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Does information substitute or complement energy? - A mediation analysis of their relationship in European economies

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Abstract

In its decarbonization efforts, the European Union aims to decrease energy consumption through technological advances. One of the most prominent advances is the increased extension and utilization of digital information and communication technologies. However, there is little understanding of how precisely digitalization and energy consumption are related. This study aims to empirically analyze the impact and transmission channels of digitalization on energy consumption in the European Union. We build our empirical analysis in two steps. First, we employ the two-step sys-GMM estimator to examine the direct impact of digitalization on energy consumption, controlling for the effects of the mediation variables. Second, we use the causal mediation approach to estimate the relative importance of each mediation variable through which digitalization affects energy consumption. We rely on a sample of 28 European countries from 2007 to 2019. The empirical results suggest that digitalization significantly reduces energy consumption. We find that a 10% increase in digitalization reduces energy consumption by 0.4%, on average. The causal mediation analysis reveals that digitalization has an indirect positive effect on energy consumption through GDP per capita and industrial structure and an indirect negative impact through financial development and human capital.

Keywords: Digitalization, Mediation Analysis, Energy Consumption, Digitalization indices, Embodied Energy, Panel data, two step sys-GMM

JEL classification: C33, C50, Q41, Q43, Q55.

1. Introduction

Governments worldwide have increasingly incorporated objectives and strategies in their policy-making to reduce carbon emissions. This is mainly achieved by increasing the pace of energy transition (i.e.,

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replacing the use of fossil fuels with renewable energy sources) and reducing overall energy consumption (Valero et al., 2018). However, there is a concern about pursuing the latter while maintaining current economic output (i.e., the decline in energy intensity per unit of economic output) (Lange et al., 2020). Scholars suggest that digitalization could play a decisive role in decoupling. They provide evidence that digitalization can substitute energy as a production factor and, accordingly, decrease overall energy consumption (Ishida, 2015; Schulte et al., 2016; Khayyat et al., 2016; Santarius et al., 2020). Indeed, digital technologies are increasingly penetrating all societies, especially modern ones. For example, the internet users are projected to grow in Western Europe from 345 million users in 2018 (82% of the regional population) to 370 million in 2023 (87% of the regional population) (Cisco, 2020). In the meantime, digitalization has been developed in various applications in the energy-consuming sectors substantially through the proliferation of communication systems, autonomous cars, intelligent home systems, and advanced analytics (International Energy Agency, 2017).

These trends are discernible in the European Union (EU), where ambitious decarbonization targets have been defined. Accordingly, the EU policymakers aim to improve energy efficiency through technological advances to reduce total energy consumption (Thomas and Rosenow, 2020). Within energy consumption analyses, the EU provides a unique sample of countries that share general similarities concerning their decarbonization targets, demography, and degree of economic development, while differentiating substantially in the details of their energy consumption, industrial structure, or technological development. Therefore, there has been extensive work on the determinants of energy consumption in the subset of EU countries (e.g., Brodny and Tutak, 2022; Li and Leung, 2021; Thomas and Rosenow, 2020; Martins et al., 2018; Sadorsky, 2011; Liaskas et al., 2000). However, since the penetration of digital technologies and applications is recently high, it may be insightful to focus on the relationship between digitalization and energy consumption within this set of countries. Thus, this study aims to answer the question of to which extent digitalization is a significant prospective determinant of energy consumption in the EU. To the best of our knowledge, no other published study answers this question.

Against this backdrop, we aim to fulfill this gap and contribute to empirical literature in three ways. First, we investigate the direct relationship between energy consumption and digitalization in the EU from 2007 to 2019. We employ the two-step system generalized method of moments (two-step sys-GMM, henceforth) to consider the dynamic effect of energy consumption. Also, we distinguish between this effect on total, fossil, and embodied energy consumption. In moving toward decarbonization and decreasing the energy dependency, the latter two variables are of interest. Fossil fuel consumption, including gas, oil, lignite, and coal, causes a significant share of the emissions in the EU. At the same time, it is mainly imported from foreign sources (e.g., imports made 57.5% of gross available energy in the EU in 2020 (eurostat, 2022)). Besides the domestic energy consumption, embodied energy measures the net energy

embedded in traded goods (measured as the difference in energy embedded in exported goods and imported goods), reflecting the potential outsourcing of energy-intensive production. Second, we estimate the indirect effect between digitalization and energy consumption through the transmission channels of GDP, industrial structure, human capital, and financial development using the causal mediation analysis. Third, instead of using a single indicator (e.g., internet penetration) to measure digitalization, we construct an index that comprehensively measures three dimensions of digitalization: information generation (through the usage of digital devices), information transmission (through communication infrastructure), and information storage (through servers). We also construct an index that combines the three dimensions to analyze the aggregated effect of digitalization and to make our findings comparable to previous studies.

Our results can be summarized as follows: First, we find that digitalization has a negative and significant impact on total energy consumption per capita. On average, a 10% increase in aggregated digitalization reduces total energy consumption by 0.4%. Moreover, our findings provide evidence that this result holds for fossil and embodied energy consumption per capita. Second, our mediation analysis suggests that digitalization has an indirect positive effect on energy consumption through GDP per capita and industrial structure and an indirect negative effect through financial development and human capital. Third, from the three digitalization dimensions, we show that the that information generation has the most significant effect on energy consumption.

The paper is structured as follows. Section 2 provides an overview of the literature in the relevant streams on energy consumption in the European Union, the measurement of digitalization, and the relationship between digitalization and energy consumption. Section 3 describes our empirical approach. In section 4, the data used is described. Section 5 shows our empirical findings, and section 6 discusses their implications. Finally, section 7 concludes.

2. The relationship between digitalization and energy consumption

Finding the determinants of energy consumption has been a broadly acknowledged research field. Recently, a new strand of research has emerged that captures digitalization as a determinant for energy consumption. Three aspects of this literature stream are of particular interest for revealing the underlying relationship between digitalization and energy consumption: the main factors affecting energy consumption, the introduction of digitalization as a determinant, and how digitalization is measured.

An extensive body of literature discusses the determinants of energy consumption by focusing mainly on how economic activity impacts energy consumption (Apergis and Payne, 2010; Kraft and Kraft, 1978). In environmental science, the *Stochastic Impacts by Regression on Population, Affluence and. Technology (STIRPAT)* model has proven helpful in formulating the essential determinants of energy consumption (Shahbaz et al., 2017; Rosa and Dietz, 1998). It links energy consumption to population, affluence, and

technology in the respective economy. In recent years, scholars have augmented this model and identified various factors affecting energy consumption. Theoretical and empirical works find that economic growth (Ahmad et al., 2020; Ozturk, 2010), industrial structure (Mi et al., 2015; Adom et al., 2012; Lee et al., 2021), financial development (Acheampong, 2019; Sadorsky, 2010), research and development expenditures (R&D) (Churchill et al., 2021; Godil et al., 2021), and demographic structure (Liddle, 2014) are primary drivers of energy consumption. In recent efforts, the literature approaches the question of whether previous findings also hold for renewable energy consumption (Usman and Hammar, 2021; Omri and Nguyen, 2014). However, there is not much literature on digitalization as a prospective determinant of energy consumption. This paper contributes to the literature stream on energy consumption determinants by empirically analyzing the relationship between digitalization and energy consumption on a dataset of EU countries, and distinguishing this effect on total, fossil, and embodied energy consumption.

Existing research already provides several findings regarding the relationship between digitalization and energy consumption (Horner et al., 2016). Some authors find energy consumption to be reduced by increasing digitalization (Schulte et al., 2016; Han et al., 2016). Accordingly, digitalization is a substitute for energy consumption. Other authors suggest that the energy consumption increasing effects of digitalization dominate the benefits (Kouton, 2019; Saidi et al., 2017; Sadorsky, 2012). This view stresses that digitalization is best understood as a complement to energy consumption. These conflicting results can be ascribed to applying different econometric approaches, diverging samples of countries, and inconsistent periods among studies. These studies also neglect the multifaceted channels through which digitalization affects energy consumption. The presence of these channels has to be taken into consideration (Lange et al., 2020; Börjesson Rivera et al., 2014; Koomey et al., 2013). Moreover, Horner et al. (2016) show in their review that most analyses focus either on the direct effect of digitalization on energy consumption (Andrae, 2019; Schulte et al., 2016; Aebischer and Hilty, 2015) or on only one of the indirect effects, e.g., economic growth (Ishida, 2015), energy efficiency (Santarius et al., 2020; Joyce et al., 2019), or sectoral change (Rieger, 2020; Fix, 2018).

There is still little research that unites the seemingly conflicting results in a comprehensive empirical framework. Recently, Xu et al. (2022) and Ren et al. (2021) have introduced econometric mediation models which capture both direct and indirect effects between digitalization and energy consumption. While Ren et al. (2021) focus on China, Xu et al. (2022) focus on a sample of 109 major economies in the world. The two studies use the energy consumption scale (energy consumption per capita), energy intensity (energy consumption per unit of GDP), and energy consumption structure (the ratio of natural gas or renewable energy consumption to energy consumption) as proxy variables for energy consumption. They also analyze the transmission channels from digitalization to energy consumption, including economic growth, technological progress, industrial structure upgrading, human capital, and financial

development. This paper contributes to analyzing the transmission channels between digitalization and energy consumption by providing a consistent and relevant framework for the EU countries.

These works on digitalization as a determinant of energy consumption use new combinations of parameters to measure digitalization. For example, Wu et al. (2021) create an index consisting of measures for internet infrastructure, internet industry development, internet business application, and internet development environment. Beyond internet penetration level, their index captures measured values for, e.g., *number of domains*, *e-commerce sales*, and *number of internet enterprises*. Ren et al. (2021) create an index by combining measures of internet penetration, internet infrastructure, internet information resources, and internet application, including, e.g., *IPv4 proportion*, *long-distance fiber length*, and *express business volume*. Xu et al. (2022) construct an index from measures of the categories of digitalization infrastructure, digitalization application, and digitalization skill. They include *mobile phone ownership*, *the number of fixed internet users*, and *adult literacy*. Both papers rely on a Principal Component Analysis to identify the weights of every single measure within the indexes. The indexes advance beyond simple one-dimensional proxies of digitalization. This paper aims to measure three dimensions of digitalization in the EU countries, the generation, transmission, and storage of information. We create indices for each of these dimensions. Additionally, we aggregate them into a single digitalization index based on a comprehensive dataset of relevant parameters.

