The net climate effect of digitalization, differentiating between firms and households

Abstract

While public debate and prominent studies expect digitalization to substantially reduce energy use and carbon dioxide (CO_2) emissions, quantitative research has produced ambiguous results. This study addresses the challenges in the analysis of the relationship between a country's digitalization level and CO_2 emissions by employing the Group Fixed Effects estimator for panel data of EU and OECD countries and by differentiating between emissions associated with digitalization in firms and households.

Results are highly robust to the statistical procedure and indicate that digitalization in both households and firms generally decreases emissions. At the sample median, a 10% increase in firm (household) level digitalization would, on average, decrease emissions by 0.3% (0.8%). In countries of the three lowest deciles in the income distribution, however, the effect is reversed: Here, an increase in digitalization is also associated with an increase in emissions.

The results are further interpreted beyond the median effect and differentiate between countries of different incomes through a non-parametric approach. This analysis also has implications for the discussion of the EKC hypothesis, as the empirical analysis nests an estimation of an EKC model, extended by a measure of digitalization.

Keywords: climate change; greenhouse gas emissions; digitalization; ICT.

JEL Codes: Q54, Q55, Q58

1 Introduction

Digitalization has inspired great hopes for the attempt to alleviate environmental challenges such as climate change and the overuse of natural resources. Such hopes are nurtured by governmental stakeholders (Mickoleit, 2010; Federal Government of Germany, 2014; Federal Ministry for Education and Research, 2014) and business stakeholders alike (Kargermann and Wahlster, 2013; GeSI and Accenture, 2015; Schebek et al., 2017). The Global e-Sustainability Initiative, for example, an international network of IT companies, argues that digitalization could decrease global carbon emissions by an impressive 20% (GeSI and Accenture, 2015). However, many such hopes are based on weak foundations, as environmental costs of increasing digitalization tend to be underestimated (Lange and Santarius, 2020; Hilty and Bieser, 2017).

Despite its many facets, the process of digitalization is often discussed as the panacea for environmental degradation, be it because of the efficiency gains through improved logistics (Moberg et al., 2010a), more efficient manufacturing due to robot use (Wang et al., 2022), lower input agriculture due to precision farming (Griepentrog, 2017), or, on the household side, less environmental effects through media consumption (Shehabi et al., 2014) or less commuting for shopping (Mangiaracina et al., 2015; Loon et al., 2015; Horner et al., 2016; Buldeo Rai, 2021) or work related traveling (Hischier and Hilty, 2002; Faber, 2021). It is therefore necessary to understand the aggregate effect of digitalization on environmental degradation.

The mechanisms through which environmental outcomes are affected by digitalization differ between firms and households. What the two have in common is that mechanisms, which lead to an increasing effect of digitalization on emissions, are equally plausible as oppositely directed effects. On the firm level, the application of information and communication technologies (ICT) promises to increase energy and resource efficiencies of production processes (e.g., Renn et al., 2021). Their application could also optimize logistics (GeSI and Accenture, 2015) or ensure more precise and therefore reduced use of pesticides and fertilizers in agriculture (Griepentrog, 2017). However, such increases in efficiencies are based on new robotic technologies, additional sensors, or new (farming) machines, which must be produced, powered, and disposed of - necessitating additional energy and resource use. Furthermore, the new technologies often increase production by increasing the productivity of energy and resources, as well as that of labor (Brynjolfsson and McAfee, 2014). These higher production levels can lead to a net increase of energy and resource use, constituting an example for rebound effects (Chan and Gillingham, 2015; Hertel, 2018). Such detrimental effects have been found for increasing levels of science and technology in different contexts (Fisher-Vanden and Ho, 2010; Cole et al., 2013).

At the household level, digitalization promises to decrease energy and resource consumption through two mechanisms. First, physical goods can be substituted by digital services – for example replacing DVDs by video-streaming services (Shehabi et al., 2014). Second, digital appliances can be used to change everyday behavior in an environmentally sustainable manner – such as using video-conferencing instead of traveling to a conference (Hischier and Hilty, 2002; Faber, 2021). However, two countervailing effects may come into play. First are direct effects related to the use of digital appliances, such as the increased electricity consumption related to video-streaming (Shehabi et al., 2014; The Shift Project, 2019; Faber, 2021). Second, digitalization may increase consumption and thereby require additional resources. For example, video-conferencing might lead to an increase in physical traveling to visit the people one has first met online (Hischier and Hilty, 2002).

Since opposite effects of increased digitalization on CO_2 emissions are plausible, an empirical analysis is conducted to determine which of the two dominates. However, measuring the aggregate effect of digitalization on the environment is challenging (Heijungs et al., 2009; Finkbeiner et al., 2014; Miller and Keoleian, 2015). Most feasible is investigating the direct effects and efficiency increases on a microeconomic scale by measuring the energy and resources used to produce and use ICT, and by estimating changes in energy and resource efficiencies when producing specific goods and services (see Section 2). However, even these investigations are methodologically challenging (Hilty, 2015). Isolating the effect of digitalization on CO_2 emissions at the macroeconomic scale is a complex undertaking as well, given that economies undergo a multitude of transformations and macroeconomic shocks (Lange et al., 2020). One approach to address those challenges for analyses at the macro level is to compare economies within the same historical setting through a panel data approach (Schulte et al., 2016). Such an approach allows digitalization effects to be isolated from other factors and enables to determine whether economies experiencing higher levels of digitalization produce more carbon emissions, compared to economies with lower digitalization levels in the same time period.

While the focus of the study is to understand the environmental consequences of the intensity of digitalization, the inclusion of GDP per capita as a control variable results in an estimation that can also be used as an empirical test for the Environmental Kuznets Curve (EKC) while controlling for digitalization. The EKC hypothesis states that the relation between a country's per capita income and its emissions is characterized by an inverted U-shape. This hypothesis of an inverted U-shape means that an initial increase in average income leads to higher emissions, up to a turning point, from which on a further increase in income leads to reductions in emissions. Dinda (2004), Stern (2004), Romero-Ávila (2008), Al-Mulali et al. (2015), Ridzuan (2019), and Saqib and Benhmad (2021) offer comprehensive reviews of the EKC literature. The implications of our results for the discussion on the EKC hypothesis are provided in the results section.

Few studies have assessed the overall effect of ICT on greenhouse gas emissions. As shown below, they provide conflicting results. Also, they are all based on digitalization indicators on the individual (rather than firm) level, and they do not differentiate between economies of different income levels. By working with two different indicators – one for households and one for firms - and by allowing for different effects depending on the average income level, we shed additional light on the relationship between digitalization and greenhouse gas emissions. Due to availability of data on measures of digitalization, the study is limited to high income, western countries and the period from 1995 to 2019 on the firm side and 2002 to 2016 on the household side.

2 The environmental effects of digitalization

This section first presents the mechanisms that moderate the effects of increasing digitalization on CO_2 emissions. It shows that at both the firm and the household level, oppositely directed mechanisms are plausible. Subsequently, we summarize the existing evidence on the net effects of increasing digitalization on CO_2 emissions.

2.1 Households

On the household side, the literature largely focuses on the effect of single technologies. Moberg et al. (2010b) find that digital newspapers can save up to 60% of the energy consumed by producing the printed versions. Martin and Rivers (2018) conclude that digital, real-time meters of electricity use help households in reducing their energy consumption. Several studies on the implications of online shopping (and other delivery services) on energy consumption come to lesser clear conclusions. Whether replacing traditional commerce by e-commerce reduces energy intensity and the net environmental impact depends on various circumstances, such as population density, freight mode, the return rate, trip allocation, and the type of packaging used (e.g., Mangiaracina et al., 2015; Loon et al., 2015; Horner et al., 2016; Buldeo Rai, 2021). The complexity of the relationship between e-commerce and environmental impact is also due to the multidimensional nature of a household's travel behavior in its particular shopping environment. Le et al. (2021) review 42 studies on the relation between online shopping and travel behavior, but although they find some evidence that online shopping reduces shopping travel, they describe the evidence as being far away from overwhelming. Shi et al. (2021) rely on a propensity score matching approach to compare travel behavior of car owners and non-car owners in China. They find that car owners are less likely to reduce trip frequencies due to online shopping than non-car owners. The authors suggest that the size of the substitution effect for car owners may vary geographically according to the dependence on private cars. To sum up, the discussion in the literature about the effect of online shopping on shopping travel behavior is not settled. Ambivalent results have also been found for media substitution regarding online video streaming compared to renting DVDs. Here, the net environmental effect depends on several parameters, in particular on the distance the average consumer travels to the DVD rental establishments (Shehabi et al., 2014).

2.2 Firms

For the firm side, the literature can be categorized into analyses on how digital technologies change greenhouse gas emissions in different sectors of the economy and on the greenhouse gas emissions of the ICT sector itself. A first strand of literature finds that digitalization has the potential to increase efficiency throughout economic sectors. However, many of those studies assess the potential of digital technologies to reduce greenhouse gas emissions in the future, rather than observed impacts in the past (Lange et al., 2023). Regarding mobility, the role of autonomous vehicles is controversially debated. Whether they can contribute to climate protection depends on whether they will be used in a future mobility system that continues to be based primarily on cars or a system focusing on public transport (Creutzig et al., 2019). In the agricultural sector, the energy intensive production of fertilizers can be reduced through precision farming (Griepentrog, 2017). However, precision farming technologies can only reduce greenhouse gas emissions to a limited degree and go along with negative side effects such as intensive cultivation methods (Finger et al., 2019). In industrial production, increasing efficiency in manufacturing through smart operation of industrial robots reduces their energy requirements (Wang et al., 2022). However, increasing ICT capital only reduces the energy intensity of manufacturing to a small extent (Clausen et al., 2022; Schulte et al., 2016). Whether digital technologies increase energy consumption or decrease it depends on the concrete technology applied (Chiarini, 2021).

