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Industry 4.0 and energy in manufacturing sectors in China

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A R T I C L E I N F O

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A B S T R A C T

Digitalisation in manufacturing (or “industry 4.0”) is expected to improve energy efficiency and thus reduce energy intensity in manufacturing, but studies show that it may also increase energy consumption. In this article, we investigate to what extent the degree of industry 4.0 is linked to energy consumption and energy intensity in ten Chinese manufacturing sectors between 2006 and 2019. We approximate the degree of industry 4.0 by combining data on a) patent intensity of industry 4.0-related technologies and b) industrial robot intensity. Our results indicate that there is no significant overall relationship between the degree of industry 4.0 and energy consumption or energy intensity, in contrast to some earlier studies in the Chinese context which find energy intensity reducing effects of digitalisation. We argue that industry 4.0 in China might have fewer energy related benefits than expected by politics and industry. Growth-inducing effects and outsourcing of energy-intensive manufacturing tasks, for instance, may counteract efficiency-related savings. To decarbonise manufacturing in line with China’s proclaimed objective of carbon neutrality by 2060, policy makers and industry should identify specific opportunities and take seriously risks of industry 4.0. The focus should be on reducing absolute energy consumption as opposed to energy intensity, which may disguise digital rebound effects; and on integrating renewable energies, particularly in the most energy-intensive sectors (metals, chemicals, non-metallic minerals).

List of abbreviations

AI	artificial intelligence
GDP	gross domestic product
GVA	gross value added
ICT	information and communication technology
I4.0	industry 4.0/digitalisation in industry
PPI	purchasing price index
RD	research & development
RVA	real value added

1. Introduction

The sustainability-related effects of digitalisation in industry,[1] or industry 4.0 (I4.0), receive increasing attention in research, industry and politics. I4.0 can be defined as the transformation of manufacturing organisations and human interactions within these organisations through digital technologies, with mutual dependencies between organisations, humans and technologies in manufacturing systems [1]. There are expectations by industry and policy makers that I4.0 will not only create economic opportunities, but also positively impact sustainability of industry, e.g., through the provision of real-time environmental data along supply chains [2–6]. China, being the largest manufacturer in the world with 30% of global manufacturing value added, increasingly frames I4.0 as a means to create economic growth while simultaneously helping to achieve energy saving goals, for instance, in the 14th 5-year-plan (2021-2025), “Made in China 2025”, the “Internet +” action plan or in the white paper “Energy in China’s New Era” [7,8]. Despite government-promoted energy intensity reductions[2], however, the Chinese manufacturing sectors’ total energy consumption has increased in

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[1] According to the ISIC classification, the “industry sector” includes the sectors manufacturing, construction, mining and quarrying, electricity, gas and water supply. However, in this study we use the term “industry“ synonymous with “manufacturing” [104].

[2] Energy intensity is defined as energy consumption per unit of value added.

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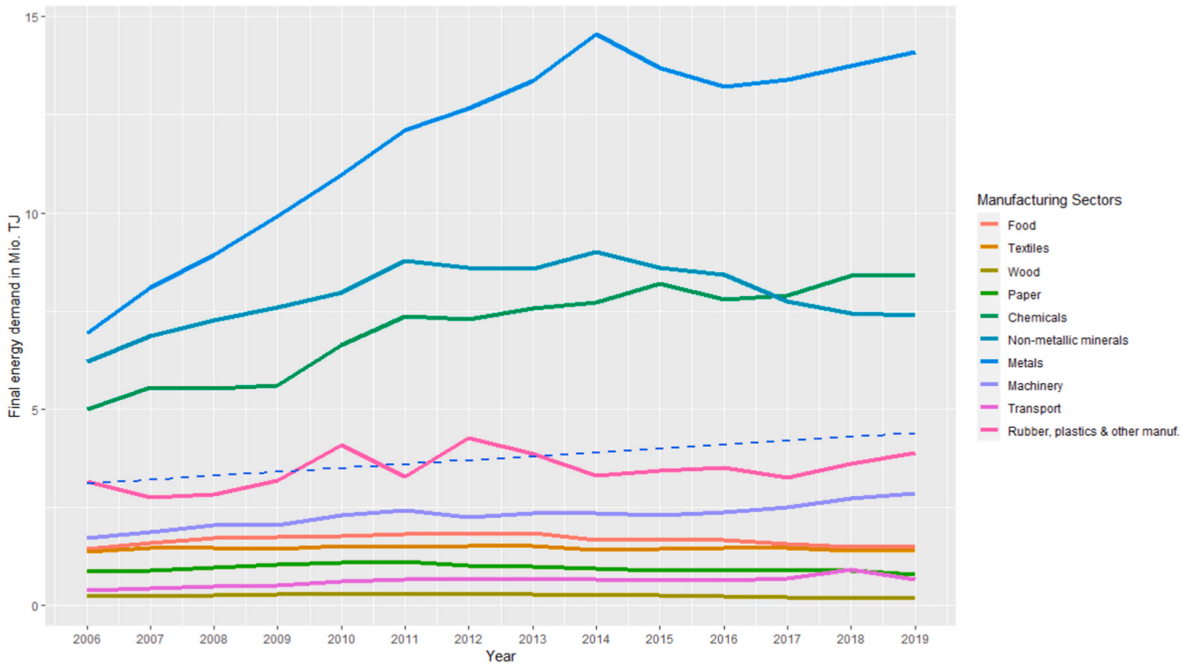

Fig. 1. Energy consumption by manufacturing sector in China 2006-2019.

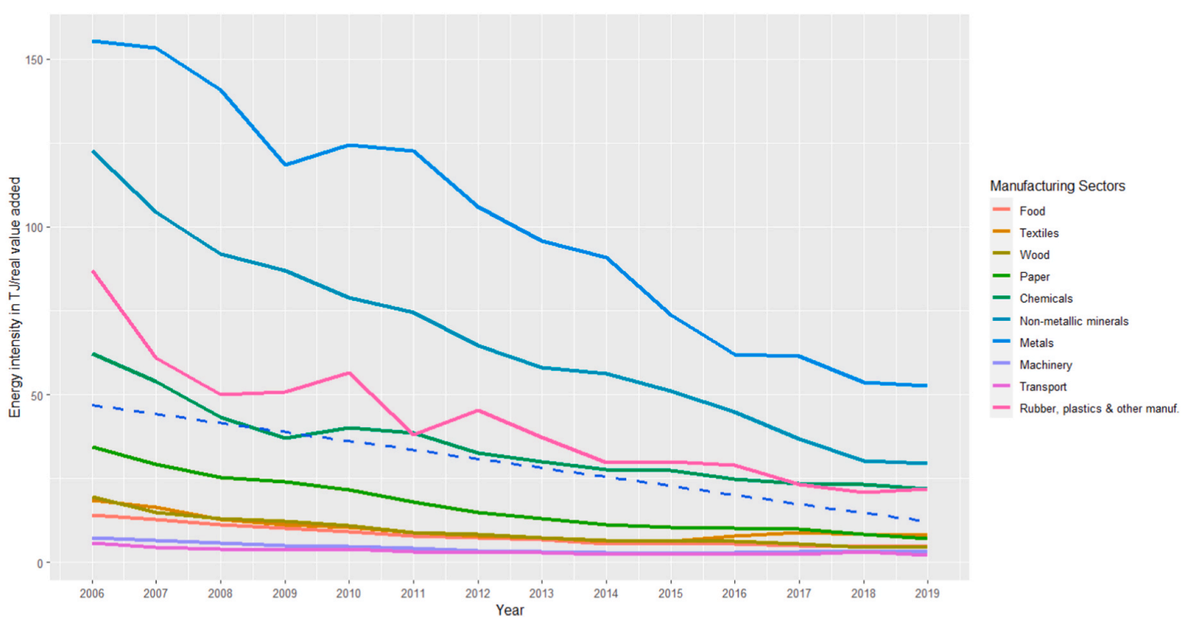

Fig. 2. Energy intensity by manufacturing sector in China 2006-2019.

past decades (as shown in Figs. 1 and 2). Given the industry sector's crucial role for the country's energy savings [9], the question arises how I4.0 will affect industrial energy consumption.

Empirical analyses of the effect of digitalisation and industry 4.0 on energy consumption and intensity have shown mixed results [10]. Studies posit both energy-consuming and energy-saving effects of digitalisation [11–13] (see section 2). There are gaps in the literature, which further complicate the assessment of digitalisation's effects. Many studies analyse the broader effects of digital technologies on energy consumption [14,15], but fewer do so in the Chinese context [16–19] and even fewer studies compare the heterogeneity of digital technologies' impact across manufacturing sectors [20,21]. Moreover, there is little recognition of the concept of I4.0 in previous studies, and subsequently little diversity of manufacturing-specific proxies for measuring I4.0, as opposed to more widely used indicators of digitalisation, such as ICT capital, broadband coverage and mobile internet subscriptions (for a list of indicators, see Ref. [22]). In some studies in the context of China, authors oversimplify the concept of I4.0, for instance, by equating robot use with artificial intelligence (AI) use [23–25], leaving out the innovation and knowledge dimension of technologies. Additionally, previous studies on robot use in China mainly frame econometric models around the efficiency and energy intensity related effects of digitalisation, thereby neglecting the aggregate energy consumption. All in all, it is remains unclear whether the proliferation of I4.0 is associated with higher or lower energy consumption and energy intensity in manufacturing.

This study aims to provide an empirical perspective on the relationship between I4.0, energy intensity and energy consumption in

Chinese manufacturing sectors over time and investigate the expectation that I4.0 is associated with decreasing energy intensity and energy consumption in industry. We ask the following research question: How far is the degree of I4.0 linked to energy consumption and intensity in industry sectors? We address this question by conducting a panel data analysis of the degree of I4.0 and energy consumption and energy intensity in ten industry sectors over a 14-year period (2006–2019). We construct a combined index of robot and I4.0 patent intensity as a proxy for the degree of I4.0 in manufacturing sectors. The robot data is sourced from the International Federation of Robotics and the patent data is sourced from the China National Intellectual Property Administration (CNIPA) via the European Patent Office's PATSTAT database. It comprises patents in eight core technology fields of I4.0, namely, big data and analytics, robotics and autonomous systems, cloud computing, the internet of things, artificial intelligence (AI), 3D printing, digital security and, digital measuring tools and sensors. The technology fields were adapted from Martinelli et al. [26], and the definitions and IPC codes, which characterise patens, were adapted from the UK IP Office [27–30], Ardito et al. [31], Martinelli et al. [32] and the OECD [33].

Our study aims to extend the existing literature in several dimensions. Firstly, we extend the time frame and the granularity of previous studies by differentiating between ten manufacturing sectors in China between 2006 and 2019. Secondly, to face the lack of indicators and data for I4.0 we introduce a novel way of conceptualising I4.0 and operationalising its measurement by approximating I4.0 through robot intensity and patent intensity. Robot intensity is one indicator reflecting the tangible dimension of the concept of I4.0, i.e., it should be a proxy for the dimension of hardware equipment and automation of manufacturing. Patent intensity is one indicator reflecting the intangible dimension of I4.0, i.e., it should be a proxy for the dimension of knowledge, intellectual property and innovation regarding I4.0. Both indicators have been used before separately in similar studies, e.g., robot data to analyse AI, I4.0 and automation [20,34,35], and patent data in the context of energy intensity [36,37] and digitalisation [38,26]. To the best of our knowledge, however, we are the first to use sectorally attributed patent data in eight I4.0 technology fields as a proxy for I4.0 and to combine robot and patent data to assess their joint impact of I4.0 on energy indicators. Thirdly, we include both energy consumption and energy intensity in the econometric model to investigate differences in the effect of digitalisation on energy consumption and energy intensity and discuss the interaction between energy consumption, energy intensity and I4.0 on the level of sectors in manufacturing in China. This allows us to reflect on the role of I4.0 for absolute energy consumption and rebound effects, as opposed to intensity/efficiency-focused accounts in previous studies.