3. Methodology

Figure 1 displays a schematic diagram summarizing our methodology. We build our econometric approach in two steps. In the first step, we examine the direct impact of digitalization on energy consumption, controlling for the effects of the mediation variables. In the second step, we use the causal mediation analysis (Baron and Kenny, 1986; Zhao et al., 2010) to estimate the significance of the mediation variables through which digitalization could affect energy consumption. In the last step, we provide some robustness checks to our analysis.

3.1. Estimating the direct effect of digitalization on energy consumption

We use the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model introduced by Dietz and Rosa (1994) and York et al. (2003) as a theoretical framework for our analysis. The general form of the STIRPAT model is given as:

$$E = \alpha P^b A^c T^d \mu \quad (1)$$

Where E_t is energy consumption which is a function of the population (P), affluence (A), and technology (T), and the error term μ . We extend this model by incorporating financial development, real energy prices, human capital, and industrial structure. As a consequence, our augmented STIRPAT model is written as:

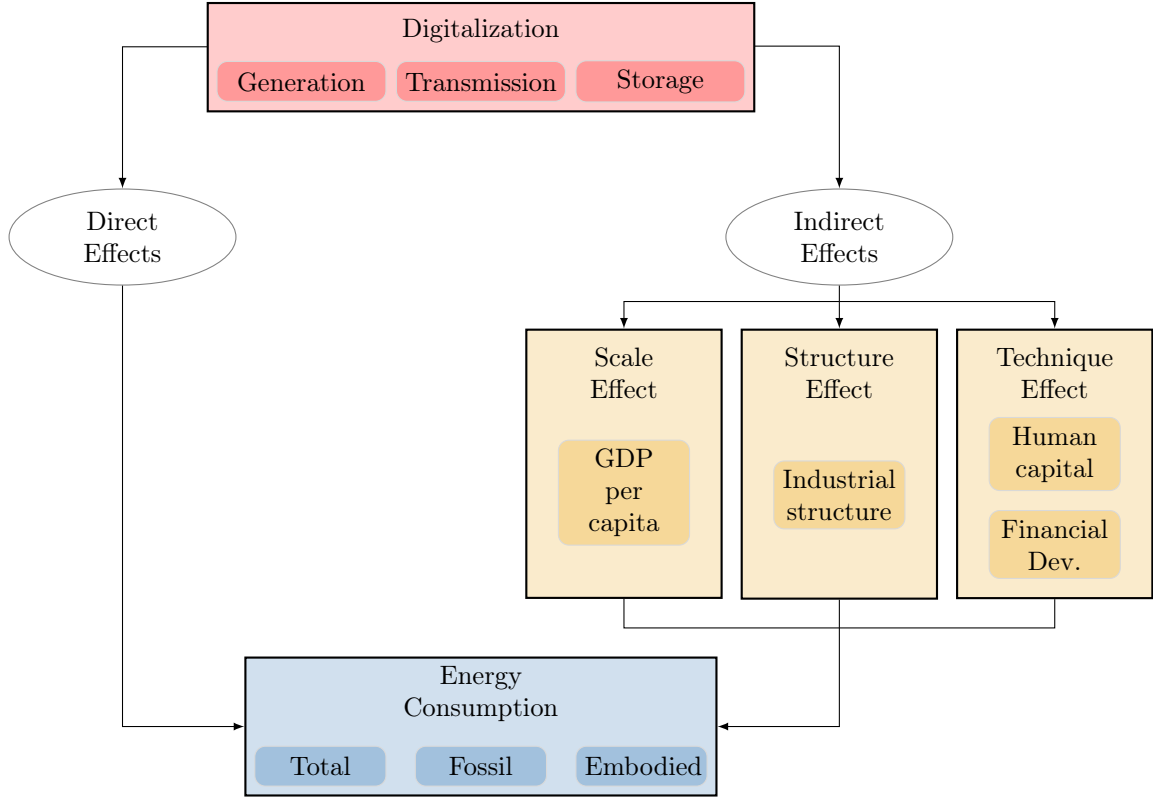


Figure 1: The structure of the mediating analysis with direct and indirect effects from digitalization on energy consumption.

$$E = \alpha P^b A^c T^d Z^e \mu \quad (2)$$

Where Z_t is a vector that includes the additional variables that could affect energy consumption. Taking the logarithmic transformation, the linearized STRIPAT model is given as:

$$\ln E = \alpha + b \ln P + c \ln A + d \ln T + e \ln Z + \mu \quad (3)$$

For the empirical analysis, equation 3 is re-parameterized into an estimable form as follows:

$$\ln E_{it} = \beta_0 + \beta_1 \ln GDPC_{it} + \beta_2 \ln DIG_{it} + \beta_3 \ln Z_{it} + \epsilon_{it} \quad (4)$$

where i refers to the country ($i = 1, \dots, 28$) and t refers to the time period ($t = 2007, \dots, 2019$). Moreover, following the existing empirical literature (e.g., Sadorsky, 2010; Çoban and Topcu, 2013), energy consumption in the last period has a dynamic effect on current energy consumption. Therefore, Equation 4 should be further extended as follows:

$$\ln E_{it} = \beta_0 + \theta \ln E_{it-1} + \beta_1 \ln GDP_{it} + \beta_2 \ln DIG_{it} + \beta_3 \ln Z_{it} + \beta_4 \ln OIL_{it} + \epsilon_{it} \quad (5)$$

Where E_{it-1} is the first lag term of E_{it} . We estimate Equation 5 with the two-step sys-GMM. The sys-GMM is derived from a combination of the first-difference equation (whose independent variables are instrumented by lagged levels) with another equation in levels (whose independent variables are instrumented by their lagged first-differences) and then estimates the two equations simultaneously arellano1995another, blundell1998initial. If there is heteroscedasticity and serial correlation, the two-step sys-GMM applies a consistent estimate of the weighting matrix, taking the residuals from the one-step estimate (Davidson et al., 2004). Nevertheless, the two-step sys-GMM can suffer from two main issues. The first one is related to the over-identification problem that might result from using many instruments. In contrast, the second problem is that the two-step standard errors tend to be downward biased. Accordingly, to avoid the first problem, we keep the number of instruments to a minimum by collapsing the instrument matrix to restrict the proliferation of the instruments. We also use little lags rather than using all available lags as instruments. To solve the second problem, we apply the Windmeijer (2005) finite sample correction to the two-step covariance matrix.

To test for the consistency of the GMM estimates, we conduct two primary diagnostic checks. First, we apply the Arellano and Bond (1991) test to the residuals in differences with the null hypothesis of no serial correlation. Second, we use the Hansen (1982) test of over-identifying restrictions with the null hypothesis of instruments validity.

To check the robustness of our estimation of the direct effect of digitalization, we re-estimate Equation 5 using the Panel Corrected Standard Errors (PCSE) estimator while including country fixed effects to control for unobservables and the lagged dependent variable to control for the dynamic effect of energy consumption. The PCSE can remove heteroscedastic disturbances, serially correlated, and contemporaneously correlated across panels. It also performs substantially better than the Feasible Generalized Least Squares (FGLS) when several cross-sections are greater than the number of periods Reed and Ye (2011).

3.2. Estimating the possible transmission channels from digitalization to energy consumption

In this step, we follow Papyrakis and Gerlagh (2004) and Avom et al. (2020) to examine the transmission channels between energy consumption and digitalization. Specifically, we use the causal mediation analysis (Baron and Kenny, 1986; Zhao et al., 2010) to investigate the mediating variables between the two variables in two steps. In the first step, we estimate the following model to analyze the effect of digitalization on each transmission channel:

$$\ln M_{it} = \lambda_0 + \lambda_1 \ln DIG_{it} + \zeta_{it} \quad (6)$$

where M_{it} is a vector of the mediation variables, and λ_1 is the effect of digitalization on each transmission channel. If λ_1 is statistically significant, digitalization explains part of the variation in the respective mediation variable. After that, we move on to the second step to analyze the indirect effects of digitalization on energy consumption by substituting equation 6 in equation 5 to get the following model:

$$\ln E_{it} = \beta_0 + \lambda_0 \gamma + \theta \ln E_{it} + \beta_1 \ln GDPC_{it} + (\beta + \lambda_1 \gamma) \ln DIG_{it} + \beta_3 \ln DIG_{it} + \beta_4 \ln Z_{it} + \beta_5 \ln OIL_{it} + \epsilon_{it} \quad (7)$$

where β measures the direct effect of digitalization on energy consumption; $\lambda_1 \gamma$ is a coefficient estimated in the second step and measures the indirect effect of digitalization on energy consumption, and $(\beta + \lambda_1 \gamma)$ is the total effect of digitalization on energy consumption. The mediation analysis is valid if the estimated $\lambda_1 \gamma$ (i.e., the indirect effect) is statistically significant (Zhao et al., 2010). We use the structural equation model to estimate these effects. Also, we control for country-fixed effects and use robust standard errors.

Our analysis considers four transmission channels: GDP per capita, financial development, human capital, and industrial structure.

Several studies provide evidence that digitalization enhances economic growth, showing that information and communication technologies as a capital input, combined with labor, can lead to capital deepening and increase labor productivity in other sectors of the economy (Myovella et al., 2020; Niebel, 2018; Jorgenson and Vu, 2016). The literature also provides evidence that economic growth is closely related to more energy consumption in the EU countries (Pirlogea and Cicea, 2012).

There is also growing interest in how the structural changes in the economy can affect economic growth. In this context, the literature relies on two main processes: (1) tertiarization, or the growing trend of employment and output in service activities; (2) de-industrialization, or the contraction of the share of the manufacturing industry within an economy, which started in the economic crisis of the 1970s. Moreover, Engel's law can explain that the increased levels of income in the developed countries can positively influence tertiarization in those economies (Maroto-Sánchez, 2012). Meanwhile, some studies argue that globalization has shifted some energy-intensive industries, such as textiles, steel, and cars, to countries of the Global South and promoted tertiarization in developed countries (Lange et al., 2020). The current study argues that digitalization is accompanied by tertiarization (or de-industrialization) in high income countries through the re-allocation of resources. Hence, this might lead to lower energy consumption.