However, the material base for digitalization, most prominently the ICT sector, is also responsible for a substantial (and growing) amount of global climate gas emissions. Electricity consumption of the ICT sector has been growing for decades and is expected to continue rising in the future. Studies that measure ICT's share of total global electricity consumption come to similar results, with differences being caused by the exact time under consideration and empirical methodology employed in the respective analysis. Malmodin et al. (2010) assess it to have been 3.9% in 2007. Malmodin and Lundén (2018) find that electricity consumption did not change significantly between 2010 and 2015, staying constant at around 4%. Van Heddeghem et al. (2014) calculate it to have risen to 4.6% in 2012, while Corcoran and Andrae (2013) derive a value of 7.4% for the same year. Andrae and Edler (2015) predict that this share will rise by 2030 - depending on the scenario parameters chosen - to up to 51%. Regarding specific technologies, Moberg et al. (2010a) find that electronic invoicing can increase the energy efficiency of invoicing.

In line with the increase of the ICT sector's energy consumption, all reviewed studies agree that the greenhouse gas emissions of the ICT sector have grown over the past decades (Andrae and Edler, 2015; Belkhir and Elmeligi, 2018; Malmodin and Lundén, 2018; The Shift Project, 2019). The share of emissions stemming from the ICT sector were estimated to be between 1% and 1.6% of all global greenhouse gas emissions in 2007 (Belkhir and Elmeligi, 2018), 2.1% in 2010 (Andrae and Edler, 2015), 1.4% in 2015 (Malmodin and Lundén, 2018) and 3.7% in 2018 (The Shift Project, 2019). In a study for the leading industrial association of ICT companies in Germany, Bieser et al. (2020) estimate the share of ICT in global CO_2 emissions to be between 1.8% and 3.2%. Taking into account supply chain pathways, Freitag et al. (2021) find that this share might actually be between 2.1% and 3.9%. Their meta-analysis identified a trend in the absolute CO_2 footprint of ICT, which increased by 40% between 2002 and 2012.

Regarding future developments, the predictions differ widely. While Andrae and Edler (2015) expect emissions caused by ICT to rise to 23% of all emissions in 2030, Belkhir and Elmeligi (2018) estimate that, if the current pathway continues, ICT's greenhouse gas emissions could exceed 14% of total greenhouse gas emissions of the 2016 level by 2040. Malmodin and Lundén (2018), on the other hand, observe a stagnation of the emission share since 2010. A possible explanation for the increase in CO_2 emissions being less clear than the increase in electricity consumption is that digital appliances are increasingly powered by renewable energy (Greenpeace, 2017) – albeit it is unclear how fast this transformation process is taking place (Cook and Jardim, 2019).

2.3 Economy-wide net effects

Since some of the mechanisms that determine the CO_2 emissions as a consequence of increasing digitalization act in opposing directions, empirical analyses are required to identify which of these dominate. Studies on economy-wide net effects of digitalization estimate the overall environmental effect, allowing for both negative and positive effects.

The existing literature provides empirical evidence that increasing digitalization increases electricity consumption. This relationship has been found for OECD countries (Salahuddin and Alam, 2016; Schulte et al., 2016), emerging economies (Sadorsky, 2012; Afzal and Gow, 2016), and in case studies for Japan (Cole et al., 2013; Ishida, 2015) and China (Fisher-Vanden and Ho, 2010). However, these results do not allow for deriving clear conclusions on the relationship between ICT and overall energy use: Schulte et al. (2016) find a positive relation between digitalization and electricity consumption but a negative relation between digitalization and non-electric energy. Similarly, Khayyat et al. (2016) conclude that ICT reduces energy use in industrial production in South Korea. Ishida (2015) finds that ICT investments decrease overall energy consumption. Levinson (2015) identifies reducing effects of technology change on climate gas emissions in US manufacturing, but without discussing the nature of the technology change.

A number of studies identify environmental effects of digitalization at the country level, controlling for time-invariant country characteristics and common macroeconomic shocks by using fixed effects panel estimation approaches, similar to the approach that this analysis builds upon. However, the overall results of this body of literature are ambiguous. It appears that whether emissions are found to increase or decrease with digitalization depends critically on the inclusion of energy use as a covariate. Two relevant studies focus on the aggregate net effect and assess the relations between ICT, economic growth, and emissions (Lee and Brahmasrene, 2014; Salahuddin et al., 2016). They find that digitalization increases greenhouse gas emissions. Salahuddin et al. (2016) find a positive relation between digitalization (measured in mobile cellular subscriptions) and CO_2 emissions in OECD countries between 1991 and 2012. Lee and Brahmasrene (2014) also report a positive relation for nine ASEAN countries between 1991 and 2009 (using fixed telephone lines and mobile subscriptions as an indicator). Contrastingly, two other studies focus on the actual mechanisms between increasing digitalization and CO_2 emissions by including more covariates, most importantly energy use (Lu, 2018; Haseeb et al., 2019). Those studies find that ICT reduces CO_2 emissions but increases energy use, which in turn causes greater CO_2 emissions. Lu (2018) reports that higher digitalization levels are associated with a decrease in carbon dioxide emissions for 12 Asian countries between 1993 and 2013, using the number of internet users as an indicator. Haseeb et al. (2019) also find a negative relation between digitalization (measured in mobile cellular subscriptions) and CO_2 emissions for the BRICS economies between 1994 and 2014. The study at hand adds to the literature of the first kind, i.e., measuring the aggregate net effect of increasing digitalization, regardless of the transmission channel.

In summary, microeconomic studies indicate the potential of digitalization to reduce environmental pressure while there are also examples of detrimental environmental effects for individual technologies. The majority of the literature finds that global CO_2 emissions of the material base of digitalization (i.e., ICT), are rising. However, the literature also yields conflicting results about the net effect of the entire process of digitalization on CO_2 emissions. The following analysis takes a step towards improving the understanding of this relationship by differentiating between income levels. While all of the studies cited above measure digitalization at the household rather than the firm level, the present study is - to the best of our knowledge - the first to combine the analyses of CO_2 emissions originating in the production and consumption sides of the economy.

3 Methodology

3.1 Estimation method

Our analysis relies on the *Group Fixed Effects* (GFE) estimator (Bonhomme and Manresa, 2015), which allows unobserved heterogeneity between countries to vary over time, in contrast to the conventional fixed effects approach. The inclusion of time-varying, unobserved heterogeneity is achieved by first assembling all countries into groups according to changes in the *observables*. Then a panel estimation is exercised, supplemented by dummy variables for each group-year combination instead of individual country effects. The use of grouped fixed effects instead of country fixed effects is also advantageous in panel estimations with many countries in terms of degrees of freedom. As the GFE bundles all countries within a relatively small number of groups (all literature reviewed that employs the GFE estimator relies on fewer than ten groups:

Bonhomme and Manresa, 2015; Grunewald et al., 2017; Kopp and Nabernegg, 2022), the number of dummy-covariates decreases substantially.

The estimated relationship between digitalization and environmental damage can be biased due to omitted variables, as carbon emissions are also determined by other factors. To address this potential cause of endogeneity, we control for three of those factors. First is the gross domestic product *per capita* (GDP *p.c.*), as income is one of the main determinants of carbon emissions. Next, differences between countries depend not only on the state of technology and the size of the economy but also on the economy's sectoral composition (Lange et al., 2020). Regarding the consumption side estimation, a change in the sizes of economic sectors of an economy leads to a change in the composition of imports and exports when consumption patterns remain stable. As we analyze consumption-based greenhouse gas emissions in the household side estimation, we want to control for the emissions that are embodied in traded goods. The respective shares of economic sectors influence the composition of imports and exports, which, in turn, affects the emissions that are embodied in traded goods because the footprint of producing the same good differs across countries. Including the composition of the domestic economy allows us to control for the environmental footprints of production of the same goods being different across countries. Regarding the production side estimation, digital tools applied across different economic sectors have different potentials to increase energy and resource efficiencies. Therefore, the impact on an economy with a prominent service sector differs from the impact on a country with a high share of manufacturing or agricultural production. We control for the sectoral composition by including the shares of GDP being generated in agriculture, manufacturing, and the service sector. We further control for the share of population living in urban areas, as suggested by Grunewald et al. (2017) and Kopp and Nabernegg (2022). The reason is that urban consumers' consumption bundles are systematically different from the one of the rural population, especially in the use of public infrastructure, heating, and cooking (Muñoz et al., 2020).

Digitalization may affect CO_2 emissions not only directly but also by affecting the GDP *p.c.*, as discussed in the literature on digitalization-induced rebound effects (e.g., Pohl et al., 2019). The estimated coefficient of GDP *p.c.* may therefore capture part of the effect of digitalization increases on emissions if not controlled for. For that reason, we include an interaction term between GDP *p.c.* and digitalization. The measures of digitalization and income also enter in squares to allow for non-linear effects of digitalization and income on CO_2 emissions (see the literature on the environmental Kuznets curve, e.g., Grossman and Krueger, 1995; Dinda, 2004; Carson, 2010; Hamit-Haggar, 2012).

This leads to the following equation to be estimated for both production and consumption analyses:

$$\ln CO2_{it} = \alpha + \beta_1 \ln Digi_{it} + \beta_2 (\ln Digi_{it})^2 + \beta_3 \ln GDP_{it} + \beta_4 (\ln GDP_{it})^2 + \beta_5 (\ln GDP_{it} * \ln Digi_{it}) + \Gamma X_{it} + \delta_{gt} + \epsilon_{it}, \tag{1}$$

where $CO2_{it}$ stands for climate gas emissions and $Digi_{it}$ for the level of digitalization at time t in country i. GDP_{it} denotes each country's GDP $p.c.$ $\ln GDP_{it} * \ln Digi_{it}$ is a variable capturing interaction effects between GDP $p.c.$ and the measure of digitalization on the outcome variable. This variable allows for the possibility that the effect of one of the variables depends on the state of the other i.e. that digitalization's effect on CO_2 emissions in richer countries is systematically different to the effect in poorer countries. X_{it} is the vector of control variables (economic sectors' GDP shares and urban population share) and Γ the vector of the corresponding coefficients. δ_{gt} stands for the coefficients of the time-variant group fixed effects (which are generated by interacting group and time dummies), of which one is omitted from the estimation to avoid collinearity. α is a constant and ϵ_{it} represents Gaussian errors with mean zero. The dependent and explaining variables are described in the following sections.

