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The impact of digitalization on energy intensity in manufacturing sectors – A panel data analysis for Europe

Marcel Matthess, Stefanie Kunkel, Melissa Fiona Dachrodt, Grischa Beier *

Digitalization and Sustainability Transformations, Research Institute for Sustainability (RIFS) - Helmholtz Centre Potsdam, Berliner Straße 130, 14467, Potsdam, Germany

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ABSTRACT

Digitalization of industrial production, also known as Industry 4.0, may have profound environmental impacts, raising both hopes and fears with regards to the environmental friendliness of manufacturing. We investigate the relationship between Industry 4.0 and manufacturing energy intensity using panel data covering 15 countries and 8 manufacturing sectors or clusters for the years 2012–2020, providing insights for three different variables related to Industry 4.0. Firstly, we find a significant negative association (−0.059 in the preferred specification) between robot density and energy intensity. Secondly, we find a significant positive association (+0.025 in the preferred specification) between digital capital intensity and energy intensity. Lastly, the relationship between the share of companies employing ICT specialists and energy intensity is insignificant in our data sample. We thus highlight the potentially varying effects of Industry 4.0 on manufacturing energy intensity, encouraging further investigations to provide a more nuanced view of the environmental impacts of digital technology utilization in industry.

1. Introduction

A high environmental burden is associated with industrial production. The manufacturing sector is a significant energy consumer (IEA, 2020b) and emits a large portion of greenhouse gases (Climate Watch, 2021), while also being related to various other forms of environmental degradation. As manufacturing – and the industrial sector more broadly – undergoes changes and more profound revolutions, it is inevitable that this will impact the environmental friendliness of industrial production as well (Beier et al., 2022a).

At the same time, hopes have risen of digital technologies to transform manufacturing industries in many ways, especially since the dawn of Industry 4.0 a decade ago. However, many effects remain uncertain and risks regarding environmental sustainability should not be overlooked (Beier et al., 2020). There are different ways in which digitalization may impact industrial energy intensity, defined as energy use per value added (Lange et al., 2020). For instance, various studies highlight the energy use of digital technologies in the midst of the proliferation of various digital technologies and increasing interconnectedness (Jones, 2018). However, other studies argue that digitalization may decrease energy intensity due to mechanisms influencing energy efficiency of production (GeSI, 2020). In recent years, scientific scrutiny of the relationship between digitalization and environmental sustainability has notably increased. For instance, Han et al. (2016) investigate the effect of information and communication technologies (ICT) on energy consumption in China. Similarly, Dehghan Shabani and Shahnazi (2019) conduct a panel analysis regarding the relationship between digitalization, greenhouse gas (GHG) emissions and other factors for Iranian economic sectors.

Notwithstanding the increased public and scientific interest in this field, the majority of empirical studies have investigated the effects of digitalization on energy intensity and related impacts on different geographic scales, but few have researched these effects for different economic activities and sectors. For instance, national impacts of digital technologies on energy intensity or energy consumption have been investigated for the cases of China (Wang et al., 2019) and South Africa (Atsu et al., 2021). In addition, regional differences have been investigated both nationally (Ren et al., 2021; Sun and Kim, 2021) and internationally (Sadorsky, 2012). Among the studies researching the impacts of digitalization on energy consumption for specific economic activities, few have focused on manufacturing sectors explicitly (Bernstein and Madlener, 2010). Studies tend to model the effects of Industry 4.0 using

* Corresponding author.
E-mail addresses: marcel.matthess@web.de (M. Matthess), stefanie.kunkel@rifs-potsdam.de (S. Kunkel), melissa.fiona@hotmail.com (M.F. Dachrodt), grischa.beier@rifs-potsdam.de (G. Beier).

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single variables or proxies representing well-established digital indicators which are however not very representative of the technological concept Industry 4.0, such as internet usage (Faisal et al., 2020). Although such studies provide valuable insights regarding long-term trends of past decades, they are arguably less suitable to extrapolate findings for the concrete technological concept Industry 4.0.

In summary, it becomes apparent that several studies exist in the literature investigating the effects of a specific class of technologies on variables such as emissions or economic growth. The few existing studies that focus on the manufacturing sector tend to model the effects of Industry 4.0 using single variables or proxies representing well-established digital indicators (such as national ICT usage or internet coverage) which are however not very representative of the technological concept Industry 4.0. To our knowledge, our study is the first of its kind investigating the effects of Industry 4.0 (operationalized by three variables specific for this technological concept) on manufacturing energy intensity covering multiple manufacturing sectors and countries.

Specifically, we address the aforementioned research gaps by investigating the relationship between Industry 4.0 and manufacturing energy intensity for 8 manufacturing sectors (or clusters) of 15 European countries, analyzing data from 2012 to 2020. Likewise, we widen the view on the impacts of Industry 4.0 by incorporating three related variables, namely robot density, digital capital intensity, and the share of companies employing ICT specialists. The results of our regression analysis suggest that these variables may have varying effects on energy intensity, emphasizing the need to understand the heterogeneous impacts of technologies involved in Industry 4.0 as well as potential interactions.

