

# Digitalization and Productivity: Evidence from EU Manufacturing Sector

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## ABSTRACT

Manufacturing sector productivity is one of main driver for economy grow in Europe. In the context of manufacturing sector digitalization, importance of influencing factors for productivity increase plays a key role. This paper aims to evaluate digitalization impact on EU manufacturing sector productivity, considering variables as relative size measures for the period of 2012-2020. There are strong believe that digitalization is an engine of innovation and competitiveness in manufacturing sector. Changing processes and integration of digital technologies leads manufacturing sector towards productivity increase. We perform OLS regression on sample of 5013 records covering 27 EU countries and 642 manufacturing firms over the years 2012-2020. Analysis consists of such factors as operating revenue, number of employees per company, tangible fixed assets, intangible fixed assets, profit and loss, investment to digitalization. We study ratio of digital investment to total assets as dependent variable to understand how investment decision of company can be evaluated with independent variables, identified in literature review. We build 3 models for regression analysis. Highest value of R-Square calculated for operating revenue as dependent variable is 0.299 and significance level is sufficient. Our results indicate that R-Square is 0.366 for relationship between digital investment and independent variables in analysis. Moreover, intangible assets impact is not significant considering digital investment outlay, which contradict believe stated in literature for direct intangible impact on digitalization. The main variable is number of employees per company with identified significant negative route.

**Keywords:** digital investment, European union, impact measurement, manufacturing industry, productivity

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## 1. Introduction

Digitalization is a key performance development tool for all firms (Nasiri et al., 2020). Digitalization itself refers to upgrading production processes, integrating robotics, smart production systems and other digital technologies (Horvat et al., 2019, Horvat et al., 2018, Hsu & Spohrer, 2009). Such variety of technology used at company level place an empirical challenge to assess impact of digitalization for firm performance and productivity.

Only few research papers focus on the impact of digitalization on productivity, and those that do, mainly concern specific digital technology (Cette et al., 2021) or have very narrow exclusive set of data. Horvat et al. (2019) investigated impact of automation and digitalization on manufacturing companies labour productivity in early stage of Industry 4. In their work they document statistically significant and positive impact on labour productivity. However, data used in study represents only German Manufacturing survey in year 2012. Cette et al. (2021) investigated impact of information communication technology (ICT) and digitalization on total factor and labour productivity. Their find out that the employment of ICT specialists and the use of digital technologies improves firms labour productivity by 23%

and its total factor productivity by about 17%. Their conclusions come from analysis of 1065 French firms in 2018.

Digitalization is often seen as the potential source of huge productivity increase, hence over the last decade productivity growth declined in most countries, regardless of its distance to technological frontier (Cette et al., 2021). Despite of continuously increasing investment to digitalization, productivity growth show no notable increase (Gebauer et al., 2020, Kohtamaki et al., 2020, Pinsonneault & Rivard, 1998). Digitalization paradox raise several questions that makes this study even more important and complementary on providing empirical insights.

Nevertheless, manufacturing sector at European Union accounts for 15% of European GDP and provides about 33 million jobs. It generates almost two-thirds of total factor productivity growth in EU (Euraxess, 2020). Technological advances have driven increases in manufacturing sector productivity (Rüßmann et al., 2015). On 2018 McKinsey reported that considering world outlay, only one-third of firms had positive and sustainable effect because of digitalization. Considering the fact that digitalization changes the ways companies operate (Volkova & Romanyuk, 2020), those players who are unable to overcome digitalization challenges have increased uncertainty for future prospects (Jantunen et al., 2018). Considering this background, understanding which factors increase or limits relationship between digitalization and firms' performance is critical for academic and empirical knowledge (Li et al., 2022).

There are several studies examining digitalization impact on firm performance. Cheng, Ho and Huang (2022) findings show that digitalization increases profitability in manufacturing firms by improving the efficiency of asset utilization. Chen and Srinivasan (2022) defined positive relation between asset turnover ratio and digitalization considering U.S. firm data. Lyu and Liu (2021) proved for energy sector positive advantage of digital technologies considering 2010- 2019 data of U.S. Our study contributes to this literature by providing insight how digitalization impact company performance and which factors should be considered as key drivers being affected by digitalization. Our study consists of such company level factors as operating revenue, number of employees per company, tangible fixed assets, intangible fixed assets, profit and loss, investment to digitalization. Company performance in our study is expressed as operating revenue variable. We target to overcome limited data and specific technology in consideration research challenge. We consider whole digital investment of the company done in year, without elimination of specific investment to technology type. In this study we exploit European Union (EU) Manufacturing Sector data from period 2013-2020 to define relation between digitalization and labour productivity.

