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Abstract

Digitization-related services and applications are based on the information and communications technology (ICT) ecosystem and encompass almost all areas of society and economic sectors nowadays and exert numerous opposing effects in regard to electricity consumption and corresponding CO2 emissions. Our analysis aims to inform policy decision makers about the actual climate relevance of the ICT ecosystem by providing sound empirical evidence on the net effect of various ICT core elements based on recent OECD panel data utilizing panel econometric estimation methods that include instrumental variables. We found that the CO2-reducing positive indirect effects seem to outweigh the negative, in other words, CO2-increasing direct and indirect effects on average. Specifically, we found that, in addition to the lowering effect related to the use of basic broadband connections, there was another lowering effect—albeit smaller—related to new fiber-based broadband connections. In contrast, other elements of the ICT ecosystem, such as mobile broadband networks or electronic end-user devices, showed no significant net impact on CO2 emissions. Our main findings suggest that broadband networks can give rise to positive environmental effects for society. We conclude that undifferentiated climate policy measures imposed on the ICT ecosystem would not do justice to the identified heterogeneity, with numerous in part opposing effects, and likely would be accompanied by inefficiencies and market distortions.

Schlüsselwörter: ICT, digitization, CO2 emissions, electricity consumption, OECD data, panel econometrics

JEL-Klassifikation: L52, L96, Q40, Q55

1 Introduction

Measures to contain climate change are internationally decisive topics in public debate. Critical reports, such as those of the Intergovernmental Panel on Climate Change (IPCC) of the United Nations, have attracted much public attention and have contributed to concerns related to role of information and communication technologies (ICT) and digitization[1] on climate change. Negative effects of digitization are often cited regarding increasing electricity and energy consumption and related greenhouse-gas (GHG) emissions. For example, the process of *Bitcoin mining* stands out in a striking way, as enormously high computing power and energy consumption have arisen around the globe in order to generate this virtual money. Likewise, the massive expansion of digital network infrastructures due to constantly increasing Internet traffic and its related rapid growth in respond to rising capacity and quality requirement demands go hand in hand with high electricity and energy consumption that result in high carbon dioxide (CO2) emissions. At the content level, another area of concern relates to the massive increase in Internet data traffic from video streaming services in recent years. At the household level, video streaming has apparently become a "killer app" that requires massive energy consumption throughout the whole ICT ecosystem (Madlener et al., 2021).

At the same time, "megatrend" digitization based on ICT also offers considerable potential for efficiency improvements and the reduction of transaction costs in almost all major economic areas. As a so-called "general-purpose technology" (Bresnahan & Trajtenberg, 1995), ICT-based digital applications bring high welfare gains due to their universal applicability in a wide variety of ICT-based industries and in less ICT-intensive industries, as well as numerous other societal benefits in the form of product and process innovations and consumer surplus. In addition to the efficiency potentials already identified in the literature,[2] positive external effects can also be realized for environmental and climate protection.

[1] The ICT sector includes relevant telecommunication infrastructures (such as broadband access and backbone networks) as well as ICT hardware and ICT software and other information services and forms the infrastructural basis for digitization across all sectors of the economy. Digitization is defined as the phenomenon of steadily increasing adoption and implementation of ICT.

[2] Cardona et al. (2013) reviewed the ICT-related literature, Bertschek et al. (2015) the basic broadband-related literature and Arbrardi and Cambini (2019) have provided a survey focusing on new (fiber-based) broadband networks.

Nowadays, digitization encompasses almost all areas of society and economic sectors, exerting numerous opposing effects on the consumer, industry, and macroeconomic levels in regard to electricity consumption and corresponding CO2 emissions. Whereas direct effects, which are related to the production, operation, and disposal of ICT components, increase electricity needs and thus CO2 emissions, indirect effects are related to potential efficiency gains as well as to enabler effects at the application level, which might considerably lower CO2 emissions; there are, however, also opposing indirect effects that give rise to an increase in total energy consumption and CO2 emissions due to various rebound and obsolescence effects. Considering all these effects across all areas of digitization suggests a high degree of heterogeneity within the ICT ecosystem, which needs to be addressed empirically to truly inform policy decision makers. We therefore want to contribute to the very scant empirical literature by examining the net effect of ICT on CO2 emissions differentiated by the core elements of the ICT ecosystem comprising fixed and mobile broadband networks, the ICT affinity of consumers, and their main end-user devices.