The structure of the remaining paper is as follows: Section 2 explains the analytical methods, variables, models and data sources used for this study, while Section 3 provides an overview the relevant theory and reviews related literature. In Section 4 the results of the analysis are reported that are subsequently discussed in Section 5. Supplementary information is provided in Appendices A-C.

2. Methods and data sources

2.1. Variable selection and data sources

Table 1 provides an overview of selected variables, their definitions and data sources. Energy intensity is our dependent variable. The data is sourced from Eurostat's energy balances data. Energy data represents final energy consumption of industrial sectors, including all energy sources, and is measured in Terajoule (TJ). To construct the variable of energy intensity, energy consumption is divided by the respective sectors' gross value added (GVA) in constant 2015 USD (PPP). Likewise, GVA data is sourced from Eurostat.

Table 1
Variable definitions and data sources.

Variable	Symbol	Definition	Unit	Data sources
Energy intensity	EI	Final energy consumption divided by GVA	TJ/GVA (Million, 2015 USD, PPP)	Eurostat
Robot density	ROBOT	Industrial robot stock divided by employees	Industrial robots/ 1000 workers	IFR Industrial Robots Report
Digital capital intensity	DIGCAP	Digital capital GFCF divided by GVA	Digital capital GFCF/GVA (Million, 2015 USD, PPP)	Eurostat, EU KLEMS
Digital skills	SKILLS	Share of companies employing ICT specialists	Percentage (%)	Eurostat
R&D intensity	R&D	R&D GFCF divided by GVA	R&D GFCF/GVA (Million, 2015 USD, PPP)	Eurostat
Trade intensity	TRADE	Sum of imports and exports divided by GVA	Trade (XR)/GVA (Million, 2015 USD, PPP)	Eurostat
Energy prices	EP	Energy end-use prices	Index (2015 = 100)	IEA

Among the three variables related to Industry 4.0, robot density represents the first independent variable of interest. Robot density is calculated as the ratio of the stock of industrial robots per 1000 employees. Robot stocks are sourced from the International Federation of Robotics (IFR). Employment data is sourced from Eurostat's National Accounts data and is based on the total employment domestic concept.

The second independent variable related to Industry 4.0 in our model is digital capital intensity. To construct digital capital intensity, digital capital is divided by GVA. It is measured as gross-fixed capital formation in constant 2015 USD (PPP) divided by GVA in constant 2015 USD (PPP). Digital capital data is sourced from Eurostat's National Accounts database on non-financial assets. Unlike other studies such as (Schulte et al., 2016), we focus specifically on intangible digital capital to exclude tangible capital which may capture similar aspects that are already included in the robot density variable. There exist different attempts to capture digital capital using national accounts data. To overcome data limitations for one country in our sample (Germany), we used the EU KLEMS database for digital capital data. Both Eurostat and EU KLEMS have similar approaches measuring digital capital and could thus be used in conjunction without issues.

Our third independent variable relating to Industry 4.0 is digital skills. Digital skills data is sourced from Eurostat's Digital Economy and Society data and is defined as the share of companies employing ICT specialists. ICT specialists are defined as persons who have the ability to develop, operate and maintain ICT systems and for whom ICTs constitute the main part of their job (OECD, 2004). With this variable, we aim to capture the human component of Industry 4.0. Regarding the rationale to include this variable, to fully assess the state of industrial digitalization, other studies have highlighted the importance to incorporate the "digital-related human capital embedded in production" (Calvino et al., 2018).

Concerning further variables of interest, we include research and development (R&D) intensity in our model. R&D data is sourced from Eurostat. It is measured as GFCF of R&D divided by GVA. Moreover, we include trade intensity as a further independent variable. Trade data has also been sourced from Eurostat. It is calculated as the sum of the value of exports and imports, adjusted by constant 2015 exchange rates in USD, and then divided by GVA. Furthermore, we include energy prices as an independent variable. Energy price data is sourced from the International Energy Agency's (IEA) Energy Prices and Taxes (IEA, 2020a) database. Energy prices represent industries' energy end-use price as an index (base year = 2015). Thus, it measures relative changes from the base year. Lastly, for the calculation of purchasing power parities (PPP) in USD, we used data from the Penn World Table (PWT) 10.0. PWT PPPs are based on output prices, which are argued to be suitable for the analysis of industrial sectors since they intend to measure the production possibilities of an economy (Feenstra et al., 2015).

Combining these data sources inherently involves issues of harmonization, for instance concerning the definition and clustering of manufacturing industries. In total, our sample includes data from 2012 to 2020, 8 manufacturing sectors (clusters), and 15 countries, resulting in 1044 observations. For an overview of the sector definitions and the countries included please see Appendices A and B.