One challenge when conducting statistical analyses based on panel data is the potential presence of spurious regressions, i.e., the apparent correlation of non-stationary data which are in fact unrelated (Hsiao, 2014) - an issue that is known from the empirical literature on the EKC hypothesis, which represents a structurally similar econometric question (Wagner, 2015). To rule out spurious regressions, the time series, which the panel is composed of, must either be stationary, or - if they are non-stationary - must show patterns of cointegration between the variables (Breitung and Pesaran, 2008). As this study is interested in the relationship between the level of digitalization and environmental impact in the long run, the analysis relies on the original variables in levels instead of estimating the equation in differences as one would do for the analysis of short run effects. For the firm side analysis, the panel displays a sufficient number of observations over time (25 years) for non-stationarity and cointegration tests to be feasible. We provide a detailed analysis of unit-root and cointegration tests in Appendix A.2.1. The results of those tests are diverse for the 24 countries within the panel in terms of both stationarity and cointegration. As a response, robustness checks are conducted for different subsets of the original data set. Those subsets are generated such as to rule out spurious regressions in the corresponding estimations. The results of all robustness checks are displayed in Appendix A.2.2 and show that the main results are highly stable when a) reducing the panel to non-stationary and cointegrated countries, as well as b) when splitting the panel into time periods which are short enough to rule out spurious regressions. The latter approach also addresses the issue of including the squared transformations of the integrated processes which are not integrated processes themselves (Wagner, 2015; Wagner and Hong, 2016). The household side estimation relies on data from 31 countries over a time span of 15 years. In such a case of large N and small T, spurious results are less likely to occur (Pesaran, 2015; Breitung and Pesaran, 2008; Banerjee, 1999). The short duration of the time series (15 years) makes it also unfeasible to run most of the standard tests for non-stationarity and cointegration: 5 out of 6 possible tests for a unit root and 2 out of 3 cointegration tests failed to execute because of the short span of the time series[1]. The impossibility to run those tests supports the point that the series is too short to display spurious regressions.

To test the robustness of the results against the choice of the estimation technique, two additional econometric approaches were conducted in addition to the GFE estimator. First, instead of applying the GFE method to correct for time-unvarying unobserved heterogeneity, we estimated a dynamic panel data model that includes the lag of the dependent variable on the right-hand side of the equation. In this estimation, we address the potential bias arising from this approach ("Nickell-Bias", NICKELL, 1981) by applying the widely used instrumental variable approach estimated via the General Method of Moments (2Step-Sys-GMM) method, developed by ARELLANO and BOND (1991), ARELLANO and BOVER (1995), and BLUNDELL and BOND (1998). A second approach maintains the GFE and also includes the lagged dependent variable, controlling for the bias of the LDV with a two-stage least square estimation that instruments the LDV with an earlier lag.

The two GFE models and the 2Step-Sys-GMM yield very similar results (see Table 3 and Table A.1 in the appendix). The substantial differences between those estimation approaches in combination with the similarity of the results suggests that the results are not driven by the choice of the econometric approach. Direct reverse causality is also not possible because within the time frame of observation (the timely frequency of the data set is one year), a country's CO_2 emission level at the left hand side of the estimation equation does not affect its level of digitalization. Further, including country mean incomes at the right hand side of the estimation equation controls for the main confounding variable which likely affects both our explanatory variable of interest, the level of digitalization, as well as the depending variable, CO_2 emissions. Its exclusion would otherwise lead to spurious correlation. The intermediary variable energy use is omitted on purpose to allow for the identification of the net effect of digitalization, similar to the "reduced form" estimation of the Environmental Kuznets Curve (GROSSMAN and KRUEGER, 1995, p. 359, DINDA, 2004; CARSON, 2010).

3.2 Measurement of digitalization and data description

The dynamics in the digitalization process can be segregated into those taking place within the production side of the economy (i.e., in firms) and those associated with the consumption decisions of private households. The first group of dynamics includes the consequences from increased technical and environmental efficiency due to the use of ICT in production processes (as laid out in section 2.2), while the latter refers to changing consumption patterns (section 2.1). We therefore approach the question raised in this study from two sides: First from the

[1]The tests were conducted with Stata packages `xtunitroot` and `xtcointtest`, which include a number of unit-root and cointegration tests for panel data. HLOUSKOVA and WAGNER (2006) provide an overview of simulated test performances for panel unit-root tests with small T.

firm perspective and then from the household perspective.

Firms

To estimate firm level effects, we measure all CO_2 emissions associated with one country's aggregate production and investigate how these emissions are affected by the country's level of digitalization in companies. The level of industrial digitalization is captured by the annual stock of the ICT infrastructure. This variable is provided by the Vienna Institute for International Economic Studies (WIIW, 2021) and contains information for European Countries, Japan and the USA (for detailed country list, see Table A.9 in the appendix). The dependent variable is CO_2 emissions, generated by all production processes in one country. This variable, as well as the control variables, are taken from the World Development Indicators (The World Bank, 2021). Descriptive statistics for all variables entering the firm-side regression are provided in Table 1.

Table 1: Summary statistics of all variables entering the firm-side regression.

Variable	Observations	Mean	SD	Min	Max	Median
CO_2 emissions p.c. (metric tons)	519	8.91	4.07	2.93	25.60	8.17
ICT stock p.c. (const 2010 USD)	519	12,164	37,541	48	231,577	1,652
GDP p.c. (const. 2010 USD)	519	33,509	19,835	3,193	112,418	33,558
Agriculture (% of value added)	519	2.38	1.85	0.21	17.07	1.97
Manufacture (% of value added)	519	23.92	5.33	9.97	38.15	23.75
Service (% of value added)	519	63.50	6.64	40.28	80.08	63.75
Urban population (%)	519	74.48	11.07	52.77	97.96	75.78

On the firm side, the following model is estimated:

$$\begin{aligned}\ln CO2_{P,it} = \; & \alpha_P + \beta_{1P} \ln ICT_{it} + \beta_{2P} (\ln ICT_{it})^2 + \beta_{3P} \ln GDP_{it} + \\ & \beta_{4P} (\ln GDP_{it})^2 + \beta_{5P} (\ln GDP_{it} * \ln ICT_{it}) + \\ & \Gamma_P X_{it} + \delta_{P,gt} + \epsilon_{it},\end{aligned} \tag{2}$$

where subscript P indicates the firm-side coefficients to be estimated.

Households

The analysis on the household side considers all CO_2 emitted during the production of the goods and services consumed in one country, including those produced abroad, and associates them with a measure of digitalization on the consumer side. The key explanatory variable is the share of individuals who used the internet to purchase goods or services during the previous three months, which serves as a proxy for digitalization in households. The data is provided by EuroStat, the statistics service of the European Commission (Eurostat, 2021a), so all EU countries enter the empirical analysis for the household side. CO_2 emissions caused in a country by consuming goods and services are measured by the sub-index for CO_2 emissions in the ecological footprint (EF), provided by the Ecological Footprint Network (Lin et al., 2016; Global Footprint Network, 2019). Unlike other accounts of emissions, the EF not only captures the emissions produced in the country under consideration but also accounts for the emissions embodied in all goods and services imported and exported. Since the database provides the EF as "global hectares", the measure was converted back to CO_2 emissions, based on average sequestration capacity of forests, which is the measure used to construct the EF in the first place. The control variables are the same as in the firm-side analysis. Descriptive statistics of all variables entering the household side regression are provided in Table 2.

Table 2: Summary statistics of all variables entering the household side regression.

Variable	Observations	Mean	SD	Min	Max	Median
Carbon Ecological Footprint	343	3.49	1.87	1.36	13.03	3.26
OnlineShopping (%)	343	25.21	19.74	1	78	21
GDP p.c. (const. 2010 USD)	343	34,873	24,536	3,591	111,968	29,875
Agriculture (% of value added)	343	2.57	2.04	0.21	11.55	2.03
Manufacture (% of value added)	343	14.09	4.52	3.95	33.10	13.71
Service (% of value added)	343	61.97	6.60	42.96	79.12	62.15
Urban population (%)	343	71.75	12.16	51.31	97.92	73.29

The household side is estimated as follows:

$$\begin{aligned} \ln carbonEF_{it} = \;& \alpha_C + \beta_{1C} \ln OnlineShopping_{it} + \beta_{2C} (\ln OnlineShopping_{it})^2 + \\ & \beta_{3C} \ln GDP_{it} + \beta_{4C} (\ln GDP_{it})^2 + \\ & \beta_{5C} (\ln GDP_{it} * \ln OnlineShopping_{it}) + \Gamma_C X_{it} + \delta_{C,gt} + \epsilon_{it}, \end{aligned} \tag{3}$$

where subscript C indicates the household side coefficients.

The countries entering the analysis, their descriptive statistics, and group assignments are displayed in Table A.9 in the appendix. The panel for the firm side analysis consists of 519 observations and covers 24 countries from 1995-2019, and for the household side, the panel includes 343 observations for 31 countries from 2002-2016[2].

4 Results

Results of both regressions are displayed in Table 3, and the robustness checks are in the appendix (Table A.1)[3]. Different signs are yielded by the coefficients of the measures of digitalization - *ICT* and *OnlineShopping* - which appear in the regression results as single, quadratic,

[2] The panels are unbalanced due to missing values in *ICTstock* and *OnlineShopping* for some country-year combinations.

[3] We refrained from displaying *p-values* and asterisks representing statistical significance because of increasing concerns about over-emphasizing statistical significance and *p*-hacking (Ziliak and McCloskey, 2011; Imbens, 2021). In addition, note that this study does not attempt to isolate treatment effects at a single point in the

and interaction terms. These non-linear relationships between digitalization and environmental effects impede a straight-forward interpretation of the coefficients directly from the regression output. We therefore first assess the effects at one specific point in the sample - the sample median - and interpret the effect of digitalization at this particular point. In a second step, we interpret the econometric results over the entire sample range through two- and three-dimensional, graphical illustrations of the results.

All results are highly robust across alternative, fundamentally different estimation procedures. Appendix A.1 contains the estimation equations of the robustness checks and corresponding results.