In order to identify causal effects, we employed the most recent panel data from 34 OECD countries for the years 2002 to 2019 using two-way fixed-effects estimation techniques that include instrumental variables. Using various sets of instruments allowed us to assess the validity of the instruments and the robustness of our baseline regression estimates. We have expanded on the existing literature by employing the most recent data for developed countries, using more comprehensive measures of the ICT ecosystem as our main variables of interest along with a large set of control variables. We found that the CO2-reducing *positive* indirect effects outweighed the *negative*, in other words, the CO2-increasing direct and indirect effects, on average. Specifically, we found that, in addition to the lowering effect related to the use of basic broadband connections, there was also a lowering effect—albeit smaller—related to the use of new fiber-based broadband connections, whereas mobile broadband networks and other ICT elements exhibited no statistically significant effect on CO2 emissions.

The remainder of this article is structured as follows. Section 2 provides an overview of the related empirical literature. Section 3 then illustrates the relevant direct and indirect effects of

ICT on CO_2 emissions in more detail. Section 4 outlines our empirical baseline specification and identification strategy, as well as our OECD panel data. Section 5 discusses our main estimation results, while Section 6 concludes with a review of our main findings and the most relevant policy implications for the ongoing debate on ICT and climate change.

2 Literature review

2.1 Macroeconomic, institutional, and political determinants

General determinants of CO_2 emissions can be roughly grouped into three categories: (socio-)economic, institutional, and political determinants. These are discussed briefly below, and Table 1 summarizes the expected effects based on the theoretical hypotheses and empirical evidence.

Gross domestic product (GDP), or, more precisely, GDP per capita, is considered one of the most important explanatory drivers of CO_2 emissions. A linear relationship between CO_2 emissions and GDP per capita has been confirmed in earlier studies (Shafik, 1994). However, decoupling the increase of CO_2 emissions from economic growth seems possible if either CO_2 emissions decline as a by-product of other abatement activities (Holtz-Eakin & Selden, 1995) or institutions as well as environmental regulations are adjusted to reflect rising per capita income. The hypothesis of the Environmental Kuznets Curve (EKC) states that environmental impacts first increase but later decrease when an economy grows resulting in an inverted U-shaped functional relationships between emissions and GDP (per capita) (De Bruyn et al., 1998; Holtz-Eakin and Selden, 1995). Shahbaz and Sinha (2019) provided an analysis of the EKC hypothesis specifically for CO_2 emissions. In developed countries, sectoral change also goes hand in hand with digitization, which in turn accompanies a “tertiarization” of value creation. Tertiarization occurs when the share of services in total GDP increases. This raises the question of whether digitization leads to less or more CO_2 emissions via the use of ICT and tertiarization (Lange et al., 2020).

Another determinant associated with CO_2 emissions in the literature is *international trade*. Opposing effects are attributed to free trade. On the one hand, an increase in the volume of trade increases pollution through an increase in production or transport. On the other hand, trade can improve environmental quality through a technology effect (i.e., when income increases through trade, environmental regulations are tightened, which promotes pollution reduction through additional innovation) and/or a composition effect. This composition effect is attributed to two interrelated hypotheses: the *displacement hypothesis* and the *pollution haven hypothesis.* Both suggest that the composition of production will change in both developed and developing countries through the relocation of emission-intensive operations. The pollution-haven hypothesis suggests that differences in environmental regulations between developing and developed countries induce a shift away from production in the developed world toward developing countries that specialize in environmentally intensive production sectors. The pollution effect can be reduced by entering into free trade agreements that include environmental safeguards (Brandi et al., 2020). Further work shows that the effect of trade on emissions depends, in particular, on the type of exports. A (causal) emissions-reducing effect of trade in environmentally friendly goods has been found by Zugravu-Soilita (2018). A less strong relationship in this direction has also been shown by Mealy and Teytelboym (2020), who proposed an index of complexity based on exports of environmentally friendly products.