2.2. Empirical model

Following the description of data sources included, our empirical model consists of the dependent variable energy intensity (EI) and six independent variables, namely: robot density (ROBOT), digital capital intensity (DIGCAP), digital skills (SKILLS), R&D intensity (R&D), trade intensity (TRADE), and energy prices (EP). In its basic form, the model can be formulated as:

$$EI_{it} = \alpha ROBOT_{it}^{\beta 1} + DIGCAP_{it}^{\beta 2} + SKILLS_{it}^{\beta 3} + R\&D_{it}^{\beta 4} + TRADE_{it}^{\beta 5} + EP_{it}^{\beta 6}\varepsilon \quad \text{(Eq. 1)}$$

where i represents the manufacturing sector(s), t represents the year, α represents the constant term, β represent the parameters to be estimated, and ε represents the error term. Eq. (1) is modified to take the natural logarithm of both sides of the equation, with the exception of variables SKILLS and EP, because these variables are already measured as percentages. We thus get the following equation:

$$lnEI_{it} = \alpha_i + \beta_1 lnROBOT_{it} + \beta_2 lnDIGCAP_{it} + \beta_3 SKILLS_{it} + \beta_4 lnR\&D_{it} + \beta_5 lnTRADE_{it} + \beta_6 EP_{it} + \varepsilon_{it} \quad \text{(Eq. 2)}$$

where α_i are individual (i.e. country-sector) specific effects.

Given the nature of our study, we employ panel estimation techniques, namely the fixed-effects estimator. Before estimating the effects of the included variables on energy intensity, we ensure the suitability of our model by testing for (i.a.) multicollinearity, serial correlation, cross-sectional dependence, heteroskedasticity, and unit roots. To test for serial correlation, we conduct the Durbin-Watson test and the Breusch-Godfrey test (BREUSCH, 1978) which indicate serial correlation. To test for cross-sectional dependence, we conduct the Pesaran CD test (Pesaran, 2021) which indicates cross-sectional dependence. Given the existence of cross-sectional dependence, second-generation unit root tests are necessary. The cross-sectionally augmented Dickey-Fuller (CADF) test (Pesaran, 2007) indicates no unit roots.

3. Related literature

Our study is related to different strands of literature which we will briefly summarize in the following subsections. Firstly, we discuss the broader impact of digital technologies on industrial production, namely productivity, growth, employment and income in industry. Secondly, we turn to the drivers of energy intensity in industry. Lastly, we assemble studies that investigate the link between digital technologies and energy intensity in industry.

3.1. Impacts of digital technologies on industrial production

The impacts of digital technologies on productivity and growth of industry is intensively researched in the literature. Studies often report a positive association between digital technologies and growth of national economies. For instance, positive correlations between digital technologies and GDP growth have been found in a number of studies (Farhadi et al., 2012; Irawan, 2014; Qiang et al., 2004; Vu, 2011). There seem to be declining returns to digital technology penetration (Qiang et al., 2004; Vu, 2011), i.e., the higher the level of digital technology use, the lower the additional benefit of a one unit increase of digital technology use. On the firm level, digital technology use generally tends to increase productivity, e.g., in developing economies (Banga and te Velde, 2018) or in young firms (Jin and McElheran, 2017).

Regarding employment and income in the economy, digitalization tends to polarize the job market. Middle-skilled occupations are rather substituted by ICT, low- and high-skilled occupations show positive correlations in terms of demand and wages (Goos et al., 2014) for instance because high-skilled occupations become more productive through the use of digital technologies and low-skilled service jobs are non-automatable and complementary to these digitally-enabled occupations.

The impact of digital technologies on the labor market is assessed differently in the literature. It is widely undisputed that digitalization will make certain manual tasks obsolete, automation may also reduce repetitive tasks, reduce working hours and therefore enable workers to share productivity gains (Edwards and Ramirez, 2016; Krzywdzinski, 2017). While early studies suggesting an imminent mass technological unemployment (Frey and Osborne, 2017) have been questioned with findings that paint a much more nuanced picture (Fu et al., 2021; Shuttleworth et al., 2022). Some scholars argue that jobs comprise multiple elements, of which not all can be automated (Autor, 2015). Therefore, domains with on average higher skill profiles are less prone to expected job losses compared to domains with lower skill profiles (Beier et al., 2022b). However, other scholars find, that the technological progress boosted the labor market, while the substitution effect of employment was greater than the creation effect (Su et al., 2022).

Due to the complex nature of studying the effects of digitalization on industrial employment, a broad variety of potentially influencing factors have to be taken into account. Some studies emphasize that employees can participate in shaping the way in which new tools and work processes are embodied into their daily work routines (Hammershøj, 2019; Helming et al., 2019). But the impact of digitalization also depends on contextual factors such as countries' social protection mechanisms, education policies, or the structure of the workforce (Grigoli et al., 2020; OECD, 2019).