Understanding the nexus between energy and I4.0 in China could have significance not only for Chinese industry representatives and policy makers. The European Union and countries in other world regions are facing similar challenges in shaping I4.0 to promote the goals of sustainable development. For instance, the EU pursues a "green and digital transition" in industry [27], aiming to achieve both environmental and digital innovation targets. Moreover, numerous industrial policy strategies in Asia and Africa draw similar links between environmental sustainability and digitalisation in industry. However, it often remains unclear in these policy visions how digitalisation will translate into environmental benefits in the economy [2]. Thus, empirical evidence of the environmental effects of digitalisation in industry, such as the relationship between I4.0 and energy in manufacturing sectors, could inform countries' policy measures to steer the implementation and environmental effects of I4.0 towards the goals of sustainable development.

2. Theory & evidence: impacts of digitalisation and industry 4.0 on energy consumption and energy intensity

Taking into account the broader literature on the effects of information and communication technology (ICT) on the environment of the past 25 years, digital technologies have been theorised to cause direct effects and indirect (including systemic) effects on the environment. Direct effects result from the resources and energy required in production, use and disposal/reuse of digital technologies [28]. Indirect effects arise, when digital technologies are used in other domains, such as agriculture or industry and affect environmental indicators in these domains. Systemic effects occur when digitalisation induces long term structural shifts in how and what is produced in the economy [29,30]. Furthermore, when viewed from an economic standpoint, the indirect effects of digitalisation in industry on the environment can be decomposed into a scale effect, a technique effect, and a structure effect [19, 31]. For the case of energy, these effects can be defined as follows:

- **Scale effect** is the effect of digital technologies on energy consumption that occurs through their impact on growing the economy (e.g., sales of products and services; also called income effect, or final demand effect).
- **Technology effect** is the effect of digital technologies on energy intensity in other sectors (also called technique effect). It is argued that innovation and technological progress have a decreasing effect on energy intensity, since they promote the development of more efficient technology (as a result of the innovation itself) and technological spillover into other areas, and thus lead to more energy-efficient production [33,39].
- **Structure effect** is the effect of digital technologies on the size, composition and value added of sectors which can influence energy consumption and intensity in the economy. For instance, the introduction of digital technologies in the automotive sector may shift the value added from manufacturing to the service sector, as value added grows stronger in the accompanying services (e.g., repair of board electronics) than in the manufacturing of the car [40]. This may affect energy consumption and intensity of the automobile sector.

Empirical studies on the environmental impacts of digitalisation come to varying, or even opposite results [10,41]. Regarding energy consumption, for instance, Schulte et al. [13] conducting a multi-country OECD panel investigation find an overall negative relationship between ICT and energy consumption. The direct effect of using ICT and its indirect growth-accelerating effect (scale effect) increase energy demand whereas the technology effect and the structure effect reduce energy demand. Han et al. [19], analysing the impact of ICT on energy consumption in China, find that the net effect of ICT is initially negative (until 2014) and then becomes positive. The authors assume that the reason for this U-shaped effect is the industrial structure optimisation through ICT. The optimisation process of moving away from energy-intensive industries happened before 2014. The scale effect, including household income growth through ICT, direct energy consumption of ICT as well as lower energy costs outweigh the savings of ICT after 2014 [19]. Applying a machine learning approach to firm level data of 25000 firms in Germany, Axenbeck et al. [42] find that ICT more frequently leads to an increase than a decrease in energy consumption in the observed firms.

Regarding energy intensity, Zhou et al. [43] scrutinise the impact of ICT on Chinese energy intensity changes from 2002 to 2012 using a three-tier structural decomposition analysis. Their results indicate that ICT contributed to a 4.54% increase in energy intensity. However, ICT input in other sectors had an energy intensity decreasing effect. Effects seemed to be stronger in the service sectors and the more technology intensive sectors. For heavy manufacturing sectors and other energy-intensive sectors the effects were negligible. Wang et al. [44], on the other hand, find an energy intensity reducing effect of the use of industrial robots across 38 countries. They argue that increased productivity, optimised factor structures, and technological innovation in production improve energy efficiency depending on the application field and country. They also find that after the introduction of the concept of

Table 1
Data.

Variable (availability)	Definition	Unit	Data sources
Industry 4.0			
Degree of industry 4.0	(Stock of industrial robots divided by real value added (standardized)) + (Stock of industry 4.0 related patents divided by total stock of patents (standardized))	Standardized index, mean = 0, normally distributed	International Federation of Robotics Industrial Robots Report China National Intellectual Property Administration (CNIPA) via the European Patent Office's PATSTAT database
Industrial robot stock (2006–2020)	Stock of industrial robots (including implicit depreciation rate, depreciation of robots every 12 years)	Number of robots	International Federation of Robotics Industrial Robots Report For methodological notes see [50,51]
Industry 4.0 patent stock (2006–2019)	Stock of industry 4.0 related patents (including 10% depreciation rate per year).	Number of patens	CNIPA via the European Patent Office's PATSTAT database
Environmental impact			
Energy consumption	Total final energy consumption in tera joule (TJ) in the end-use industrial sectors	TJ	International Energy Agency (IEA) World Energy Balances 2021 Edition. "Total final consumption"
Energy intensity (2006–2019)	Total final energy consumption in TJ in the end-use industrial sectors per unit of GVA	TJ/US-Dollars	
Control			
Gross Value Added (GVA) and real value added (RVA) (2006–2018)[a]	Sectoral Gross Domestic Product (GDP); GVA is GDP subdivided by sectors with taxes deducted and subsidies added; real value added (RVA) is GVA adjusted by annual sectoral purchasing price indeces (PPI)	US-Dollars, Millions	OECD Input-Output Table (2021 Edition)
Energy Price Index (2000–2020)	PPI for industrial producers of fuel and power	Index (Year 2000 = 100)	China National Bureau of Statistics (NBS)
Emission intensity of imports (2006–2018)[b]	Total CO2 emissions embodied in gross imports	1000 tonnes	OECD
R&D Expenditure (2008–2018)[c]	R&D Expenditure (2008–2018)[a] R&D Expenditure of large and medium sized enterprises (2003–2010)	Yuan, Millions	OECD ANBERD, NBS
Trade intensity	Sum of imports and exports divided by GVA	-	OECD Input-Output Table (2021 Edition)
Foreign capital (2006–2019)	Foreign capital of industrial enterprises above designated size	Yuan, Millions	NBS

Notes.
[a] 2019 value extrapolated based on China NBS; assumption: Value added (VA)/R&D expenditure has increased at the same rate in each sectors, as total VA/R&D has increased for industry as a whole.
[b] 2019 is imputed by taking the average growth rate over the past 5 years and multiplying the 2018 value with that rate.
[c] 2006–2007 missing in OECD ANBERD: Approximation of 2006 and 2007 values by calculating annual percentage changes in NBS database and applying to last available value in OECD database (e.g., 2008 to 2007 change from NBS used to impute 2007 OECD value); Industry 9 (transport) in the period of 2008–2011 missing: approximation of Industry 9 in that period using annual percentage changes observed in the NBS data "R&D expenditure of large and medium sized enterprises".

I4.0 in 2011 the negative impact of robots on energy intensity increased compared to before 2011, and thus conclude that I4.0 has an energy intensity decreasing effect. Lee et al. [45] similarly find a positive relationship between industrial robots the introduction of I4.0 and green technology innovation. Li et al. [20] equate industrial robot use with AI use, and find that AI use contributed to decreasing energy intensity in Chinese industry sectors by increasing output value and reducing energy consumption. They also demonstrate that efficiency gains due to AI vary across industries. The negative effect of AI on energy intensity is found to be most pronounced in technology-intensive sectors and its positive effect on output value (scale effect) greater in labour- and technology-intensive sectors than in capital intensive sectors. As is the case for energy consumption, several studies come to the conclusion, that there is a non-linear effect of digital technologies on environmental and energy intensity [10,20,42,46,47]. Initially, digital technologies are found to be associated with increasing energy intensity and later with decreasing energy intensity, as the reference variable (e.g., financial development, income, and technological development) increases.

To conclude, several studies find an energy intensity reducing (technology) effect of digitalisation, analysing different indicators, such as ICT investment or industrial robot use. Some studies hint to growth-inducing effects and the non-linearity of digitalisation's impact on energy, depending on other development indicators. Wang and Xu [10] reviewing 46 articles on the econometric analysis of environmental impacts of ICT conclude that the variation in results is due to differences in the underlying contexts, study periods, indicators and/or estimators. Zhang and Wei [41] alert to the omission of system level effects which have led to confounded results in previous studies.

3. Methods

3.1. Data

Drawing from standard econometric textbooks and a recent review of econometric approaches to the analysis of environmental effects of ICT [10,48,49], in this analysis we choose an econometric panel data estimation approach. We firstly construct a panel data set with a cross-sectional dimension ($N = 10$ sectors) and a time dimension ($T = 14$ years). The dataset is balanced, as each panel member (sector) is observed every year, which results in 140 observations. An overview of the variables in the dataset can be found in Table 1.

The *degree of industry 4.0* is constructed by standardising and adding *industry 4.0 patents intensity* and *robot intensity* for each industry and each year (details can be found in Appendix B):

Degree of industry 4.0 = industry 4.0 patent intensity (standardized) + robot intensity (standardized)

Industry 4.0 patent intensity is constructed by dividing the stock of industry 4.0 related patents (each including 10% depreciation rate per year) by the stock of all patents in the sector. Our dataset on industry 4.0 related patents has been constructed by aggregating patent applications in eight technology fields: big data and analytics, robotics and autonomous systems, cloud computing, the internet of things, artificial intelligence (AI), 3D printing, digital security, and digital measuring tools and sensors. Details about the origin of these patent fields and the underlying methodology can be found in Appendix A.

Robot intensity is constructed by dividing the stock of industrial robots (including full depreciation of robots every 12 years) by the real value added (RVA) generated in the industry sector. We standardize both variables (mean = 0, normally distributed).

Energy consumption and energy intensity are used as proxies for the environmental impact of industry sectors. Energy data is taken from the International Energy Agency (IEA). Energy intensity is constructed by dividing energy consumption by sectoral real value added. More details on the data preparation and additional descriptive results and can be found in Appendix B and C.

3.2. Estimation strategy

We estimate econometric models of the association between the degree of industry 4.0 and energy consumption as well as energy intensity separately in ten Chinese manufacturing sectors (see Fig. 3). We specify static, parametric panel models as frequently used in related studies [10] with the following specification:

$$\ln(ener)_{it} = \beta_1 I4.0degree_{it} + \beta_2 \ln RVA_{it} + \beta_3 \ln foreign_{it} + \beta_4 \ln RD_{it} + \beta_5 \ln trade\_int_{it} + \beta_6 \ln CO2imp_{it} + \beta_7 PPIener_t + u_{it}$$

We test various estimators to explore our research question: Ordinary Least Square, one-way fixed effects, two-way fixed effects, random effects and first difference estimators. Comparing the results of various specifications allows us to determine how sensitive our results are to changes in the estimators. We use the data analysis software "R". We log-transform (natural logarithm) all variables except the degree of I4.0 (standardized) and PPI (index variable). For each estimator, we tested the relevant model assumptions according to standard procedures for panel data analysis [48,49]. We performed several tests, testing for linearity, multicollinearity, error structure (including serial correlation, cross-sectional dependence, heteroskedasticity, and unit roots (i.e., stationarity of variables)). We use the Breusch-Godfrey test [53] which indicates serial correlation in the error terms. We use the Pesaran cross-sectional dependence test [54] which indicates cross-sectional dependence between the errors of the units of observation (sectors) for the intensities' model but not for the level model. Given the existence of cross-sectional dependence, second-generation unit root tests are necessary. The cross-sectionally augmented Dickey-Fuller [55] test indicates no unit roots, although our time series might be too short to detect unit roots, as the question of co-integration/unit roots is rather relevant for long time series [56]. Due to serial correlation and cross-sectional dependence, we use cluster-robust standard errors from the "msummary" function in R (option "HC3" recommended for small samples). We use clustered standard errors. More details about our methodological approach can be found in Appendix D.