Urbanization and *population density* can lead to higher CO2 emissions, as urbanization goes hand in hand with industrialization. This further implies a shift away from the primary sector toward industry and services. Thus, greater urbanization can be associated with higher per capita and the land use of fossil fuels and industrial chemicals. On the other hand, urbanization can also lead to lower levels of energy consumption, as cities benefit from energy efficiency by enabling high-rise living and shortening the distance to work, enabling travel by foot or bicycle. However, most evidence in the literature points to a positive relationship between urbanization and emissions (e.g., Knight et al., 2013; Menz and Welsch, 2012) or a non-linear one (Martinez-Zarzoso & Maruotti, 2011; Zhu et al., 2012).

The impact of technological progress on CO2 emissions is also a priori uncertain. Given the positive effects of *R&D intensity* on growth and trade (Castellani & Pieri, 2013; Minniti & Venturini, 2017), they may negatively affect environmental quality through economies of scale of greater production associated with higher growth and greater trade openness. Despite new technologies that have the potential to improve efficiency, increasing output may still require the use of additional natural resources, which could increase CO_2 emissions. This potential problem is compounded by diminishing returns from R&D over time. As the stock of existing knowledge increases, it becomes more difficult to make new breakthroughs, leading to lower levels of induced R&D over time (Newell, 2009). At the same time, however, economic growth continues to require more input from natural resources.

One particularly problematic feature that significantly hinders international cooperation on environmental quality is that reducing CO_2 emissions can be viewed as a global community problem with political dimensions, which makes free-riding particularly problematic. Several political factors influence CO_2 emissions. For example, ideologically *left-wing governments* usually advocate a large increase in taxes on fuels (Neumayer, 2004). Other political factors, however, while not opposing reduction, may slow the reduction process. Government fragmentation could lead to reduced impact and problems in implementing certain measures, as decision-making transaction costs increase with the number of decision makers in governments. Generally, however, *democracy* should be associated with higher environmental protection through more efficient revelation of preferences for environmental quality (Farzin & Bond, 2006).

The *quality of institutions* represents another political dimension that seems to influence the level of CO_2 emissions. Panayotou (1997) addressed the role of politics and institutions and their relationship with environmental quality. He found that more inclusive and institutionally independent governance and policies can significantly improve environmental quality. Dasgupta et al. (1999) emphasized the importance of institutional development and environmental regulation. Nevertheless, it is also possible that the quality of institutions leads to higher CO_2 emissions through a positive impact on economic growth.

The relationship between *income inequality* and environmental quality is unclear. According to one argument, environmental quality is primarily a concern of upper and upper-middle income groups, who already have their basic needs met and enjoy a relatively high standard of living. In contrast, it is argued that poverty forces people to prioritize employment over environmental quality, which is reflected in the choice of occupations and residences that are much more exposed to toxic pollutants and wastes from industries. Accordingly, since the growth of these industries increases urban employment and thus reduces income inequality, a negative relation can be expected between income inequality and the measurement of certain types of urban pollution. Empirical evidence on the question, however, is mixed (e.g., Scruggs, 1998; Torras & Boyce, 1998). Scruggs (1998) showed that higher levels of education and wealth, which imply greater income inequality, are also associated with “pro-environment” preferences and hence less CO2 emissions.

Table 1: Main explanatory variables and expected effects

Relevant explanatory variables	**Expected marginal effects on CO2 emissions /**
Macroeconomic var.:	
GDP per capita	+/-/non-linear
GDP per capita # tertiarization	+/-
GDP per capita # tertiarization#ICT	+/-
Trade	+/- / - for developed countries
Population density	+/-/non-linear
Urbanization rate	+/-/non-linear
R&D intensity	+/-
Political & institutional var.:	
Left-wing government	-
Government fragmentation	+
Democracy	-
Quality of institutions	+/-
Income inequality	+/-
Income inequality # education	+

Notes: "+" refers to a CO2 increasing effect; "-" refers to a CO2 lowering effect; "+/-" indicates that one cannot derive unambiguous effects from theory and empirical evidence which is in some cases also related to non-linear functional relationships; "#" indicates that the effect of one variable might depend on the level of another explanatory variable.

