *The World Economy* 30 (1), 5-32.
- Wagner, Joachim (2025). Digitalization Intensity and Extensive Margins of Exports in Manufacturing Firms from 27 EU Countries – Evidence from Kernel-Regularized Least Squares Regression. *Economic Analysis Letters* 4 (1), 22-29.
- Wagner, Joachim (2026). A note on estimation of empirical models for margins of exports with unknown non-linear functional forms: A Kernel-Regularized Least Squares (KRLS) approach. *Journal of Economics and Statistics* (in press).

**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) <sup>1</sup>	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
<hr/>				
Exporter (Dummy; 1 = yes)	0.570	0,495	0	1
Number of Export Destinations	1.307	1.621	0	7
<hr/>				
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 (Dummy; 1 = yes)	0.0295 [0.000]	0.0004 [0.218]	0.000082 [0.001]	0.0721 [0.009]
N of firms	1,587			
Number of Destinations (Index; 1 – 7)	0.0654 [0.001]	0.0048 [0.001]	0.0011 [0.000]	0.2011 [0.101]
N 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 [0.064]	-0.085 [0.390]
Cloud computing (Dummy; 1 = yes) <sup>1</sup>	0.037 [0.093]	0.124 [0.157]
Robotics (Dummy; 1 = yes)	0.079 [0.002]	0.222 [0.017]
Internet of things (Dummy; 1 = yes)	-0.021 [0.386]	0.180 [0.066]
Digital tech. for security (Dummy; 1 = yes)	0.065 [0.004]	0.066 [0.453]
Blockchain (Dummy; 1 = yes)	-0.060 [0.193]	0.047 [0.792]
Biotechnology (Dummy; 1 = yes)	-0.040 [0.334]	-0.033 [0.853]
Micro- and nanoelectronics (Dummy; 1 = yes)	-0.017 [0.687]	0.252 [0.114]
Advanced materials (Dummy; 1 = yes)	0.070 [0.021]	0.007 [0.951]
Clean technologies (Dummy; 1 = yes)	0.039 [0.125]	0.065 [0.503]
Firm size (Number of employees)	0.00005 [0.002]	0.0005 [0.000]
Firm age (years)	0.00045 [0.126]	0.0047 [0.000]
Innovations (Dummy; 1 = yes)	0.051 [0.023]	0.1651 [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

# Working Paper Series in Economics

(recent issues)

---

- No. 437 *Joachim Wagner*: Ten Years Data Observer – A service for empirical researchers in economics , October 2025
- No. 436 *Joachim Wagner*: nep-iaf A new e-mail service to stay up to date with working papers on international activities of firms, October 2025
- No. 435 *Christoph Kleineberg*: The Effect of Price Transparency: Assessment of the German Highway Retail Gasoline Sector, July 2025
- No. 434 *Joachim Wagner*: Firm characteristics and survival in times of COVID 19: First evidence from Kernel Regularized Least Squares regressions, July 2025
- No. 433 *Joachim Wagner*: Firm characteristics of two-way traders: Evidence from Probit vs. Kernel-Regularized Least Squares regressions, May 2025
- No. 432 *Institut für Volkswirtschaftslehre*: Forschungsbericht 2024, January 2025
- No. 431 *Thomas Wein*: Kampf an falschen Fronten - Verbrenner-Aus, Gebäudeenergiegesetz (GEG) oder Brennstoffemissionshandelsgesetz (BEHG)?, December 2024
- No. 430 *Mats Petter Kahl und Thomas Wein*: Existiert Wettbewerb beim Laden von Elektrofahrzeugen in Deutschland?, October 2024
- No. 429 *Joachim Wagner*: Data Observer – A guide to data that can help to inform evidence-based policymaking, April 2024
- No. 428 *Joachim Wagner*: Digitalization Intensity and Extensive Margins of Exports in Manufacturing Firms from 27 EU Countries - Evidence from Kernel-Regularized Least Squares Regression , April 2024
- No. 427 *Joachim Wagner*: Cloud Computing and Extensive Margins of Exports -Evidence for Manufacturing Firms from 27 EU Countries, February 2024
- No. 426 *Joachim Wagner*: Robots and Extensive Margins of Exports - Evidence for Manufacturing Firms from 27 EU Countries, January 2024
- No. 425 *Institut für Volkswirtschaftslehre*: Forschungsbericht 2023, January 2024
- No. 424 *Joachim Wagner*: Estimation of empirical models for margins of exports with unknown non-linear functional forms: A Kernel-Regularized Least Squares (KRLS) approach, January 2024
- No. 423 *Luise Goerges, Tom Lane, Daniele Nosenzo and Silvia Sonderegger*: Equal before the (expressive power of) law?, November 2023
- No. 422 *Joachim Wagner*: Exports and firm survival in times of COVID-19 – Evidence from eight European countries, October 2023
- No. 421 *Joachim Wagner*: Big Data Analytics and Exports – Evidence for Manufacturing Firms from 27 EU Countries, September 2023
- No. 420 *Christian Pfeifer*: Can worker codetermination stabilize democracies? Works councils and satisfaction with democracy in Germany, May 2023