4.1 Marginal effects at the sample median

To provide an understanding of the marginal effects at the sample median, we first transform equation (1) from the logarithmic form to levels and then differentiate with respect to the measure for digitalization, building upon Kopp and Nabernegg (2022). Equation (1) in levels is given by

$$CO2_{it} = Digi_{it}^{(\widehat{\beta_1}+\widehat{\beta_2}\ln Digi_{it}+\widehat{\beta_5}\ln GDP_{it})} * GDP_{it}^{(\widehat{\beta_3}+\widehat{\beta_4}\ln GDP_{it})} * e^{\left(\widehat{\alpha}+\widehat{\Gamma}X_{it}+\widehat{\delta_{gt}}\right)}, \tag{4}$$

where the $\widehat{\text{hats}}$ indicate estimated coefficients. The marginal effect at the sample median is obtained by differentiating equation (4) with respect to $Digi_{it}$, yielding

$$\begin{aligned} \frac{\partial CO2_{it}}{\partial Digi_{it}} = \; & \overline{GDP}_{it}^{(\widehat{\beta_3}+\widehat{\beta_4}\ln \overline{GDP}_{it})} * e^{\left(\widehat{\alpha}+\widehat{\Gamma}\overline{X}_{it}+\widehat{\delta_{gt}}\right)} \\ & * (\widehat{\beta_1} + 2\widehat{\beta_2}\ln \overline{Digi}_{it} + \widehat{\beta_5}\ln \overline{GDP}_{it}) \\ & * \overline{Digi}_{it}^{(\widehat{\beta_1}+\widehat{\beta_2}\ln \overline{Digi}_{it}+\widehat{\beta_5}\ln \overline{GDP}_{it}-1)}, \end{aligned} \tag{5}$$

in which the horizontal $\overline{\text{bars}}$ indicate values at the sample median[4]. The effect of a 10% increase in digitalization is calculated as $\frac{0.1\overline{Digi}*\frac{\partial CO2_{it}}{\partial Digi_{it}}}{\overline{CO2_{it}}} * 100\%$.

Table 4 displays the marginal effects at the sample median, as well as the effects of a 10% increase in digitalization. On the firm side, a 10% increase of investments in ICT is associated

range of observations (such as the mean effect) but is interested in digitalization's effect on carbon emissions over the whole sample range of country incomes and digitalization levels. So the discussion of statistical significance of individual coefficients could even be potentially misleading, independent of the concerns raised by Ziliak and McCloskey (2011) and Imbens (2021). Finally, individual significance of the variables is of less interest, as the digitalization variable is included in three terms in the right side of the regression equation. Joint significance tests for all terms including *ln(ICT)* in the firm side regression and *ln(OS)* in the household side regression show that they are jointly, significantly different from zero. We provide detailed results for the joint significance test in Tables A.7 and A.8 in the appendix.

[4]The advantage of using the median instead of the mean is its resilience to extreme values and wide ranges, which both occur in the *GDP*, *ICT*, and *OnlineShopping* data series.

Table 3: Regression results from Group Fixed Effects estimation.

	(1 - Firms)	(2 - Households)
Dependent Variable	ln CO_2	ln *carbonEF*
ln *ICT*	2.830	
	(6.905)	
(ln *ICT*)^2	0.009	
	(0.396)	
(ln *ICT**ln *GDP*)	-0.287	
	(-4.446)	
ln *OnlineShopping*		2.022
		(3.385)
(ln *OnlineShopping*)^2		0.020
		(1.397)
(ln *OnlineShopping**ln *GDP*)		-0.217
		(-3.369)
ln *GDP p.c.*	-7.235	-6.145
	(-6.462)	(-5.983)
(ln *GDP p.c.*)^2	0.483	0.363
	(7.376)	(6.667)
Agriculture	0.054	-0.043
	(1.021)	(-1.493)
Manufacture	0.022	-0.008
	(0.765)	(-0.437)
Service	0.021	-0.005
	(0.777)	(-0.216)
Urban	0.002	0.001
	(0.336)	(0.385)
Constant	23.517	26.560
	(3.857)	(5.392)
Observations	519	343
R-squared	0.774	0.855
Number of Groups	4	4
Time Fixed Effects	Yes	Yes

Robust t-statistics in parentheses.

Levels of statistical significance are not indicated by asterisks (see Footnote 3 in Section 4). The joint significance tests for terms including *ln(ICT)* in column (1-Firms) and *ln(OS)* in column (2-Households) are provided in Tables A.7 and A.8 in the appendix.

with a 0.29% decrease in emissions, *ceteris paribus* (*c. p.*), while a 10% increase in households' online shopping is associated with a reduction in emissions by 0.80%, *c. p.*

The relation between digitalization and carbon emissions at the sample median is an important first insight. Nevertheless, the different signs of the coefficients that include digitalization in both regressions, as well as the statistical significance of the respective interaction terms (see

Table 4: Marginal effects of digitalization on measures of CO_2 emissions at the sample median.

Dimension	$\frac{\partial CO_2}{\partial Digi}$	Effect of 10% increase in $Digi$
Firms	-0.000145	-0.29 %
Households	-0.0123	-0.80 %

Own calculations, based on equation (5) with data from estimation results (Table 3) and descriptive information (Tables 1 and 2). Column $\frac{\partial CO_2}{\partial Digi}$ displays the marginal effect of Digitalization on CO_2 emissions at the sample median.

Table 3) indicate that any interpretation that imposes a *ceteris paribus* assumption represents a substantial simplification. The econometric results rather suggest that the effect of digitalization on carbon emissions depends both on a country's income level and on the initial level of digitalization. To allow for statements on the net effect of digitalization over the entire sample range, the following section provides a more nuanced, graphical illustration of the regression results.

4.2 Graphical representation and interpretation

To facilitate an intuitive interpretation of the parameterized equation (4), Figures 1 to 4 visualize the effect of digitalization (companies' ICT investments and households' online shopping behavior, respectively) within the range of digitalization and GDP *p.c.* levels in the observed data.

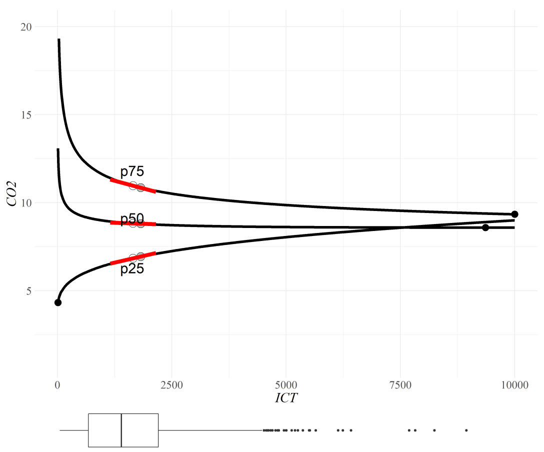
First, the analysis is condensed to two dimensions to show the marginal effects of digitalization on carbon emissions at different initial levels of digitalization, holding the value of GDP *p.c.* at a constant level (Figures 1 and 3). Plotting levels of digitalization on the horizontal axis and corresponding carbon emission levels on the vertical axis reveals how their relationship depends on the initial level of digitalization. Figure 1 illustrates the relation between firm-side digitalization and emissions while holding GDP *p.c.* constant at different levels. Figure 3 illustrates the relation between household-side digitalization and consumption-based emissions. The relations are displayed for three different levels of GDP *p.c.* (p25, p50, and p75 percentiles) because the respective signs of the effect of digitalization on emissions is different for the lower income percentiles (p25). To indicate the range of values for digitalization observed in the data, the observations that enter the analysis are displayed by boxplots in Figures 1 and 3[5]. These graphs show whether the relationship between digitalization and emissions is convex or concave. The figures further indicate the marginal effect of 10% increases in $Digi$ on CO_2 emissions.

To illustrate the effects that stem from the interaction between digitalization and income, the GDP dimension is added to the graphical analysis by displaying the parameterized equation (4)

[5] Country averages, calculated over time.

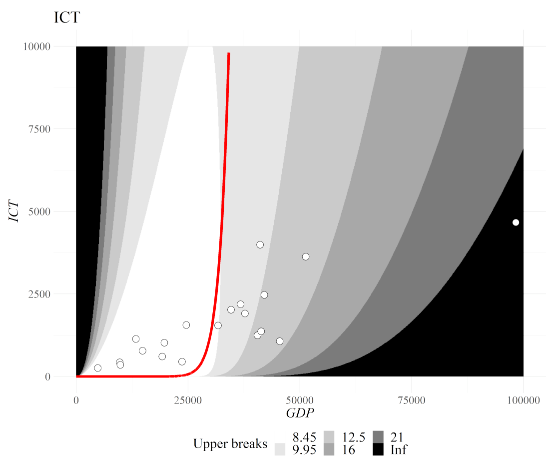
as surface graphs (Figures 2 and 4). The horizontal axes represent income (GDP *p.c.*) and the vertical axes the digitalization level. The CO_2 emission level is indicated by the shading, with darker shading representing higher emissions. The red lines in Figures 2 and 4 indicate minima along the *Digi*-gradient[6]. If a country converges towards the respective red line by increasing or decreasing levels of digitalization, carbon emissions decrease. Whether increasing levels of digitalization lead to an increase or a decrease in carbon emissions depends on whether the country under consideration is located above or below the line. In other words, the existence of minima in Figures 1 and 3 indicates that the sign of digitalization's effect on carbon emissions depends on the initial digitalization level. The exact location of a country's emission minimum along the digitalization gradient is affected by the country's initial income level.

Figure 1: Effects of *ICT-Investments* on domestic CO_2 emissions.



Black points indicate minima at the percentiles p25, p50 (median), and p75 of the GDP *p.c.* distribution. White point represents the sample median of ICT. The red line indicates the derivative $\frac{\partial CO_2}{\partial ICT}$ at the sample median of ICT. Grey point indicates the change in CO_2 at a 10% increase in $ICT - Investment$.

Figure 2: Effects of *ICT-Investments* and *GDP p.c.* on CO_2 domestic emissions.