2.2 ICT determinants

In addition to the general determinants of CO2 emissions at the macro-economic level, the more recent empirical literature also examined the impact at industry or sectoral economic levels. As motivated in the introductory section, ICT- and digitalization-related effects regarding electricity consumption and the resulting CO2 emissions have been of particular interest. Table 2 contains a structured presentation of the available empirical contributions that have investigated individual ICT-relevant variables as determinants of CO2 emissions.[3]

Almost all studies reported in Table 2 use country-level panel data. Danish et al. (2019), Khan et al. (2018) and Zhang et al. (2019) identified positive (i.e., CO2-increasing) relationships. However, the focus of these studies was on developing low-income countries. Zhang et al.

[3] In this subsection, we only reviewed quantitative research that attempts to identify causal links between measures of ICT elements and CO2 emissions, and we therefore excluded qualitative as well as simulation-based studies. Moreover, we excluded empirical studies that offered a credible identification strategy but focused on other related outcome variables, such as electricity or energy consumption; see Lange et al. (2020) for a recent overview of the empirical literature on the effects of ICT on energy consumption.

(2019) as well as Danish et al. (2019) found negative coefficients for high- and middle-income countries and positive coefficients for developing and low-income countries, respectively. All the other studies described the relationship between ICT variables and CO2 emissions as significant and negative (Godil et al., 2020; Kopp & Lange, 2019; Zhang & Liu, 2015; Zhang et al., 2019) or insignificant (Amri, 2018). It thus appears that, overall, developing countries attract more environmentally intensive industrial production and at the same time benefit less from the positive efficiency and enabling effects offered by ICT. In a recently published study Haini (2021) finds that this result also holds for the group of Southeast Asian countries (ASEAN member states).

In summary, most studies examining the impact of ICT on CO2 emissions have shown a negative relationship; in other words, a higher ICT intensity reduced total CO2 emissions. Interestingly, all the studies using data from developed countries found a statistically significant negative impact of various elements of the ICT ecosystem on CO2 emissions. The number of available studies is, however, still very limited, and none of the available studies provides causal effect estimation using instrumental variables or other estimators that explicitly address potential endogeneity concerns. Also, almost all the studies measured only a single or very few elements of the ICT ecosystem, which appears to be insufficient to appropriately capture the ICT ecosystem and the ubiquitous digitization of the society and economy. In answering our research question, we employed the most recent OECD panel data and, when compared with previous empirical contributions, more comprehensive measures of the ICT ecosystem.

Table 2: Overview of the empirical contributions analyzing the impact of ICT variables on CO_2 emissions

Authors	Data	ICT Variables	Method	Results	+/-
Haini (2021)	10 South-East Asian countries 1996-2019	Internet users per 100 persons Mobile-internet users per 100 persons	Fixed Effects	ICT variables exert negative and significant impact on CO2 emissions	-
Godil et al. (2020)	Pakistan 1995–2018 (Quarterly)	Internet users per 100 persons Mobile-internet users per 100 people	Quantile Autoregressive Distributed Lag	The lowest two and the highest three quantiles show a significant negative sign; thus, in Pakistan, regardless of the emission level, CO2 emissions were reduced by an increase in Internet users.	-
Kopp & Lange (2019)	37 OECD countries 1990–2009 (production) 2008-2014 (consumption)	ICT investment People who have used the Internet for purchases (goods and services) in the last three months	Fixed Effects	A 1% increase in ICT investment would, ceteris paribus, reduce CO2 emissions by 0.56%. A 1% increase in online shopping would reduce CO2 emissions by 0.34%.	-
Zhang et al. (2019)	73 countries 1990-2015	Mobile and fixed network connections	Fully Modified & Dynamic Ordinary Least Squares	Both ICT variables show significant negative results in connection with CO2 emissions in high- and middle-income countries. In low-income countries, the results were significant and positive.	- +
Danish et al. (2019)	Different sets of high, middle and low income countries 1990-2015	Fixed telephone and mobile cellular subscriptions	Dynamic & fully modified ordinary least square	ICT variables reduce level of CO2 emissions across high- and middle-income countries; however, contrary to this, ICT variables increase CO2 emissions in low-income countries.	- +
Amri (2018)	Tunisia 1975-2014	Mobile and fixed network connections per 100 people	Autoregressive Distributed lag	Insignificant results in relation to the ICT variable.	~
Khan et al. (2018)	11 developing countries 1990-2014	Internet users per 100 persons Mobile-internet users per 100 persons	(Augmented) Mean Group Estimator	The coefficient of Internet users showed a significant positive relationship with CO2 emissions, which increased CO2 emissions in the developing countries studied when the ICT variable was expanded.	+
Zhang & Liu (2015)	29 provinces in China 2000-2010	Gross output of the electronics and information industry	Fixed Effects, Generalized Least Squares	CO2 emissions in China decreased by 0.024% when the ICT industry grew by 1%.	-