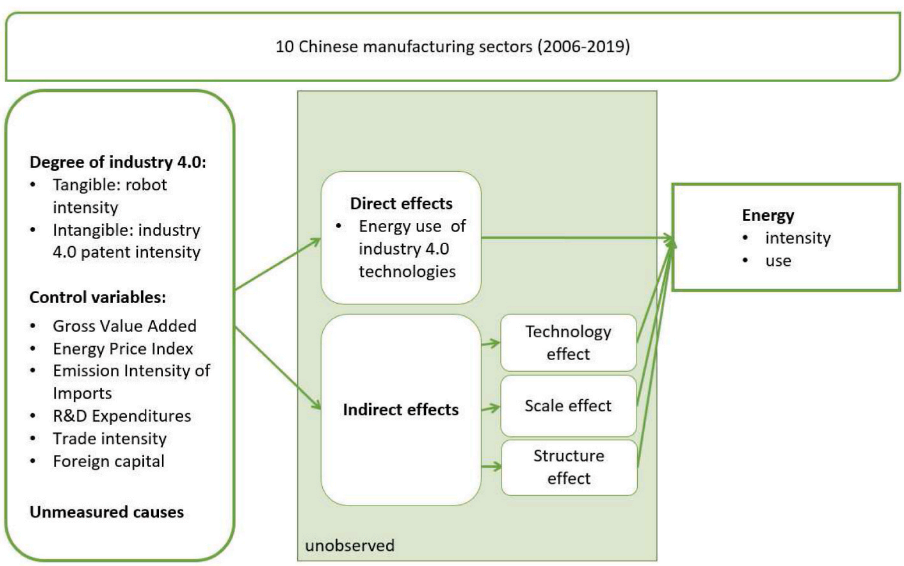

Fig. 3. Conceptual framework: The total effect of industry 4.0 on a sector's energy intensity and consumption depends on the size of the direct effect, the technology effect (efficiency changes in sector due to industry 4.0), scale effect (growth of sector due to industry 4.0) and structure effect (shift of composition of sectors due to industry 4.0) [12], also see section 2. Please note that we do not intend to estimate (decompose) the size of the direct and different indirect effects on energy consumption and intensity. For decomposition studies, please see Ref. [52].

$$\ln(ener\_int) = \beta_1 I4.0degree_{it} + \beta_2 \ln foreign\_int_{it} + \beta_4 \ln RD\_int_{it} + \beta_5 \ln trade\_int_{it} + \beta_6 \ln CO2imp\_int_{it} + \beta_7 PPIener_t + u_{it}$$

where *ener/ener_int*$_{it}$ is energy consumption/energy intensity of sector *i* at time *t*, respectively; where $\beta_1 \ldots \beta_8$ are estimation parameters; where *I4.0degree* is the degree of I4.0 at time *t* in sector *i;* where *RVA, foreign/foreign_int, RD/RD_int, trade/trade_int, CO2imp/CO2imp_int* are control variables at time *t* in sector i in levels and intensities, respectively; where *PPIener* is a control variable for energy prices (proxied by the purchasing price index of energy) at time *t* irrespective of the sector (equal for all sectors); where depending on the estimator used $u_{it} = \gamma_i + \delta_t + \varepsilon_{it}$, with γ_i being a sector specific error, δ_{it} being a sector-time specific error and ε_{it} being a random error.

It should be noted that our estimation strategy does not allow to draw conclusions about causal effects. Specifically, our study design and available data does not allow to rule out endogeneity. For instance, energy intensity of sectors might affect innovation activities in these sectors, and thus reverse causality might apply. Additionally, energy consumption is likely to be influenced by other factors not accounted for in the model, such as sectoral policy decisions, which inflicts the problem of omitted variable bias. Therefore, we interpret our results as correlations, informed by our underlying conceptual framework through which we hypothesise and discuss potential causal relationships.

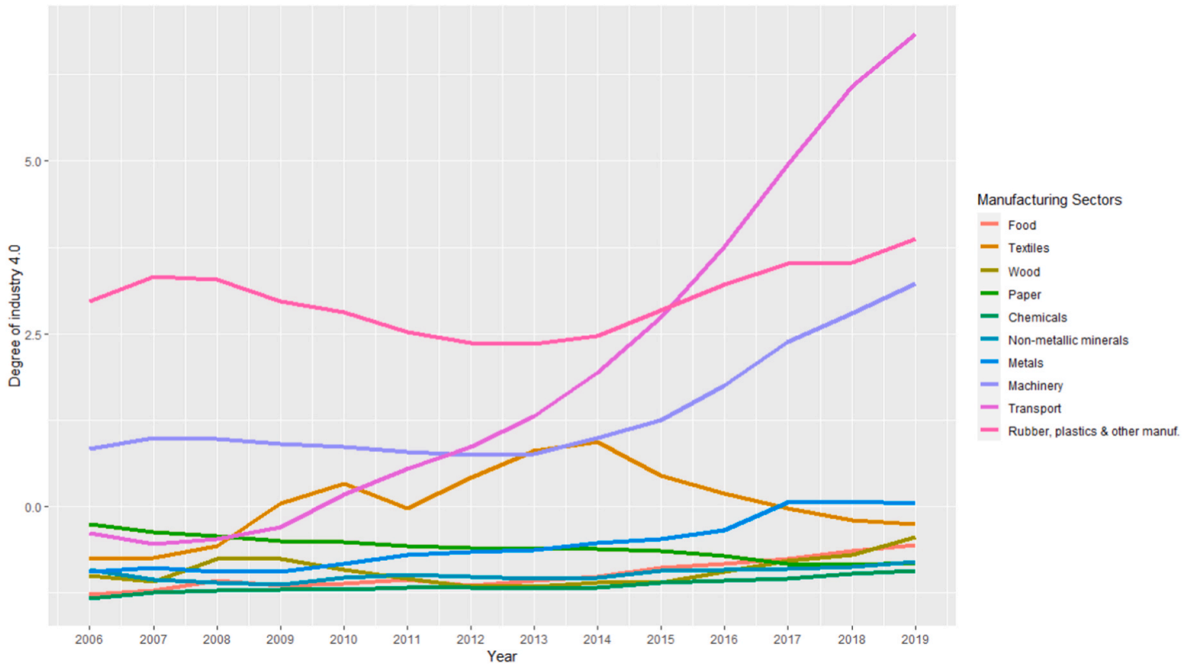

Fig. 4. Degree of Industry 4.0 by manufacturing sector in China 2006–2019ote: due to standardization, values can be below 0.

4. Results

4.1. Descriptive analysis

The degree of I4.0 (Fig. 4) has remained relatively stable for most sectors until 2012, except for the transport sector, where a steady increase can be observed since 2007. Machinery, rubber, plastics and other manufacturing experience an accelerated increase in the degree of I4.0 since 2012. All other sectors remain below average (standardized scale) for most of the observed period.

Energy consumption (Fig. 1, see introduction) has increased over time, while energy intensity (Fig. 2, see introduction) has decreased over time for most sectors, but is highest in the sectors metals, non-metals, chemicals and rubber, plastics and other manufacturing. Energy intensity decreases teepest for the sectors with the highest energy intensity to start with.

To better understand sectoral heterogeneity, we plot mean energy consumption and mean energy intensity against mean I4.0 degree (Fig. 5). The visual inspection suggests that there are three groups of industries: low energy consumption and low degree of I4.0 in the lower left corner (food, textiles, paper, wood), high degree of I4.0 and low energy consumption in the lower right corner (machinery, transport and, relatively far out, rubber, plastics and other manufacturing) and low degree of I4.0 and high energy consumption in the upper left corner

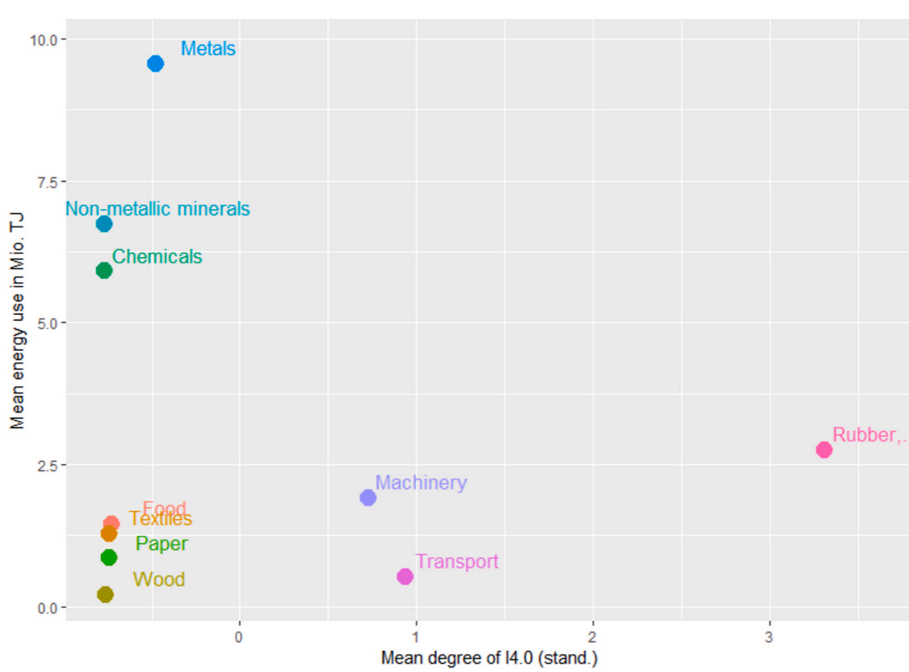

Fig. 5. Scatterplot of sectors by mean energy use and mean degree of industry 4.0.

(metals, non-metallic minerals, chemicals)

To conclude, industry sectors show heterogeneity in the indicators of interest. Particularly, there are only a few sectors with relatively high degrees of I4.0 (machinery, transport, rubber, plastics and other manufacturing), and the other sectors have similar mean degrees of I4.0, but display diverging mean energy consumptions. This skewness poses challenges to our estimation approach which we will discuss in the limitations section. In the following, we will explore whether any systematic statistical relationship between these indicators can be detected.

4.2. Inference

We report two models with four different specifications each. Model 1 uses energy consumption as the dependent variable, model 2 uses energy intensity as the dependent variable.

Regarding energy consumption as dependent variable (Model 1, Table 2), no significant effects of the degree of I4.0 can be detected in either model specification. Real value added and energy price index have a significant positive association with energy in the random effects and fixed effects specification. Regarding energy intensity as dependent variable (Model 2, Table 3) no significant effects of the degree of I4.0 can be detected in either model specification. The energy price has a significant energy intensity reducing effect in the fixed effects and random effects specification. Foreign capital intensity has a significant positive effect on energy intensity. Figs. 6 and 7 summarize the results of the sector fixed effects estimators of Model 1 and 2.

Table 2
Dependent variable: ln(energy), independent variables: levels.

Model 1 Energy consumption	No control variables	Pooled OLS	Time and sector fixed effects	Sector fixed effects	Random effects	First difference
(Intercept)	14.563***	6.409+			11.156***	−0.011
	(0.102)	(3.660)			(1.152)	(0.018)
I4.0degree	**−0.049**	**−0.152**	**0.032**	**0.019**	**0.019**	**0.011**
	(0.048)	(0.142)	(0.026)	(0.018)	(0.018)	(0.028)
ln(RVA)		0.418	0.320+	0.263*	0.259*	0.154
		(0.364)	(0.178)	(0.102)	(0.102)	(0.143)
ln(realRD2)		−0.419	−0.112	−0.092	−0.091	0.046
		(0.268)	(0.083)	(0.062)	(0.063)	(0.040)
ln(trade_int)		0.189	0.027	0.023	0.023	0.009*
		(0.118)	(0.020)	(0.017)	(0.018)	(0.004)
ln(PPIener)		−0.112		0.297**	0.292**	0.192*
		(0.474)		(0.088)	(0.091)	(0.074)
ln(realforeign)		−0.020	0.071	0.147	0.153	0.130*
		(0.298)	(0.138)	(0.104)	(0.103)	(0.050)
ln(CO2imp)		0.818**	−0.081	−0.068	−0.062	−0.034
		(0.291)	(0.055)	(0.057)	(0.055)	(0.025)
Num.Obs.	140	140	140	140	140	130
R2	0.005	0.501	0.427	0.614	0.601	0.151
R2 Adj.	−0.003	0.475	0.282	0.564	0.580	0.102
AIC	4521.3	1109.6	463.4	486.0	495.4	465.1
BIC	4530.1	1136.0	484.0	509.5	521.9	490.9
Log.Lik.	−219.694					
F	1.009					
RMSE	1.16	0.82	0.08	0.09	0.09	0.08

Notes: + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, standard deviations in parentheses.

