ASSESSING THE DRIVING FACTORS OF BUSINESS PROFITABILITY IN EUROPEAN HIGH-TECH VERSUS LOW-TECH INDUSTRIES

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Abstract
Our paper proposes a new approach for the study of high-tech versus low-tech industries to investigate the most important industry and country-based determinants that explain their performance. We cover the 2010-2017 period based on data availability and the deliberate exclusion of the turbulent years of the Global financial crisis. We include in our research twelve EU member states that, collectively, hold shares between 65 and 85% in the turnover recorded in the selected EU industries. Profitability is described in our study by business profitability, measured through the Gross operating rate (the ratio between gross operating profit and turnover). Also, we use a set of independent variables split into nine industry variables and eight country variables. The methodology we use is a machine-learning-based Random forests regression, which generates several trees, followed by an aggregation of their results, and combines random sample selection and feature selection. Labor productivity, the share of value in total turnover, and the number of persons employed are the highest influencers of business profitability for all industries, but our results indicate significant differences in terms of both industry and country-related variables for what concerns business profitability across the selected industries, but they are, in general, in line with our expectations of profitability drivers. For industries with higher technological intensity industry characteristics are more important than country characteristics, while for low technology industries the reverse applies. FDI intensity is more important for profitability in higher technologically intensive industries than in lower technologically intensive industries. These differences point towards a better view on the specificities of business performance so that improved policies aiming at enterprise support may be designed. This is even more needed given the current health and economic crisis.

Keywords
High-tech industries; competitiveness; performance; European Union; industry versus country factors.

Introduction

The Lisbon Strategy launched in 2000 has announced the European Union's commitment to becoming, by 2010, the most dynamic and competitive knowledge-based economy in the world. The concept of the knowledge economy that encompasses aspects of the economy where knowledge in the core of the value-added chain, has been further carried on through the Europe 2020 Strategy. The latter strategy targets an increase in R&D (Research and development) investments to a share of 3% of GDP by 2020. In this general framework, the European Union has focused on programs and policies that directly enhance the importance of high-tech industries in the EU GDP, such as the digitalization of the economy or research and development programs. R&D investments are seen as a major economic growth and competitiveness driver and able to foster high levels of productivity, that have the potential to turn into high value-added outputs and increased wages.

The European Union uses a taxonomy of industries depending on their degree of technological intensity – based on their R&D expenditure per unit of value-added - and distributes them into four main categories, i.e. high-technology, medium high-technology, medium low-technology, and low-technology industries. Figure 1 displays an overview of the size of the four technology levels in the value added at factor costs of total manufacturing for the EU-27 in 2010.

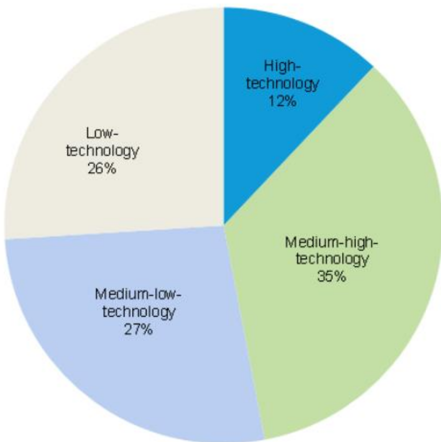


Figure 1. Share of different technology levels in total manufacturing, value added at factor costs, EU27, 2010

Data source: Statistics Explained - Eurostat

In 2016, the EU had almost 48,000 enterprises in the high-tech manufacturing sector (0.2 % of the total number of enterprises), which generated a turnover of EUR 724 billion (2.6 % of total turnover in the EU) and a value-added of EUR 200 billion (2.8 % of total value added in the EU), according to Eurostat data.

In this light, our paper proposes a new approach for the study of high-tech industries to investigate the most important industry and country-based determinants that explain their performance.

Our paper is structured as follows. The following section offers insights into the research directions and results in the existing literature. The next section describes the data and methodology used. Then, the following section outlines the most relevant results and the last section concludes and indicates directions for future research.

Literature review

Competitiveness and performance

The empirical literature on companies' performance and competitiveness is concentrated at the microeconomic level, in a firm-specific characteristics framework that explains performance. Nevertheless, the ever-expanding digital economy necessitates an integration of business idiosyncrasies in terms of industry and location in the interpretation of differences in competitiveness across companies and industries. Moreover, competitiveness has been intensively used in the last decades in conjunction with the economic performance of industries or countries. Thus, an increasingly interdependent, globalizing economic environment has heightened the interest of analysts and policymakers in the international competitiveness of companies, industries, or countries.