The remaining section of this paper is structured as follows. In Section 2 we present Literature Review and Method. In Section 3 we discuss Empirical Results and Section 4 present Conclusion.

## **2. Literature Review**

This section covers the existing literature available on studies for digitalization impact for company performance and labour productivity. The first part focuses on methods to measure digitalization and labour productivity, second part discuss limitations for the study, method, and variables in use.

### **2.1. Measuring Digitalization Impact on Company Performance**

Creating and sharing knowledge are mechanisms through which digitalization can improve firm performance (Li et al., 2022). First of all, manufacturing firms pursue profitability growth through digitalization process (Abou-foul et al., 2021). Integrated digital technologies to

firms' operation processes can smooth information flow to make fast and data-based decisions (Bresciani et al., 2021). For example, big data analytic deliver high value in decision-making process because data contains in depth information (Khanra et al., 2020). Data can be collected not only from production process, but also from consumer, supply chain players and other involved parties for knowledge-based decision making. So second main argument is that application of digital technologies, such as cloud computing, can help to collect data across whole supply chain (Bresciani et al., 2021). It also helps involved parties be in closer relationships and get information just in time for ongoing changes (Ferraris et al., 2018). McKinsey (2020) reports that firms that use digital supply chain systems have 4.9% growth in EBIT, up to 10% lower operational expenses, and up to 10% higher revenue than firms without digitalization in supply chain.

However current body of research work provides contraindicative results on digitalization impact for firm performance. For example, Cheng, Ho and Huang (2022) develop measure of digitalization using firm performance dataset, which covers manufacturing and service companies. Their findings show that digitalization increases profitability in manufacturing firms by improving the efficiency of asset utilization but have no effect for service companies.

Furthermore, Sanchez-Riofrio et al. (2021) found that firms' adoption of digital technologies (i.e., digitalization) enhances transaction efficiency and improves firm performance. In research work variables in use are return on investment, gross profit, net margin. Chen and Srinivasan (2022) defined positive relation between asset turnover ratio and digitalization considering U.S. firm data. However, they have no effect on return on assets. Lyu and Liu (2021) proved for energy sector positive advantage of digital technologies (i.e., Artificial Intelligence, Big data, Internet of Things, Robotics, Blockchain technology, and Cloud computing) considering 2010-2019 data of U.S. Main research limitation is only one variable used to represent firm performance, which is revenue per work, there are no other firm performance data variables under consideration. Based on research findings mentioned, we formulate hypothesis as follows:

### *Hypothesis 1: Digitalization Has Positive Impact on Firm Performance*

Our work focus on manufacturing industry digitalization in EU. We take digital investment as a value to represent digitalization maturity at firm level in manufacturing sector. Nowadays, competitive manufacturing sector environment challenges acceleration of technological progress, force companies become more adaptive of technology and remain competitive (Porter & Heppelmann, 2015; Khan & Turowski, 2016). Considering competitive manufacturing sector environment, we assume that all investments in manufacturing companies are linked to the origins of digitalization. Digital Investment calculation formula is presented in methodology section.

## **2.2. Measuring Digitalization Impact on Labor Productivity**

Productivity represents relationship in production between inputs and outputs. The most common measures of productivity usually used in research work are labor productivity or output per person employed or per hour work (Dunn & Weidman, 2015; Horvat et al., 2018). In our work we use labor productivity as it focusses on efficiency using human resource in companies (Varlamova, & Larionova, 2020). Labor productivity is easy to understand and estimate. Other things being equal, labor productivity will increase with capital intensity. Furthermore, changes in output per employed person can be seen as the outcome of production, employment, and capital investment decisions (Mahmood, 2008).

Labor productivity indicator is most important in assessing the efficiency as it reflects how rationally businesses using its labour resources and indirectly signals how modern technologies it has, how intelligently it conducts businesses (Volkova & Romanvuk, 2020). As our research focus on manufacturing sector players, in our work labour productivity is represented as operating revenue and number of employees in the company. It fits to standard formula expression, where operating revenue is divided into employee number. In our work we check relationship and consider digital investment impact to operating revenue (dependent variable), taking employee number as independent variable.