Regarding financial development, the use of digital technologies positively affects the financial sector performance by increasing productivity, reducing intermediate costs, enhancing efficiencies in resource allocation within the banking sector, and promoting economic opportunities that increase financial access (Muganyi et al., 2022). However, there are two conflicting views on how financial development can affect energy consumption. The first view argues that the growing development of the financial sector can lead to increased lending capital to households and firms, which increases energy consumption. In contrast, the

second view argues that financial development can be an incentive for increased energy substitution by offering credits for local firms to adopt energy-efficient technologies at low financing costs, which can help decrease energy consumption (Chang, 2015). In the EU policy context, we argue that the second view is more relevant, especially with the sustainable finance initiative under the recent European Green Deal (UN environmental program, 2022).

As for human capital, digitalization can help improve technical knowledge and contribute to scientific and technical progress. Accordingly, the quality of human capital within the context of digitalization contains different characteristics such as a high level of education, mobility, independence, new competencies, and knowledge and skills (Zaborovskaia et al., 2020). Theoretically, the effect of human capital on energy consumption is ambiguous. Human capital may drive higher income and increase energy consumption through the income effect. Meanwhile, through technological effect, human-capital accumulation has a role in stimulating inventions and innovations in energy-efficient technologies (Salim et al., 2017). We argue that the latter effect is the dominant in the EU countries.

4. Data

The empirical analysis is based on panel data of 28 EU countries from 2007 to 2019. Our analysis includes data on energy consumption, data on ICT indicators to construct our digitalization index, and data on mediating variables. Table 1 displays summary statistics of our variables and their data sources.

4.1. Energy consumption

Our dataset on energy consumption comprises three variables, namely total energy consumption per capita (*Total EC pc*), fossil fuel consumption per capita (*Fossil EC pc*), and Consumption-based (trade-adjusted) energy consumption per capita (*Embodied EC pc*). *Total EC pc* comprises all domestic energy consumption. *Fossil EC pc*, however, covers only the final energy consumption of the primary energy carriers: oil, natural gas, coal, and lignite. This is a subset of the *Total EC pc* excluding, e.g., nuclear and renewable energy. On average, European countries consumed 28 MWh pc between 2007 and 2019, while consuming on average 18 MWh energy of fossil origin over that period. *Embodied EC pc* captures, similar to *Total EC pc*, all domestic final energy consumption. Then, from this domestic energy consumption, energy used to produce exported goods is subtracted, and energy used to produce imported goods is added. The mean of *Embodied EC pc* over the considered countries is 51 MWh. Although the averages are not weighted by the number of inhabitants of the countries, this shows that European countries are rather net importers of embodied energy.

We include Fossil and Embodied EC pc in our analysis because they allow us to analyze two aspects that are not captured by the commonly used variable of *Total EC pc*. *Fossil EC pc* is an interesting variable since its reduction is crucial for decarbonization, as Europe thrives for climate neutrality in 2050, and

Table 1: Descriptive statistics of all variables

Variable	Symbol	Obs.	Mean	Min.	Max.	St. Dev.	Unit	Source
Energy consumption								
Total energy consumption per capita	Total EC pc	364	28.423	10.568	95.652	14.041	MWh	IEA (2022b)
Fossil energy consumption per capita	Fossil EC pc	364	17.893	6.403	77.619	11.015	MWh	IEA (2022b)
Embodied energy consumption per capita	Embodied EC pc	364	51.283	18.5	136.861	20.119	MWh	Our World in Data (2022)
Digitalisation								
Aggregated Index	Digitalization	364	0.442	0.115	0.754	0.145		
Generation dimension	Gen.	364	0.466	0.114	0.734	0.128		
Transmission dimension	Tra.	364	0.364	0.044	0.788	0.186		
Storage dimension	Sto.	364	0.406	0	0.959	0.218		
Mediation variables								
Gross domestic product per capita	GDP pc	364	30617	5964	105455	20102	Constant 2015 USD	Worldbank (2022)
Share of industry sector in GDP	Industrial GDP	364	22.846	9.985	38.695	5.907	%GDP	Worldbank (2022)
Financial Development	Financial Dev.	358	91.550	24.735	255.310	45.716	%GDP	Worldbank (2022)
Human capital		364	3.246	2.282	3.849	0.299		Feenstra et al. (2015)
Control variables								
Oil Price		364	78.958	43.548	11.652	23.089	Dollars per Barrel	IEA (2022a)

for Europe’s energy independence, as the largest share of its fossil energy carriers are imported (eurostat, 2022). Moreover, fossil energy consumption may include a residual that is hardly electrifiable or hardly substitutable by digitalization, e.g., heavy industrial processes or transport of goods. Thus, analyzing the relationship between *Fossil EC pc* and digitalization may reveal to which extent digitalization can contribute to decreasing the dependence of an economy on fossil fuels. Similarly, *Embodied EC pc* is of interest because it widens the considered energy balance. Accounting for the embodied energy in exported and imported goods yields the total energy needed to supply the domestic demand. As digitalization may shift an economy’s structure towards higher shares of the service sector and an increased import of goods from the agricultural and industrial sector, the Embodied EC pc variable may highlight the actual energy reductions excluding outsourcing of energy-intensive production.

4.2. Digitalization Index

Compared with the traditional determinants of energy consumption, the understanding and creation of measures for digitalization are still underdeveloped. It is yet unclear which aspects of digitalization have the most considerable impact on economic activity and which aspects are most relevant to be measured (Goodridge et al., 2021; Coyle and Nguyen, 2019). As a result, there is a lack of theoretical foundation for refined digitalization measures. Digitalization can generally be applied in various contexts, and its actual economic value depends highly on these applications (Nguyen and Paczos, 2020; Rieger, 2020; Fix, 2018). Available digitalization measures focus on parameters of access to ICT, use of ICT, and ICT skills as a proxy for digitalization. Popular indices of this kind are the Digital Opportunity Index (DOI), the ICT Development Index (IDI), the Digital Economy and Society Index (DESI), the Digital Evolution Index, and the Network Readiness Index (NRI) (Marginean and Orastean, 2017).

The energy consumption literature has built on these ICT parameters to analyze the effects of digitalization on energy consumption. In the early attempts to grasp this relationship, approaches relying on internet infrastructure as an explanatory variable have dominated the empirical literature. Usman et al. (2021); Avom et al. (2020); Kouton (2019); Saidi et al. (2017); Sadorsky (2012) use *percentage of internet users* and *mobile cellular subscriptions* as proxies for digitalization. However, in high-income environments, such as the EU, internet penetration and mobile phone use have approached their saturation level during the last decade. Thus, using these variables to proxy digitalization might not reflect its actual impact beyond this saturation. To reflect those aspects, we introduce composite digitalization indices consisting of parameters obtained from the Digital Economy and Society Index (DESI; European Union, 2022), the ICT Development Index (IDI; International Telecommunication Union, 2022), and the Network Readiness Index (NRI; Portulans Institute, 2022). The composite indices include measures of ICT infrastructure (e.g., servers and broadband speed), ICT applications (e.g., e-commerce and use at work), or ICT skills (e.g., personal ICT skills and business training).

We include three dimensions of digitalization representing essential aspects of information usage in an economy to examine their relationship to energy consumption. These dimensions are the generation of information through digital devices, the transmission of information through communication infrastructure, and the storage of information through servers. The generation of information represents the actual tracking of information and the processing of information to generate new insights. The transmission of information captures the sharing of information over long distances, which may substitute physical transport. The storage of information captures keeping information available for future use, which physical goods may have previously achieved. The value generated by these functions may substitute energy consumption in some applications. For each dimension, we construct a separate index². Then, the aggregated index is constructed by including all available parameters.

For robustness, we apply two methods to weigh the parameters within each index. The first is to construct an index by uniformly weighting all relevant parameters. The second is to perform a Principal Component Analysis and weight the parameters accordingly. We refer the reader to the Appendix for a detailed description of our indices' construction.

4.3. Mediation Variables

We use GDP per capita, industrial structure, human capital, and financial development as measures for the mediating variables. The mediating variables are expected to be affected by digitalization and to influence energy consumption by themselves. We measure real GDP per capita as constant 2017 US\$ in millions. We measure industrial structure by the share of the industrial sector's value-added to GDP. We use the human development index based on years of schooling and returns to education. Financial development is proxied by domestic credit to the private sector (% of GDP). We also control for real energy prices, measured by dividing Europe's spot oil prices by each country's consumer price index (cpi, 2010 = 100).

5. Results

We present our results as follows. First, we estimate the direct effect of digitalization on energy consumption using the Two-step sys-GMM model. Then, we analyze the transmission channels between energy consumption and digitalization using the causal mediation analysis. Further, we examine the direct effect of the different dimensions of the digitalization index. Lastly, we check the robustness of the results obtained by the two-step sys-GMM model with the PCSE model and the robustness of our digitalization indices by constructing them with the Principle Component Analysis (PCA).

²We refer the reader to the Appendix for further details about the variables used to build our indices.

5.1. Direct effects of digitalization on energy consumption

Table 3 presents the results of the two-step sys-GMM model for the direct effect of the aggregated index of digitalization on the three energy consumption variables. Consistent with most of the existing literature, we find that the estimated magnitude of the lagged dependent variables is statistically significant and positive, meaning that Total EC pc, Fossil EC pc, and Embodied EC pc in a specific year are highly influenced by their previous values. Results of the AR(2) test are statistically insignificant, supporting the validity of the specification of our model. Also, the insignificant test statistics of the Hansen test support the validity of the instruments in our models.