Notes: “+” in connection with red shading refers to a CO2 increasing (statistically significant positive) relationship; “-” in connection with green shading indicates a CO2 lowering (statistically significant negative) relationship; “~” in conjunction with a white background refers to a CO2 neutral (statistically insignificant) relationship.

3 ICT and CO2 emissions: Macrolevel effects, direct and indirect effects

Digitization is a general phenomenon that encompasses almost all areas of society and major economic sectors with numerous opposing effects of consumer, industry, and macroeconomic levels on electricity consumption and corresponding CO2 emissions.

Direct effects, which are related to the production, operation, and disposal of ICT elements, increase electricity consumption and thus CO2 emissions (Kopp & Lange, 2019). This primarily concerns hardware in the form of servers and data centers, the deployment of new wireline and wireless digital network infrastructures, and electronic devices, as well as small sensors and measuring points for the IoT as well as the production of media content, such as online videos. The development of direct effects depends on the growth of the ICT sector and the changes in the sector´s energy intensity (Lange et al., 2020).

Positive indirect effects describe, in particular, the technical potential to save raw materials and reduce electricity consumption and energy intensity (efficiency); in addition, there is the potential to enable entirely new and innovative applications that were simply not possible previously or only become conceivable through ICT use (enabler), as well as to replace traditional goods and services with digital ones (replacement) and thus not only save time and costs, but also lower CO2 emissions considerably. All major sectors can benefit from these effects, examples include intelligent production systems in major economic sectors, such as in energy (*smart grids* that enable the integration of decentralized generators of renewable energies), transportation (*smart traffic control* that enables connected driving), health (*telemedicine* that enables digital health services and online consultations), agriculture (*smart farming* that enables data-based fertilization planning or tractors networked with management programs), or in industry (*smart manufacturing* that connects digitally networked mechanical, electronic, and software components). In addition, there are numerous cross-sectoral applications, such as home offices (based on video-conferencing, virtual private networks or VPNs, and intranet access), e-learning and e-teaching tools, and the possibility of networking countless other devices (the “Internet of Things” or IoT) by linking data in real time.

There are, however, also *negative indirect effects* that give rise to an increase in electricity consumption and related CO2 emissions due to various rebound and obsolescence effects. Rebound effects arise when efficiency gains achieved are offset by increased consumption due to e.g. substitution of other physical factors of production which can even lead to a worse environmental situation. An example refers to video-streaming services which have become highly popular among Internet users with steadily increasing data traffic which might outweigh any efficiency gains related to data centers, transmission technologies or consumer devices (Madlener et al., 2021). Obsolescence effects (the premature disposal of components that are still in working order) also represent indirect effects that result from the application and adoption of new technologies (Colmenares et al., 2020).

At the macroeconomic level, economic growth and sectoral change in particular influence energy consumption and resulting CO2 emissions. The overall impact of these macrolevel determinants will in turn be influenced by digitization. On the one hand it is well established in the related empirical literature that digitization and ICT foster economic growth. On the other hand, digitization and ICT might impact CO2 emissions via structural change in the form of tertiarization. If tertiarization substitutes industrialization it might decrease CO2 emissions as the service sector on average exhibits much lower levels of energy intensity (Lange et al., 2020). The impact of tertiarization, however, also depends on the composition of ICT production and consumption within a country (e.g. ICT manufacturing vs. ICT services).