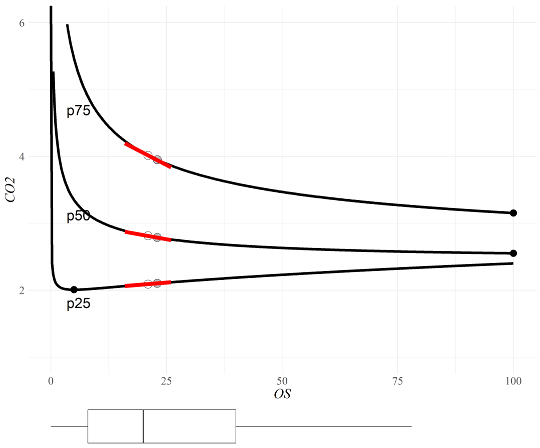
The shading indicates the predicted amount of CO_2 emissions as a function of ICT and $GDP\ p.c.$, based upon the regression results displayed in Table 3. The dots represent the distribution of ICT and $GDP\ p.c.$ of all countries in our sample, averaged between 1995 and 2019.

Figures 1 and 2 illustrate that the level of digitalization in firms can lead to substantial differences in the CO_2 emissions. The lines in Figure 1 for income levels at and above the median (percentiles p50 and p75) indicate that in those income levels, higher levels of ICT stock are associated with lower levels of CO_2 emissions. At percentile p25 within the income distribution, increases in ICT stock raise CO_2 emissions and the relation between ICT stocks and emissions is concave. Figure 2 illustrates that the lowest emissions are located at different levels of digitalization, depending on the country's GDP *p.c.*. Increases in digitalization are associated with decreases in emissions in countries with higher GDP *p.c.*, while in countries with an average income below percentile

[6]The extreme points are obtained by setting the parameterized version of equation (5) to zero and solving for $Digi_{it}$, which yields $Digi_{it} = e^{\left(\frac{-\beta_1-\beta_5 \ln GDP_{it}}{2\beta_2}\right)}$.

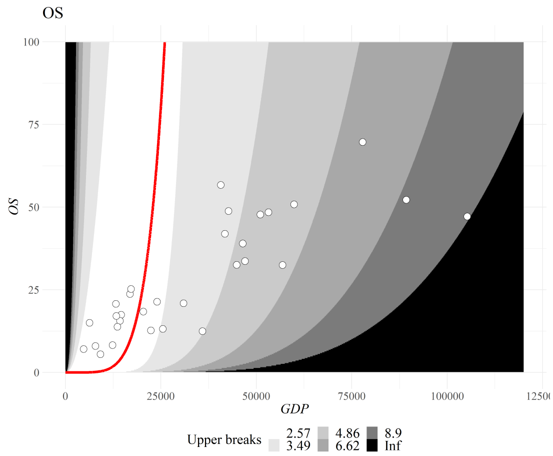
44[7], increases in the ICT stock are associated with increases in the CO_2 emissions.

Figure 3: Effects of *Online-Shopping* on CO_2 emissions (accounting for imported/exported emissions).



Black points indicate minima at the percentiles p25, p50 (median), and p75 of the GDP *p.c.* distribution. White points are the sample median of *OnlineShopping*. Red lines indicate the derivative $\frac{\partial CO_2}{\partial OS}$ at the corresponding percentile of *OnlineShopping*. Grey points indicate the change in CO_2 at a 10% increase in *OnlineShopping*.

Figure 4: Effects of *Online-Shopping* and *GDP p.c.* on CO_2 emissions (accounting for imported/exported emissions).



The shading indicates the predicted value of the CO_2-emission-based EF as a function of *Online-Shopping* and *GDP p.c.*, based upon the regression results displayed in Table 3. The dots represent the distribution of *Online-Shopping* and *GDP p.c.* of all countries in our sample, averaged between 2002 and 2016.

On the household side (Figures 3 and 4), the effects are similar to the firm side. Figure 3 indicates that, for income levels at and above the median (percentiles p50 and p75), higher levels of *OnlineShopping* are associated with lower levels of CO_2 emissions, whereas at percentile p25 the relationship between *OnlineShopping* and CO_2 emissions is positive. All sampled countries above the 34th-percentile[8] of incomes engage in *Online Shopping* at a less-than-optimal rate from an environmental perspective, indicating that more *Online Shopping* would be associated with lower CO_2 emissions, irrespective of the initial level. For lower income countries (within the 34th-income-percentile), on the other hand, we observe that increasing *OnlineShopping* is associated with an increase in CO_2 emissions, or - formulated differently - a reduction of the carbon EF would require a reduction in *OnlineShopping*[9]. In Figure 4, the red line represents, again, minima along the vertical axis and splits the sample into a group of poorer countries that all lie above the line and richer countries that all lie below the line. Thus, in poorer countries, increasing levels of online shopping are associated with increases in CO_2 emissions and vice versa in richer countries.

[7]Exactly at the 43.67th percentile where *GDP p.c.* is at a level of 30,495 USD.

[8]Exactly at the 33.819th percentile where *GDP p.c.* is at a level of 19,519 USD.

[9]This holds for all but five country-year observations, i.e., for 98.5% of all observations in the p34 percentile of mean incomes. These five country-year observations are probably statistical outliers. The five observations stem from Montenegro, North Macedonia, and Romania.

Those results also have implications for the discussion on the Environmental Kuznets Curve hypothesis (Wagner and Hong, 2016; Wagner, 2015). A recent empirical meta study concludes that 57% of all studies find that the EKC hypothesis is valid, while 47% do not (Saqib and Benhmad, 2021). The main reasons for the heterogeneous results are the choice of the econometric methodology and the data selection, including the measure of environmental degradation. Luzzati et al. (2018) conclude that the existing (unstable) evidence in support of the EKC depends too strongly on the chosen method and data as to be convincing. Their own findings do not support the EKC hypothesis. The results of this paper's model are in line with the part of the literature that rejects the EKC hypothesis (e.g., Luzzati et al., 2018), as the estimated coefficient for the squared GDP term are positive for both the firm and the household side analysis. The explanation for the statistically significant effect on the household side may lay in the choice of the dependent variable, a consumption-based measure, i.e., accounting for emissions embedded in imports and exports. The meta study of Saqib and Benhmad (2021) does not consider the inclusion of trade in the LHS variable. And Destek et al. (2018), who also use a consumption-based measure (albeit relying on the aggregated EF, not only the sub index that captures carbon emissions as in our case), also identify a U-shaped relationship between income and emissions. Note that the positive coefficients in both the firm and household side regressions do not necessarily imply that the countries with lower average income first decrease their emissions with increasing GDP p.c. until the relation reverses. As Figures 4 and 2 show, all countries are either located within the lightest (i.e., lowest) area of the parameterized function or already on the increasing side, i.e., increasing income is associated with increasing emissions in all countries. For the firm side, those findings suggest that increasing production activities lead to increasing emissions. For the household side, the emissions embedded in the imports of higher income countries are large enough to outweigh the emission reductions that occur within the importing countries' industries.

5 Discussion

The overall results indicate a decreasing effect of firm side digitalization on emissions at the sample median and also a reducing effect for household level digitalization. A view beyond the median reveals that an optimal level of both firm and household level digitalization exists in terms of CO_2 emissions. Both analyses yield coherent results regarding the countries' positionings relative to this optimum: While in lower income countries (bottom third in our sample), nearly all observations are above the optimum, all countries in the top two-thirds of incomes are below the optimum.

The existence of an optimal amount of firm-side digitalization in terms of CO_2 emissions can be explained by the different channels through which digitalization affects emissions. As discussed before, gains from digitalization have been shown to emerge from improved environmental efficiency, for example due to precision farming, efficiency gains in factories, and the replacement of in person meetings by video conferences. These gains can, on the other hand, be negated by the detrimental effect of emissions stemming from the production, use, and disposal of ICT devices and from constructing and maintaining the ICT infrastructure. The results of this analysis, especially regarding the differences between poorer and richer countries, can be therefore explained by the different effects of efficiency gains with increasing digitalization in firms in combination with the material base of the ICT sector.

The variation in the location of the optimum with changing incomes is likely due to the relative sizes of the environmentally beneficial and detrimental effects of firm level digitalization, depending on the average income of the country under consideration. The results suggest that the detrimental relationship is more pronounced in countries of lower average incomes, *c.p.*, where the negative environmental effects outweigh the environmental efficiency gains. This may be due to poorer countries producing more labor intensively, while production in richer countries is more capital intensive. Given that the environmental efficiency gains from digitalization are larger in capital intensive production (think, for example, of the benefits of a 5G mobile network that can create substantial improvements in already digitalized agricultural practices through precision farming in contrast to low-tech farming in lower income countries which does not benefit in any way from high speed mobile internet access), increases in digitalization can have higher potential for improvements in environmental efficiency in richer countries. A further possible explanation is that an increase in the ICT stock in poorer countries is used to set up the initial digital infrastructure, which creates emissions where there were none before while in richer countries, increases in the ICT stock are more likely to replace existing infrastructure by more efficient solutions, therefore reducing the CO_2 emissions (note that the ICT stock is relatively short-lived, with depreciation periods of less than five years).

At the household level, the prevalence of the negative effects of emissions caused by digitalization's material base over digitalization's efficiency enhancements also holds for the lower income percentiles. For higher income countries, the beneficial effects prevail throughout the entire distribution of digitalization levels in our sample. This indicates that in richer countries, the efficiency gains of digitalization are always higher than the damage caused by the households' use of digital devices. This effect of income levels on the location of the optimum might be due to the ICT devices already existing in the vast majority of richer countries' households at relatively low levels of digitalization[10], meaning that an increase in digitalization would require a smaller broadening of the material base and thus few additional resources and energy expenditures to produce the devices used in these countries. A second reason may be that the CO_2 efficiency gains from digitalization are more pronounced in higher income countries, given that a major part of emissions stemming from online shopping emerges in transporting goods between stores and households. Given that a larger share of the population in higher income countries has access to individual motorized vehicles while in lower income countries, more people rely on public transport (see above), the beneficial effect of CO_2-efficient transport between

[10] Data from Eurostat (2021b) indicate a positive correlation between mean income and number of ICT devices per household.

stores and households through the centralized delivery associated with online shopping may save more emissions caused by private households' shopping in richer countries because, in poorer countries, the number of private cars is smaller in the first place.

6 Conclusion

This paper is the first to differentiate between firms and households when assessing the environmental effects of digitalization. We make use of a unique data set linking firm-based CO_2 emissions to digitalization levels in firms and consumption-based CO_2 levels, that account for emissions embedded in imports, to digitalization levels in households. The econometric analyses apply the Group Fixed Effects estimator to avoid the assumption of time-invariant fixed effects in panel data analyses.