Table 3: Results of the two-step sys-GMM regressions

	(1)	(2)	(3)
	Total EC pc	Fossil EC pc	Embodied EC pc
Lag.dep	1.012*** (0.0185)	0.965*** (0.0387)	0.509*** (0.0791)
Digitalization	-0.0401** (0.0158)	-0.0562** (0.0268)	-0.0933** (0.0377)
GDP pc	0.960*** (0.124)	1.047*** (0.173)	0.240*** (0.0507)
Industry GDP	-0.0423* (0.0241)	-0.0693* (0.0408)	-0.119 (0.110)
Human Capital	-0.0335 (0.0661)	0.163 (0.133)	0.241 (0.286)
Financial Dev.	0.0153 (0.0192)	0.00733 (0.0171)	-0.121** (0.0571)
Oil Price	-0.0389*** (0.00869)	-0.0347*** (0.0107)	0.0251 (0.0209)
AR(2)	0.3108	0.5207	0.593
Hansen test	25.263	25.0456	24.6111
P-value of Hansen	0.236	0.2452	0.2644
Observations	332	332	332
Number of countries	28	28	28

Note: *, **, and *** represent significance levels of 10, 5, and 1 percent, respectively. Robust standard errors are reported in parentheses of estimated coefficients and they estimated following (Windmeijer, 2005). AR (2) gives the p-values for the null hypothesis of no second-order serial correlation in the first-differenced residuals. Hansen test is a test for over identification restrictions. We do not control for the time fixed effects because they are found to be statistically insignificant

Our findings suggest that digitalization significantly affects Total EC pc, Fossil EC pc, and Embodied EC pc at the 5% significance level. The estimated coefficients are -0.040, -0.056, and -0.093, respectively.

All else being equal, a 10% increase in digitalization reduces total energy consumption by 0.4%, fossil energy consumption by 0.6%, and embodied energy consumption by 0.9%, on average. This implies that European countries characterized by an increasing rate of digitalization are likely to reduce their energy consumption. The estimated coefficient of digitalization on total energy consumption per capita also confirms the finding of Xu et al. (2022). Moreover, Column 3 shows that the magnitude of the digitalization coefficient is relatively higher than those estimated in Columns 1 and 2, showing that digitalization’s substitution effect may be the highest for *Embodied EC pc*. Nevertheless, the dependent variable used in Column 3 is the Consumption-based (trade-adjusted) energy consumption which measures domestic energy use minus energy used to produce exported goods plus the energy used to produce imported. Thus, it is still unclear how digitalization affects embodied energy explicitly because this variable still includes domestic energy consumption. Therefore, we perform an additional regression that uses a dependent variable that includes only Net energy embedded in traded goods (measured as the difference in energy embedded in exported goods and imported goods). The results of this regression show that digitalization has a positive and significant coefficient on Net energy embedded in traded goods³. This finding implies that digitalization may increase the import of embodied energy as countries shift to the service sector and rely more on importing energy-intensive goods. For Consistency, we move the results of this additional regression to Table C.14 in the Appendix.

Concerning the control variables, our findings suggest that the impact of GDP per capita on energy consumption is significant at the 1% level for all three energy consumption variables. The positive sign of the coefficients is in line with the literature, indicating that higher economic growth positively affects higher energy consumption. The industrial structure is statistically significant at the 10% level for *Total EC pc* and fossil EC per capita, whereas it is insignificant for *Embodied EC pc*. As the latter accounts for the energy embodied in exported and imported products, the domestic production composition has no longer impacted energy consumption. The driver of this energy consumption measure is the actual consumed products, regardless of where they have been produced. Therefore, a change in the domestic structure does not affect embodied energy consumption. The negative sign of the coefficients is counter-intuitive as, generally, the industrial sector in the European countries has a higher energy intensity per produced economic output than the other sectors. However, it may be the case that the marginal components of the industry that are responsible for the high GDP levels are less energy-intensive than the corresponding marginal units of the other sectors, causing a negative effect on energy consumption when industry GDP replaces GDP from other sectors. We also find that oil price has a negative and significant effect on Total and Fossil EC at 1% significance level, revealing that energy demand decreases once oil prices increase as a proxy of energy

³More specifically, in this additional regression, we use net energy embedded in traded goods which is the difference in energy embedded in exported goods, and imported goods. A positive value means that a country is a net importer; a negative means it is a net exporter.

prices. Human capital and financial development are insignificant in all three models; the only exception is the effect of financial development on *Embodied EC pc*, which is significant at 5%.

5.2. Indirect effects of digitalization on energy consumption

The significance of digitalization’s impact on energy consumption does not reveal any information about the nature of this impact. We further employ a causal mediation analysis to specify the relationship between digitalization and energy consumption. We consider four possible transmission channels: GDP per capita, industrial structure, financial development, and human capital.

Table 4: Results of the structural equation model

	GDP pc	Industry GDP	Human Capital	Financial Dev.
Digitalization	0.126*** (0.016)	-0.128*** (0.014)	0.198*** (0.009)	-0.256*** (0.036)
Constant	10.251*** (0.014)	2.978*** (0.012)	3.422*** (0.008)	4.190*** (0.032)
country FE	YES	YES	YES	YES

Notes: Robust standard errors in parentheses; *** are statistical significance at 1% level.

We report the results of the effect of digitalization on each transmission channel in Table 4. Since this effect is similar for all three measures of energy consumption, we only report the results of the direct effects of digitalization on each transmission channel within the regression of energy consumption per capita. We find that the estimated coefficient of digitalization on the transmission channels GDP pc and human capital is positive and significant. At the same time, it is negative and significant for industrial structure and financial development. All things being equal, an increase in digitalization stimulates GDP per capita and human capital, whereas it reduces industry GDP and financial development. More concretely, a 10% increase in digitalization increases GDP per capita by 1.26% and human capital by 1.98%, whereas this reduces the industry GDP by 1.28% and the financial development by 2.56%⁴. The positive and significant effect of digitalization on GDP per capita is consistent with the findings obtained by [Evangelista et al. \(2014\)](#). The estimated coefficient for the effect of digitalization on human capital confirms the finding of [Xu et al. \(2022\)](#). However, the estimated coefficient on industrial structure contradicts the results obtained by [Xu](#)

⁴It should be noted that the fixed effects cause the negative sign of the estimated coefficient of digitalization on financial development. We estimate another model with random effects, and the estimated coefficient of digitalization on financial development is 0.136, with 5% significance level. The estimated coefficients of the other variables are relatively similar to those obtained by the regression with fixed effects. However, we prefer to include the fixed effects at this stage to control for the unobservables. Also, our main objective in this step is to examine whether digitalization explains part of the variation in our mediating variables.

et al. (2022). However, our finding aligns with the argument that digitalization is accompanied by higher economic growth and tertiarization (or de-industrialization) in high-income countries. Our results suggest that digitalization explains part of the variation in each transmission channel. The varying signs of the relationship between digitalization and the transmission channels indicate that the contradicting results on the effect of digitalization on energy consumption in the literature can be explained by differing transmission effects. Therefore, we estimate the indirect effect of digitalization on the dependent variables using Sobel’s product of coefficient approach (Sobel, 1982).

Table 5: Indirect effects of digitalization through the mediation variables

	GDP pc	Industry GDP	Human Capital	Financial Dev.
Total EC pc	0.079*** (0.012)	0.007* (0.004)	-0.093*** (0.011)	-0.015*** (0.005)
Fossil EC pc	0.094*** (0.014)	0.008 (0.005)	-0.128*** (0.015)	-0.014** (0.007)
Embodied EC pc	0.103*** (0.017)	0.086 (0.010)	-0.041 (0.029)	-0.005 (0.009)

The results of the indirect effects are provided in Table 5. We find evidence that the four transmission channels mediate the impact of digitalization on our variables of interest. Specifically, digitalization indirectly increases all three measures of energy consumption through GDP pc and industry GDP, whereas it reduces energy consumption through human capital and financial development. The indirect effect of GDP per capita is significant at the 1% level for the three underlying energy consumption variables. This means that a 10% increase in digitalization increases *Total EC pc* by 0.79%, *Fossil EC pc* by 0.94%, and *Embodied EC pc* by 1.03% through an increase in GDP pc, on average. The economy stimulating effect of digitalization, therefore, increases the energy consumption of an economy. The larger this effect is in the European countries, the lower is the energy consumption reducing effect of digitalization. Analogously, the indirect effect of digitalization through industrial structure is statistically significant only for *Total EC pc* the coefficient. A 10% increase in digitalization increases *Total EC pc* by 0.07%, on average. Human Capital has a significant negative coefficient for *Total EC pc* and *Fossil EC pc* at the 1% level. Hence, an increase in digitalization by 10% reduces *Total EC pc* by 0.93% and *Fossil EC pc* by 1.28% through increased human capital. Similarly, the indirect effect of digitalization through financial development is significant at the 5% level for *Total EC pc* and *Fossil EC pc*. A 10% increase in digitalization decreases *Total EC pc* by 0.15% and *Fossil EC pc* by 0.14%. Generally, except for the scale effect, the transmission channels are not significant for *Embodied EC pc*. As embodied energy is trade adjusted, changes in the domestic economic structure are more probable to be balanced within the trad balance so that the digitalization effect through the domestic structure and technology diminishes.

5.3. Dimensions of digitalization

As several digitalization dimensions are subsumed under the aggregated digitalization measure, we divide it into three sub-indices, each capturing a different digitalization dimension. Table 7 shows the results of the two-step GMM model for the three indices: information generation, information transmission, and information storage.