In one Mexican study, labor demand was increasing despite growing automation in jobs with a low and very low risk of automation, but demographic factors were also identified as relevant, as the direction of labor demand was found to be inverse to the characteristics of gender, age, and education (Ramos et al., 2022). In an Asian context, Focacci (2021) compared the effects of increasing automation in China and Korea and concluded that robots did not always increase unemployment growth.

In summary, digitalization should not be regarded as an automatic job destroyer, but rather as a process which incorporates a complex interplay of different social and technological factors which transform business processes and job profiles.

3.2. Energy intensity of industrial production and its drivers

Energy intensity of industrial production has various drivers, two important of which are structural and technological change. Firstly, technological factors determine energy intensity (Huang et al., 2017; Voigt et al., 2014). Using panel data of 30 Chinese provinces between 2000 and 2013, Huang et al. (2017) state that indigenous R&D (expenditure and personnel) in China contributed significantly to declining energy intensity. Foreign direct investment (FDI) leading to technology spillovers also played a role. Secondly, Voigt et al. (2014) analyze energy intensity developments between 1995 and 2007 in 40 countries where the importance of technological change in energy intensity reduction is also highlighted but where structural change, i.e. a change in the distribution of economic activities, had a greater impact in several economies (Japan, the United States, Australia, Taiwan, Mexico and Brazil). Still, they highlight the key role of technological advancements especially in countries with lower energy efficient economies (Voigt et al., 2014).

Moreover, "green innovation" in terms of directed technological change towards more environmentally friendly technologies seems to be particularly effective in reducing energy intensity. Analyzing 14 industrial sectors in 17 OECD countries over 20 years (1975–2005), Wurlod and Noailly (2018) detect a 0.03% reduction in energy intensity associated with a 1% increase in green patenting.

Ye et al. (2020) focus on the question of how countries' collective technological progress affect each country's energy intensity and suggest that raising the global technological frontier and raising countries' position in the global value chain reduce energy intensity.

Analyzing the drivers of GHG emissions in the Chinese manufacturing industry between 2000 and 2015, Shi et al. (2019)underline the relationship between energy intensity and GHG emissions and highlight the need for technology-induced efficiency improvements in carbon intensive sectors. Moreover, Lin and Chen (2020) emphasize the importance of a variety of factors including transport infrastructure, economic growth, technological progress and energy prices regarding energy efficiency of the Chinese manufacturing industry. Investigating the energy consumption of European industries, Del Pablo-Romero et al. (2019) come to the more general conclusion that energy use patterns vary between industry sectors and hence efficiency measures should be targeted at specific sectors instead of the overall industry. Furthermore Yang and Shi (2018) investigate the relationship between intangible capital (e.g. R&D, organizational capital) in 40 economies between 1995 and 2007 and find a diminishing effect of intangible capital on reducing energy intensity with increasing income level.

3.3. Impacts of digital technologies on environmental sustainability and energy consumption

The relationship between digitalization and energy intensity is disputed, i. e. both positive and negative associations are described. In the following, we make the distinction between studies according to their focus on manufacturing sectors specifically (latter part of the subchapter) and all other studies (first part).

3.3.1. Non-manufacturing specific studies

Regarding non-manufacturing specific studies, several studies analyze ICT's impact on environmental sustainability across countries.

Higón et al. (2017) analyze whether there are any threshold effects of ICT on CO2 emissions depending on the level of ICT development in a country. Using a panel dataset of 142 economies from 1995 to 2010 they find that ICT contributes to CO_2 emission reduction above a certain level of ICT development.

Chimbo (2020) conducts a regression analysis on 21 transitional economies between 1994 and 2014 interested in how internet use affect electricity consumption and report a positive relationship. However, while contributing to an increase in electricity consumption, Haseeb et al. (2019) report that ICT (as measured by internet users and mobile cellular subscriptions) had also contributed to mitigating CO_2 emissions in some countries (Brazil, Russia). They analyzed the effect of ICT on CO_2 emissions in BRICS countries between 1994 and 2014. In line with Higón et al. (2017), they confirm that environmental quality decreases with an increase in the ICT indicators for countries like India, China, and South Africa.

Yan et al. (2018) use World Development Indicators and OECD patent data to investigate the link between energy productivity and ICT innovation in 50 economies between 1995 and 2013. They find a significant positive relationship between both indicators. As a reason why energy consumption in several fields increases despite efficiency increases they note the possibility of rebound effects.

3.3.2. Studies investigating manufacturing sectors

Regarding manufacturing specific studies, Schulte et al. (2016) use panel data from OECD countries and find that ICT is associated with a significant reduction in total energy demand, which, however, depends on the type of energy. Analyzing 8 EU countries between 1991 and 2005, Bernstein and Madlener (2010) conclude for their data that ICT diffusion tends to enhance electricity efficiency in production.