Many studies examine the influence of competition on industries' and companies' performance, but the results are rather mixed. Some authors found negative relationships between company performance and industry competition (Ghosal, 2002; Slade, 2004; Peress, 2010; Beiner et al., 2009). Other authors discovered a positive impact of industry competition on companies' performance (Mitton, 2004; Bozec, 2005; Karuna, 2007; Irvine & Pontiff, 2009; Giroud & Mueller, 2010; Wang et al., 2014). Wang et al. (2014) examined how firm performance is modified in accordance to industry's intensity of competition under agency problems in the US, UK, Germany, and France and found that higher competition level is positively correlated with better operating performance.

The traditional framework of business performance was supplemented with some contributions that suggest ownership type, i.e. foreign or domestic, as an explanatory factor explaining business performance. For example, Bobenič, Hintošová, and Kubíková (2016) found that a higher involvement of foreign ownership tends to improve companies' performance in Slovakia. From another point of view, Barbosa and Louri (2005) show that foreign ownership does not produce a significant difference in performance for companies in Portugal and Greece. Moreover, Horobet (2018) examines the competitiveness of foreign- and locally-owned companies in eleven Central and Eastern European countries and discovers that depending on the country and indicators used, the dissimilarities are not always in favor of foreign-owned companies.

High-tech versus low-tech industries

Most studies that investigate the differences between companies from high- and low-tech industries analyze them in relation to the number and type of innovations generated or how companies manage the process of commercialization. For instance, Covin and Prescott (1990) discovered that low-tech product innovators differed from their high-tech counterparts in the matter of structure, market orientation, or need for external financing. Later on, Raymond and St-Pierre (2010) indicate that high-tech companies' higher investment propensity into product R&D, and low-tech companies' higher investments in the R&D process, may not be a good approach to innovation for SMEs. More recently, Reboud et al. (2014) concentrated on companies that have both high and low levels of innovation intensity to investigate the nature of innovation within SMEs from Australia and France. Their results indicate that SMEs which may not be officially considered high-tech companies can be vigorously interested in innovation commercialization practices.

Concerning driving factors of performance in companies from high- and low-tech industries, there are only a few studies on this subject, to the best of our knowledge. For example, Hamilton et al. (2002) examined whether the growth of Canadian high-tech companies is constant across size or related to business demographic factors (size, age, and legal or ownership status). They proved there is no evidence in favor of higher growth induced by foreign ownership. Another example belongs to Cozza et al. (2012) who investigated the impact of product innovation on the economic performance of Italian companies from medium- and high-tech industries. They discovered significant differences between innovative and non-innovative companies in the matter of profitability and growth rates. More specifically, they found that the differences in the matter of profitability are notable when taking into consideration micro- and small-sized companies, while these differences seem to fade in the case of medium and large firms. Later on, Reichert and Zawislak (2014) examined the relationship between technological capability and firm performance using data of 133 Brazilian companies. They found that industries of lower technology intensity do not require investments in technological capability to achieve superior economic performance. Moreover, Hirsch-Kreinsen (2008) suggested that the productivity of the LMT sector is in reliance on high-tech innovations, but at the same time, the innovative competence of the high-tech sector relies on their narrow relationship with LMT industries. In other words, the performance of these two sectors is inextricably linked.