Table 7: Results of the two-step GMM model for the dimensions of digitalization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Total	Total	Fossil	Fossil	Fossil	Embodied	Embodied	Embodied
	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc
Lag.dep	1.020*** (0.018)	1.016*** (0.016)	0.998*** (0.027)	1.017*** (0.020)	1.017*** (0.017)	1.001*** (0.027)	0.866*** (0.056)	0.900*** (0.067)	0.874*** (0.066)
Gen.	-0.053*** (0.016)			-0.040** (0.019)			0.021 (0.038)		
Tra.		-0.009 (0.012)			-0.004 (0.012)			-0.013 (0.026)	
Sto.			-0.028*** (0.011)			-0.026* (0.013)			0.014 (0.009)
GDP pc	0.832*** (0.134)	0.911*** (0.147)	0.922*** (0.118)	1.042*** (0.173)	1.067*** (0.183)	1.096*** (0.195)	1.287*** (0.249)	1.368*** (0.382)	1.176*** (0.295)
Industry	-0.035 (0.025)	-0.010 (0.032)	-0.042 (0.026)	-0.041 (0.034)	-0.012 (0.031)	-0.056* (0.029)	-0.073 (0.071)	-0.080 (0.091)	-0.078 (0.082)
Human	-0.079 (0.081)	-0.098 (0.098)	0.013 (0.083)	-0.063 (0.086)	-0.091 (0.085)	0.036 (0.108)	0.221 (0.180)	0.157 (0.234)	0.270 (0.236)
Capital	0.015 (0.021)	0.014 (0.016)	0.015 (0.018)	0.019 (0.018)	0.013 (0.017)	0.014 (0.019)	0.109** (0.050)	0.094 (0.060)	0.093* (0.051)
Financial	-0.040*** (0.008)	-0.027*** (0.008)	-0.036*** (0.009)	-0.039*** (0.012)	-0.027*** (0.009)	-0.037*** (0.010)	0.021 (0.022)	0.005 (0.017)	0.034* (0.018)
Oil Price									
AR(2)	0.291	0.281	0.225	0.58	0.533	0.73	0.457	0.488	0.49
Hansen test	25.339	26.145	23.815	23.838	24.006	25.18	23.764	23.39	24.572
P-value of Hansen	0.232	0.201	0.302	0.301	0.292	0.239	0.304	0.323	0.266
Obs.	332	332	332	332	332	332	332	332	332
Number of countries	28	28	28	28	28	28	28	28	28

Note: *, **, and *** represent significance levels of 10, 5, and 1 percent, respectively. Robust standard errors are reported in parentheses of estimated coefficients and they estimated following (Windmeijer, 2005). AR (2) gives the p-values for the null hypothesis of no second-order serial correlation in the first-differenced residuals. Hansen test is a test for over identification restrictions. We do not control for the time fixed effects because they are found to be statistically insignificant

In the case of *Total EC pc*, our results suggest that generation and storage of information are statistically significant at 1% significant level. On average, European economies can reduce their energy consumption by 0.53% and 0.28% by a 10% increase in their data generation and storage, respectively. This indicates

that data generation within an economy decreases energy consumption more than data storage. A possible explanation could be that the data generated within an economy is a better proxy for actual digital activities than data storage capacities. Due to the comparably easy data transfer, their storage capacities can often be found outside of the country. Therefore, controlling data transmission between countries would be a promising approach to improve the model. The transmission variable constructed uniformly from the parameters reveals insignificant results. However, this may be explained by the particular sparse data in constructing the transmission index. The uniformly created index may not account sufficiently for the missing values in the dataset. Within the robustness check with a PCA-constructed index, we obtain significant results for data transmission.

Regarding the effect on *Fossil EC pc*, we find that generation and storage of information are statistically significant at 5% and 10% significance levels, respectively. The estimated coefficients indicate that a 10% increase in information generation and storage can decrease *Fossil EC pc* 0.4% and 0.6%, respectively. Notably, the decrease of *Fossil EC pc* appears to be lower than the decrease of *Total EC pc* induced by information generation and storage. While the aggregated effect of digitalization is higher for *Fossil EC pc*, the disaggregated effects appear to be higher for *Total EC pc*. Analogously to *Total EC pc*, data transmission is insignificant. All three dis-aggregated indices show insignificant results for *Embodied EC pc*.

5.4. Robustness checks

We check the robustness of our estimated direct effect of digitalization on energy consumption in two ways. First, we replace the digitalization index with another index constructed employing the Principle Component Analysis (PCA). Second, we use the Panel Corrected Standard Errors (PCSE) estimator, including the lagged dependent variable and country fixed effects. We construct a dynamic model and evaluate to which extent it obtains similar results as the two-step sys-GMM model.

Table 9 presents the results of the constructed indices using the PCA. We use the two-step sys-GMM method to obtain these results. Generally, the PCA-constructed indices support the findings obtained by the uniformly-weighted indices. Digitalization is significant at least at the 90% level, with a negative coefficient. Data generation and transmission are significant and negative at least the 90% confidence interval for total and fossil EC. In contrast to the uniformly-weighted index, the transmission of information is significant for *Total EC pc* at the 95% confidence interval. The coefficient, however, remains comparably low. A 10% increase in information transmission decreases *Total EC pc* by 0.01%. Meanwhile, the parameters subsumed under data generation still appear to have a higher impact on energy consumption than data transmission and storage. Also, we find that all disaggregated indices are insignificant in explaining the variation of *Embodied EC pc*. Therefore, for brevity, these results are not reported here, but they are available upon request.

Table 9: Results of Two-step GMM model - Digitalization indices constructed with PCA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total	Total	Total	Total	Fossil	Fossil	Fossil	Fossil
	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc
Lag.dep	0.992*** (0.0182)	0.991*** (0.0171)	0.996*** (0.0189)	1.011*** (0.0201)	0.962*** (0.0367)	0.987*** (0.0293)	0.992*** (0.0298)	0.998*** (0.0251)
Digitalization	-0.0155*** (0.00552)				-0.0170* (0.00933)			
Gen.		-0.0217*** (0.00735)				-0.0267* (0.0157)		
Tra.			-0.00999** (0.00486)				-0.0109 (0.00829)	
Sto.				-0.00486* (0.00281)				-0.00937** (0.00449)
GDP pc	1.025*** (0.133)	0.988*** (0.123)	1.005*** (0.145)	0.929*** (0.159)	1.119*** (0.196)	1.226*** (0.237)	1.169*** (0.214)	1.129*** (0.200)
Industry	-0.0445** (0.0217)	-0.0516** (0.0257)	-0.0364 (0.0254)	-0.0197 (0.0225)	-0.0549 (0.0344)	-0.102** (0.0512)	-0.0691 (0.0481)	-0.0585* (0.0324)
Human	0.0274 (0.0705)	0.0464 (0.0772)	-0.000336 (0.0857)	-0.0640 (0.0787)	0.131 (0.127)	0.224 (0.161)	0.121 (0.151)	0.0610 (0.126)
Capital	0.0234 (0.0185)	0.0231 (0.0171)	0.0208 (0.0191)	0.0145 (0.0188)	0.0192 (0.0175)	0.0104 (0.0160)	0.0114 (0.0183)	0.0135 (0.0178)
Financial	0.0234 (0.0185)	0.0231 (0.0171)	0.0208 (0.0191)	0.0145 (0.0188)	0.0192 (0.0175)	0.0104 (0.0160)	0.0114 (0.0183)	0.0135 (0.0178)
Dev.	0.0234 (0.0185)	0.0231 (0.0171)	0.0208 (0.0191)	0.0145 (0.0188)	0.0192 (0.0175)	0.0104 (0.0160)	0.0114 (0.0183)	0.0135 (0.0178)
Oil Price	-0.0392*** (0.00801)	-0.0390*** (0.00822)	-0.0344*** (0.00801)	-0.0310*** (0.00920)	-0.0357*** (0.0114)	-0.0327*** (0.0109)	-0.0285*** (0.00915)	-0.0363*** (0.0123)
AR(2)	0.3699	0.3331	0.3586	0.2824	0.5467	0.4394	0.4211	0.6432
Hansen test	25.0484	25.0594	25.69	25.8	24.3026	25.4849	24.2342	24.4797
P-value of Hansen	0.2451	0.2446	0.2185	0.2142	0.2786	0.2268	0.2818	0.2704
Obs. Number of countries	332 28	332 28	332 28	332 28	332 28	332 28	332 28	332 28

Note: *, **, and *** represent significance levels of 10, 5, and 1 percent, respectively. Robust standard errors are reported in parentheses of estimated coefficients and they estimated following (Windmeijer, 2005). AR (2) gives the p-values for the null hypothesis of no second-order serial correlation in the first-differenced residuals. Hansen test is a test for over identification restrictions. We do not control for the time fixed effects because they are found to be statistically insignificant

Table 11 shows the results obtained by PCSE estimator. We include the lagged dependent variable as an additional independent variable to create a dynamic form of the PCSE artificially. We also control for the country fixed effects ⁵. Columns (21) to (23) report the results of the regression models with the uniformly-constructed aggregated digitalization index, whereas columns (24) to (26) show the result of the digitalization index with PCA weights. The results support the results of the sys-GMM model. The lagged

⁵For the sake of brevity, we remove the estimates of the fixed effects. However, they are available upon request.

variables are positive and statistically significant in all models at the 1% level. The uniformly-constructed index is significant at the 1% level for the three energy consumption variables. The PCA-constructed index is significant at 5% level for total and *Fossil EC pc*. The coefficients are negative in all models.

Table 11: Results of PCSE regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Fossil	Embodied	Total	Fossil	Embodied
	EC pc	EC pc	EC pc	EC pc	EC pc	EC pc
Lag.dep	0.584*** (0.0420)	0.600*** (0.0432)	0.344*** (0.0553)	0.586*** (0.0440)	0.604*** (0.0460)	0.352*** (0.0565)
Digitalization	-0.0355*** (0.0123)	-0.0446*** (0.0161)	-0.0594** (0.0267)	-0.00815** (0.00415)	-0.0101* (0.00548)	-0.0117 (0.00865)
GDP pc	0.256*** (0.0403)	0.301*** (0.0519)	0.656*** (0.0784)	0.252*** (0.0408)	0.294*** (0.0526)	0.648*** (0.0782)
Industry GDP	-0.0294 (0.0282)	-0.0334 (0.0350)	0.0685 (0.0847)	-0.0205 (0.0282)	-0.0223 (0.0349)	0.0867 (0.0848)
Human Capital	-0.135*** (0.0465)	-0.194*** (0.0578)	-0.124 (0.100)	-0.145*** (0.0472)	-0.205*** (0.0586)	-0.151 (0.106)
Financial Dev.	0.00706 (0.0139)	0.00147 (0.0179)	-0.000269 (0.0333)	0.0114 (0.0135)	0.00684 (0.0174)	0.00851 (0.0329)
Oil Price	-0.0156** (0.00641)	-0.0183** (0.00830)	0.0235* (0.0140)	-0.0133** (0.00628)	-0.0156* (0.00812)	0.0286** (0.0140)
Constant	-0.760** (0.360)	-1.280*** (0.479)	-4.248*** (0.809)	-0.716** (0.360)	-1.213** (0.481)	-4.157*** (0.805)
Observations	332	332	332	332	332	332
R-squared	0.995	0.993	0.968	0.995	0.993	0.968
Number of countries	28	28	28	28	28	28
Country FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The first three columns use Dig. Index constructed by uniformly weighting all parameters of the indexes, whereas the last three columns use Dig. Index constructed by the PCA.