Table 3
Dependent variable: ln(energy intensity), independent variables: intensities.

Model 2 Energy intensity	No control variables	Pooled OLS	Time and sector fixed effects	Sector fixed effects	Random effects	First difference
(Intercept)	2.763***	4.314***			3.515***	−0.073***
	(0.095)	(0.881)			(0.357)	(0.017)
I4.0degree	**−0.196****	**−0.177**	**0.033**	**−0.021**	**−0.022**	**0.040**
	(0.061)	(0.170)	(0.030)	(0.020)	(0.020)	(0.049)
ln(RD_int)		−0.497	−0.022	−0.141	−0.146	0.158***
		(0.420)	(0.044)	(0.129)	(0.130)	(0.017)
ln(trade_int)		0.184	0.018	−0.011	−0.010	0.006
		(0.135)	(0.020)	(0.022)	(0.022)	(0.005)
PPIener		−0.158		−0.207***	−0.209***	−0.050
		(0.114)		(0.057)	(0.055)	(0.045)
ln(foreign_int)		0.011	0.245	0.768***	0.758***	0.295*
		(0.316)	(0.152)	(0.102)	(0.100)	(0.118)
ln(CO2imp_int)		0.882*	0.135+	0.213+	0.218+	0.042
		(0.358)	(0.073)	(0.110)	(0.111)	(0.031)
Num.Obs.	140	140	140	140	140	130
R2	0.076	0.453	0.334	0.868	0.861	0.281
R2 Adj.	0.069	0.429	0.173	0.852	0.855	0.246
AIC	1201.6	624.3	2.2	106.5	117.3	−6.2
BIC	1210.5	647.8	19.8	127.1	140.8	16.7
Log.Lik.	−214.233					
F	10.134					
RMSE	1.12	0.86	0.09	0.14	0.14	0.08

Notes: + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, standard deviations in parentheses.

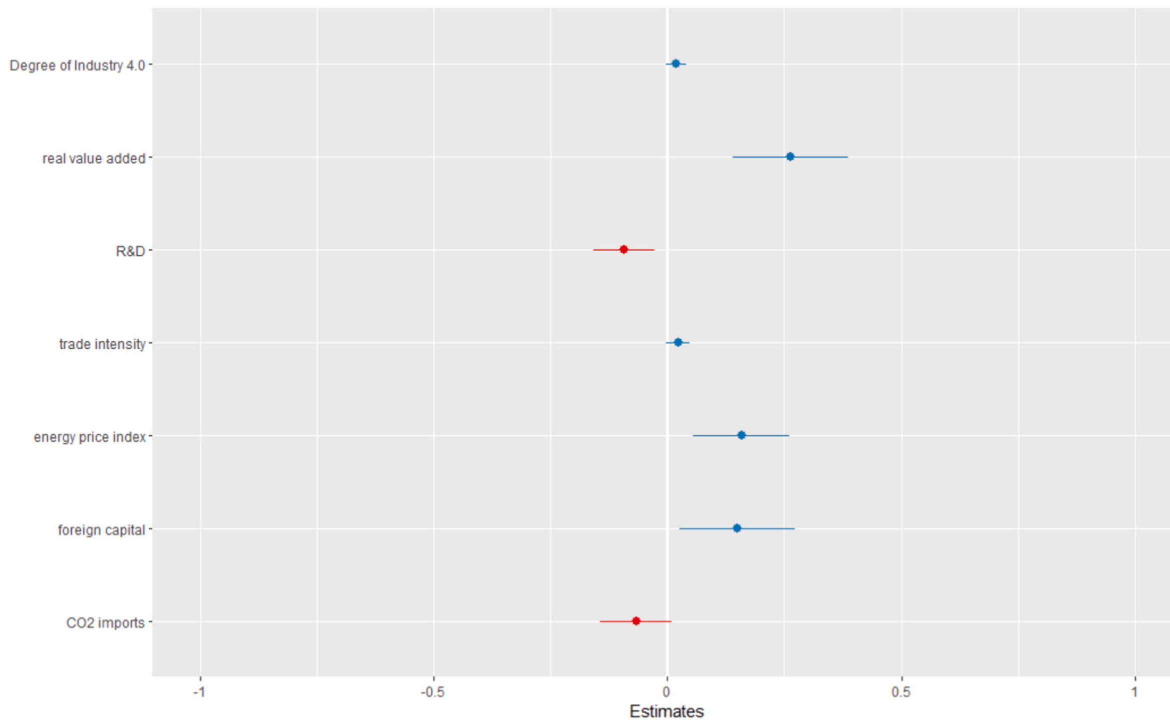

Fig. 6. Variables' correlation with energy consumption, sector fixed effects estimator.

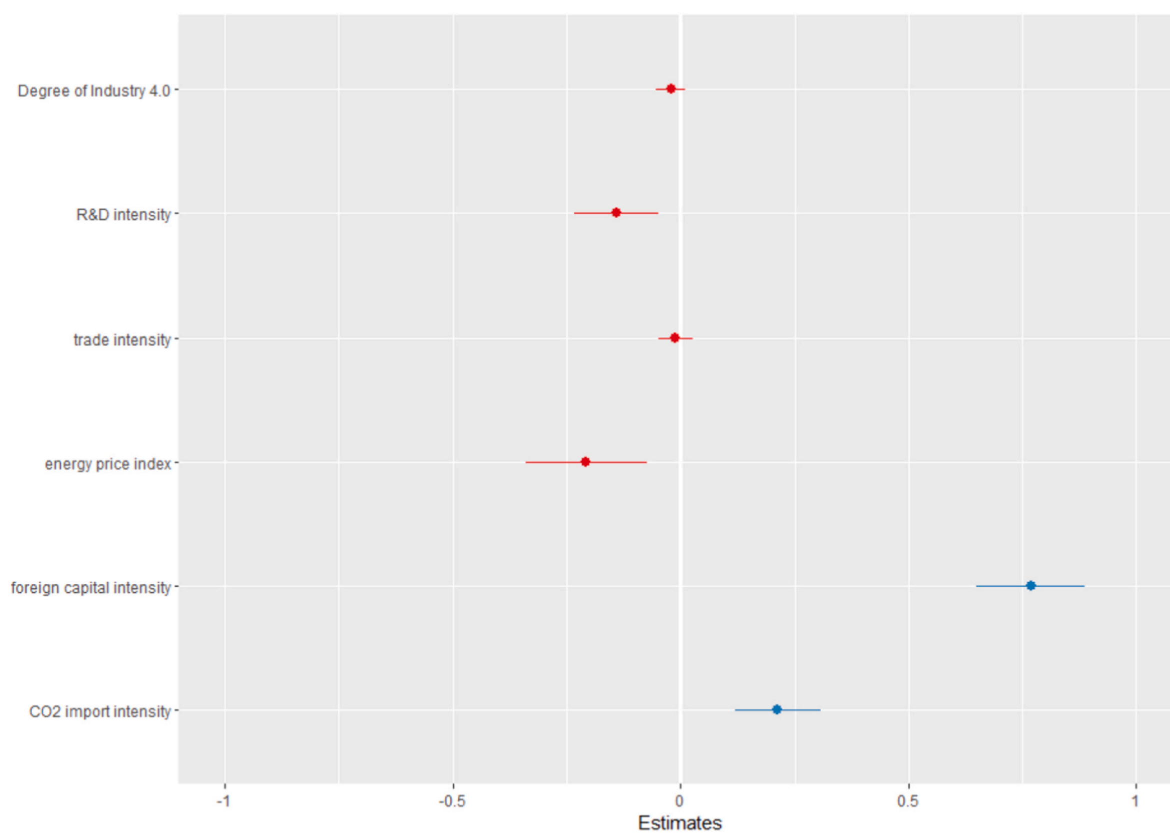

Fig. 7. Variables' correlation with energy intensity, sector fixed effects estimator.

Table 4
Dependent variable: ln(energy), independent variables: levels, Sector fixed effects estimator.

Model 3	High ener sectors	Low ener sectors	High digi sectors	Less digi sectors
I4.0degree	**0.046**	**0.040***	**0.018+**	**−0.023**
	(0.105)	(0.015)	(0.009)	(0.082)
ln(RVA)	0.163	0.214	−0.172	0.357***
	(0.118)	(0.141)	(0.175)	(0.080)
ln(realRD2)	−0.037	−0.133*	0.089	−0.169*
	(0.060)	(0.058)	(0.077)	(0.070)
ln(trade_int)	0.020	0.017	−0.019**	0.022
	(0.017)	(0.016)	(0.006)	(0.020)
ln(PPIener)	0.361**	0.322**	0.561***	0.163*
	(0.103)	(0.113)	(0.130)	(0.073)
ln(realforeign)	0.383**	0.090	0.311	0.127
	(0.139)	(0.101)	(0.242)	(0.096)
ln(CO2imp)	−0.001	−0.051	0.130*	−0.022
	(0.043)	(0.127)	(0.062)	(0.076)
Num.Obs.	56	84	42	98
R2	0.762	0.625	0.776	0.577
R2 Adj.	0.709	0.562	0.713	0.512
AIC	199.8	268.9	142.0	344.3
BIC	216.0	288.4	155.9	364.9
RMSE	0.08	0.08	0.08	0.09
Std.Errors	HC3	HC3	HC3	HC3

Notes: + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, standard deviations in parentheses.

Table 5
Dependent variable: Ln(energy intensity), independent variables: intensities, Sector fixed effects estimator.

Model 4	High ener sectors	Low ener sectors	High digi sectors	Less digi sectors
I4.0degree	**0.107**	**0.002**	**−0.019***	**−0.076**
	(0.099)	(0.021)	(0.007)	(0.112)
ln(RD_int)	−0.055	−0.313**	0.217***	−0.343*
	(0.078)	(0.111)	(0.009)	(0.133)
ln(trade_int)	0.029	−0.023	−0.056**	−0.021
	(0.044)	(0.034)	(0.016)	(0.028)
PPIener	−0.101+	−0.204*	0.023	−0.201**
	(0.060)	(0.089)	(0.035)	(0.074)
ln(foreign_int)	0.887***	0.761***	0.965**	0.662***
	(0.096)	(0.091)	(0.280)	(0.059)
ln(CO2imp_int)	0.076	0.484***	0.401	0.339**
	(0.102)	(0.121)	(0.281)	(0.123)
Num.Obs.	56	84	42	98
R2	0.927	0.877	0.896	0.896
R2 Adj.	0.912	0.858	0.870	0.881
AIC	71.8	10.1	−5.7	92.3
BIC	85.9	27.1	6.5	110.4
RMSE	0.10	0.13	0.11	0.13
Std.Errors	HC3	HC3	HC3	HC3

Notes: + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, standard deviations in parentheses.