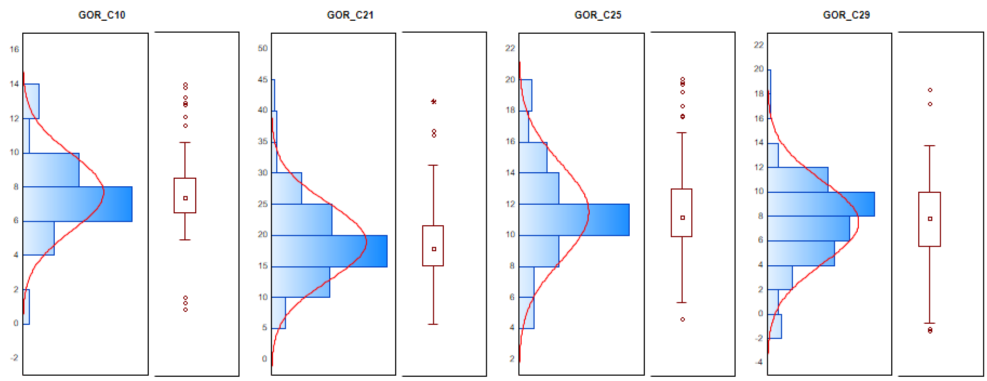
Data and research methodology

Our paper's objective refers to the driving factors of business profitability in the EU depending on the industries' level of technological intensity by highlighting the similarities and differences between lower versus higher technologically intensive industries. Four industries from the manufacturing sector have been selected, according to the EU High-tech classification of manufacturing industries based on NACE Rev.2 2-digit codes[1]: High-tech - C21 (Manufacture of basic pharmaceutical products and pharmaceutical preparations); Medium-high-technology manufacturing - C29 (Manufacture of motor vehicles, trailers, and semi-trailers); Medium-low-technology - C25 (Manufacture of fabricated metal products, except machinery and equipment); Low-technology - C10 (Manufacture of food products).

[1] Available online at https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries.

Business profitability is measured by Gross Operating Rate (GOR), computed as the ratio between gross operating profit and turnover, which is our dependent variable. Figure 2 presents the frequency distribution of GOR values across years and countries, as well as the corresponding boxplots and descriptive statistics. GOR varies widely across the four industries – C21 has the highest mean and median (18.84% and 17.90%, respectively), followed by C25 (11.44% and 11.15%). C29 and C10 have similar GORs, but significantly lower than the other two industries. The mean GORs are statistically different between industries, except for C10 against C29. GOR varies across years and countries for each industry – C21 displays the highest standard deviation and C10 shows the lowest. Skewness values indicate the positive asymmetry of GOR, except for C29.

The set of independent variables is split into nine industry variables and eight country variables – see Table 1. We also mention in the table the significance of variables for our research.



Industry	No. obs.	Mean	Median	Min	Max	SD	Skewness
C10	108	7.63	7.35	0.90	14.00	2.23	0.44
C21	106	18.84	17.90	5.80	41.50	6.16	0.90
C25	108	11.44	11.15	4.70	20.00	3.09	0.55
C29	108	7.46	7.85	-1.30	18.30	3.36	-0.08

Note: The center of the boxplot whisker indicates the mean, the whisker shows the non-outlier minimum and maximum values, the outside-whisker points are outliers.

Figure 2. Frequency distributions, boxplots, and descriptive statistics of GOR, 2011-2017
(Authors' work)

The period covered is 2010-2017, excluding the years of the global financial crisis. Our sample, based on data availability from Eurostat, includes 12 EU member countries (at end of 2017): Austria, Czech Republic, France, Germany, Hungary, Italy, Netherlands, Poland, Portugal, Romania, Spain, and the United Kingdom. The number of observations for each variable varies between 61 and 108 (the lowest number is for EXPINT). Collectively, these countries held between 65-85% in the selected industries' turnover at the EU level in 2017 – see Table 2. A quick look at Table 2 shows that C29 generates the highest turnover, followed by C10, but the high-tech industry (C21) has the highest share of value-added in turnover (36.04%), closely followed by C25 (35.67%).

Tables 3 and 4 present a brief statistical description of the industry dependent variables. C29 is the industry with the highest turnover per enterprise, turnover growth rate, number of persons employed per enterprise, and investment rate, but the lowest value-added share in turnover. C21 enjoys the highest wage-adjusted labor productivity and value-added share in turnover, but also the lowest investment rate. C25 has the highest dependence on the labor force, as it records the highest value of personnel costs share in turnover. C25 is also the industry with the smallest average company size, turnover growth rate, and labor productivity. C10 has the lowest share of personnel costs in turnover.

Table 1. Description of variables (Authors' work)

Variable	***Significance***	***Acronym***	***Measurement***
Industry variables[1]			
Turnover per enterprise	Size	TURNENT	Mil. EUR
Turnover growth rate year on year	Growth	TURNGR	%
Persons employed per enterprise	Size and labor force dependence	PEENT	number
Personnel costs share in turnover	Labor force dependence	PCOST_TURN	%
Wage-adjusted labor productivity	Labor productivity	WALP	%
Investment rate	Investment intensity	INVR	%
Value-added share in turnover	Value-added creation	VA_TURN	%
Foreign direct investments intensity[2]	International exposure	FDI	%
Export intensity[3]	International exposure	EXPINT	%
Country variables			
Gross domestic product per capita	Development level	GDPC	EUR
Growth of GDP per capita[4]	Economic growth	GDPCGR	%
Trade openness[5]	Economy's international exposure	TRADEOP	%
Population with tertiary education	Education level	TERTED%	%
Research and development costs paid by businesses per inhabitant	R&D intensity	RDBCAP	EUR
Percentage of households with an Internet connection	Access to Internet	INT_H	%
Percentage of enterprises with an Internet connection	Access to Internet	INT_BUS	%
Real effective exchange rate	Price competitiveness	REER	Index