6. Discussion

The analysis of the panel data set provides insights into how digitalization has affected the energy consumption of European countries during the last decade. Also, it may help understand in which economic contexts digitalization substitutes energy consumption and in which contexts it rather complements it. Additionally, the analysis shows which aspects of digitalization may provide efficient levers for reducing energy consumption and which instead increase energy consumption.

In analyzing the relationship between digitalization and energy consumption, we compare three different energy consumption balances: total domestic energy consumption, fossil domestic energy consumption, and total embodied trade-adjusted energy consumption. The comparison of the respective regression models

reveals two insights. First, at its current stage of development, our findings suggest that digitalization also substitutes the consumption of fossil energy carriers (i.e., oil, gas, lignite, and coal). With the thrive towards decarbonization, substituting this hardly electrifiable fossil energy consumption would stress the relevance of digitalization. The results indicate that digitalization could achieve this substitution. However, this raises the question of whether there is a saturation level of the substitution process. There may be a residual of fossil energy consumption that cannot be substituted by digitalization, e.g., energy consumption in the material production for digital goods. Furthermore, the decrease in fossil energy consumption may improve the energy security of the European countries as a significant share of their fossil fuel energy consumption is supplied by imports. If digitalization decreases the consumption of fossil fuels, investments in digital technologies may become a lever for increasing the energy independence of Europe. The second insight from comparing the different energy consumption balances is revealed by the decrease in total energy consumption, including the net embodied energy in traded products. This decrease indicates that the substitution of domestic energy consumption and the substitution of goods with high embodied energy exceeds the possible shift of domestic energy-intensive production into foreign countries and the import of the respective goods. However, this may only represent the last decade of digitalization in Europe. Once the substitution gains of energy-intensive goods and processes may saturate, digitalization could mainly affect outsourcing domestic energy-intensive production outside the country.

Our findings suggest that GDP pc as a proxy for the scale of an economy, industrial structure as a proxy for the structure of an economy, and human capital and financial development as proxies for the economic efficiency of an economy are transmission channels between digitalization and energy consumption. Notably, digitalization decreases energy consumption through human capital and financial development channels, whereas it increases it through GDP. The former effect can be interpreted such that digitalization corresponds with improving scientific and technical progress and increasing the productivity of the financial sector. Thus, human-capital accumulation has a role in stimulating innovations in energy-efficient technologies and a more developed financial sector can offer credits to adopt those technologies. In contrast, the positive effect of digitalization on energy consumption through the channel of economic growth can be interpreted as digitalization enabling a general higher productivity of the economy by increasing capital deepening and labor productivity in the whole economy. This higher productivity increases the energy consumption of the respective country. In the case of the European countries, the efficiency gains in the past decade outweigh the scale increase since the overall effect of digitalization on energy consumption remains negative. However, the rebound effect through increased productivity does not exceed the energy consumption decreases by the efficiency gains through digitalization. This balance could turn with a higher saturation of digitalization in the economy.

We divide digitalization into three dimensions, each measured with different indices. These dimensions are information generation (e.g., the usage of mobile apps), information transmission (e.g., the extension of

communication channels), and information storage (e.g., the extension of server capacity). We find significant results for all three PCA-constructed indices on total domestic energy consumption. The results suggest that all dimensions reduce energy consumption. The highest reduction effect is achieved by generating information, followed by information transmission. The storage of information obtains the most minor energy consumption reduction effect. This indicates that the generation of information associated with digital devices and their application in personal and economic activities has substituted energy consumption over the past decade. This application of personal devices may reflect the first years of digitalization at the beginning of the 20th century. More extensive transmission and storage infrastructure has recently become available and may dominate the upcoming digitalization. The effect of transmission of information on energy consumption may have two sides. First, advanced communication channels may increase efficiency within the economy and replace energy-intensive transport (e.g., teleworking replaces commuting). However, there might also be a rebound effect (i.e., the availability of advanced communication channels increases the total communication). The storage of information shows a minor impact on energy consumption. It has to be noted that the storage index mainly captures large data storage centers and does not include the high storage capacities of personal devices. Only in the past years, with the development of cloud technologies, central storage and process capacities have become popular. Additionally, domestic information storage may not be a good predictor of domestic energy consumption. Due to the comparably easy transmission of information, a control for the information import and export would be helpful to isolate the effect of information storage on energy consumption. Otherwise, the server capacities do not necessarily reflect the information storage of an economy as its information may mainly be stored abroad.

7. Conclusion

Digitalization is one of the main technological developments in the 21st century. Its advances are expected to change today's social and economic structures fundamentally. Despite these expectations, explicit scenarios on how these changes would affect the energy consumption of economies are rare. One reason is that the underlying economic relation between information and energy is still to be understood. In this study, we examine digitalization's direct and indirect effects on energy consumption and energy dependence in 28 European countries from 2007 to 2019. We include three energy balances as energy consumption measures, four digitalization measures (i.e., one aggregated index and three indices for dimensions of digitalization), and four transmission channel variables as potential mediators between digitalization and energy consumption. The two-step GMM model is employed to analyze the direct effect, whereas the causal mediation analysis is used to examine the indirect effect of digitization on energy consumption.

Our findings from the dynamic panel model show that digitalization development has a statistically significant and negative effect on energy consumption. A 10% increase in digitalization decreases total final

energy consumption by 0.4%. The mediation analysis indicates that GDP per capita, industrial structure, human capital, and financial development are channels through which digitalization could affect energy consumption. Specifically, we find that digitalization has an indirect positive effect on energy consumption by impacting GDP per capita and industrial structure and a negative indirect effect through human capital and financial development. While the direct effect results also held for fossil and embodied energy consumption, the indirect effect weakens for embodied energy which only is affected through GDP. Furthermore, among the three dimensions of digitalization, our results suggest that the generation of information has achieved the most considerable energy consumption substitution.

From a policy perspective, our findings suggest that digitalization can play a vital role in decreasing the energy consumption of an economy at the current state of the European countries. Therefore, technologies that conceive human capital and financial development should be adopted to increase the energy-saving potentials of digitalization. Simultaneously, policymakers should control the importance of industrial goods in this process as digitalization could lead to outsourcing industrial activities to other countries, potentially increasing the net emissions due to less strict regulatory legal environments in these places.

We show that it is essential to distinguish the dimension of digitalization to grasp its effect on energy consumption. However, the used indices are still not precise enough to fully separate these dimensions. Future research could create additional physical information usage, transmission, and storage measures or construct new indices. A second promising research field is to investigate further the existence of saturation effects in digitalization. A first step could be a quantile regression to reveal the relationship at the edges of the distribution.

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References

- Acheampong, A.O., 2019. Modelling for insight: does financial development improve environmental quality? *Energy Economics* 83, 156–179.
- Adom, P.K., Bekoe, W., Amuakwa-Mensah, F., Mensah, J.T., Botchway, E., 2012. Carbon dioxide emissions, economic growth, industrial structure, and technical efficiency: Empirical evidence from ghana, senegal, and morocco on the causal dynamics. *Energy* 47, 314–325.
- Aebischer, B., Hilty, L.M., 2015. The energy demand of ict: A historical perspective and current methodological challenges 310, 71–103. doi:10.1007/978-3-319-09228-7{\textunderscore}4.
- Ahmad, N., Aghdam, R.F., Butt, I., Naveed, A., 2020. Citation-based systematic literature review of energy-growth nexus: An overview of the field and content analysis of the top 50 influential papers. *Energy Economics* 86, 104642.
- Andrae, A.S.G., 2019. Projecting the chiaroscuro of the electricity use of communication and computing from 2018 to 2030 doi:10.13140/RG.2.2.25103.02724.
- Apergis, N., Payne, J.E., 2010. Energy consumption and growth in south america: Evidence from a panel error correction model. *Energy Economics* 32, 1421–1426.
- Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The review of economic studies* 58, 277–297.
- Avom, D., Nkengfack, H., Fotio, H.K., Totouom, A., 2020. Ict and environmental quality in sub-saharan africa: Effects and transmission channels. *Technological Forecasting and Social Change* 155, 120028. doi:10.1016/j.techfore.2020.120028.
- Baron, R.M., Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology* 51, 1173.
- Börjesson Rivera, M., Håkansson, C., Svenfelt, Å., Finnveden, G., 2014. Including second order effects in environmental assessments of ict. *Environmental Modelling & Software* 56, 105–115. doi:10.1016/j.envsoft.2014.02.005.
- Brodny, J., Tutak, M., 2022. Analysis of the efficiency and structure of energy consumption in the industrial sector in the european union countries between 1995 and 2019. *Science of The Total Environment* 808, 152052.
- Chang, S.C., 2015. Effects of financial developments and income on energy consumption. *International Review of Economics & Finance* 35, 28–44.
- Churchill, S.A., Inekwe, J., Ivanovski, K., 2021. R&d expenditure and energy consumption in oecd nations. *Energy Economics* 100, 105376.
- Cisco, 2020. Cisco annual internet report (2018-2023).
- Çoban, S., Topcu, M., 2013. The nexus between financial development and energy consumption in the eu: A dynamic panel data analysis. *Energy Economics* 39, 81–88.
- Coyle, D., Nguyen, D., 2019. Cloud computing, cross-border data flows and new challenges for measurement in economics .
- Davidson, R., MacKinnon, J.G., et al., 2004. *Econometric theory and methods*. volume 5. Oxford University Press New York.
- Dietz, T., Rosa, E.A., 1994. Rethinking the environmental impacts of population, affluence and technology. *Human ecology review* 1, 277–300.
- European Union, 2022. Digital economy and society index. URL: <https://digital-agenda-data.eu/datasets/desi/visualizations>.
- eurostat, 2022. Energy statistics - an overview. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview#Energy_dependency.
- Evangelista, R., Guerrieri, P., Melicani, V., 2014. The economic impact of digital technologies in europe. *Economics of Innovation and new technology* 23, 802–824.
- Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the penn world table. *American economic review* 105, 3150–82. URL: <https://www.rug.nl/ggdc/productivity/pwt/>.
- Fix, B., 2018. Dematerialization through services: Evaluating the evidence doi:10.31235/osf.io/bw5gm.
- Godil, D.I., Sharif, A., Ali, M.I., Ozturk, I., Usman, R., 2021. The role of financial development, r&d expenditure, globalization and institutional quality in energy consumption in india: New evidence from the qardl approach. *Journal of environmental management* 285, 112208.
- Goodridge, P., Haskel, J., Edquist, H., 2021. We see data everywhere except in the productivity statistics. *Review of Income and Wealth* .
- Han, B., Wang, D., Ding, W., Han, L., 2016. Effect of information and communication technology on energy consumption in china. *Natural Hazards* 84, 297–315. doi:10.1007/s11069-016-2188-1.
- Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the econometric society* , 1029–1054.
- Horner, N.C., Shehabi, A., Azevedo, I.L., 2016. Known unknowns: indirect energy effects of information and communication technology. *Environmental Research Letters* 11, 103001. doi:10.1088/1748-9326/11/10/103001.
- IEA, 2022a. Energy prices. URL: <https://www.iea.org/data-and-statistics/data-product/energy-prices>.
- IEA, 2022b. World energy balances. URL: <https://www.iea.org/reports/world-energy-balances-overview>.
- International Energy Agency, 2017. Digitalization & energy.
- International Telecommunication Union, 2022. Ict development index. URL: <https://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx>.
- Ishida, H., 2015. The effect of ict development on economic growth and energy consumption in japan. *Telematics and Informatics* 32, 79–88. doi:10.1016/j.tele.2014.04.003.
- Jorgenson, D.W., Vu, K.M., 2016. The ict revolution, world economic growth, and policy issues. *Telecommunications Policy* 40, 383–397.