Zhou et al. (2018) scrutinize the impact of ICT on Chinese energy intensity changes from 2002 to 2012. Their results indicate that while production structure had an energy intensity decreasing effects, ICT contributed to a 4.54% increase in energy intensity. However, ICT input in sectors had an energy intensity decreasing effect, i.e., while ICT industry itself increases overall energy intensity, ICT input in other sectors can be conducive to reducing these sectors' energy intensity. Effects seem to be stronger in the more technology-intensive sectors.

Zhou et al. (2019) focus on the carbon emissions of the ICT sector. Using input output modelling for the Chinese case, they point to the induction of emissions through carbon intensive inputs in the ICT sector, especially intermediate inputs from non-ICT sectors such as the electricity and basic material sectors. They call for supply chain wide carbon management strategies.

Using a STIRPAT modelling approach and various regression techniques to analyze relationships between robot data and energy intensity, Liu et al. (2021) conclude that industrial robot use contributed to decreasing energy intensity in Chinese industry sectors.

Modelling the relationship between ICT investment and energy use through the calculation of partial elasticities of substitution in 30 sectors in South Korea and Japan over a time span of almost 30 years, Khayyat et al. (2016) find that ICT capital can generally substitute energy (and labor) demand, but that the size of the substitution effect determines the development of the overall development of energy use.

4. Results

In this section we will present the results of our analysis based on our empirical model consisting of the dependent variable energy intensity (EI) and six independent variables (robot density (ROBOT), digital capital intensity (DIGCAP), digital skills (SKILLS), R&D intensity (R&D), trade intensity (TRADE), and energy prices (EP)) as described in Section 2. In subsection 4.1. The descriptive results are presented, while subsection 4.2 focusses on the baseline regression results of the analysis.

4.1. Descriptive results

We present our descriptive findings in Table 2 and Figs. 1–4.

Overall, we see a decline in the energy intensity of the manufacturing sectors included in our sample from 2012, followed by a marginal increase in until 2020. Energy intensity varies greatly between manufacturing sectors and clusters. Notably, the increase in recent intensity of overall manufacturing can largely be attributed to the energy-demanding manufacturing of basic metals (Fig. 1, "C24").

Looking at the three main variables of interest related to Industry 4.0, we also find varying trends for our overall sample. Firstly, robot density nearly doubled between 2012 and 2020 (Fig. 2). Secondly, digital capital intensity also increased significantly, but more so in recent years (Fig. 3). Thirdly, and in contrast to the other variables, digital skills, representing the share of companies employing ICT specialists, decreased slightly between 2012 and 2020 (Fig. 4).

To proceed with the analysis, a few observations were dropped as outliers based on Cook's distance (1027 as opposed to 1044 observations of our original sample).

4.2. Baseline results

Our baseline results are presented in Table 3 and include four different specifications. Specification (1) shows the results with only the three digitalization variables included (robot density, digital skills, digital capital intensity) using the individual fixed-effects estimator. Specification (2) uses the pooled OLS estimator including all six independent variables. Specification (3) shows the results using the individual random-effects estimator including all six independent variables. Specification (4) is our preferred specification and shows the results using the individual fixed-effects estimator including all six independent variables. As can be seen, the results between specifications are robust

Table 2
Descriptive statistics.

Variable	N	Mean	St. Dev.	Min	Max
Energy intensity	1044	8.4	10.7	0.5	115.3
Robot density	1044	9.1	16.3	0.01	124.1
Digital skills	1044	24.5	10.1	3.0	60.3
Digital capital intensity	1044	0.02	0.02	0.000	0.3
R&D intensity	1044	0.05	0.1	0.000	0.3
Trade intensity	1044	2.0	1.4	0.2	11.1
Energy prices	1044	102.3	7.3	83.4	128.6

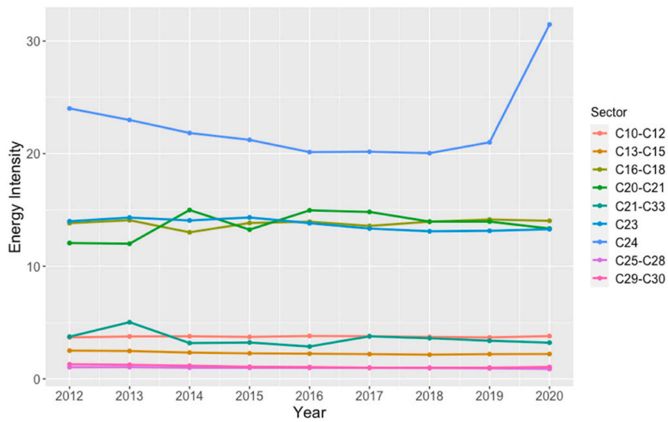

Fig. 1. Mean energy intensity per sector (TJ per million GVA (2015 USD PPP)) over time.