Note: 1. Variables' definitions are available at https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Category:Structural_business_statistics_glossary. 2. FDI intensity is the ratio between turnover generated by foreign-controlled enterprises and turnover generated by locally-controlled enterprises in the industry. 3. Share of exports in industry turnover. 4. Compound annual growth rate (CAGR) between 2010 and 2017. 5. Ratio of exports and imports value to GDP.

Table 2. Brief description of selected industries, 2017 (Eurostat)

Industry	Turnover (mil. EUR)	Share in the manufacturing sector. Turnover at the EU level (%)	Value-added at factor cost (mil. EUR)	Share in the manufacturing sector. Value-added at the EU level (%)
C21	284,210.0	3.58	102,420.5	5.07
C29	1,144,502.4	14.43	217,821.0	10.78
C25	516,229.17	6.51	184,136.1	9.12
C10	1,030,000.0	12.99	199,000	9.85

Table 4 shows the descriptive statistics of the two variables that describe industries' international exposure: FDI and export intensity. Foreign investors are more prevalent in C29 (the mean ratio between the turnover generated by foreign-controlled companies to the locally-controlled companies' turnover is 8.72), and least prevalent in C25 and C10 (locally-controlled companies generate on average and overall a significantly higher turnover compared to foreign-controlled companies). C21 and C29 are the most export-intensive industries (the mean ratios of exports to turnover are 0.62 and 0.57, respectively), while C25 and C10 show export intensity ratios at almost a third of the values for C21 and C29.

The macroeconomic or country variables used in our research are statistically presented in Table 5. The average annual GDP per capita for the countries included in the sample is 24,201.39 EUR, but varying between 6,150 EUR and 43,090 EUR, and has enjoyed an annual average growth rate (as CAGR) of 2% (within the -15%-13% range). Our countries have rather high trade openness ratios (mean of 92.83%), and an average of 22.91% of their populations has graduated tertiary education. Businesses from these countries spend an average of 289.39 EUR per inhabitant per year for R&D, and households and businesses have good access to broadband internet (on average, almost 71% of households and 90% of businesses enjoy access). REER shows a mean value of below 100, which indicates that these countries' currencies have increased their exchange rate related to price-based competitiveness against their trading partners during the investigated period.

The methodology used is a machine-learning-based random forest (RF) regression, an algorithm introduced by Breiman (2001), which consists of an ensemble of decision trees that form a forest. Put in a simpler way, RF builds decision trees and merge them together to create a more accurate and stable estimation (or prediction) of the dependent variable based on a set of independent variables. The algorithm starts at a root node containing all observations and splits the data into child nodes whose structure looks like an upside-down tree. This method combines random sample selection (bagging) and random feature selection where the former involves the repeated sampling of observations with replacement as a way to construct the trees. In our case, 30% of the sample represents the out-of-bag sample (which tests for the accuracy of the model) while the training sample represents the rest (70%). We have estimated a number of 100 trees for each industry and used a 5% decrease in training error as a stopping condition of the algorithm. All variables have been standardized before introduced in the algorithm.

Table 3. Descriptive statistics of 7 industry variables, 2010-2017 (Authors' work)