- Joyce, P.J., Finnveden, G., Håkansson, C., Wood, R., 2019. A multi-impact analysis of changing ict consumption patterns for sweden and the eu: Indirect rebound effects and evidence of decoupling. *Journal of Cleaner Production* 211, 1154–1161. doi:10.1016/j.jclepro.2018.11.207.
- Khayyat, N.T., Lee, J., Heo, E., 2016. How ict investment influences energy demand in south korea and japan. *Energy Efficiency* 9, 563–589.
- Koomey, J.G., Scott Matthews, H., Williams, E., 2013. Smart everything: Will intelligent systems reduce resource use? *Annual Review of Environment and Resources* 38, 311–343. doi:10.1146/annurev-environ-021512-110549.
- Kouton, J., 2019. Information communication technology development and energy demand in african countries. *Energy* 189, 116192. doi:10.1016/j.energy.2019.116192.
- Kraft, J., Kraft, A., 1978. On the relationship between energy and gnp. *The Journal of Energy and Development* , 401–403.
- Lange, S., Pohl, J., Santarius, T., 2020. Digitalization and energy consumption. does ict reduce energy demand? *Ecological Economics* 176, 106760. doi:10.1016/j.ecolecon.2020.106760.
- Lee, C.C., Wang, C.W., Ho, S.J., Wu, T.P., 2021. The impact of natural disaster on energy consumption: International evidence. *Energy Economics* 97, 105021.
- Li, R., Leung, G.C.K., 2021. The relationship between energy prices, economic growth and renewable energy consumption: Evidence from europe. *Energy Reports* 7, 1712–1719.
- Liaskas, K., Mavrotas, G., Mandaraka, M., Diakoulaki, D., 2000. Decomposition of industrial co2 emissions:: The case of european union. *Energy Economics* 22, 383–394.
- Liddle, B., 2014. Impact of population, age structure, and urbanization on carbon emissions/energy consumption: evidence from macro-level, cross-country analyses. *Population and Environment* 35, 286–304.
- Marginean, S., Orastean, R., 2017. Measuring the digital economy: European union countries in global rankings. *Revista Economica* 69, 73–80.
- Maroto-Sánchez, A., 2012. Productivity in the services sector: conventional and current explanations. *The Service Industries Journal* 32, 719–746.
- Martins, F., Felgueiras, C., Smitková, M., 2018. Fossil fuel energy consumption in european countries. *Energy Procedia* 153, 107–111.
- Mi, Z.F., Pan, S.Y., Yu, H., Wei, Y.M., 2015. Potential impacts of industrial structure on energy consumption and co2 emission: a case study of beijing. *Journal of Cleaner Production* 103, 455–462.
- Muganyi, T., Yan, L., Yin, Y., Sun, H., Gong, X., Taghizadeh-Hesary, F., 2022. Fintech, regtech, and financial development: evidence from china. *Financial Innovation* 8, 1–20.
- Myovella, G., Karacuka, M., Haucap, J., 2020. Digitalization and economic growth: A comparative analysis of sub-saharan africa and oecd economies. *Telecommunications Policy* 44, 101856.
- Nguyen, D., Paczos, M., 2020. Measuring the economic value of data and cross-border data flows: A business perspective .
- Niebel, T., 2018. Ict and economic growth—comparing developing, emerging and developed countries. *World Development* 104, 197–211.
- Omri, A., Nguyen, D.K., 2014. On the determinants of renewable energy consumption: International evidence. *Energy* 72, 554–560.
- Our World in Data, 2022. Consumption-based (trade-adjusted) energy use per person. URL: <https://ourworldindata.org/grapher/consumption-based-energy-per-capita?country=CHN~TUR~JPN~USA~GBR~IND~ZAF~AUS~BRA~DEU~FRA~SWE~ESP~KOR~NOR~MEX>.
- Ozturk, I., 2010. A literature survey on energy–growth nexus. *Energy Policy* 38, 340–349.
- Papyrakis, E., Gerlagh, R., 2004. The resource curse hypothesis and its transmission channels. *Journal of Comparative Economics* 32, 181–193.
- Pirlogea, C., Cicea, C., 2012. Econometric perspective of the energy consumption and economic growth relation in european union. *Renewable and Sustainable Energy Reviews* 16, 5718–5726.
- Portulans Institute, 2022. Network readiness index. URL: <https://networkreadinessindex.org/>.
- Reed, W.R., Ye, H., 2011. Which panel data estimator should i use? *Applied economics* 43, 985–1000.
- Ren, S., Hao, Y., Xu, L., Wu, H., Ba, N., 2021. Digitalization and energy: How does internet development affect china’s energy consumption? *Energy Economics* 98, 105220. doi:10.1016/j.eneco.2021.105220.
- Rieger, A., 2020. Does ict result in dematerialization? the case of europe, 2005-2017. *Environmental Sociology* 30, 1–12. doi:10.1080/23251042.2020.1824289.
- Rosa, E.A., Dietz, T., 1998. Climate change and society: Speculation, construction and scientific investigation. *International sociology* 13, 421–455.
- Sadorsky, P., 2010. The impact of financial development on energy consumption in emerging economies. *Energy Policy* 38, 2528–2535.
- Sadorsky, P., 2011. Financial development and energy consumption in central and eastern european frontier economies. *Energy Policy* 39, 999–1006.
- Sadorsky, P., 2012. Information communication technology and electricity consumption in emerging economies. *Energy Policy* 48, 130–136.
- Saidi, K., Toumi, H., Zaidi, S., 2017. Impact of information communication technology and economic growth on the electricity consumption: Empirical evidence from 67 countries. *Journal of the Knowledge Economy* 8, 789–803. doi:10.1007/s13132-015-0276-1.
- Salim, R., Yao, Y., Chen, G.S., 2017. Does human capital matter for energy consumption in china? *Energy Economics* 67, 49–59.

- Santarius, T., Pohl, J., Lange, S., 2020. Digitalization and the decoupling debate: Can ict help to reduce environmental impacts while the economy keeps growing? *Sustainability* 12, 7496. doi:10.3390/su12187496.
- Schulte, P., Welsch, H., Rexhäuser, S., 2016. Ict and the demand for energy: Evidence from oecd countries. *Environmental and Resource Economics* 63, 119–146. doi:10.1007/s10640-014-9844-2.
- Shahbaz, M., Chaudhary, A.R., Ozturk, I., 2017. Does urbanization cause increasing energy demand in pakistan? empirical evidence from stirpat model. *Energy* 122, 83–93.
- Sobel, M.E., 1982. Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological methodology* 13, 290–312.
- Thomas, S., Rosenow, J., 2020. Drivers of increasing energy consumption in europe and policy implications. *Energy Policy* 137, 111108.
- UN environmental program, 2022. Energy efficiency taxonomy and green tagging: Effig launches call for expressions of interest. URL: <https://www.unepfi.org/news/regions/europe/energy-efficiency-taxonomy-and-green-tagging-eefig-launches-call-for-expressions-of-interest/>.
- Usman, A., Ozturk, I., Hassan, A., Maria Zafar, S., Ullah, S., 2021. The effect of ict on energy consumption and economic growth in south asian economies: An empirical analysis. *Telematics and Informatics* 58, 101537. doi:10.1016/j.tele.2020.101537.
- Usman, M., Hammar, N., 2021. Dynamic relationship between technological innovations, financial development, renewable energy, and ecological footprint: fresh insights based on the stirpat model for asia pacific economic cooperation countries. *Environmental Science and Pollution Research* 28, 15519–15536.
- Valero, A., Valero, A., Calvo, G., Ortego, A., Ascaso, S., Palacios, J.L., 2018. Global material requirements for the energy transition. an exergy flow analysis of decarbonisation pathways. *Energy* 159, 1175–1184.
- Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step gmm estimators. *Journal of econometrics* 126, 25–51.
- Worldbank, 2022. World development indicators. URL: <https://databank.worldbank.org/source/world-development-indicators>.
- Wu, H., Xue, Y., Hao, Y., Ren, S., 2021. How does internet development affect energy-saving and emission reduction? evidence from china. *Energy Economics* 103, 105577.
- Xu, Q., Zhong, M., Li, X., 2022. How does digitalization affect energy? international evidence. *Energy Economics* , 105879.
- York, R., Rosa, E.A., Dietz, T., 2003. Stirpat, ipat and impact: analytic tools for unpacking the driving forces of environmental impacts. *Ecological economics* 46, 351–365.
- Zaborovskaia, O., Nadezhina, O., Avduevskaya, E., 2020. The impact of digitalization on the formation of human capital at the regional level. *Journal of Open Innovation: Technology, Market, and Complexity* 6, 184.
- Zhao, X., Lynch Jr, J.G., Chen, Q., 2010. Reconsidering baron and kenny: Myths and truths about mediation analysis. *Journal of consumer research* 37, 197–206.