The ICT sectors appears to be very prone to both positive and negative indirect effects.[4] Therefore, taking all these potential effects across all areas of digitization into account, the overall quantitative effect of ICT and digitization on CO2 emissions is basically indeterminate on a priori reasoning and needs to be addressed empirically. We aim to address the underlying heterogeneity of relevant ICT elements by distinguishing between fixed (wireline) and mobile (wireless) broadband networks with substantial differences in electricity consumption due to

[4] This can be illustrated by contrasting two well-known stylized laws which are based on historic trends (rather than physics) and idicate that increases in output commonly balance out increases in energy efficiency: whereas Koomey´s law suggests that energy intensities of processing units halve about every 1.5 years, Moore's law suggests a doubling of processing capacities every 1.5 years.

fundamentally different network architectures. We further captured differences in end-user devices with varying electricity needs in regard to, for example, resolution, and display size and, finally, differences in ICT exports (production) of, for example, network equipment and devices and ICT imports (usage) of services, such as video-streaming and smartphone apps.

4 Empirical framework

4.1 Baseline regression specifications

Our empirical baseline estimating equation to examine testable hypotheses related to our main research question employs a linear panel model with fixed country-specific and period effects and reads as follows:

$$ln(CO2_{it}) = \alpha_0 + \boldsymbol{ICT}_{it}^{'}\boldsymbol{\beta} + \boldsymbol{X}_{it}^{'}\boldsymbol{\gamma} + \alpha_i + \alpha_t + \varepsilon_{it}, \quad (1)$$

where the dependent variable, which measures total CO2 emissions (*CO2*) in country *i* in year *t*, is expressed in logarithmic form. This allowed us to interpret estimation coefficients as percentage changes. Furthermore, the distribution of the dependent variable was positively skewed and exhibited outlier values,[5] and our dependent variable took on only values greater than zero. The independent variables are subdivided into two vectors: a $K \times 1$ vector of ICT-specific variables and a $M \times 1$ vector of other independent country-level control variables, denoted by $\boldsymbol{ICT}_{it}$ and $\boldsymbol{X}_{it}$, respectively.

The vector $\boldsymbol{ICT}_{it}$ contains several variables that capture the core elements of the ICT ecosystem. Wireline (fixed) and wireless (mobile) broadband networks capture market investment by all network operators in new broadband infrastructures on the supply side (coverage) as well as consumer´s broadband adoption decisions on the demand side. Actual Internet usage and utilization of broadband devices are measured by the diffusion of end-user devices. Note that whereas the number of consumers adopting broadband connections depends on the availability of installed broadband capacity (network coverage), the consumers´ willingness to adopt and pay higher connection fees for a (new) broadband connection under a commercial contract is a pre-condition for actual usage of various ICT and broadband services. The latter, in turn, will also be crucially determined by the overall ICT affinity of consumers in a certain country. Although digitization is a multidimensional and very

[5] The U.S. exhibits by far the highest mean values of electricity consumption (billion kilowatt-hours) and CO_2 emissions (million tons) of about 3861 and 5659, respectively, whereas Luxemburg marks the bottom end with mean values of about 6.2 and 10.5, respectively.

complex phenomenon, all digital services and applications depend on these infrastructural and behavioural elements of the ICT ecosystem.

The vector $\boldsymbol{X}_{it}$ comprises various macroeconomic, political, and institutional control variables, as identified in the relevant empirical literature (Table 1) and for which information is also available in our panel data. The coefficient α_i represents country-specific fixed effects that account for any time-invariant unobserved heterogeneity at the country level. One might think here, for example, of country-specific (more or less) restrictive environmental regulations that have changed little over our analysis period. The coefficient α_t represents the time-specific effects that capture all unobserved macroeconomic “shocks” influencing all units (OECD countries) at the same time (in a similar form). One might think here of the Paris climate agreement, which applies similarly to all OECD countries from a certain point in time (2016). Because CO2 emissions show heterogeneous trend effects across countries (Table 3), country-specific trend effects, $\alpha_{1i}\, t$, are also allowed for in our robustness analysis instead of common period effects (Wooldridge, 2010). In addition to testing the average level of ICT variables, we also test for non-linearities, in other words, if ICT variables—or other explanatory variables, as suggested in Table 1—depend on some variables in $\boldsymbol{X}_{it}$, by including appropriate interaction terms. Finally, ε_{it} represents in additive form the idiosyncratic error.