Variable	Industry	Mean	Median	Min	Max	SD
TURNENT	C10	4.52	2.74	0.85	14.14	4.00
	C21	38.37	36.68	4.43	178.79	29.71
	C25	1.45	1.02	0.24	4.12	1.09
	C29	40.49	28.67	6.16	201.42	37.96
TURNGR	C10	0.02*	0.02	-0.16	0.19	0.06
	C21	0.01*	0.015	-0.59	0.24	0.10
	C25	0.01*	0.02	-0.32	0.22	0.11
	C29	0.11*	0.07	-0.33	4.48	0.45
PEENT	C10	21.19	20.10	0.00	59.67	12.52
	C21	122.52	113.39	45.83	384.89	61.74
	C25	11.15	9.39	0.00	22.14	5.19
	C29	129.78	108.88	24.22	394.64	94.07
WALP	C10	161.07	156.40	106.60	202.90	23.44
	C21	219.88	211.65	130.60	412.30	47.04
	C25	143.66	139.90	119.20	211.00	18.78
	C29	175.12	164.30	93.40	295.10	43.99
PCOST_TURN	C10	0.11*	0.11	0.08	0.17	0.02
	C21	0.16*	0.15	0.11	0.24	0.03
	C25	0.22*	0.22	0.14	0.29	0.04
	C29	0.11*	0.11	0.06	0.17	0.02
INVRATE	C10	20.29	17.90	9.30	57.60	8.47
	C21	13.78	12.60	0.00	29.40	5.53
	C25	15.67	13.10	5.70	39.80	7.56
	C29	24.35	20.90	6.40	102.50	13.61
VA_TURN	C10	0.19*	0.18	0.11	0.28	0.03
	C21	0.39	38.85	24.30	56.40	6.32
	C25	0.33*	0.33	0.23	0.45	0.04
	C29	0.18*	0.18	0.12	0.29	0.03

Note: * - the mean is statistically significant at 95% confidence level.

Table 4. Descriptive statistics of international exposure industry variables, 2010-2017 (Authors' work)

Variable	Industry	Mean	Median	Min	Max	SD
FDI	C10	0.41*	0.38	0.11	0.96	0.23
	C21	2.45	1.50	0.42	7.70	2.15
	C25	0.37*	0.29	0.08	0.94	0.24
	C29	8.72	6.69	0.16	33.62	8.65
EXPINT	C10	0.21*	0.19	0.08	0.39	0.09
	C21	0.62*	0.56	0.30	1.40	0.25
	C25	0.35*	0.36	0.11	0.61	0.13
	C29	0.57*	0.68	0.00	0.87	0.22

Note: * - the mean is statistically significant at 95% confidence level.

The advantage of using RF relies on its easy measurement of the relative importance of each independent variable in the prediction/estimation of the dependent variable. Thus, the features which do not add value to the prediction can be easily eliminated; this idea is crucial in estimating random forest models as the more variables are introduced the more prone is the model to be overfitted.

Table 5. Descriptive statistics of country variables, 2010-2017 (Authors' work)

Variable	Mean	Median	Min	Max	SD
GDPC	24201.39	25720.00	6150.00	43090.00	11392.62
GDPCGR	0.02*	0.02	-0.15	0.13	0.05
TRADEOP	92.83	82.70	45.40	168.50	37.21
TERTED%	22.91	22.00	11.20	38.70	7.06
RDBCAP	289.39	176.10	8.50	934.70	248.62
INT_H	70.86	73.50	23.00	98.00	14.77
INT_BUS	89.75	93.00	41.00	100.00	10.38
REER	98.73	98.95	90.52	116.15	3.80

Note: * - the mean is statistically significant at 95% confidence level.

RF models have been used in the prediction of credit risk (Khandani et al., 2010), employee turnover (Gao et al., 2019), in the classification of neuroimaging data in Alzheimer's disease (Sarica et al, 2017), in the outcome prediction in antibody incompatible kidney transplantation (Shaikhina et al., 2019), in the modeling of travel mode choice behavior (Cheng et al., 2019), and many other works.

In our research, RF regression uses GOR as a dependent variable and the 17 industry and country variables as independent variables. Initially, we have tested the regression by including more variables, we have excluded the ones displaying high correlations. The reported results show the most robust outcomes. Data processing and random forest estimates were performed in Tibco Statistica 13.3.

Results

As in any prediction, there is an amount of uncertainty inherent in performing it. Table 6 shows the risk estimates for the four RF algorithms implemented, one for each industry, calculated as a residual variance. These risk estimates are associated with the prediction of the dependent variable by the set of independent variables, and also to the train versus test samples used to perform the estimation. The values show that the model was most accurate for C25 and C21, but is performed the best for C29 and C21.

Table 6. Risk estimates (Authors' work)

	C10		C21		C25		C29	
	Risk estimate	SE	Risk estimate	SE	Risk estimate	SE	Risk estimate	SE
Train	0.501	0.120	0.402	0.135	0.533	0.091	0.221	0.069
Test	0.426	0.330	0.424	0.250	0.322	0.100	0.500	0.381

Note: SE – standard error.