The relationship between digitalization and labour productivity have been studied before. Horvat et al. (2019) investigated effect of automation and digitalization on manufacturing companies labour productivity in early stage of Industry 4. In their work they document statistically significant and positive effect on labour productivity. However, data used in study represents only German Manufacturing survey in year 2012. Studies have found that the use of digital technology by various companies is associated with higher labour productivity and firm growth (Clarke et al., 2015). Cette et al. (2021) investigated impact of information communication technology (ICT) and digitalization on total factor and labour productivity. Their find out that the employment of ICT specialists and the use of digital technologies improves firms labour productivity by 23% and its total factor productivity by about 17%. Their conclusions come from analysis of 1065 French firms in 2018. The positive impact of ICT on labor productivity has also been established for countries belonging to organization for economic cooperation and development (OECD) in Ceccobelli et al. research (2012). Digitalization investment, as a factor affecting labour productivity, requires scientific examination. Based on research findings mentioned, we formulate the hypothesis:

*Hypothesis 2: Digitalization positively influences companies labour productivity*

Digitalization enables transformation of company knowledge into intangible assets (Mayer, 2018). Intangible assets that today are crucial for the productivity gains are incorporated in the general-purpose technologies of digitalization (Schneider, 2018). Chen et al. (2018) finds out that operational digitalization and intangible asset investment are positively correlated with financial performance. However opposite finding been presented by Chappell et al. (2018) as examining firm performance, they found that higher intangible investment is not associated with productivity or profitability but associates with higher labour and capital input. In our work we also check intangible assets relation to operational revenue and labour productivity concept.

### **2.3. Limitations of Available Studies and Data**

The existing studies analyzed in literature review section provide insights on digitalization impact on company performance and labor productivity, however these studies contain limitations. One of main limitation refers to small sample size and period. Horvat et al. (2019) conducted an analysis based on a dataset from the Fraunhofer Institute for Systems and Innovation Research 2012 German manufacturing survey. In linear regression model of effects on labor productivity were used 1035 observations. The expected contribution of Industry 4 technologies for industrial performance was investigated by Dalenogare et al. (2018). In their study they used Brazilian industry data of year 2016 of 27 industrial sector and 2225 companies. Cette et al. (2021) relied on analysis of survey in 2018 of 1065 French firms belonging to manufacturing sector with at least 20 employees. So, all the studies before on digitalization impact been done for limited target year and specific country.

In our study we use European Union Manufacturing sector corporate company level data of 2013 - 2020 period. All companies with a known value, exclusion of companies with no

recent financial data and public authorities, States, Governments. Observations with negative digital investment are eliminated. Data is winsorized at the 1 and 95 percent to eliminate outlier effects. The final sample contains 5013 observations covering 22 countries and 624 firms. European Union Company data is drawn from the Orbis Database.

Another limitation is that many forms of digitalization are being considered separately and impact measured based on digitalization type (Horvat et al., 2019) not as digitalization overall. Dalenogare et al. (2018) digitalization expected benefits investigated based on industry sector and technology. Independent variable in research model was technology, such as integrated engineering systems, big data, additive manufacturing and expected benefits (dependent variables) were optimized automation process, increase productivity, increased energy efficiency and other. In the study was used ordinary least square regression. Cette et al. (2021) empirically investigate how the use of cloud and big data have an impact on firm productivity and labor share. To address this issue, we will cover whole digitalization on company level, not segregate the technology in use. Digital investment in our study represents all type of investment related to company with an assumption that major focus for efficiency and grow at all company type and size focusing on digital grow.

In addition, Lyu and Liu (2021) in their paper on digital technologies effect in energy sector used revenue per work to measure firm productivity, reflecting only one dimension of firm performance (Lyu & Liu, 2021). Kohtamaki et al. (2020) in their study for capturing financial potential of digitalization use total assets, cash flow and number of patents to records changes of company profit performance. Where Cheng et al. (2022) employed ROA (return on asset), ROS (net profit per dollar in sales) and ATR (sales per dollar of assets) dependent variables to represent company performance. In our work we use for company performance measure multiple variables, such as profit and loss, operating revenue, tangible and intangible fixed assets to examine the benefit of digitalization to firm.

### 3. Method and Variables

The variables presented in Table 1 below were selected by assessing various theoretical and empirical works. Main statistical data as mean, standard deviation (Std.) and minimum and maximum value for variables are presented in Table 2. In order to have comparable results with available data, we use relative size measures for calculations. It means that all variables being divided from total asset value for regression calculation.