As mentioned in the introductory section, the immediate impact of ICT is initially in the consumption of electricity and only indirectly via digital services and applications on CO2 emissions. There is, however, typically a very strong statistical relationship between electricity consumption and CO2 emissions. Based on our OECD panel data, we obtained an elasticity estimate of 0.82 from a simple log-log fixed effects model that relates electricity consumption to CO2 emissions.[6] In addition to the strong statistical correlation between the two alternative outcome variables the main reason for focusing on CO2 emissions is that it allowed us to take into account all direct and indirect environmental effects, as described in Section 3.

[6] Detailed estimation results are available by request from the authors.

4.2 Identification strategy

Separating ICT-related effects from macroeconomic and political effects on CO2 emissions is inherently difficult. However, controlling for country fixed and period effects, as well as for most of the relevant control variables in the vector $\boldsymbol{X}_{it}$ is already supportive for the “selection on observables” identifying assumption. To deal with the remaining endogeneity concerns related to reciprocal relationships (simultaneity bias) and time-variant heterogeneity (omitted variable bias), we also performed Granger (1969) causality tests and two-way fixed-effects regressions that utilized instrumental variables and employed distinct sources of exogenous variation, where $\boldsymbol{Z} = (\boldsymbol{z}_1, \boldsymbol{z}_2, \boldsymbol{z}_3)$ was a matrix containing all excluded exogenous variables.

The *first* set of external instruments ($\boldsymbol{z}_1$) refers to competition variables, as investment in (new) broadband networks is crucially determined by the extent of competition in broadband markets (Aghion et al., 2005; Briglauer et al., 2018; Sacco and Schmutzler, 2011). Relevant forms of competition stem from (wireless) mobile broadband networks, such as 4G (“Long-Term-Evolution” or LTE/LTE+) networks but also from alternative fixed (wireline) broadband networks, such as bidirectional broadcasting cable-TV (CATV) networks in particular. We expected competition in broadband markets, expressed in terms of market shares, to significantly affect investment incentives as well as the price and quality of broadband services and, thus, broadband adoption on the demand side but not CO2 emissions directly. The *second* set of external instruments ($\boldsymbol{z}_2$) is related to relevant broadband policies. Average deployment costs will typically be much higher in rural than in urban areas, as deployment costs will be distributed among fewer customers; consequently, broadband deployment will become unprofitable for private network operators in some of the more rural regions. For this reason, in most OECD countries, national and/or local governments have provided substantial public funds in combination with broadband targets (OECD, 2018) to lower total investment costs for operators and hence foster broadband investment and related adoption decisions of consumers on a nationwide scale. Public funding measures to foster deployment of (new) broadband networks are expected to directly increase broadband infrastructure (Bourreau et al., 2020; Briglauer & Grajek, 2021; OECD, 2018) and the related adoption of broadband connections, whereas these policy measures have not been impacted by the climate debate in recent years in any verifiable way. Likewise, investment incentives of network operators, and thus indirectly the adoption decisions of consumers, are impacted by so-called “net neutrality” rules that represent rather interventionist regulations imposed on local broadband access network operators. Empirical studies found that these rules diminish investment incentives of network operators and indirectly the broadband adoption decisions of consumers (Briglauer et al., 2021; Ford, 2018). Third, we construct Hausman-type spatial (“internal”) instruments ($\boldsymbol{z}_3$) as a sort of political economy variable at the international level. In view of ubiquitous broadband targets in most OECD member states and at the EU level (OECD, 2018), the average deployment and adoption level in all other (“non-focal”) states should exert spillover effects toward national decision-makers. We expect strong benchmarking effects, as national policymakers do not want to see national broadband coverage and adoption levels in crucial broadband infrastructures substantially below the average levels in comparable countries (Briglauer & Gugler, 2019). Consequently, we expect below-average countries to catch up, and that, at the same time, average deployment levels in non-focal states will not be impacted by CO2 emissions in a certain (focal) state.

Finally, we assumed that ICT variables were not impacted by the level of our dependent variable (CO2 emissions). Based on plausibility considerations and the existing literature on the main determinants of broadband network investment (Briglauer et al., 2018; Grajek & Röller, 2012) and related broadband service adoption, we saw no reason why our dependent variable (CO2 emissions) should have had a causal impact on ICT investment or ICT usage in the past. Remaining concerns regarding reciprocal causality can be attenuated by conducting panel-specific Granger causality tests (Dumitrescu & Hurlin, 2012). The latter can also be employed to test the assumed one-way causal relationship between electricity consumption and CO2 emissions.