The most important results delivered by the RF algorithm refer to the independent variables' importance for explaining the dependent variable. Figure 3 and Table 7 present these results. Table 7 reports the importance obtained by each independent variable, as well as an average of variable importance for all four industries, to highlight variables' importance in terms of influencing GOR. Averages of importance are calculated separately for industry and country variables, as well as for international exposure variables. In interpreting them, we are interested in seizing differences between the four industries that are related to their degree of technological intensity, and in particular in differences between industry versus country variables importance.

WALP is, by far, the most important independent variable that explains industry profitability for all four industries. In second place is VA_TURN (importance varying from 0.850 for C29 to 0.593 for C25, and an overall average across industries of 0.779). Other variables with high importance (above 0.50) are PEENT (C10 and C25), TERTED% (C25), FDI (C25 and C29), TURNENT (C10), and EXPINT (C25). The highest influence on profitability, regardless of industries' technological intensity, is the wage-adjusted labor productivity, followed by the share of value-added in total turnover. Still, the number of persons employed is a highly ranked variable only for C10 and C25 (an LT industry and an MLT industry). Turnover per enterprise is also highly influential for C25, as well as export intensity, although the mean share of exports in industry turnover for C25 is only 0.346, lower than the value for C21 or C29. FDI intensity is ranked second as the importance for C25 and third for C29, suggesting the high relevance of foreign-controlled enterprises in these industries.

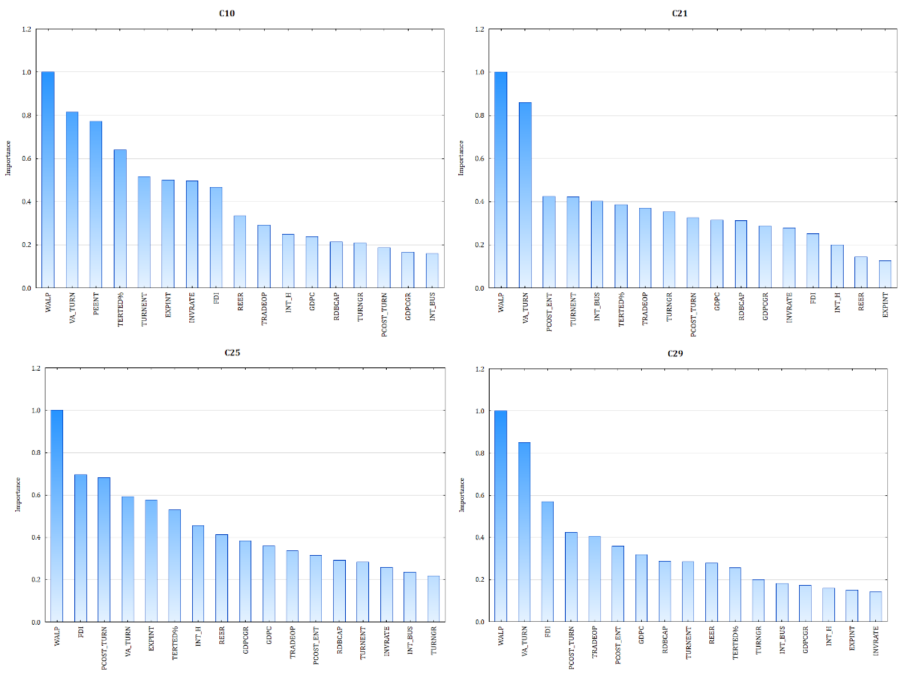


Figure 3. Plots of variable importance
(Authors' work)

Among the last variables as importance are several industry variables – turnover growth rate (C10, C25), investment rate (C25, C29), and export intensity (C21, C29) – and country variables - households or businesses access to the internet (all industries), GDP growth rate (C10), and REER (C21). Averaging variables' importance for all four industries, WALP, VA_TURN, and PEENT are ranked the highest, while INT_BUS, TURNGR, and GDPGR are ranked the lowest.

Of the industry variables, the highest-ranked are WALP, VA_TURN, PEENT, and FDI, and the lowest-ranked are TURNGR, INVRATE, and PCOST_TURN. The most important country variables are TERTED%, TRADEOP and GDPC, and the least important are INT_BUS, INT_H, and GDPGR. As an average importance, industry and country variables have close values, but with differences among the four industries; industry variables have higher average importance compared to country variables for C21, C25, and C29, but not for C10. This indicates that industry characteristics are more important for industry profitability than country variables for industries with higher technological intensity (as suggested also by Cozza et al., 2012), while locational or country characteristics seem to be more important for low technology industries (as suggested also by Reichert and Zawislak, 2014). At the same time, international exposure variables have higher average importance than all industry variables only for C10 and C25, suggesting the more significant contribution that FDI presence and export activity have for these industries' profitability. FDI intensity is more important for profitability in higher technologically intensive industries (C21 and C29), compared to industries with lower technological intensity.