Table 1.  
*Summary of variables used in analysis and calculations*

<b>Variable</b>	<b>Description</b>	<b>Category</b>
DigIn	Digital Investment th Euro $X_1$	Continuous
TanFA	Tangible fixed assets th Euro $X_2$	Continuous
IntanFA	Intangible fixed assets th Euro $X_3$	Continuous
NoE	Number of Employees $X_4$	Discrete
P&L	Profit and Loss th Euro $X_5$	Continuous
OR	Operating Revenue th Euro $Y$	Continuous
TatalA	Total assets th	Continuous

For representation of labor productivity calculated as operating revenue divided from number of employees per company, we use numerator and denominator on separate sides of equation, where employee number is used as main independent variable. Labor productivity representation method background presented in literature review section.

In recent years expectations have developed concerning digitalization impact on manufacturing industry performance (Horvat et al., 2019). Digitalization in manufacturing sector relates to improvements and investments towards production processes. Integrating robotic solutions, digital technologies and automating production processes is key target for manufacturing sector (Horvat et al., 2018). From operational perspective, integrated digital technologies can reduce production set up times, labor and material cost, processing times, resulting in higher firm productivity (Dalenogare et al., 2018). Digital technology can provide value-creating and revenue-creating opportunities (Sklyar et al., 2019). Against this background, manufacturing sector is focusing on performance improvement through investment to digitalization. There would be difficult to argue that nowadays investment has no connection with digitalization trend itself. In our research work, we consider financial year investment into digitalization as value representing digitalization on company level.

Table 2.

*Descriptive Statistics of variables used in analysis and calculation*

Variable	N	Mean	STD	MIN	MAX
DigIn	5013	996237	3496584	2	39913000
TanFA	5013	1046952	4432526	0.00	84391000
IntanFA	5013	1330901	7182034	0.00	171381344
NoE	5013	12107	14246721	1	259859000
P&L	5013	274037	1172637	(11729000)	259859000
OR	5013	3501128	14246721	0.00	259859000
TatalA	5013	5312187	25041700	198.12	497114000

Chappel et al. (2018) in their study investigated intangible asset variable relation to firm performance particularly considering relation to technology. Cette et al. (2021) used labour productivity variable for digitalization impact analysis on firms' productivity. Cheng et al. (2022) used several measures in their study to represent firm performance, such as Return on Assets (ROA) and Return on Sales (ROS). Since our main purpose is to understand the expected benefits of digitalization to firm performance and labour productivity (according to hypothesis), independent variables in our study are number of employees, total tangible and intangible fixed assets in thousands of Euros, profit and loss in thousands of Euros. Main independent variable is digital investment (DigIn) in thousands of Euros, which is calculated from Plant & Machinery (PlantMachinery) and Plant & Machinery depreciation (PlantMachineryDepreciation) values of financial year. Records with result of calculated negative digital investment value are removed from regression analysis. Digital investment calculation formula for this study is expressed as (Eg.1):

$$\text{DigIn}_{i,t} = \text{PlantMachinery}_{i,t} - (\text{PlantMachinery}_{i,t-1} - \text{PlantMachineryDepreciation}_{i,t}) \quad (1)$$

In this work hypothesis are tested using comparative and systematic analysis as well as a statistical correlation method. Correlation calculation results are being evaluated using comparison method. Variance inflation factor (VIF) used to measure multicollinearity among independent variables in regression model. Regression method for this analysis been chosen with a reference to existing body of work (Cette et al., 2021, Dalenogare et al., 2018, Dunn & Weidman, 2015; Horvat et al., 2019, Horvat et al., 2018, Mahmood, 2008) where authors used linear regression analysis. Variables in the models described in Table 1 and Table 2.

Model 1 tests for the relationship between operating revenue and independent variable considering digital investment per same financial year. We use relative size measures for accurate comparison reasons. The regression function in model 1 presented in Eg.2:

$$Y = a + b_1(X_1) + b_2(X_2) + \dots + b_5(X_5) + \varepsilon \quad (2)$$

In model 2 to reduce the effect of endogeneity, the main independent variables digital investment is lagged with (t-1) throughout the model. We employ regression Eq.3:

$$Y_{i,t} = a + b_1(X_1)_{i,t-1} + b_2(X_2)_{i,t} + \dots + b_5(X_5)_{i,t} + \varepsilon \quad (3)$$

Model 3 considers digital investment as dependent variable and operating revenue as independent, where other variables remain the same. In the following section, the results of Pearson correlation analysis and multiple regression analysis are presented.