4.3. Heterogeneity analysis

We perform one-way fixed effects analysis for energy and energy intensity on subsets of the data, splitting the dataset according to 1) sectors and 2) time. Firstly, we separate sectors according to whether they are comparatively a) high or low energy as well as b) highly or less digitalised. We calculate the average of energy intensity per sector over time and take those sectors as high energy which are above average. We calculate the average of the degree of I4.0 over time per sector and take those sectors as highly digitalized sectors which are above average. The results are largely in line with the visual inspection of the plots in section 4.1 and with a classification by Calvino et al. [57] for the OECD context.[3] This results in the following classification:

- "high energy sectors": metals; non-metallic minerals; chemicals; rubber plastics and other manufacturing
- "low energy sectors": food; textiles; wood; paper; transport, machinery
- "highly digitalised sectors": machinery; transport; rubber, plastics and other manufacturing
- "less digitalised sectors": food; textiles; wood; paper; metals; chemicals; non-metal minerals

Secondly, we separate the data into two time periods (2006–2011; 2012–2019) and see if there are differences in the significance of results for each period. The date is chosen because the concept of I4.0 has been published in 2011 and has gained relevance thereafter. However, since the regression on the split time span does not yield any additional significant results (see Appendix D) we only report the results of separating sectors according to energy and degree of I4.0 (Models 3 and 4).

Regarding energy consumption, the heterogeneity analysis with regressions on subgroups of the data suggests that the degree of I4.0 has a significant positive association with energy in low energy sectors and a significant positive effect to the 10% level in highly digitalised sectors (Model 3, Table 4). Furthermore, in highly digitalised sectors, CO2 embodied in imports is positively correlated with energy consumption. Regarding energy intensity, the degree of I4.0 has a significant negative

[3] Calvino et al. find the sector "wood and paper" to be of medium-high digital intensity in the OECD context [105].

effect on energy intensity in highly digitalised sectors (Model 4, Table 5). Among the control variables, foreign capital intensity has a strong positive association with energy intensity. Here, CO2 intensity embodied in imports has a positive association with energy intensity in low energy sectors and less digitalised sectors.

5. Discussion

5.1. Relationship between the degree of industry 4.0, manufacturing energy intensity and energy consumption

The main intention of this study is to understand how far the degree of I4.0 in sectors is linked to overall energy consumption and energy intensity of manufacturing sectors in China and thus whether the expected benefits of industry 4.0 for energy savings can be detected in our statistical analysis.

Regarding overall energy consumption in manufacturing sectors in China, our results indicate that there is no significant relationship between the degree of I4.0 and energy consumption. The relationship is positive but not significant for the fixed effects, random effects and first difference model. In our heterogeneity analysis, the degree of I4.0 has a significant positive relationship with energy consumption in the group of low energy industries. This is in line with the general notion that the digital technologies associated with I4.0 require energy in their operation (direct effect; see [44,58]). For instance, using robots instead of manual labour in currently less digitalised textiles manufacturing, may likely increase energy consumption of textile manufacturing. Additionally, digitalisation has an economic growth-inducing effect (scale effect) which typically increases energy consumption [44,59–61].

Regarding energy intensity, our results indicate that there is no overall significant relationship between the degree of I4.0 and energy intensity. Energy intensity reductions observed in China in the past decades in most sectors (see Fig. 2 in the introduction section) can thus not be linked statistically to the degree of I4.0 in our study. Our results coincide with the results of Zhou et al. [52] for high energy sectors who equally find negligible effects of ICT on energy intensity. For the metallurgy industry in China, Lin and Xu [62] find that the replacement of labour with energy through mechanization of production processes, hinders energy intensity reduction in the sector – an effect which might similarly occur for industry 4.0-induced automation and technological upgrading in sectors. However, there are also several studies which contradict our results, finding an energy intensity reducing impact of robots and industrial digitalisation [20,23,44,63], which we only find for highly digitalised sectors.

We identified several reasons for the differences between our results and interpretations and those in previous studies. Firstly, this may have methodological reasons, as explained in more detail in the limitations section. For instance, since patents are a forward-looking indicator, effects on energy indicators may only unfold at a later point in time. Moreover, both robot and patent data, are unequally distributed across sectors. Some sectors thus display very low, some sectors very high degrees of industry 4.0, which has to do with heterogeneous technology uptake in sectors but also with our method of assigning patent data to industry sectors. The remsulting low variability of the degree of I4.0 in some sectors over the analysed period makes it more difficult to identify effects of industry 4.0 on energy indicators. Lastly, other studies use other econometric specifications which also has been found to lead to inconsistent results across studies [10].

Secondly, the technological change associated with I4.0, and thus presumably its impact on energy, is heterogeneous. By including patents in eight technology fields, we captured a wide variety of innovation in the field of I4.0. While it is often argued that innovation can foster energy intensity reductions [e.g., Ref. [64]], it is not clear whether this is true for *all* I4.0 technologies which we subsume in our patents indicator. For instance, the use of computing-intense algorithms, such as artificial intelligence, requires high amounts of energy [61] and can be hypothesized to increase energy intensity in sectors that apply such algorithms. Equally, the impacts of hardware and software might be heterogeneous. In a study on the digital economy in China, Wang et al. [65] find that telecommunication services as inputs in other industries have helped to decrease emissions in China, while the increased input of electronic components have contributed to an increase in emissions through indirect structural effects. Ji et al. [66] estimating a two-way fixed effects model of the impact of the digital economy on green development equally do not find a significant effect of the digital manufacturing industry on green development, but find a positive effect of the digital service industry on green development mediated by innovation. Due to a lack of detailed data for industry 4.0 related hard- and software, such heterogeneous effects are difficult to disentangle.

Thirdly, many econometric studies on the effects of digitalisation in industry do not control for the possibility of offshoring (energy-intensive) industrial activities to other countries. While trade is often included as an indicator in related studies, the variable does not allow to draw conclusions about the structure (e.g., energy intensity) of goods and services that are being imported and exported. I4.0 is expected to affect companies' manufacturing location decisions [67], for instance, by reducing transaction costs and facilitating collaboration with international partners. This may lead to changes in domestic and foreign energy intensity of manufacturing, e.g., when energy-intensive production steps are outsourced to other countries or more energy-intensive inputs are imported from other countries [68]. In studies which omit this possibility, energy intensity reductions that arise through digitalisation-related offshoring may mistakenly be attributed to digitalisation itself, and foreign energy intensity increases may be neglected. Regarding China, some of the energy intensity decreases through digitalisation in China detected in previous studies may stem from energy-intensive production steps having been outsourced. To partly capture such effects, we included the indicator CO2 imports as a proxy for energy intensity of imported goods. We find significant positive associations between CO2 imports and the degree of I4.0, suggesting that a higher degree of I4.0 is linked to higher CO2 imports, but further research is required to understand the underlying dynamics.

Lastly, irrespective of how large the energy intensity reducing effects of I4.0 are, it should be noted that energy intensity changes can have different origins and that this may affect the effectiveness and desirability of energy intensity reductions from an environmental point of view. As Hardt et al. [68] point out, energy intensity changes can be differentiated into 1) a component of thermodynamic conversion efficiency[4] and 2) a component of changing monetary output per unit of useful exergy.[5] If energy intensity (energy consumption divided by value added) decreases mainly due to increasing value added (case 2)), as found for the case of energy intensity reductions in the UK [68], the technology-driven increase in conversion efficiency (case 1)) is much smaller than expected. In other words, energy intensity reducing impacts of I4.0 might stem from a scale (growth-inducing) effect rather than from a technology effect. Scale effect driven energy intensity effects have been found for the case of robot adoption in Chinese firms [57] and for the digital economy in China [69]. What does this mean for the relationship between energy, energy intensity and industry 4.0? As argued above, the expectation that I4.0 will not only contribute to energy intensity reductions but also to absolute energy reductions may be dampened. If energy intensity reductions mainly result from scale effects, then efficiency increases may be (partly) compensated by the simultaneous scale effect. This digital rebound effect makes it difficult to

[4] Thermodynamic conversion efficiency is the “efficiency with which final energy is transformed into useful exergy in each sector” [79].

[5] Exergy is the "work that is delivered at the last stage of the energy conversion chain that can still be measured in energy units, for example useful heat, mechanical drive, or light” (qualitative measure), may be called “available energy” [68,70].

achieve aggregate reductions of energy consumption. Studies by Brockway et al. [70] who find a large energy rebound of technological change for China between 1981 and 2010 and Jin and Yu who detect a rebound effect of ICT in energy-intensive industries in China [71] support this concern.

5.2. Other drivers of changes in energy consumption in manufacturing sectors

Chinese energy consumption and energy intensity in manufacturing is affected by a number of other drivers, such as policy interventions [72], R&D [73] and renewable energy development [74,75]. Two drivers which may be particularly relevant in the discussion of the impact of I4.0 on energy indicators are discussed below.

5.2.1. Research and development

Huang et al. [39] show that there are differences in the energy intensity reducing effect of R&D at different stages of the innovation process and by different actors. Effects are found to be higher in the experimental and developmental stage than in basic research, and higher if performed by industrial enterprises than by higher education institutions. The authors highlight that higher human capital, defined as the average years of education, has a positive effect on energy intensity reduction, as it increases absorptive abilities for technological innovation of companies. Thus, transferred to I4.0 innovation, similar questions about mediating factors may arise: Who produces I4.0 innovation at which stage of the industrial innovation process, and do human capabilities exist (in the firm) to enable absorption of innovation, in order to reduce energy intensity and consumption?

5.2.2. Renewable energy development

Liu et al. [74] find that renewable energy development first has an energy intensity increasing effect which reverses for high levels of per capita GDP (56500 yuan). Nonetheless, employment of renewable energies can help to reduce emissions, and the emission-reducing effect of renewable energies has been found to be strengthened by R&D [76]. The digital economy seems to play a role in renewable energy development, too. Shahbaz et al. [77] show that, mediated by governance, digital economy can have a positive role for the employment of renewables. Thus, the question arises how I4.0 can specifically help to replace fossil fuel-based processes with renewable energy-based processes in manufacturing. For instance, a 10-year study on flexibilization of energy-intensive industries (e.g., glass manufacturing, raw material melting and electric steel) in the German context investigates the potential of industrial demand-side management and the role of information technology for flexibilization in the energy market [78].

5.3. Limitations

There are several limitations to our data and methodology that might lead to bias in our results.

Firstly, our concept and measurement of I4.0 can be challenged. While we acknowledge that I4.0 refers to a broad manufacturing transformation, which is coined by interactions between the technological, organisational and human dimensions, we only analyse a fraction of the variables that may indicate such a transformation. For instance, Beier et al. provide a list of features of the concept of I4.0, such as employees, collaboration, and decentralization [1], which we have not captured in our analysis. The reason for this narrow focus is the (un-)availability of time series or panel data on additional features of I4.0 on a sectoral level in China. Additionally, due to the relatively recent emergence, broadness and interdisciplinarity of the concept of I4.0, no unified definition and measurement standards have been determined yet [1,79]. An extensive review of data has been performed prior to the analysis to identify how other research has dealt with this issue. It has been concluded that few other relevant datasets were available on the sector level in China to perform the desired research. We decided to use a yet less common indicator for the measurement of I4.0, namely I4.0 patents. We believe that patents are a good proxy for innovative endeavours, especially in the field of I4.0 where recent technology developments could not otherwise be captured [80]. Patent indicators are also highly correlated with R&D, a widespread indicator of innovation activity. We combine this indicator with robot stock, an indicator which has repeatedly been used to analyse I4.0 and AI in previous works [20,23,34,33,81].

Secondly, notwithstanding the advantages of the data used, it comes with limitations. Regarding robot data, a large share of robots falls in the category "unspecified", and no further classification is possible. This number could be as high as 45% [63]. Moreover, the lack of continuous depreciation of the robot stock does not reflect typical capital decumulation processes assumed in the mainstream literature. Another downside is that robots developed in-house are also not counted in the statistics. Lastly, there is no quality measurement incorporated in the International Federation of Robotics measure, thus each industrial robot is counted as one irrespective of its monetary and use value [50].