Appendix A. Construction of digitalization indices

The indices are constructed from parameters of the digitalization indices used to build the Digital Economy and Society Index (DESI; [European Union, 2022](#)), the ICT Development Index (IDI; [International Telecommunication Union, 2022](#)), and the Network Readiness Index (NRI; [Portulans Institute, 2022](#)). In total, the set of available parameters contains 43 measures, 11 from DESI, 8 from IDI, and 24 from NRI. For the aggregated index, we include all available parameters, while for the digitalization dimensions, we select a subset of the parameters respectively. For each index, we choose two weightings, one based on PCA and one based on a uniform distribution among all parameters. The results of the parameter selection and weighting are shown in [Figure A.2](#).

The aggregated index comprises all available parameters. Choosing the weights with the PCA shows in comparison to the uniformly-constructed index, that *Mobile download speeds*, *Level of internet access*, and *Mobile take up* drop out of the index. On the opposite, *Fixed broadband* and *Speed* with 6% receive are weighted greater.

For the construction of the generation of information index, we select 15 parameter. The constructed index is supposed to be a proxy for the information that is generated by either measuring digital activities (e.g. tracking of consumer behavior or machine performance) or by recombining available digital information to generate new information (e.g. by forecasts or simulations). However, pure measures for the actual generation of information are missing in the available parameter set. Therefore, we include measures of activities which are associated with the generation of additional information, e.g. *Internet purchases by individuals* for consumer behavior data, *Process integration* for business applications, or *eGovernment* for authority applications. The PCA finds *E-commerce sales* and *eGovernment* as defining for the parameter set.

The transmission of information index contains 20 parameter. The index proxies information transferred within an economy via digital infrastructure. A direct measure of yearly Bits maintained of a countries communication infrastructure is not available. However, there are several measures for the state of this infrastructure. Therefore, we include infrastructure capacity variables like *4G coverage* and proxies for the utilization of this infrastructure like *Communication* and *Cost of data*. *Speed* and *Fixed broadband* are found to be defining for this subset.

For the dimension of information storage, we select 8 parameter. Supplementing the transmission dimension, information storage is designed to capture the available information storage capacity (e.g. central on data centers or decentral on private computers) and its utilization. We proxy this index with, e.g., the number of *Secure Internet Servers* within a country or the number of *Top-Level Domains*, which are also identified as the most significant with the PCA.



Figure A.2: The composition of the eight digitalization indices

The resulting indices are correlated since they measure the digitalization developments of the respective countries. However, they focus on different aspects of this digitalization so that differences remain. Table A.12 lists the correlation factors between the four uniformly-constructed indices and Table A.13 shows the correlation of the pca-constructed indices.

Table A.12: The correlation between the uniformly-constructed digitalization indices

	Generation	Transmission	Storage	Aggregated
Generation	1			
Transmission	0.95	1		
Storage	0.89	0.96	1	
Aggregated	0.97	1	0.97	1

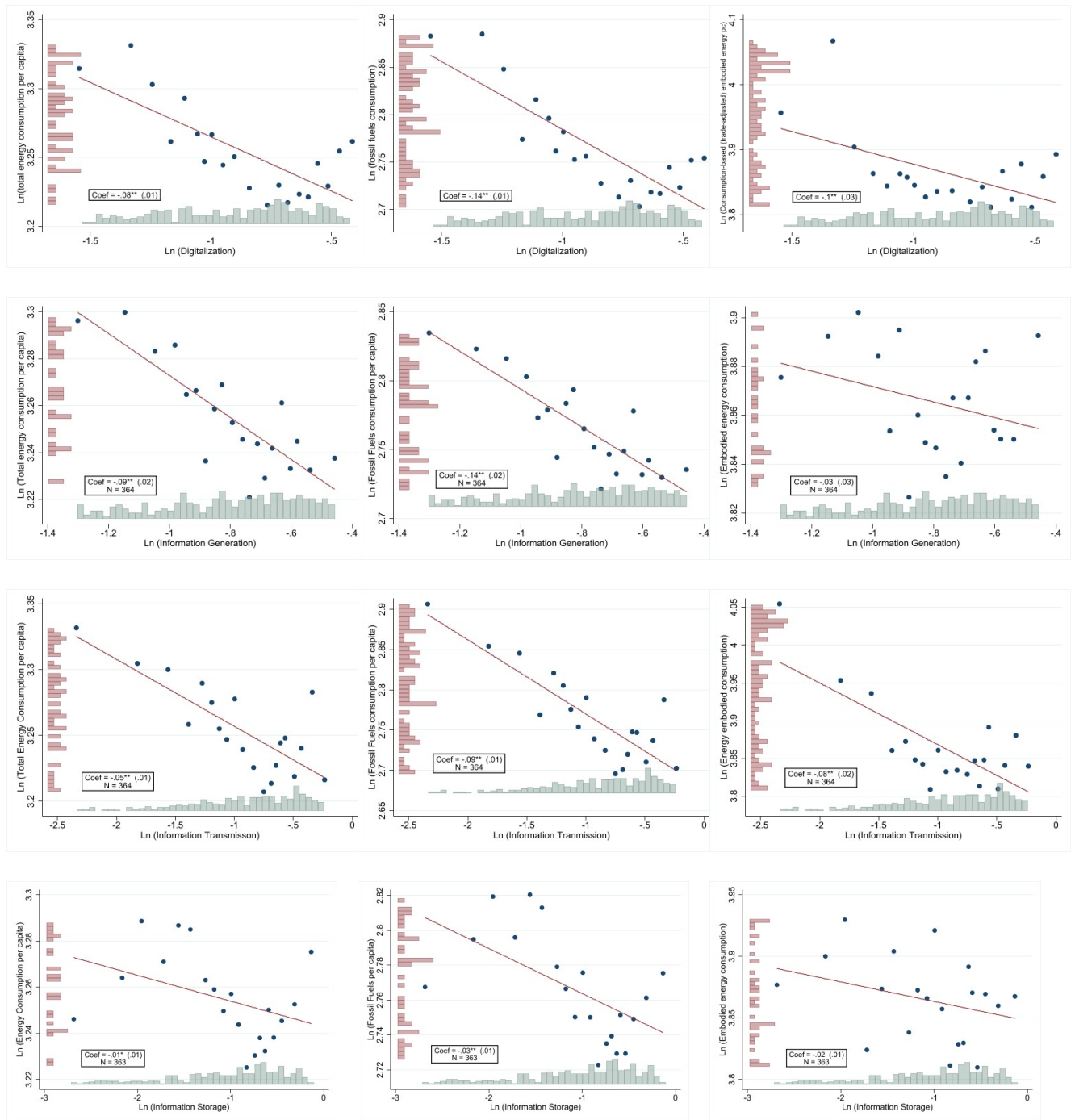
Table A.13: The correlation between the pca-constructed digitalization indices

	Generation	Transmission	Storage	Aggregated
Generation	1			
Transmission	0.95	1		
Storage	0.88	0.96	1	
Aggregated	0.97	1	0.97	1

All indices are highly correlated with each other with correlation factors between 0.88 and 1. This is not surprising since digitalization has been a broad development over the past years so that most of its dimensions have experienced a continuous growth.

Appendix B. Binned scatter plots between digitalization and energy consumption

Figure B.3 displays binned scatter-plots for the relationship between energy consumption and our constructed digitalization indices in a two-dimensional space based on the densities of the respective variables. These plots also include country fixed effects and robust standard errors. The three graphs suggest a negative and statistically significant relationship between digitalization and *Total EC pc*, *Fossil EC pc*, and *Embodied EC pc*, with a statistically significant slope of -0.08, -0.14, -0.1 respectively. Also, the relationship between energy consumption and the other sub-indices are negative and statistically significant. A priori, this might indicate that higher development of digitalization is associated with lower levels of energy consumption.



Notes: The fitted regression estimated in each graph controls for country fixed effects and uses robust standard errors to estimate the slope. The first, second, and third columns are devoted to total energy consumption per capita, total fossil fuels per capita and energy embodied per capita. The first, second, third, and fourth rows show the aggregated digitalization index, information generation index, information transmission index, and information storage index, respectively. *, **, and *** represent significance levels of 10, 5, and 1 percent, respectively.

Figure B.3: Binned scatter plots for the relationship between energy consumption and Digitalization.

Appendix C. Estimating the effect of digitalization on net energy embodied in traded goods

Table C.14: Results of the two-step sys-GMM regression estimating the effect of digitalization on net embodied energy in traded goods

	(1) Net embodied energy
Lag.dep	0.913*** (0.108)
Digitalization	18.10* (10.50)
GDP pc	128.4** (65.29)
Industry GDP	42.02 (26.89)
Oil price	19.77*** (6.215)
Financial Dev.	1.358 (15.52)
Human Capital	-98.95 (78.90)
Observations	332
Number of countries	28

Note: *, **, and *** represent significance levels of 10, 5, and 1 percent, respectively. Robust standard errors are reported in parentheses of estimated coefficients and they estimated following (Windmeijer, 2005). We do not control for the time fixed effects because they are found to be statistically insignificant