#### 4. Results

Descriptive statistics presented in Table 2 for the sample covering 5013 records. There are no companies in 5013 observations with negative or zero digital investment, as value varies from 1.56 thousand of Euros to maximum of 39913000 Euro per year. Average number of employees per company is 12107 with standard deviation of 14 million employees indicate that in research main participants are big corporations operating in European Union. As differences between mean and standard deviation are significant for most of variables, we use relative size calculations to have comparable results.

Pearson correlation matrix is presented in Table 3, which shows the correlation among the different variables in the model. The coefficients are based on full sample of 5013 observations. Values above 0.9 are considered as a strong correlation (Akoglu, 2018), which needs to be addressed in the following analysis. Moderate correlation is between operation revenue and tangible fixed assets and number of employees with the value 0.589, 0.384 accordingly. To verify for multicollinearity issue, we conduct the variance inflation factor analysis (VIF) on regression models.

Table 3.

*Pearson correlation matrix*

Variable	DigIn	TanFA	IntanFA	NoE	P&L	OR
DigIn	1					
TanFA	0.589**	1				
IntanFA	(0.311)**	(0.453)**	1			
NoE	0.096**	0.140**	(0.199)**	1		
P&L	0.023	0.101**	(0.028)*	0.028*	1	
OR	0.171**	0.066**	(0.292)**	0.384**	0.263**	1

\*\*Correlation is significant at the 0.01 level (2-tailed).

Regression analysis results are presented in Table 5. Findings indicate that R-Square is 0.295 and 0.299 for relationship between digital investment and independent variables in analysis for model 1 and model 2 respectively (refer Table 4). Significance level for both models is sufficient. Tangible and Intangible assets for the company have no positive impact for operating revenue, where standardized coefficient beta is negative ((0.242), (0.267) respectively). Operating Revenue increases with grow of employee number per company.

Table 4.  
*Regression Analysis Summary*

	<b>R Square</b>	<b>Adjusted R Square</b>	<b>Std. Error of the Estimate</b>	<b>Durbin-Watson</b>
Model 1	0,295	0,294	0,391	1,980
Model 2	0,299	0,298	0,386	1,964
Model 3	0,369	0,369	0,213	1,926

Table 5.  
*Regression Analysis Summary*

<b>Model</b>	<b>Factor</b>	<b>Unstandardized Coeff.</b>		<b>Standardized Coeff.</b>		<b>Collinearity Statistics</b>		
		<b>B</b>	<b>Std. Error</b>	<b>Beta</b>	<b>t</b>	<b>Sig.</b>	<b>Tolerance</b>	<b>VIF</b>
1	Constant	0.992	0.016		62.463	0.00		
	DigIn, X <sub>1</sub>	0.331	0.026	0.191	12.900	0.00	0.652	1.534
	TanFA, X <sub>2</sub>	(0.673)	0.044	(0.242)	(15.212)	0.00	0.567	1.763
	IntanFA, X <sub>3</sub>	(0.694)	0.035	(0.267)	(19.603)	0.00	0.7733	1.294
	NoE, X <sub>4</sub>	30.706	1.107	0.339	27.735	0.00	0.957	1.045
	P&L, X <sub>5</sub>	0.757	0.034	0.266	22.114	0.00	0.987	1.013
2	Constant	0.981	0.017		58.830	0.00		
	DigIn, X <sub>1</sub>	0.326	0.027	0.188	12.017	0.00	0.661	1.513
	TanFA, X <sub>2</sub>	(0.653)	0.046	(0.237)	(14.158)	0.00	0.577	1.732
	IntanFA, X <sub>3</sub>	(0.377)	0.037	(0.264)	(18.247)	0.00	0.773	1.293
	NoE, X <sub>4</sub>	30.883	1.167	0.345	26.450	0.00	0.956	1.046
	P&L, X <sub>5</sub>	0.749	0.036	0.268	20.906	0.00	0.986	1.015
3	Constant	(0.035)	0.012		(3.010)	0.003		
	OR, X <sub>1</sub>	0.099	0.008	0.171	12.900	0.00	0.729	1.372
	TanFA, X <sub>2</sub>	0.943	0.021	0.587	45.561	0.00	0.770	1.299
	IntanFA, X <sub>3</sub>	(0.011)	0.020	(0.007)	(0.555)	0.00	0.717	1.239
	NoE, X <sub>4</sub>	(2.637)	0.648	(0.050)	(4.068)	0.00	0.831	1.204
	P&L, X <sub>5</sub>	(0.131)	0.019	(0.080)	(6.717)	0.00	0.906	1.103