The results of this study provide evidence regarding the non-linear relationship between digitalization and its associated environmental costs in EU and OECD countries. For both firms and households, the marginal effect of increasing digitalization, measured as the effect of the ICT stock and online shopping on CO_2 emissions, is negative at the respective sample medians. The optimal digitalization level is rather low for countries within the first three income deciles but increases steeply with the level of GDP *p.c.* This finding implies for almost all lower income countries that increases in the ICT stock and/or in online shopping lead to higher CO_2 emissions, *c.p.*, while in higher income countries, more online shopping and a higher ICT stock reduce CO_2 emissions. At the firm level, this difference can be explained by environmental efficiency gains by digitalization being stronger than the direct effects of setting up and operating digital infrastructure in richer countries and the opposite in poorer countries. This can be due to a) richer countries producing more capital intensively (which involves more scope for environmental efficiency gains than in labor intensive production) and b) the fact that poorer countries start off with a lower level of digital infrastructure whose initial set-up is associated with higher emissions (outweighing the efficiency gains) while further investments in the ICT stock of rich countries are less material intensive. At the household level, two factors explain the results: The efficiency effect of the already existing digital material base in higher income countries, and the higher prevalence of individual motorized transport in higher income countries.

The results do not support the EKC hypothesis, similar to some findings in the respective literatures, for example Luzzati et al. (2018) regarding the firm side or Destek et al. (2018) for the household side.

Policy implications are that in the countries in which the level of digitalization is above the environmentally optimal level, an increase in digitalization would be associated with an increase in emissions in the business-as-usual scenario, i.e., unless counter measures are introduced, such as a tax on carbon emissions. The result of such a tax may be a speeding up of the components of digitalization which replace carbon intensive activities, while the revenues of such a tax could be used to finance research and development for a more energy efficient ICT sector. For countries that are below that optimal level, an increase in digitalization is associated with a decrease in CO_2 emissions. In those countries, policies that provide the business environment for deepening digitalization in production and consumption would likely have beneficial outcomes in terms of lower greenhouse gas emissions.

It needs to be considered for all policy scenarios that the predictions derived in this analysis only hold if digitalization is used in the manner it has been used in the past. If digital technologies were used differently and explicitly geared towards environmental sustainability (for example, due to more stringent environmental policies), the policy implications regarding the degree of digitalization could be altered.

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A Appendix

A.1 Robustness checks 1: Estimation procedure

To test the robustness of our results against the chosen estimation procedure, we repeat the econometric analysis with two dynamic panel data models. The first is a Two-Stage System General Method of Moment model (2S-SysGMM, see equation A.1), following Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998), and Roodman (2009). The second is a Two-Stage GFE model including the lagged dependent variable (equation A.2), instrumented in a first stage with its second lag as suggested by Bonhomme and Manresa (2015).

$$\begin{aligned} \ln CO2_{it} = \; & \alpha + \beta_0 \ln CO2_{it-1} + \beta_1 \ln Digi_{it} + \beta_2 (\ln Digi_{it})^2 + \beta_3 \ln GDP_{it} + \\ & \beta_4 (\ln GDP_{it})^2 + \beta_5 (\ln GDP_{it} * \ln Digi_{it}) + \Gamma_P X_{it} + \epsilon_{it}, \end{aligned} \tag{A.1}$$

$$\ln CO2_{it} = \alpha + \beta_0 \ln CO2_{it-1} + \beta_1 \ln Digi_{it} + \beta_2 (\ln Digi_{it})^2 + \beta_3 \ln GDP_{it} + \beta_4 (\ln GDP_{it})^2 + \beta_5 (\ln GDP_{it} * \ln Digi_{it}) + \Gamma_P X_{it} + \delta_{gt} + \epsilon_{it}, \tag{A.2}$$

Regression results for the Two-Stage System GMM estimation and the Two-Stage GFE estimation are shown in Table A.1. Marginal effects and the effect of a 10% increase in *Gini* at the sample median can be found in Table A.2.

Table A.1: Robustness checks: Two-Stage System GMM and Two-Stage GFE estimations.

	2S-SysGMM		GFE-2SLS	
	(1)	(2)	(3)	(4)
VARIABLES	CO_2	carbon EF	CO_2	carbon EF
lag ln CO_2	0.976		0.976	
	(31.804)		(105.527)	
ln *ICT*	0.085		0.118	
	(0.788)		(2.346)	
(ln *ICT*)^2	0.002		0.001	
	(1.520)		(0.940)	
(ln *ICT**ln *GDP*)	-0.013		-0.013	
	(-1.009)		(-2.693)	
lag ln *carbon EF*		0.739		0.350
		(6.396)		(1.475)
ln *OnlineShopping*		0.610		1.344
		(1.805)		(1.992)
(ln *OnlineShopping*)^2		0.011		0.011
		(1.155)		(1.168)
(ln *OnlineShopping**ln *GDP*)		-0.070		-0.142
		(-1.876)		(-2.002)
ln *GDP p.c.*	-0.090	-2.501	-0.177	-4.105
	(-0.321)	(-1.670)	(-1.844)	(-2.585)
(ln *GDP p.c.*)^2	0.011	0.136	0.014	0.242
	(0.567)	(1.755)	(2.252)	(2.568)
Agriculture	0.011	-0.027	0.010	-0.023
	(3.739)	(-1.545)	(4.922)	(-1.255)
Manufacture	0.004	0.007	0.003	-0.001
	(2.065)	(1.461)	(4.509)	(-0.105)
Service	0.002	0.002	0.003	-0.000
	(1.026)	(0.629)	(3.730)	(-0.004)
Urban	0.000	0.002	-0.000	0.001
	(0.122)	(1.098)	(-0.939)	(0.355)
Constant	-0.176	11.514	0.144	17.520
	(-0.175)	(1.612)	(0.399)	(2.528)
Observations	500	337	481	330
R-squared			0.991	0.931
AR(1)-pvalue	0.000621	0.00355	.	.
AR(2)-pvalue	0.320	0.301	.	.
Hansen-J-Statistic	0.130	0.864	.	.

t-statistics in parentheses.
Levels of statistical significance are not indicated by asterisks (see Footnote 3 in Section 4).

For the Two-Stage System GMM estimation, Figures A.1 for firms and A.3 for households show the marginal effect of digitalization on carbon emissions, holding GDP *p.c.* constant at its median for *ICT-investment* and including also the percentiles 25 and 75 for *OnlineShopping*. To show

Table A.2: Robustness check: marginal effects of digitalization on measures of biosphere use at the sample median.

Estimation Method	Dimension	$\frac{\partial\Omega}{\partial Digi}$	Effect of 10% increase in $Digi$
2S-SysGMM	Firms	-0.000014	-0.21 %
	Households	-0.0065	-0.42 %
GFE-2SLS	Firms	-0.000014	-0.30 %
	Households	-0.0086	-0.56 %

Own calculations, based on equations (A.1) and (A.2) with data from estimation results and descriptive information (Tables 1 and 2).

the effect over the whole GDP range, Figures A.2 and A.4 represent surface graphs where darker shading represents higher emissions and the red lines indicate extreme values.

All figures indicate that the results are highly robust to both estimation methods.

Figure A.1: Effects of lnICT-$Investments$ on domestic CO_2 emissions - 2S-SysGMM.

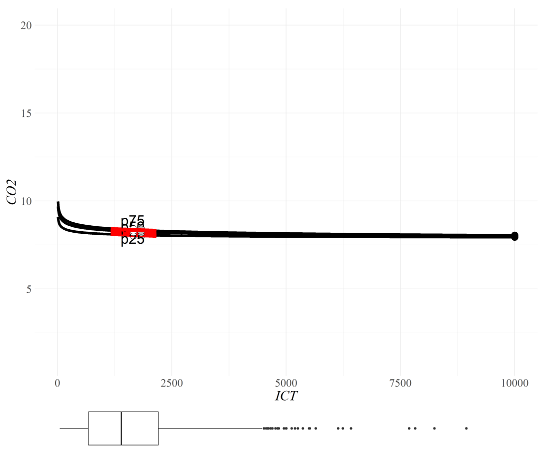
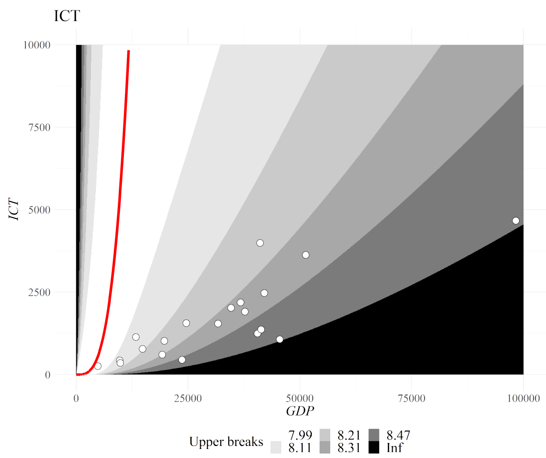


Figure A.2: Effects of lnICT-$Investments$ and lnGDP on domestic CO_2 emissions - 2S-SysGMM.



For the Two-Stage GFE estimations, Figures A.5 for firms and A.7 for households show the marginal effect of digitalization on carbon emissions, holding GDP $p.c.$ constant at its median for $ICT - investment$ and including also the percentiles 25 and 75 for $OnlineShopping$. To show the effect over the whole GDP range, Figures A.6 and A.8 represent surface graphs, where darker shading represents higher emissions and the red lines indicate extreme values.

Figure A.3: Effects of ln *Online-Shopping* on CO_2 emissions (including imported emissions) - 2S-SysGMM.

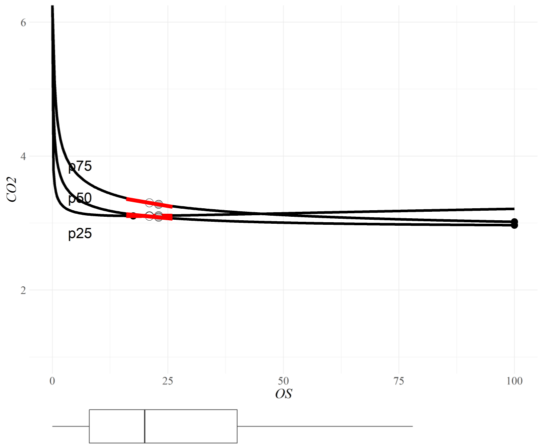


Figure A.5: Effects of ln *ICT-Investments* on domestic CO_2 emissions - GFE-2SLS.