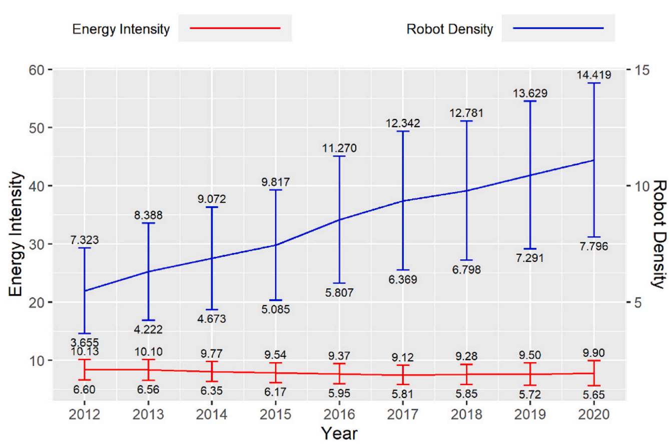

Fig. 2. Overall mean robot density (industrial robots per 1000 workers (total employment)) and energy intensity (TJ per million GVA (2015 USD PPP)) over time.

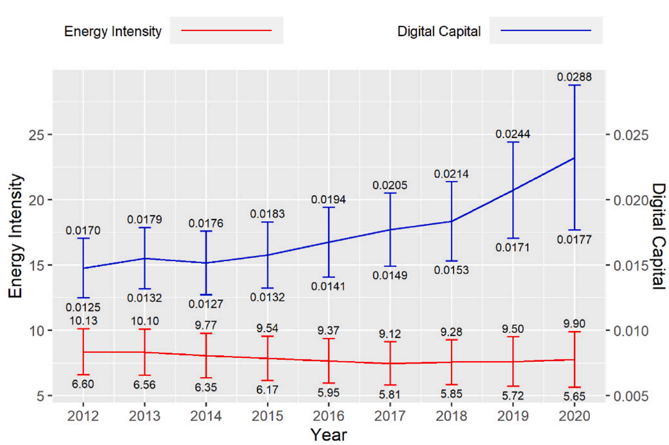

Fig. 3. Overall mean digital capital intensity (million $ digital capital per million $ GVA in 2015 USD (PPP)) and energy intensity (TJ per million GVA (2015 USD PPP)) over time.

concerning the effect of the majority of variables, but there are some differences regarding the effect of some variables.

Robot density has a significant negative coefficient in all specifications, ranging from −0.092 to −0.059. Thus, in our preferred specification, a 1% increase in robot density reduces the energy intensity of

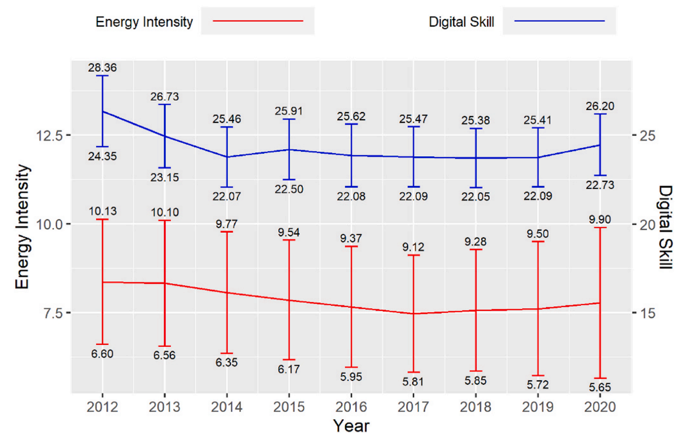

Fig. 4. Overall mean digital skills (share of companies employing ICT specialists) and energy intensity (TJ per million GVA (2015 USD PPP)) over time.

Table 3
Baseline regression results – Energy intensity as dependent variable.

	(1)	(2)	(3)	(4)
Robot density (lnROBOT)	−0.092*** (0.005)	−0.086*** (0.027)	−0.063*** (0.010)	−0.059*** (0.008)
Digital skills (SKILLS)	0.002 (0.001)	−0.022*** (0.004)	0.0004 (0.001)	0.001 (0.001)
Digital capital intensity (lnDIGCAP)	0.040*** (0.010)	−0.018 (0.042)	0.025** (0.012)	0.025** (0.012)
R&D intensity (lnR&D)		−0.218*** (0.034)	0.047*** (0.011)	0.054*** (0.009)
Trade intensity (lnTRADE)		0.469*** (0.062)	0.236*** (0.026)	0.239*** (0.026)
Energy prices (EP)		0.005 (0.005)	0.003*** (0.001)	0.004*** (0.001)
Constant		0.461 (0.542)	1.359*** (0.140)	
Observations	1027	1027	1027	1027
R^2	0.101	0.181	0.198	0.224
Adjusted R^2	−0.015	0.176	0.193	0.121
F Statistic	34.099*** (df = 3; 909)	37.457*** (df = 6; 1020)	254.208***	43.647*** (df = 6; 906)

Note: ***, **, * denote statistical significance at the 1%, 5%, 10% level; standard errors in parentheses.

manufacturing sectors by 0.059%. The impact of digital skills on energy intensity is only significant and negative in specification (2), but negligible and insignificant in all other specifications. Moreover, digital capital intensity has a positive coefficient in all specifications where the variable passes the 5% significance test. In specification (4), a 1% increase in digital capital intensity leads to a 0.025% increase of energy intensity.