Our first hypothesis focuses on digitalization impact to firm performance. To conclude results of hypothesis 1, we refer to model 1 and 2, where dependent variable is operating revenue. Regression equations relationship between dependent and independent variable are significant, as p-value equal 0.000. So, we can conclude that our sample data provide enough evidence to reject the null hypothesis. Digital investment in both models is positively associated with operating revenue, as digitalization increase so does the operating revenue. Our first hypothesis can be confirmed. Furthermore, from model 1 and 2 we can note negative impact to operating revenue due to tangible and intangible fixed assets on firm level (model 1:  $\beta_2 = (0.673)$ ,  $\beta_3 = (0.694)$ ,  $p \leq 0.01$ ).

Looking at Employee Number coefficient throughout the model 1-2, the results show strong significant positive relation with operating revenue ( $\beta_4 = 30.70$ ,  $p \leq 0.01$ ). These finding do not show direct positive impact to labour productivity as with positive grow of operating revenue, so does grow a number of employees per firm. There is no positive impact to labour productivity. This contradicts the results of Horvat et al. (2019) and Cette et al. (2021), who found evidence for labour productivity increase due to digitalization impact. Our second hypothesis that digitalization influences positively labour productivity can be rejected. Digitalization increases operating revenue, but do not increase labour productivity.

Considering model 3, digital investment relation to independent variables accounts for R-Square of 0.369. The main variable is number of employees per company with identified



significant negative route. We can highlight that with an increase in operating revenue and tangible fixed assets, companies tend to invest more to digitalization. There is no recorded positive impact of intangible assets to digitalization, as coefficient is negative for model 3. Therefore, it contradicts believe stated in literature for direct intangible impact on digitalization. Main variable positively influencing digitalization on company level is tangible fixed assets, where highest negative impact comes from number of employees per company.

## 5. Discussion

In this article, we address the relationship question for digitalization impact to firm performance and labour productivity. By investigating company level data of EU manufacturing sector, this paper supplement digitalization impact literature and contradicts to Horvat et al. (2019) and Cette et al. (2021) findings, where positive relation between digitalization and labour productivity was identified. Moreover, we take novelty path by considering digital investment as digitalization value to provide a numerical expression of the impact. This way allows us to consider digitalization as a whole impact to firm, without specific technology under investigation. We performed OLS regression on sample of 5013 records covering 27 EU countries and 642 firms over the years 2013-2020. The regression analysis was used to investigate whether digitalization in firm in previous year influence labour productivity and firm performance. We build 3 models to check our hypothesis, which varies between each other by data year and dependent variable under consideration. Our main findings are that digitalization has positive impact to firms operating revenue. However, digitalization has no impact on labour productivity, as employee number increases together with digital investment and operating revenue. Furthermore, we have not recorded positive impact of intangible assets to digitalization.

One interpretation of the main results could be that companies which have higher operating revenues invest more to digitalization processes with expectation to have future savings and decrease employee number. However, digitalization processes speed up operations, allows companies to produce more, but with an increase of different technology in use, requirements for labour grows to maintain and sustain implemented technologies. It could be considered as digitalization paradox where companies invest in digitalization but struggle to earn the expected revenue grow.

Second, considering that intangible assets have no positive affect to digitalization, we can assume that assets which are not physical in nature in manufacturing sector might have indirect impact to digitalization itself or plays different role compared to other sector or profile firms. This assumption must be investigated further.

There are few limitations to this research that should be noted. Majority of firms in our research are corporation level companies with on average 12000 employees. Although we expect these results to hold for all size manufacturing firms in EU in general, we cannot claim that this is the case. Furthermore, although the current available data did not allow for it, control variables might further have increased the significance of proposed regression models.

Future research should continue investigate how digitalization affects labour productivity. While this study looked at productivity represented as operating revenue relation to employee number, other methods of productivity calculation on firm level could be implemented and compared between each other. Finally, while this research confirmed operating revenue and digitalization positive relation, future research should investigate how type of investment in digitalization influence operating revenue structure.

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