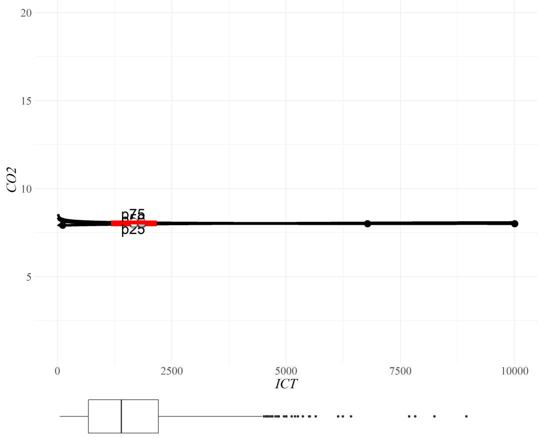


Figure A.7: Effects of ln *Online-Shopping* on CO_2 emissions (including imported emissions) - GFE-2SLS.

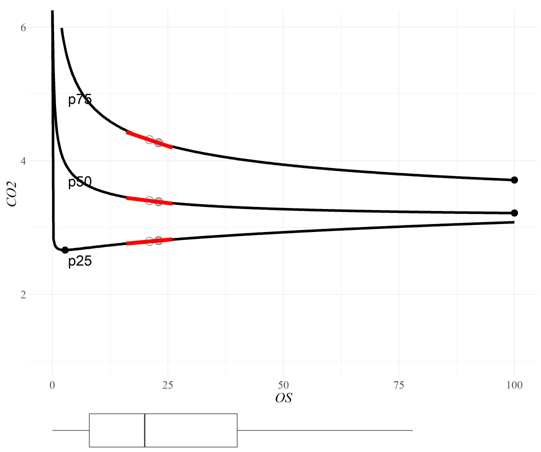


Figure A.4: Effects of ln *Online-Shopping* and ln *GDP* on CO_2 emissions (including imported emissions) - 2S-SysGMM.

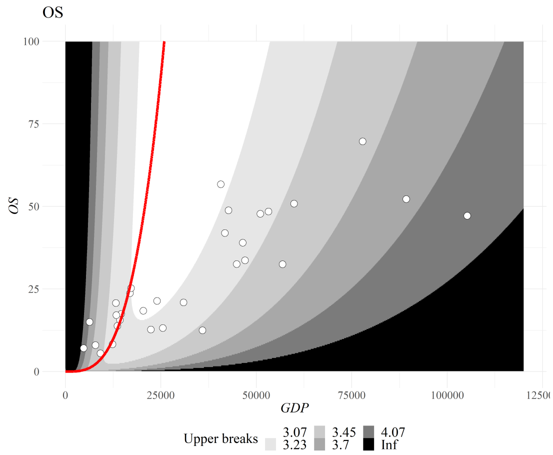


Figure A.6: Effects of ln *ICT-Investments* and ln *GDP* on domestic CO_2 emissions - GFE-2SLS.

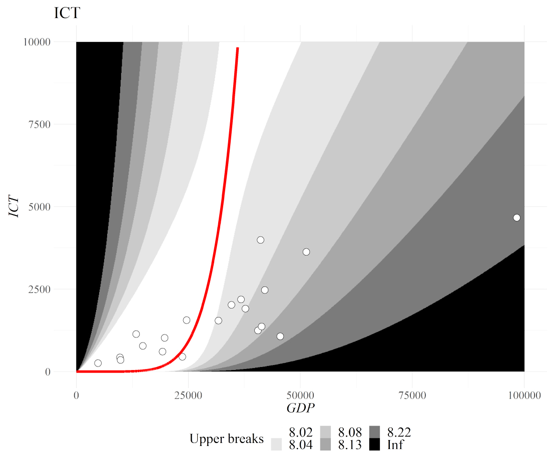
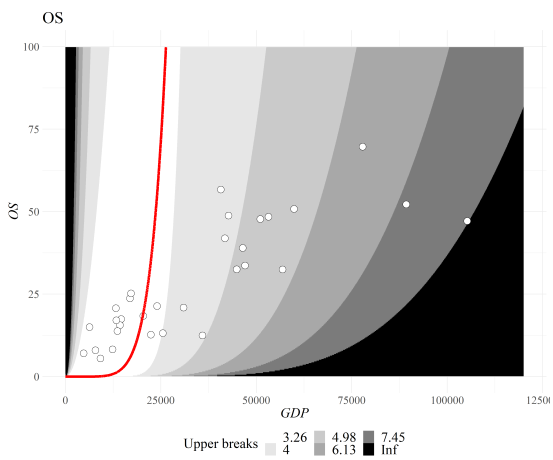


Figure A.8: Effects of ln *Online-Shopping* and ln *GDP* on CO_2 emissions (including imported emissions) - GFE-2SLS.



A.2 Unit-root and cointegration analysis for the firm side analysis

A.2.1 Tests for non-stationarity and cointegration

The firm side estimation includes 24 countries over 25 years, which is a long enough time span to test for non-stationarity and cointegration of the time series. The results of the Im-Pasaran-Shin unit-root test are displayed in Table A.3. Each row contains the test statistics for the three variables of interest ($ln(CO_2)$, $ln(ICT)$, and $ln(GDP)$). The null hypothesis of this test is that the whole panel contains a unit root for each country (and would be therefore non-stationarity, Im et al., 2003), which is rejected for $ln(ICT)$ and $ln(GDP)$, but not for $ln(CO_2)$. This implies that $ln(CO_2)$ is non-stationary in every country and that both $ln(ICT)$ and $ln(GDP)$ are stationary in at least one country, respectively.

Table A.3: Tests for unit-root for the dependent variable $ln(CO_2)$ and the independent variables $ln(ICT)$ and $ln(GDP)$ at the firm side.

Im-Pesaran-Shin unit-root test		
variable	Z_{tbar}	p-value
ln(ICT)	-7.0831	0.0000
ln(CO2)	4.9563	1.0000
ln(GDP)	-3.0535	0.0011

Z_{tbar} is a modified version of the (standardized) t-bar statistic, in which errors in individual Dickey–Fuller (DF) regressions are not assumed to be serially correlated (Im et al., 2003).

Given that the panel unit-root tests cannot rule out that some of the countries combine stationary and non-stationary series for the three main variables, we perform unit-root tests for all countries separately (Romero-Ávila, 2008). The left part of table A.4 shows Dicky Fuller and Im-Pasaran-Shin test statistics by country. Numbers are printed in *italics* whenever the null hypothesis of a unit-root is rejected. Results suggests that all three variables are non-stationary in 13 countries (from Cyprus to Estonia in the table)[11]. The right panel of the same table displays test statistics of two classes of cointegration tests: The Kao class (five tests) and the Pedroni class (three tests). For the 13 countries with non-stationary variables, the majority of tests suggest cointegration (null hypothesis is non-cointegration, and p-values are smaller than 0.05).

Based on those results, several robustness checks are carried out, displayed in Subsection A.2.2.

A.2.2 Robustness checks 2: Subsamples

Given the results of non-stationarity and cointegration tests (see Appendix A.2.1), the main estimation is repeated with several subsets of the whole data set to check for robustness. The first collection of subsets includes a different selection of countries, based on the findings displayed in Table A.4. In the following Table A.5, column (1) displays the original results, column (2) the results for the first 10 countries of Table A.4 (at least four unit-root tests show non-stationarity and strong evidence for cointegration) and the extended group of 12 countries in column (3) (non-stationary but mixed evidence for cointegration).

A second set of robustness checks is executed by splitting the sample into shorter time periods

[11] In those 13 countries, nearly all tests suggest non-stationarity. The exceptions are ESP, NLD, and EST in which one test each is significant.