Regarding patent data, patents are not classified into sectors in patent offices (see further explanation in Appendix B). They are only assigned patent classification codes by patent examiners to identify them (e.g., the "IPC" or the "CPC" classification). We therefore had to convert the patent data to sectors , which we accomplished by matching the patent data at the applicant/firm-level to the Orbis database. This means that only those patents could be matched, whose company information are in the Orbis database. However, we assume that those companies who have more financial means for research activities are more likely to be represented in the Orbis database than smaller companies with fewer patenting activities. Additionally, this leads to a concentration of patents in few sectors, where the largest innovator firms are subsumed. By applying logarithmic transformations in the regression analysis, we smooth the distribution. Furthermore, there is reason to believe that many patents have little value [82]. However, since we are only looking at one country and compare sectors, we do not assume that there are systematic differences in the share of patents with little value across industries. Lastly, not all inventions are covered by patents (e.g., open source technologies) and applicants use other appropriation mechanisms to reap benefits from their inventions. For instance, a company might be highly digitalised but does not pursue patenting activity. While these are valid concerns, we again assume that there are no systematic biases regarding the choice of appropriation mechanisms.

Thirdly, as noted above, our estimation strategy does not allow us to report causal effects. It would have been interesting to understand the counterfactual energy consumption and energy intensity developments, had I4.0 not been present in a sector, or the causal impact of the introduction of I4.0 in a manufacturing sector on energy. We considered possible ways to estimate causal models, for instance, by measuring the link between digital technologies prior to and after a policy intervention through a difference-in-difference approach. However, we could not identify a suitable causal modelling approach for our research question, since we view the proliferation of digital technologies as a gradual process with no clear time marks, and also intertwined with other developments whose influences we could not rule out due to limited panel data availability for China.

Finally, another limitation of our study is our narrow sustainability concept. Energy use is only one of many *environmental* implications of digitalisation in industry, and it also has numerous *social* implications, such as a changing task profiles and the polarisation of wages. Again, due to limited data availability, we focus on energy and hope that data sources are continuously being generated to allow future research to take a deeper look into other sustainability aspects.

5.4. Future research

Future studies could improve our research in several dimensions. The concept, measurement and data of I4.0 should be improved. Recent efforts to develop shared definitions and standards of I4.0 in practice will help researchers to refine their frameworks for analysis. More data on other characteristics of I4.0 should also be gathered and assessed. For instance, Chinese data on employees' ICT skills and the employment of ICT specialists could be evaluated to include the human dimension of I4.0, as done on the EU level by Matthess et al. [81]. Moreover, company level data and provincial level data on I4.0's technological, social and organisational features should be collected over time to track developments on a more granular (firm or local) level, including specific technologies' potential and risks in different industrial application fields and geographical regions. Regarding causality, case studies of the firm and sector level over time quantitatively and qualitatively measuring I4.0's effect on energy savings could alleviate some of the shortcomings of statistical analyses, and the case of Chinese manufacturing could be compared to other world regions' experiences.

More insights are also needed into the international relocation of environmental burden through I4.0. In the context of China it would be interesting to explore in more detail how energy-intensive industries can be made more environmentally friendly while avoiding that energy-intensive processes be moved to locations where energy might be cheaper or environmental regulations less strict. Pappas et al. [83] discuss the risk of industrial relocation of manufacturing for the environment for the examples of India and Indonesia. The emissions intensity in these countries, being destinations for Chinese offshoring in the iron and steel sector and the non-metallic minerals sector, respectively, is double the emission intensity in China. Similarly, if firms continue to increase cloud capacities and outsource tasks to digital service providers, energy consumption might shift to other sectors (e.g., telecommunication services sector) in the same country, or other countries, and might not be accounted for in a (manufacturing) sector-specific, national statistic. Thus, in future studies, it will be interesting to take an international perspective on I4.0's impacts, e.g., by including closely related trade partners of China and analyse the joint impact of I4.0 on sectoral energy intensity.

Regarding the concept of sustainability, research is currently focusing on energy and emissions, but more data should be made available and evaluated by researchers on other environmental and social effects of I4.0 in Chinese manufacturing sectors. For environmental indicators, material input/throughput, utilization and disposal of industrial wastes, land use associated with digital infrastructure, (e−) waste generation and environmentally friendly sourcing of digital technologies [10] should be assessed to determine the overall environmental impacts of I4.0. For social indicators, it would be particularly interesting to analyse possible trade-offs between social and environment effects of I4.0, for instance in a scenario where digitalisation would reduce energy consumption but simultaneously reduce wages of less skilled workers and thus increase social inequalities.

6. Concluding remarks

Energy consumption in industry made up 38% of global final energy consumption (169 EJ) in 2021 with a 5 percentage points growth since 2000 [84]. China is the largest contributor to this increase [24]. Energy demand is projected to continue to grow. Increasing renewable energcy capacities, which made up less than 3% of Chinese energy production in 2019[6], will arguably not suffice to achieve ambitious decarbonisation targets. With increasing political and industry interest in leveraging I4.0 for sustainability, it is crucial to understand how I4.0 impacts energy consumption and other sustainability indicators in industry. In this study we analysed the link between I4.0, energy consumption and energy intensity in ten manufacturing sectors in the period between 2006 and 2019 in China through a panel data analysis. We found that there is currently no clear trend that I4.0 has an either positive or negative effect on energy consumption and intensity in manufacturing sectors, in contrast to several recent studies which posit an energy intensity reducing effect of I4.0. We found differences in the correlations between less and more digitalised and less and more energy intensive sectors, pointing to heterogeneous effects in sectors. We raised and discussed hypotheses about why energy intensity reductions, including through I4.0, may not necessarily lead to reductions in energy consumption. On a conceptual level, scale effects and other energy demand increasing structural effects of I4.0 may be larger than its energy intensity reducing structural and technology effects. Specifically, I4.0 may entail digital rebound effects in industry [71,85] and lead to increasing relocation of energy-intensive industrial activities to other countries. We conclude that a narrow focus on the reduction of energy *intensity* through I4.0 can be ineffective for decarbonisation if it mainly results in energy intensity decreasing *output increase* and possibly to an overall *increasing total energy consumption*. Other factors should be considered in the design of I4.0 measures, such as its impact on industrial relocation, heterogenous and sector-specific impacts of different digital technologies, human capabilities to adopt innovations and steer them towards sustainability, and the simultaneous integration of renewable energies in manufacturing sectors. Lastly, other sustainability indicators should also be considered, such as resource consumption and e-waste through digital technologies.

The novelty of the analysis was a) to use more recent and more granular data for manufacturing sectors than previous studies, b) to approximate I4.0 with patent and robot data as opposed to general digitalisation indicators used in similar studies (such as broadband coverage), c) to discuss the interaction between energy consumption, energy intensity and I4.0 in China and its implications beyond the country case. This allowed us to reflect on the role of I4.0 for absolute reduction of energy consumption as opposed to efficiency-focused accounts, and point to global challenges, rather than isolating the debate to China. However, our approach also entailed a set of limitations, e.g., we analysed a relatively small and skewed dataset, sensitive to changes in the econometric modelling; and we did not construct a causal model, instead analysing correlations between indicators. Nonetheless, we deem our study a valuable contribution to the debate by shedding light on the assumptions, omissions and limitations of previous statistical analyses of I4.0. Specifically, we highlighted that important variables may be missing in previous studies and that the positive framing of the environmental benefits of I4.0 presented in policy or industry strategies and by scientific research may also contribute to bias in statistical analyses.

We close with some industry and policy recommendations to help make I4.0 contribute to more environmentally sustainable manufacturing. In China, special attention needs to be paid 1) to the implementation of sectoral measures and monitoring to steer I4.0 towards sustainability, particularly in the most energy-intensive sectors, where rebound effects are expected to be large [71], 2) to the prevention of offshoring of energy-intensive production processes, including due to I4.0, and 3) to the absolute reductions of energy consumption and emissions, even under a value added growth paradigm. Firstly, due to the growth-inducing effect of I4.0, the specific mechanisms and effects through which specific technologies affect energy consumption heterogeneously need to be understood to decide which (sectoral) policies might help to reduce the absolute environmental burden of industry and under which framework conditions. Secondly, political commitment and international agreements should prevent that I4.0 leads to an increased offshoring of energy-intensive manufacturing processes to countries with lower environmental standards. Thirdly, I4.0 in manufacturing should therefore be directed in its conception towards the absolute reduction of energy demand and curbing emissions along the entire

[6] The term renewable energies refers to solar thermal, wind, non-specified biofuels/waste, solar PV; own calculations based on IEA, 2021 data.

value chain. The Chinese government's current focus on upgrading industrial structure through innovation, in order to induce growth in value added and achieve energy intensity reduction targets set in the Five-Year-Plans should be complemented by ambitions to reduce energy intensity along the entire value chain. For instance, supply chain wide approaches to sustainability through I4.0 need to be fostered [86], such as through the circular economy initiatives in the EU and China [87,88], and green supply chain measures [89]. Moreover, the 2021 China Energy work conference [24] called for the introduction of a 'dual control' system covering total energy consumption and energy intensity which might help to limit rebound effects. Structural change towards a post-growth industry [90] would certainly also be helpful to save energy [91]. As a politically more likely scenario, a recent study argues that a state policy aiming at a 2-degree global warming with deep emission cuts would lead to larger economic growth rates than the baseline scenario [92]. Whether larger growth rates are desirable from the viewpoint of other environmental indicators (including pollution, resource use, biodiversity) is questionable – but at least, pursuing ambitious decarbonisation targets can be a first step towards managing the environmental effects of I4.0 and transforming traditional manufacturing towards environmental sustainability.

Credit roles

Conceptualization: S.K., M.M.; Data curation: S.K., P.N., M.D.; Formal analysis: S.K.; Investigation: S.K.; Methodology: S.K., P.N., M.M., M.D.; Validation: S.K., P.N.; Resources: P.N.; Visualization: S.K.; Roles/ Writing - original draft: S.K., P.N.; Writing - review & editing: S.K., P.N.

Statement

After the preparation and drafting of the original work, the author(s) used software in the revision process of this article in order to improve the orthography, grammar and style of the written English text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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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

Data will be made available on request.

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Appendix

A. Data

Industrial robot data

The industrial robot data used in this study stems from the International Federation of Robotics. This a private company, reporting robot data since 1993. The International Federation of Robotics definition of industrial robots builds on the definition of the ISO 8373:2012 where a robot is defined as an "actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks" (§ 2.6). An industrial robot (as opposed to a service robot) is an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" used "in industrial automation applications" (§ 2.9). The industrial robot data is generated by contributions from all major industrial robot suppliers worldwide which report data on robot installations by country, industry, and application to the International Federation of Robotics Statistical Department. Secondary data by national robotics associations is used to complement and validate the data. In the case of China, since 2013, the Chinese Robot Industry Alliance provides data from Chinese robot suppliers. Regarding depreciation of robots, the International Federation of Robotics assume an average use time of 12 years with immediate withdrawal afterwards [51].

Patent data

We use patent data from the EPO Worldwide Patent Statistical Database (PATSTAT), which provides bibliographical patent data from more than 100 million patent documents from leading industrialised and developing countries. Specifically, for the case of China, we use patent data from the Chinese State Intellectual Property Office. All patents in our sample are counted according to the year of their first filing worldwide, commonly called the priority year. This is the date that comes closest to the R&D. Furthermore, we count patents according to the "inventor principle", i.e., patents are assigned to the country where the inventor is located (e.g., Siemens is a German company, but if Siemens China branch would file the patent, it would count in the Chinese statistic). This is typically where the R&D has been performed.

In order to delineate the technology fields in our data, we make use of one of the most common classification schemes for patents, namely the International Patent Classification (IPC), in which patents are classified according to their technical implications. We combine the IPC based searches with keyword-based searches in the title and abstract of the patents for some fields (for some methodological notes, see 93 [93]). The technology field definitions and IPC codes were adapted from the UK IP Office [94–97], 98 [98], 27 [32] and the OECD [99].