With regards to further control variables, we find mixed results concerning their impact on energy intensity of manufacturing sectors. R&D intensity is the second variable with inconclusive results between specifications. Yet, given the greater suitability of the fixed-effects estimator as opposed to pooled OLS for our sample, specification (4) shows that a 1% increase in R&D intensity is associated with a 0.054% increase in energy intensity. Furthermore, trade intensity is significant, positive and substantial in all specifications. In specification (4) a 1% increase in trade intensity is associated with a 0.239% increase in energy intensity. Lastly, energy prices have a positive coefficient of small size in (0.004) in specification (4).

To further evaluate our results, we have run several robustness checks, which can be found in Appendix C.

5. Discussion

5.1. Digitalization and energy intensity of manufacturing sectors

Looking at the individual variables related to digitalization, we find that robot density has a negative coefficient, thus contributing to a decrease in energy intensity. This effect appears to be even more pronounced in highly digitalized sectors which include (i.a.) manufacturing of electronics, machinery, vehicles and others. Our results are in line with those of (Liu et al., 2021) considering the negative coefficient of robot density. It has to be considered that robot distribution among manufacturing sectors is very skewed, meaning that the majority of industrial robots are installed in a handful of sectors such as electronics, automotive, metal and machinery (IFR, 2021). Nevertheless, a preliminary conclusion could be that robotization embodies the general notion that Industry 4.0 may drive efficiency and productivity (Beier et al., 2020), as shown by Graetz and Michaels (2018) for the case of labor productivity. Furthermore, approaches for considerable efficiency improvements in the use of large robot fleets were identified in large European research projects during the time period we have analyzed (Riazi et al., 2016). However, due to the low degree of robot density in many countries and sectors, it has yet to be shown that robotization has large-scale effects on energy intensity. Notwithstanding, our results provide first insights for European manufacturing sectors in a largely under-investigated context.

For the case of digital capital intensity, our results imply that this variable is associated with an increase in energy intensity, with largely consistent findings in our robustness checks. To our knowledge, our study is the first one to investigate purely digital capital when analyzing its relationship to energy intensity. Thus, we take a narrower approach than previous studies investigating the effects of the more encompassing information and communication technology (ICT) capital such as (Khayyat et al., 2016). Whereas Khayyat et al. (2016) find that ICT capital investment in South Korea and Japan is a substitute for industrial energy use, Schulte et al. (2016) highlight the overall negative association between ICT capital and total energy demand in economic sectors of OECD countries, which however is not significant for electric energy demand specifically. Although we are hesitant to draw premature conclusions, our results allow for inferences which deserve further investigation concerning digital capital. Related to digital capital, other studies have found substantial energy consumption of applications related to artificial intelligence (Strubell et al., 2019) and of data centers (Jones, 2018). Such insights contribute to the plausibility of our findings. Similar to the previously mentioned studies, a further differentiation of energy sources may be one avenue worth investigating in the future. In conclusion, it appears logical that increases in digital capital do not automatically lead to energy intensity improvements, but instead need be to actively steered in order to accomplish efficiency gains.

With the inclusion of the variable "digital skills" we integrated a human component when analyzing the impacts of digitalization. Our results indicate that digital skills either display coefficients of marginal magnitude or are not significantly associated with the energy intensity of manufacturing sectors. Given the novelty of this approach, it is difficult to compare our results to other studies. Undoubtedly, Industry 4.0 is associated with a change in the skill requirements of employees (Beier et al., 2022b). However, we underscore the importance to not view this as a passive process but actively consider which digital skills should be fostered to improve environmental friendliness of production and how these can be better incorporated into (econometric) models. Employees shape the way (digital) tools are used and tasks are performed (Hammershøj, 2019). Moving one step further, this raises the question of which digital skills may be most impactful with regards to their potential to influence energy intensity and, on a broader level, environmental sustainability of production.

5.2. Impact of further control variables

Our model also includes the variables R&D intensity, trade intensity and energy prices. Our results suggest a significant positive association between R&D intensity and energy intensity. This comes as a surprise as it contradicts both theory and previous empirical results. Whereas Schulte et al. (2016) and Karimu et al. (2017) find insignificant relationships between R&D intensity and energy intensity or demand, Liu et al. (2021) find a negative association. In theory, R&D should be associated with (i.a.) technological process and thus with energy efficiency. Different aspects could have contributed to our results. As Karimu et al. (2017) state, it may require a longer period of time to see the efficiency increasing effects of R&D.