Table A.4: Tests for unit-root and cointegration for each country, firm side

	Unit Root tests (H0: non-stationarity)						Cointegration tests (H0: no cointegration)							
	Dicky Fuller tests			Im-Pesaran-Shin tests			Kao tests					Pedroni tests		
	ln(ICT)	ln(GDP)	ln(CO2)	ln(ICT)	ln(GDP)	ln(CO2)	MDF	DF	ADF	UMDF	UDF	MPP	PP	ADF
CYP	0.07	0.36	0.90	0.11	0.33	0.89	*0.00*	0.07	*0.05*	*0.03*	0.09	0.45	0.07	0.44
CZE	0.13	0.90	0.87	0.16	0.88	0.85	*0.00*	*0.01*	0.06	*0.00*	*0.01*	0.47	*0.01*	0.35
DEU	0.35	0.90	0.74	0.33	0.89	0.69	*0.04*	0.11	*0.00*	0.09	0.13	0.22	0.46	0.46
FRA	0.56	0.11	0.96	0.50	0.14	0.97	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	0.37	*0.00*	*0.01*
LUX	0.90	0.05	0.97	0.88	0.09	0.98	*0.00*	*0.03*	*0.01*	*0.00*	*0.03*	0.40	0.41	0.34
PRT	0.16	0.17	0.81	0.18	0.18	0.75	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	0.23	*0.00*	*0.00*
SVK	0.37	0.66	0.55	0.34	0.59	0.48	*0.02*	*0.00*	*0.00*	*0.00*	*0.00*	0.34	*0.00*	*0.01*
SWE	0.94	0.30	0.96	0.95	0.29	0.97	*0.01*	0.11	*0.01*	*0.01*	0.11	0.46	0.41	0.50
ESP	0.08	*0.04*	0.91	0.11	0.08	0.90	*0.00*	*0.02*	*0.04*	*0.00*	*0.03*	0.40	0.15	0.26
NLD	0.07	*0.03*	0.75	0.11	0.06	0.70	*0.00*	*0.00*	*0.02*	*0.00*	*0.00*	0.41	0.14	0.08
IRL	0.33	0.39	0.93	0.31	0.36	0.92	*0.02*	0.10	*0.00*	0.07	0.13	0.25	0.42	0.35
LVA	0.26	0.43	0.44	0.25	0.39	0.39	0.06	0.11	*0.01*	*0.04*	0.10	0.28	0.44	0.44
EST	*0.02*	0.15	0.06	0.06	0.17	0.10	0.39	0.39	0.06	0.46	0.44	0.09	0.08	0.15
AUT	*0.00*	0.06	0.66	*0.00*	0.10	0.60	0.09	0.23	0.06	0.24	0.29	0.15	0.20	0.21
BEL	*0.00*	0.08	0.93	*0.00*	0.12	0.93	*0.00*	*0.01*	*0.00*	*0.00*	*0.01*	0.43	*0.04*	0.30
DNK	*0.00*	0.29	0.95	*0.00*	0.28	0.95	0.06	0.17	0.11	0.06	0.17	0.39	0.39	0.37
FIN	*0.00*	*0.02*	0.82	*0.00*	0.05	0.78	*0.00*	*0.01*	*0.01*	*0.00*	*0.01*	0.42	0.14	0.09
GBR	*0.00*	0.13	1.00	*0.00*	0.15	1.00	0.42	0.44	0.20	0.43	0.33	0.12	0.07	*0.03*
GRC	*0.00*	0.51	0.99	*0.00*	0.45	1.00	*0.01*	0.10	*0.02*	0.07	0.13	0.25	0.42	0.43
ITA	*0.00*	0.36	0.99	*0.00*	0.33	1.00	*0.00*	*0.01*	*0.00*	*0.00*	*0.01*	0.21	0.05	*0.01*
JPN	*0.00*	0.73	0.15	*0.00*	0.67	0.17	*0.01*	0.06	*0.04*	0.06	0.07	0.21	0.29	0.43
LTU	*0.01*	0.62	0.37	*0.04*	0.56	0.34	*0.02*	0.18	*0.03*	0.15	0.24	0.19	0.25	0.33
SRB	0.19	*0.00*	*0.02*	0.20	*0.03*	0.06	0.41	0.35	0.44	0.36	0.30	0.08	*0.04*	*0.02*
USA	*0.00*	0.09	0.99	*0.01*	0.13	1.00	0.08	0.21	*0.00*	0.23	0.27	0.15	0.19	0.42

p-values of unit-root and cointegration tests. Italic number show p-values<0.05. The countries are ordered by the results of the unit-root test (the first 10 countries cannot reject unit roots for the three variables), and by cointegration (the first 10 countries reject the null of no cointegration).

which are so short that spurious regression is unlikely (Pesaran, 2015). We decided for three time periods of 8-9 years each (1995-2003, 2004-2011, and 2012-2019).

All coefficients and significance levels of all robustness checks (Tables A.5 and A.6) are very similar to the main results, which suggests that the main results of the econometric analysis are not the result of spurious regressions.

Table A.5: Robustness checks: Firm side regression for all, 10, and 12 countries (non-stationary and cointegrated)

	(1)	(2)	(3)
VARIABLES	GFE (all)	GFE (10 countries)	GFE (12 countries)
ln_ICT_stock	2.830	2.360	3.424
	(6.905)	(5.034)	(7.218)
ln_ICT_2	0.009	0.072	0.028
	(0.396)	(2.307)	(0.671)
ln_GDP	-7.235	-9.514	-7.940
	(-6.462)	(-1.907)	(-3.289)
ln_GDP_2	0.483	0.624	0.551
	(7.376)	(2.707)	(3.837)
ln_ICT_GDP	-0.287	-0.367	-0.381
	(-4.446)	(-6.055)	(-4.016)
agri	0.054	-0.095	-0.047
	(1.021)	(-1.257)	(-0.892)
ind	0.022	0.032	0.016
	(0.765)	(1.647)	(0.409)
serv	0.021	0.004	0.007
	(0.777)	(0.247)	(0.210)
urban	0.002	0.019	-0.000
	(0.336)	(1.262)	(-0.010)
Constant	23.517	38.339	26.898
	(3.857)	(1.384)	(2.659)
Observations	519	216	260
R-squared	0.774	0.922	0.876

Robust t-statistics in parentheses.
Estimation 2 includes 10 countries (CYP, CZE, DEU, FRA, LUX, PRT, SVK, SWE, ESP, NLD), estimation 3 includes 12 countries (in addition to the countries of (2) also IRL and LVA)

Table A.6: Robustness checks: Firm side regression for 3 time periods

	(1)	(2)	(3)	(4)
VARIABLES	GFE (all years 1995-2019)	GFE (1995_2003)	GFE (2004_2011)	GFE (2012_2019)
ln_ICT_stock	2.830	2.235	3.445	2.400
	(6.905)	(5.029)	(4.088)	(3.164)
ln_ICT_2	0.009	0.000	0.000	0.015
	(0.396)	(0.010)	(0.009)	(0.503)
ln_GDP	-7.235	-5.258	-8.229	-9.535
	(-6.462)	(-4.870)	(-5.886)	(-5.585)
ln_GDP_2	0.483	0.363	0.549	0.579
	(7.376)	(5.574)	(6.407)	(6.089)
ln_ICT_GDP	-0.287	-0.219	-0.330	-0.258
	(-4.446)	(-3.034)	(-3.734)	(-3.271)
agri	0.054	0.071	0.093	0.083
	(1.021)	(1.573)	(1.197)	(0.802)
manuf	0.022	0.035	0.023	0.037
	(0.765)	(1.049)	(0.817)	(1.347)
serv	0.021	0.031	0.023	0.042
	(0.777)	(1.027)	(0.884)	(1.609)
urban	0.002	0.009	-0.001	0.007
	(0.336)	(1.663)	(-0.148)	(0.999)
Constant	23.517	14.117	25.986	35.371
	(3.857)	(2.556)	(4.015)	(4.187)
Observations	519	194	192	133
R-squared	0.774	0.830	0.796	0.754

Robust t-statistics in parentheses.

A.3 Joint significance tests

The assessment of statistical significance of the estimated coefficients displayed in Tables 3 and A.1 is not straightforward, given that the key variables under consideration (*ln(ITC)* and *ln(OS)*) enter the RHS of the respective equations in three forms: as logs, as squared logs, and as an interaction term with *ln(GDP)*. We therefore applied joint significance tests for all terms that include the independent variable of digitalization on the firm and household side (*ln(ITC)* and *ln(OS)*). Results for the firm side indicate joint significance of the ICT terms in the main estimation (GFE) and the GFE-2SLS estimation (Table A.7). For the household side, terms including OS are jointly significant in the main estimation and the 2S-SysGMM estimation (Table A.8).

Table A.7: Joint significance test for the variables containing *ln(ITC)*.

Joint significance test (ln(ICT), $ln(ICT^2)$, ln(ICT)ln(GDP))			
Model	GFE	2S-SysGMM	GFE-2SLS
F (2,23) / chi2 (3)	19.100	1.280	9.810
Prob>F	0.000	0.303	0.020

Table A.8: Joint significance test for the variables containing *ln(OS)*.

Joint significance test (ln(OS), $ln(OS2)$, ln(OS)ln(GDP))			
Model	GFE	2S-SysGMM	GFE-2SLS
F (3,30) /chi2 (3)	6.150	4.810	4.480
ProbF	0.002	0.008	0.215

A.4 List of countries entering the analysis

Table A.9: Mean values of key variables and group membership by country.

		Production				Consumption			
Country	GDP pc	CO_2	ICT	Group	Obs	EF CO_2	OS	Group	Obs
Austria	42859.33	8.16	3992.28	2	23	3.86	33.50	1	15
Belgium	44358.29	10.08	1908.14	4	23	4.57	33	3	12
Canada	40369.74								
Croatia	14036.60					2.34	19	2	10
Cyprus	23661.70	7.00	451.42	4	22	0.142			
Czech Republic	20162.18	11.09	20191.77	2	23	3.79	16	2	14
Denmark	56190.81	9.23	21261.51	4	23	4.37	55.50	1	15
Estonia	16629.75	12.65	779.99	3	17	3.27	16	2	13
Finland	41967.74	10.76	1248.81	4	23	4.19	43	1	1
France	38942.28	5.60	2022.89	4	23	3.01	43	3	11
Germany	38366.68	9.80	2188.55	4	23	3.69	51	3	15
Greece	24730.65	8.10	1025.92	4	22	3.33	11	1	15
Hungary	13679.31					2.33	13.50	2	1
Ireland	47591.89	9.72	1072.39	2	22	3.10	34	3	1
Italy	34465.12	7.05	1547.05	4	23	3.14	10	3	14
Japan	41187.51	9.35	184735.70	1	21				
Latvia	13203.98	3.53	354.00	4	22	1.76	14	2	13
Lithuania	13209.61	3.75	433.15	4	22	2.32	10	2	14
Luxembourg	105115.03	20.47	4668.63	4	23	10.94	49.50	1	15
Montenegro	6800.25					2.13	8	2	1
Netherlands	46960.18	10.02	2474.73	4	23	4.02	52	1	15
New Zealand	27366.64								
North Macedonia	4581.50					1.97	4	2	10
Norway	88890.04					2.94	56	4	14
Poland	12909.50					2.72	20.50	2	13
Portugal	22137.11	5.34	607.68	1	17	2.74	10	3	15
Romania	8559.40					1.58	4	2	11
Serbia	5846.89	6.59	258.74	4	18	1.77	18	2	3
Slovakia	16989.15	6.55	1139.97	2	18	3.05	26.50	2	13
Slovenia	23419.01					3.43	21	2	13
Spain	29235.83	6.55	1559.98	4	22	2.55	18	1	15
Sweden	46318.83	5.44	34103.57	1	22	3.46	51.50	1	15
Switzerland	67860.24					4.01	72	3	1
Turkey	11253.18					1.84	7	2	10
United Kingdom	37285.18	8.09	1369.46	4	23	3.74	62	1	15
United States	41278.56	18.21	3628.55	4	23				

Total number of countries for firm-side: 24. Total number of countries for household-side: 31 in GFE-TFE estimation, and 28 in 2S-SysGMM and GFE-2SLS (Finland, Hungary and Ireland only have one observation of EF_carbon).