Table 7. Variables importance for the 4 industries (Authors' work)

Variable	C10	C21	C25	C29	Average importance across industries
WALP	1.000	1.000	1.000	1.000	1.000
VA_TURN	0.815	0.859	0.593	0.850	0.779
PEENT	0.773	0.326	0.683	0.424	0.552
FDI	0.639	0.386	0.530	0.257	0.453
TERTED%	0.517	0.421	0.284	0.286	0.377
TURNENT	0.500	0.127	0.577	0.152	0.339
TRADEOP	0.496	0.278	0.259	0.141	0.293
EXPINT	0.467	0.252	0.695	0.570	0.496
PCOST_TURN	0.335	0.145	0.413	0.278	0.293
GDPC	0.293	0.371	0.337	0.406	0.352
INVRATE	0.248	0.200	0.456	0.159	0.266
REER	0.239	0.315	0.360	0.318	0.308
RDBCAP	0.214	0.311	0.292	0.288	0.276
INT_H	0.210	0.353	0.218	0.199	0.245
GDPCGR	0.187	0.424	0.314	0.360	0.321
TURNGR	0.167	0.288	0.384	0.174	0.253
INT_BUS	0.161	0.401	0.235	0.182	0.245
Average of industry variables	0.426	0.444	0.457	0.417	0.436
Average of international exposure variables	0.483	0.189	0.636	0.361	0.417
Average of country variables	0.453	0.322	0.438	0.304	0.379

The higher importance of VA_TURN, TURNGR, and PCOST_TURN for the HT industry (C21) suggests that the higher value-added incorporated in this industry's products, the turnover growth rate, and the share of personnel costs in turnover are important influencers of profitability. The same is true for several country variables (TRADEOP, GDPC, RDBCAP, GDPGR, and INT_BUS), indicating that for an HT industry the development level of the host country and economic growth, coupled with internet access, investments in R&D, and country's openness towards international trade are important driving factors behind profitability compared to an LT industry.

Figure 4 shows the average performance of our RF algorithm in terms of predicting the dependent variable. As it can be easily observed, the model does not significantly underestimate or overestimate the dependent variable, which suggests that our results are robust.

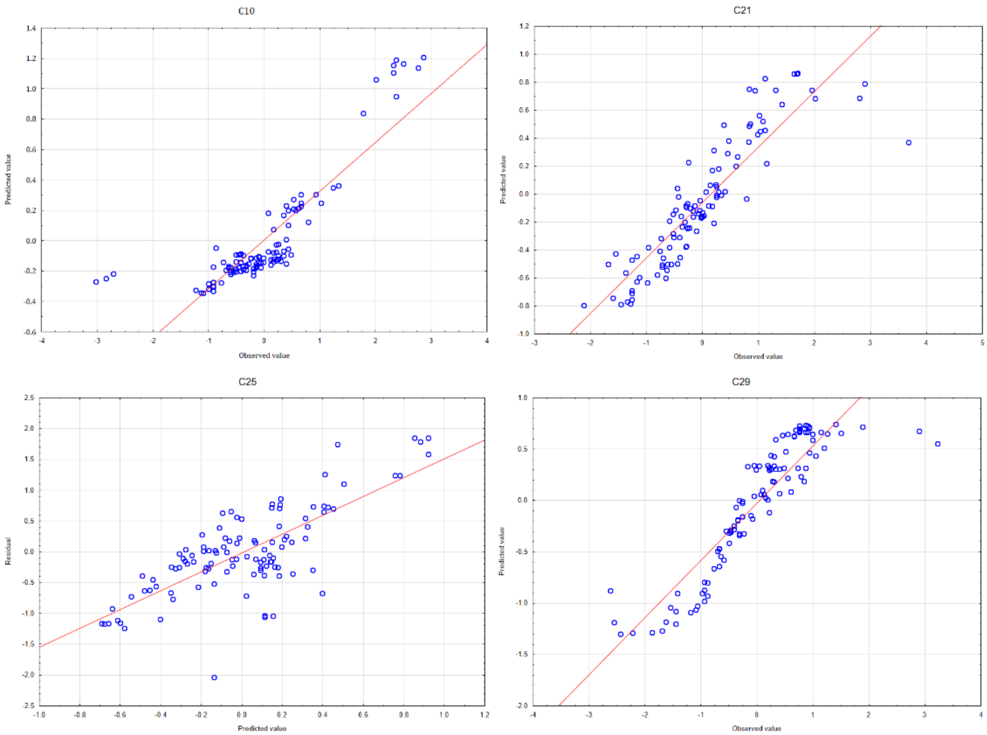


Figure 4. Predicted versus observed values
(Authors' work)