Secondly, our analysis shows a significant positive impact of trade intensity on energy intensity. Although other studies paint a mixed picture, many studies report similar results, with trade being positively associated with (i.e. increasing) energy intensity (Ajayi and Reiner, 2020; Zheng et al., 2011). Further aspects could be of relevance in the context of Industry 4.0, bearing in mind potential interactions between digitalization and trade. As Zhang (2013) holds, trade could facilitate spillover of information and technology. Reversely, digitalization may impact trade, the geography of production (Butollo, 2021) and global supply chains (Ebinger and Omondi, 2020). Hence, it could be fruitful to further investigate the relationship between trade, energy intensity and digitalization as has been shown recently (Zhang et al., 2022).

Lastly, we also included energy prices as a control variable and found a significant but negligible positive association between energy prices and energy intensity. Intuitively, rising prices should foster efficiency improvements and thus be negatively associated with energy intensity, which is also what most previous studies find (Ajayi and Reiner, 2020; Karimu et al., 2017). Our study is subject to limitations in this regard, due to the fact that energy prices were only available for the overall manufacturing sector of each country.

6. Conclusions, limitations and outlook

6.1. Conclusions

On a general level, our findings imply that Industry 4.0 may have mixed impacts on energy intensity of manufacturing sectors, highlighting the heterogeneity of the impacts of technologies and their interactions. More specifically, we find that an increase in robot density is associated with a decrease in energy intensity. To our knowledge, this is the first study investigating this link outside China, broadening our insights concerning the effects of automation. Furthermore, digital capital intensity is positively associated with energy intensity in most of our robustness tests. This may hint at differing effects of varying types of digital capital, comparing our results with previous studies' results on the overarching domain of ICT capital (Schulte et al., 2016). It also underlines assumed environmental burdens associated with digitalization such as increased energy consumption. Moreover, digital skills have an insignificant association with manufacturing energy intensity in most of our tested specifications.

Many conceptual papers on Industry 4.0 emphasized the need to use the digital transformation of industry as a window of opportunity in order to shape and accelerate the urgently needed transformation towards sustainable production patterns. However, so far little is known about the actual effects Industry 4.0 has had in that regard. We emphasize the importance to deepen our knowledge concerning the effects of Industry 4.0 on environmental sustainability and energy intensity specifically. We are convinced that our study is a first step in the direction of assessing the impacts of Industry 4.0 on energy intensity in a more detailed manner, encouraging endeavors in both areas of data provision and industry-level analysis. Although it may take a significant amount of time for clear trends of the impact of technology use to manifest, we face the challenge of anticipating and seeing these impacts as soon as possible in order to foster environmentally friendly industrial production and not risk long-term risks of technological dependencies in this regard. This is also crucial considering the limited time to reach net zero emissions, a goal many countries are committed to. We hope to stimulate further discussions and ultimately additional valuable insights.

6.2. Limitations

Our study comes with some limitations. Firstly, our methodological choices do not allow for causal inferences. Secondly, we faced well-known issues of combining different data sources that impacted (i.a.) the categorization of manufacturing sectors and sector clusters. In general, the limited amount of available sources gathering data for different manufacturing sectors impacted our study. As mentioned previously, this was (e.g.) the case for data on energy prices. Likewise, limitations of data on robot installation and density have been mentioned previously (Jurkat et al., 2022). For instance, methodological assumptions (e.g. one-hoss shay depreciation of robot stocks) as well as data structure (e.g. heterogeneity of robot installations between countries and manufacturing sectors) have to be considered. Moreover, although we sought to incorporate the core aspects of Industry 4.0 as highlighted by seminal studies with our variable choices, it requires further studies to investigate the suitability of related proxy variables, patent data being one example in the field of R&D related to digitalization. Similarly, we opted for a relatively short time span (2012–2020).

6.3. Outlook

Although this is in line with the inception of Industry 4.0, further data may provide additional insights in the coming years. In addition to this, new insights can also be gained by looking at further parameters to map the state of industrial digitalization on the one hand and the ecological consequences of its impact on the other. Future studies should also address a broader geographical focus allowing for a global perspective on the consequences of digitalization in industry.

CRediT authorship contribution statement

Marcel Matthess: Conceptualization, Methodology, Formal analysis, Validation, Investigation, Writing – original draft. **Stefanie Kunkel:** Conceptualization, Writing – original draft. **Melissa Fiona Dachrodt:** Formal analysis, Validation, Writing – original draft, Visualization. **Grischa Beier:** Conceptualization, Investigation, Writing – original draft, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.136598.

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