In our analysis we compare industry sectors. However, patents are only classified according to their technological implications but not alongside sectors. We therefore have to convert the patent data to sectors (NACE 2-digits), which is accomplished by matching the patent data at the applicant/ firm-level to the ORBIS database by Bureau van Dijk. ORBIS is a company database including information on nearly 400 million companies and entities across the globe. In order to connect the two databases, we performed a matching on the basis of applicant/company names. After a cleaning of the company and person names (e.g., conversion to lowercase letters, removal of special characters and umlauts as well as spaces, removal of legal forms), we computed the similarity scores between the two names based on the Levenshtein distance. The Levenshtein distance is a calculation of how many edits would be needed in order to align two text-strings. The lower the number of edits necessary to align two text strings, the higher the similarity between the two. All values that exceed a pre-calculated threshold ($t > 0.89$) are interpreted as a match. Based on this matching, we can assign patents to NACE codes based on the NACE code of a company. Lastly, we scanned a random sample of 156 patents by hand and identified approx. 13% of the patents as potentially inappropriate for the respective category which we deemed an acceptable error quote.

Fig. 8 shows a scatterplot of mean I4.0 patent intensity and mean robot intensity over the observed time period in the ten manufacturing sectors. The plot reveals that the majority of sectors have both relatively low patent and robot intensity. Within this group, textiles and paper show the highest mean I4.0 patent intensity, whereas the sector metals shows the highest mean robot intensity. Three sectors stand out, namely machinery rubber, plastics and other manufacturing and transport which show higher mean values in both indicators than the other sectors.

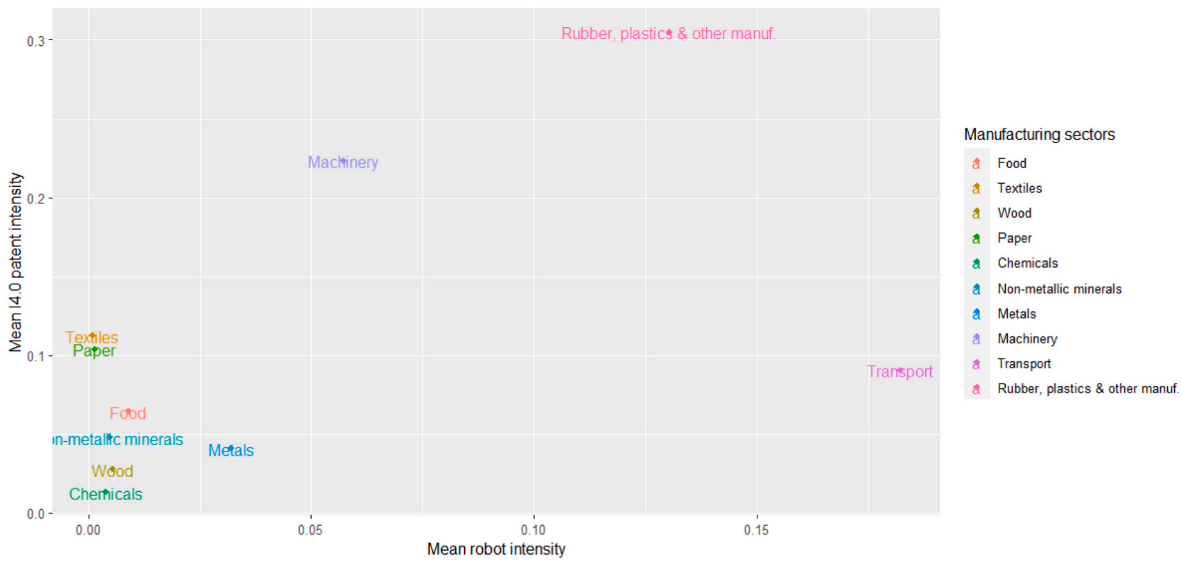

Fig. 8. Scatterplot of sectors by mean robot intensity & mean I4.0 patent intensity over time

Energy data

We use energy data provided by the International Energy Agency (IEA) since 1971 and covering up to 95% of the global energy supply. The IEA provides the World Energy Statistics as well as the World Energy Balances. The IEA data can be accessed with the Beyond 20/20 Browser. It should be noted that that some data is excluded from the IEA database: energy used for transformation processes and for own use of the energy producing industries, backflows from the petrochemical industry, international aviation bunkers and international marine bunkers except for the world total (here they are reported as world aviation bunkers and world marine bunkers in transport)". For further methodological notes on IEA see database documentation [100] and website information (URL: https://www.iea.org/reports/world-energy-balances-2019).

Whereas the World Energy Statistics contain commodity balances - key energy statistics provided in original units for the different types of energy sources, the World Energy Balances are an accounting framework of the combined national commodity balances and provides all the data in a common energy unit. Energy balances help to understand product transformation processes and shine a light on the connections among them to reveal how different energy types are being used. Employing a common energy unit permits users to see the total amount of energy used and the respective contribution of the different sources, for the whole economy and each individual consumption sector. Moreover, it enables the development of various aggregated indicators (e.g., consumption per unit of GDP) and is a frequently used data source for a variety of energy-related research. Hence, our analysis uses the World Energy Balances.

The World Energy Balances contains energy balances for 74 countries and 10 regional aggregates. The energy balances are expressed in tonnes of oil equivalent, defined as 10^7 kilocalories (41.868 GJ). For the People's Republic of China, which joined the IEA as an association country in 2015, data are available starting in 1971.

Regarding the calorific value of each fuel, the IEA has opted to base their energy balances on net energy content which excludes the energy lost to produce water vapour during combustion. Overall, the net calorific values adopted by the IEA are country-specific, time-varying and for some products flow dependent. For most products, they are supplied by national administrations and for oil products, they are based on regional default values. In the matter of another important methodological choice, the IEA has adopted the following principle: "the primary energy form is *the first energy form downstream in the production process for which multiple energy uses are practical*" (Database documentation, p. 381). This leads to the choice between electricity for primary electricity (hydro, wind, tide/wave/ocean and solar photovoltaic) and heat for heat and secondary electricity (nuclear, geothermal and solar thermal) as a primary energy form. After the primary energy form has been established for all electricity and heat produced from non-combustible sources, the IEA follows the physical energy content method to compute the corresponding primary energy equivalent amounts [101, 102].

Regarding the relationship between energy intensity and energy efficiency, aggregate energy intensity can also be viewed as the weighted average of energy efficiency across sectors (i.e., energy efficiency in a sector times the ratio of the sector's contribution to GDP) ([72]). Thus, we refer to (sectoral) energy efficiency and (sectoral) energy intensity complementarily.

B. Data preparation

Mapping sectors

To combine different data sources in our analysis, we map several classifications of manufacturing sectors onto each other as shown in Table 6. We create 10 joint sectors for our analysis which are largely compatible with international classification schemes such as NACE (see last column). As energy consumption is our main dependent variable of interest, IEA sector classifications as described in 100 [100] build the basis for our sector mapping. IEA distinguishes between 10 manufacturing subsectors. Due to data availability limitations, we combine two subsectors and create a new category "Other", arriving at 10 manufacturing subsectors.

Table 6
Sector Mapping

No.	Joint sector name	IEA	International Federation of Robotics	China NBS	OECD Stat	NACE	Federal Statistical Office Germany
1	Foods	Food and tobacco	Food products and beverages, Tobacco products	Food products, beverages, tobacco products,	Food products, beverages and tobacco	C10 – C12	WZ10-12
2	Textiles	Textile and leather	Textiles, leather, wearing apparel	Textiles, wearing apparel, leather and related products	Textiles, textile products, leather and footwear	C13 – C15	WZ13-15
3	Wood	Wood and wood products (excl. furniture)	Wood and wood products (incl. furniture)	Wood and products of wood and cork, except furniture; articles of straw and plaiting materials	Wood and products of wood and cork (probably incl. furniture?)	C16	WZ16
4	Paper	Paper, pulp and printing	Paper and paper products	Paper and paper products, printing and reproduction of recorded media	Paper products and printing	C17 – C18	WZ17-18
5	Chemicals	Chemical and petrochemical	Plastic and chemical products, pharmaceuticals, cosmetics, unspecified chemical, petroleum products	Chemicals and chemical products, medicines and chemical fibres	Chemical and chemical products; Pharmaceuticals, medicinal chemical and botanical products	C20 – C21	WZ20-21
6	Non-Metal	Non-metallic minerals	Glass, ceramics, stone, mineral products n.e.c.	Non-metallic mineral products	Other non-mineral products	C23	WZ23
7	Metal	Iron and steel, Non-ferrous metals	Basic Metals, Metals unspecified	Basic metals, non-ferrous metals	Basic metals	C24	WZ24
8	Machinery	Machinery	Metal products (non-automotive), industrial machinery, electrical/ electronics	Fabricated metal products, except machinery and equipment, computer, electronic and optical products, Electrical Machinery & Equipment, machinery and equipment n.e.c.	Fabricated metal products, Computer, electronic and optical equipment; electrical equipment; machinery and equipment n.e.c.	C25–C28	WZ25-28
9	Transport	Transport	Automotive, other vehicles	Motor vehicles, trailers and semi-trailers, other transport equipment	Motor vehicles, trailers and semi-trailers, other transport equipment	C29–C30	WZ29-30
10	Other	Industry not elsewhere specified (incl. 22: rubber, plastic products; 31: furniture; 32 other manuf. 33 repair and installation of machinery and equipment,	All other manufacturing sectors, rubber and plastic products without automotive parts	Other manufacturing, Plastics, rubber and plastics products, Manufacture of furniture, Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities	Rubber and plastics, Manufacturing nec; repair and installation of machinery and equipment	C22, C31, C32, (Misc.)	WZ22 WZ31 WZ32

Note:*NBS data is available in varying levels of granularity across sectors and time, several aggregations and decisions had to be made. For instance, manufacture of articles for education might be counted in paper & print in the NACE, while the similar category "manufacture of articles for culture, education and sports" is sometimes subsumed in "other" in China. **Our sector "Wood" excl. Furniture whereas International Federation of Robotics data includes furniture. ***IEA sector "Chemical and petrochemical" excludes petrochemical feedstocks and thus excludes rubber and plastics, rubber & plastics are incl. in "industry not elsewhere spec." ****We exclude C19: Manufacture of coke and refined petroleum products from our analysis as energy data for these products is counted among "Energy Industries". We excluded this category from our other data sources where possible, in the International Federation of Robotics data, however, category "Unspecified chemical, petroleum products" includes robots used in C19: Manufacture of coke and refined petroleum, thus number of robots is inflated in this category, roughly 25–50% of robots fall into the category "Unspecified chemical, petroleum products" each year.

Constructing the index "degree of industry 4.0"

To construct the index "degree of industry 4.0", the values of I4.0 patent intensity and robot intensity are combined. Robot intensity, defined as the stock of industrial robots divided by real GVA, and I4.0 patent intensity, defined as the stock of industry 4.0 related patents divided by total stock of all patents are both standardised (mean = 0, normal distribution) for each observation (140) and added. For instance, industry sector "food" in 2006 has a standardised robot intensity of −0.396 and standardised patent intensity of −0.42, resulting in a degree of I4.0 of −0.81. Due to standardisation, values can be below 0.

Table 7 shows the mean of the standardized degree of I4.0 of each sectors over time, ordered from lowest to highest degree of I4.0.

Table 7
mean degree of industry 4.0, calculated as the sum of standardized I4.0 patent and robot intensity

Sector	Mean degree of industry 4.0 (standardized)
Chemicals	−1.2
Wood	−1.06
Non-Metal	−0.87
Metal	- 0.86
Foods	−0.68
Paper	−0.38
Textiles	−0.30
Transport	1.18
Machinery	1.27
Rubber, plastics and other manufacturing	2.73

Accounting for price differences over the time span

To account for changes in price levels over time in China, we use purchasing price indices for industrial producers (PPI) (preceding year = 100) available from the China NBS. We construct PPI for our ten-sector classification system by averaging the PPI levels of multiple sectors, which we had aggregated according to our sector mapping. We create chain linked PPI with base year 2003 (2003 = 100) [18]. As the PPI is only available from 2004 onwards, we use the General Producer Price Index (not differentiated by sectors) for the years 2000–2002. We deflate our monetary variables: Value Added (at basic prices), R&D Expenditure and foreign investment by dividing the nominal annual value by the PPI to obtain deflated values.