- No. 419 *Mats Petter Kahl*: Was the German fuel discount passed on to consumers?, March 2023
- No. 418 *Nils Braakmann & Boris Hirsch*: Unions as insurance: Employer–worker risk sharing and workers' outcomes during COVID-19, January 2023
- No. 417 *Institut für Volkswirtschaftslehre*: Forschungsbericht 2022, January 2023
- No. 416 *Philipp Lentge*: Second job holding in Germany – a persistent feature?, November 2022
- No. 415 *Joachim Wagner*: Online Channels Sales Premia in Times of COVID-19: First Evidence from Germany, November 2022
- No. 414 *Boris Hirsch, Elke J. Jahn, Alan Manning, and Michael Oberfichtner*: The wage elasticity of recruitment, October 2022
- No. 413 *Lukas Tohoff and Mario Mechtel*: Fading Shooting Stars – The Relative Age Effect, Misallocation of Talent, and Returns to Training in German Elite Youth Soccer, September 2022
- No. 412 *Joachim Wagner*: The first 50 contributions to the Data Observer Series – An overview, May 2022
- No. 411 *Mats Petter Kahl and Thomas Wein*: How to Reach the Land of Cockaigne? Edgeworth Cycle Theory and Why a Gasoline Station is the First to Raise Its Price, April 2022
- No. 410 *Joachim Wagner*: Website premia for extensive margins of international firm activities Evidence for SMEs from 34 countries; April 2022
- No. 409 *Joachim Wagner*: Firm survival and gender of firm owner in times of COVID-19 Evidence from 10 European countries, March 2022
- No. 408 *Boris Hirsch, Philipp Lentge and Claus Schnabel*: Uncovered workers in plants covered by collective bargaining: Who are they and how do they fare?, February 2022
- No. 407 *Lena Dräger, Michael J. Lamla and Damjan Pfajfar*: How to limit the Spillover from the 2021 Inflation Surge to Inflation Expectations?, February 2022
- No. 406 *Institut für Volkswirtschaftslehre*: Forschungsbericht 2021, January 2022
- No. 405 *Leif Jacobs, Lara Quack and Mario Mechtel*: Distributional Effects of Carbon Pricing by Transport Fuel Taxation, December 2021
- No. 404 *Boris Hirsch and Philipp Lentge*: Non-Base Compensation and the Gender Pay Gap, July 2021
- No. 403 *Michael J. Lamla and Dmitri V. Vinogradov*: Is the Word of a Gentleman as Good as His Tweet? Policy communications of the Bank of England, May 2021
- No. 402 *Lena Dräger, Michael J. Lamla and Damjan Pfajfar*: The Hidden Heterogeneity of Inflation and Interest Rate Expectations: The Role of Preferences, May 2021
- No. 401 *Joachim Wagner*: The Good have a Website Evidence on website premia for firms from 18 European countries, April 2021
- No. 400 *Luise Görge*: Of housewives and feminists: Gender norms and intra-household division of labour, April 2021
- No. 399 *Joachim Wagner*: With a little help from my website. Firm survival and web presence in times of COVID-19 – Evidence from 10 European countries, April 2021