The same robustness of our results is indicated in Figure 5 that shows the normal probability of residuals. The shapes of the plots suggest clearly that the model performs well since the resulting residuals (differences between predicted and observed values of GOR) are correctly arranged around the trend line.

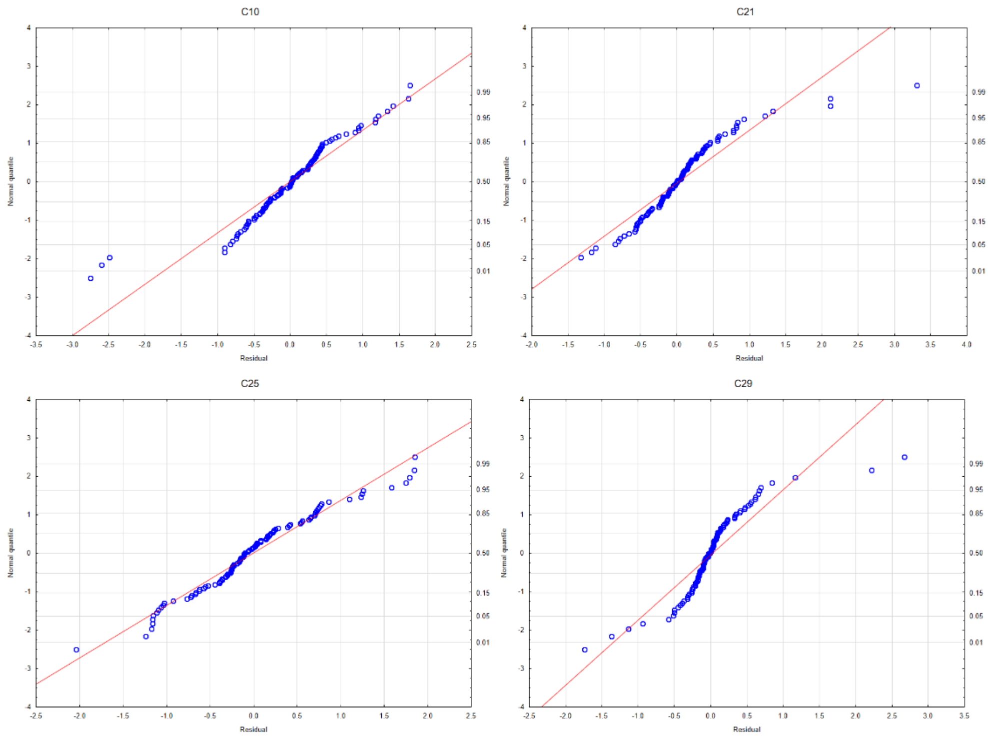


Figure 5. Normal probability plots of residuals
(Authors' work)

Conclusions

We uncover the most important industry and country or locational factors that drive profitability for EU companies in industries with different levels of technological 2010-2017 intensity between 2010 and 2017, using an innovative machine-learning-based RF regression. The variables with the highest influence on profitability for all industries is the wage-adjusted labor productivity, followed by the share of value in total turnover and the number of persons employed. For industries with higher technological intensity industry characteristics are more important than country characteristics, while for low technology industries the reverse applies. As expected, FDI intensity is more important for profitability in higher technologically intensive industries than in lower technologically intensive industries. Last but not least, our results suggest that that for an HT industry the development level of the host country and the economic growth, the internet access, the R&D investments, the country's openness towards international trade, the higher value-added incorporated in the industry's products, the turnover growth rate and the share of personnel costs in turnover are important driving factors behind profitability as compared to an LT industry. Our results bring about a better understanding of the characteristics of business performance depending on industries within EU industries with different technological level so that improved and custom policies aiming at enterprise support may be designed. Taking into account the current coronavirus pandemic caused health and economic crisis this is highly valuable as an instrument for counteracting the effects of the crisis.

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