Pre-Analysis: Data validation & pre-tests

We performed several checks to validate our data. We checked compatibility of our energy data from the IEA with Chinese NBS energy data. We checked correlation between OECD Input-Output data and Chinese Industry Sales value data. We looked at the distribution of the non-transformed variables (QQ-plots), outliers and checked for missing values. While we do not observe many “within wave missings” we are concerned with “whole-wave missings” [103] due to different time availabilities of data sources. We impute several data points as described in Table 2: Data. We checked the collinearity of variables through the variance inflation factor. Furthermore, we created scatter plots of each independent variable against the dependent variable to check for linearity of the relationship between the variables.

C. Additional descriptive results

Patents

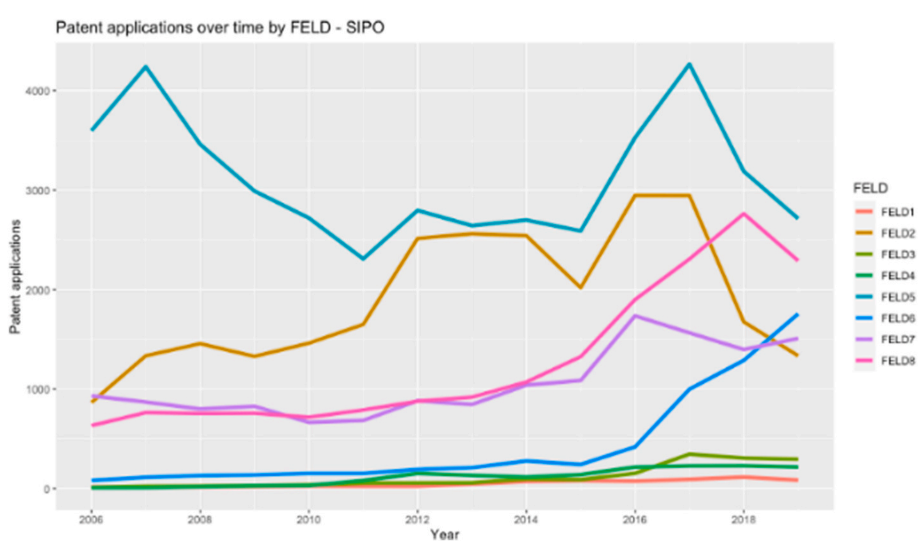

Fig. 9. Patent applications over time, transnational database, Chinese State Intellectual Property Office database, by technology field; FELD 1 to 8 refer to the 8 technology fields analysed in this study: big data and analytics, robotics and autonomous systems, cloud computing, the internet of things, artificial intelligence (AI), 3D printing, digital security, and digital measuring tools and sensors.

Regarding technology fields (Fig. 9), patent applications in all technology fields of industry 4.0 have increased since 2006 until 2015 with smaller dips for some technologies. From 2015, application numbers go down for Big Data and Digital Security, as well as briefly for Internet of Things, which however, remains the technology field with most applications over the time span. The group of 3D Printing, Robotics and Autonomous Systems and Cloud Computing patent applications develops steadily, albeit at a much lower size of applications than the other groups. The technology field “Artificial Intelligence” shows the most stable increase in application numbers in the past 10 years.

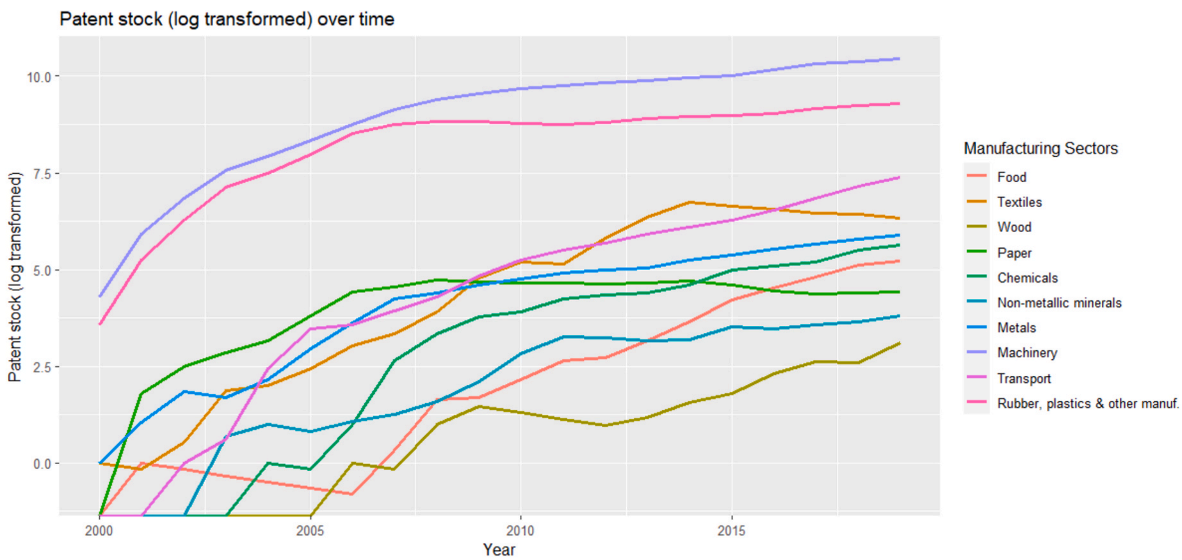

Fig. 10. Patent stock log transformed by manufacturing sector

Regarding sectoral distribution of I4.0 patents (Fig. 10), patent stocks are concentrated in two sectors: machinery and "rubber, plastics and other manufacturing" while machinery also applies for more than twice as many patents than sector "rubber, plastics and other manufacturing". Patent stocks are in the range of 400.000s at the end of the period while the maximum of patent stock in the rest of the sectors is 20.000 (transport sector). Within this group of low-patent sectors; transport, chemicals and metals have the largest patent stock over time, followed by food and textiles which experienced strong increases in stocks in the past 10 years. Non-metals, paper, and wood show declining or stagnating patent stocks. Overall, a decrease of patent stocks can be detected since 2017.

Within sectors, the density of specific technologies (as a share of I4.0 patent stock in the sector) varies. Due to low individual technology and digital patent stocks in many sectors we only interpret these shares after 2015. We do not interpret the density in the wood and non-metallic minerals sector, as the total digital patent stock in the wood sector, for instance, is only 22 (45 in non-metallic minerals) in 2019 and there are as few as one patent applications for some technologies, so density cannot be interpreted. The share of 3D printing patents is largest in the sector chemicals (between approx. 30 and 40% of all digital patents). Big data patents' share was largest in the textiles industry, making up about 60% of all digital patents in the textiles industry. Between 25 and 30% of the digital patents in machinery and transport are big data patents. Robotics and Autonomous Systems' patents' share is largest in Transport. There is a spike in the share of these patents in the wood sector in the last 5 years. Cloud computing patents' share is largest in textiles and transport with an increasing share in several industries over the past 5 years. IoT patents' density was largest in the rubber and other manufacturing sector over the time (almost 70% in 2015) period, followed by machinery, paper and textiles. IoT patents are the largest technology group of machinery's patents but experience an (almost) steady decline in share of I4.0 patents since 2000 (made up 60% today roughly 40%). The decreasing share can also be detected in other sectors, except for textiles. AI patents' share is largest in machinery and transport. AI patents' share was below 12,5% for all industries but there is an increasing tendency in recent years. Digital Security patents' share is largest in machinery. Measuring, testing, sensor technology patents' share is between 50 and 70% for metals, food, chemicals.

Robots

Fig. 11 shows the development of robot stock in manufacturing sectors. Among the sectors with comparatively little robot use, the sector “rubber, plastics and other manufacturing” has the highest robot stock, followed by metals and food. The sectors “textiles”, “wood” and “paper” exhibit very low robot stock rates over the entire time period.

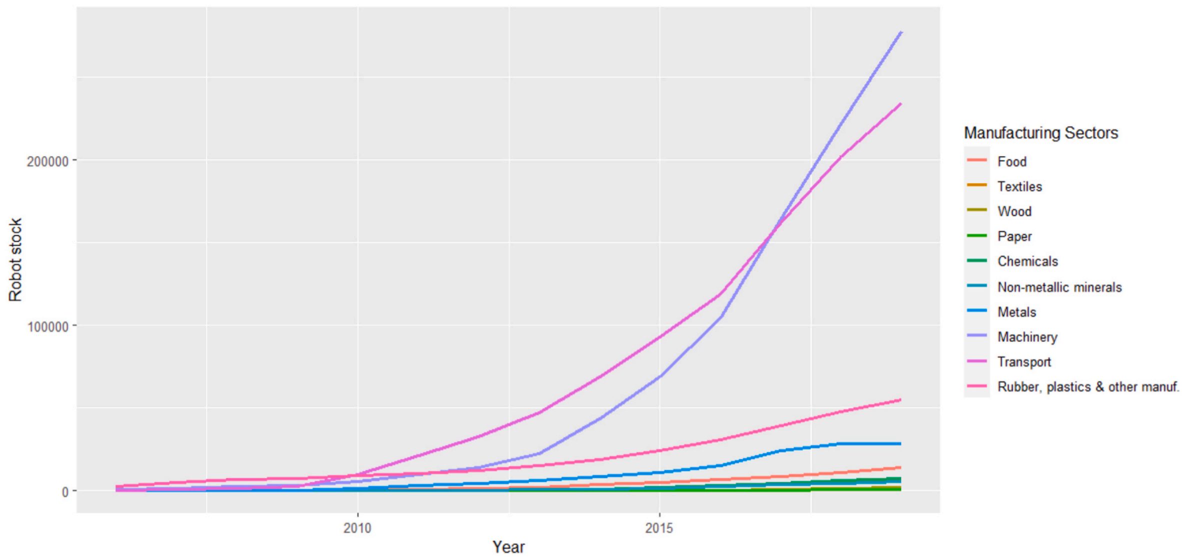

Fig. 11. Robot stock in manufacturing sectors

D. Regression models with split time span

Model 5	Up to 2011	After 2011
I4.0degree	−0.014	0.011
	(0.063)	(0.016)
ln(RVA)	**0.242***	0.017
	(0.098)	(0.116)
ln(realRD2)	0.065	−0.027
	(0.046)	(0.046)
ln(trade_int)	0.037**	0.006
	(0.013)	(0.024)
ln(PPIener)	−0.092	0.177
	(0.162)	(0.178)
ln(realforeign)	0.182	0.220
	(0.117)	(0.132)
ln(CO2imp)	0.086	−0.117
	(0.084)	(0.087)
Num.Obs.	60	80
R2	0.779	0.327
R2 Adj.	0.697	0.156
AIC	164.3	249.4
BIC	181.1	268.5
RMSE	0.06	0.07
Std.Errors	HC3	HC3

Note: Dependent variable: Ln(energy), independent variables: levels, fixed effects model with sector fixed effects; + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Model 6	Up to 2011	After 2011
I4.0degree	−0.030	−0.028
	(0.051)	(0.021)
ln(RD_int)	0.140*	−0.013
	(0.053)	(0.076)
ln(trade_int)	0.037**	−0.023
	(0.013)	(0.028)
PPIener	−0.359***	0.135
	(0.072)	(0.108)
ln(foreign_int)	0.450***	0.812***
	(0.110)	(0.110)
ln(CO2imp_int)	0.245***	0.034
	(0.068)	(0.070)
Num.Obs.	60	80
R2	0.909	0.769
R2 Adj.	0.878	0.715
AIC	−23.9	−14.7
BIC	−9.2	2.0
RMSE	0.06	0.09
Std.Errors	HC3	HC3

Note: Dependent variable: ln(energy), independent variables: levels, fixed effects model with sector fixed effects; + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

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