- No. 398 *Katja Seidel*: The transition from School to Post-Secondary Education – What factors affect educational decisions?, March 2021
- No. 397 *Institut für Volkswirtschaftslehre*: Forschungsbericht 2020, Januar 2021
- No. 396 *Sabien Dobbelaere, Boris Hirsch, Steffen Mueller and Georg Neuschaeffer*: Organised Labour, Labour Market Imperfections, and Employer Wage Premia, December 2020
- No. 395 *Stjepan Srhoj, Vanja Vitezić and Joachim Wagner*: Export boosting policies and firm behaviour: Review of empirical evidence around the world, November 2020
- No. 394 *Thomas Wein*: Why abandoning the paradise? Stations incentives to reduce gasoline prices at first, August 2020
- No. 393 *Sarah Geschonke and Thomas Wein*: Privacy Paradox –Economic Uncertainty Theory and Legal Consequences, August 2020
- No. 392 *Mats P. Kahl*: Impact of Cross-Border Competition on the German Retail Gasoline Market – German-Polish Border, July 2020
- No. 391 *John P. Weche and Joachim Wagner*: Markups and Concentration in the Context of Digitization: Evidence from German Manufacturing Industries, July 2020
- No. 390 *Thomas Wein*: Cartel behavior and efficient sanctioning by criminal sentences, July 2020
- No. 389 *Christoph Kleineberg*: Market definition of the German retail gasoline industry on highways and those in the immediate vicinity, July 2020
- No. 388 *Institut für Volkswirtschaftslehre*: Forschungsbericht 2019, Januar 2020
- No. 387 *Boris Hirsch, Elke J. Jahn, and Thomas Zwick*: Birds, Birds, Birds: Co-worker Similarity, Workplace Diversity, and Voluntary Turnover, May 2019
- No. 386 *Joachim Wagner*: Transaction data for Germany's exports and imports of goods, May 2019
- No. 385 *Joachim Wagner*: Export Scope and Characteristics of Destination Countries: Evidence from German Transaction Data, May 2019
- No. 384 *Antonia Arsova*: Exchange rate pass-through to import prices in Europe: A panel cointegration approach, February 2019
- No. 383 *Institut für Volkswirtschaftslehre*: Forschungsbericht 2018, January 2019
- No. 382 *Jörg Schwiebert*: A Sample Selection Model for Fractional Response Variables, April 2018
- No. 381 *Jörg Schwiebert*: A Bivariate Fractional Probit Model, April 2018
- No. 380 *Boris Hirsch and Steffen Mueller*: Firm wage premia, industrial relations, and rent sharing in Germany, February 2018
- No. 379 *John P. Weche and Achim Wambach*: The fall and rise of market power in Europe, January 2018
- No.378: *Institut für Volkswirtschaftslehre*: Forschungsbericht 2017, January 2018

(see [www.leuphana.de/institute/ivwl/working-papers.html](http://www.leuphana.de/institute/ivwl/working-papers.html) for a complete list)

Leuphana Universität Lüneburg

Institut für Volkswirtschaftslehre

Postfach 2440

D-21314 Lüneburg

Tel.: ++49 4131 677 2321

email: [christina.korf@leuphana.de](mailto:christina.korf@leuphana.de)

[www.leuphana.de/institute/ivwl/working-papers.html](http://www.leuphana.de/institute/ivwl/working-papers.html)