4.3 Data

In order to empirically estimate the impact of ICT on CO2 emissions, as specified in equation (1), we used country-level panel data for 34 OECD member states with yearly observations from 2002 to 2019.[7] Our period of analysis covered almost the entire fiber-based and mobile broadband deployment period, which did not start before 2002, except for a few early infrastructure projects in Japan and South Korea. The dependent variable and the main explanatory variables of interest (ICT variables) are described in Sections 4.3.1 and 4.3.2, respectively. Table A.1 in the Appendix lists the individual data sources and provides detailed definitions of the variables, whereas Table A.2 shows the descriptive statistics of all variables used.

4.3.1 Dependent variable

Data from the Global Carbon Atlas were used to measure production-based CO2 emissions in millions of tons (Mt), denoted with *CO2*.[8] In order to measure total CO2 emissions per country and year, the method of Friedlingstein et al. (2020) was applied: total CO2 emissions per country consist of the CO2 emissions that result from energy consumption in terms of the oxidation of coal, crude oil, and natural gas, as well as from the combustion of gases. Electricity consumption is generated from these raw materials but also, for example, renewable energies. Electricity or energy consumption and GHG emissions are linked by taking the average GHG intensity of the current electricity mix published by the International Energy Agency of approximately 475 grams of carbon dioxide equivalents for one kilowatt hour (IEA, 2019).

Table 3: CO2 average annual growth rates in % and mean values in Mt in 34 OECD states (2002–2019)

Country	Mean (CO2)	ΔCO2%	Country	Mean (CO2)	ΔCO2%
United States	5674,99	-0,0065	Chile	72,72	0,0270
Japan	1240,07	-0,0080	Austria	70,99	-0,0020
Germany	824,92	-0,0140	Israel	63,91	0,0065

[7] The OECD (Organisation for Economic Co-operation and Development) was founded in 1961, and as of the end of 2021, it comprises 38 countries with membership status. Our panel does not include the current OECD members Costa Rica, Columbia, Latvia, and Lithuania, as no corresponding time-series were available for them due to their later membership status. For the actual political determinants of the timing of OECD membership of these countries, there was no obvious link either to our outcome variable or our ICT indicators.

[8] As production and consumption-based CO2 emissons vary between (OECD) countries due to international trade (including ICT core elements), we control for ICT related trade effects (Section 4.3.2).

Canada	573,54	0,0009	Portugal	56,85	-0,0196
Korea	546,21	0,0170	Finland	56,02	-0,0210
United Kingdom	488,19	-0,0234	Hungary	52,75	-0,0101
Mexico	467,26	0,0042	Sweden	48,85	-0,0154
Italy	420,99	-0,0194	Denmark	45,71	-0,0291
Australia	398,28	0,0076	Norway	44,56	-0,0005
France	376,99	-0,0141	Switzerland	42,09	-0,0076
Turkey	329,55	0,0371	Ireland	42,02	-0,0118
Poland	325,28	0,0035	Slovak Republic	38,35	-0,0130
Spain	302,35	-0,0147	New Zealand	35,81	0,0038
Netherlands	169,95	-0,0070	Estonia	17,29	0,0042
Czech Republic	115,25	-0,0116	Slovenia	15,73	-0,0099
Belgium	111,31	-0,0133	Luxembourg	10,55	-0,0002
Greece	93,56	-0,0251	Iceland	3,42	0,0072

Table 3 depicts the mean values and average growth rates of our dependent variable for the underlying period of analysis. From this, we can infer that a group of countries exhibits rather constant developments; other countries are showing (slightly) declining trends (green numbers), whereas about one-third of countries exhibit upward trends (red numbers). The heterogeneity in terms of trends (average percentage growth) but also in levels (mean values) across countries provided a rationale for our two-way fixed effects baseline specification, which also allowed for heterogeneous levels and trends across countries and time.

4.3.2 ICT variables

First, we considered basic wireline broadband as well as new fiber-based broadband connections. Whereas we measured basic broadband as adoption related (*Basic Broadband*) and hence demand-side oriented, we refer to the availability of fiber-based infrastructures on the supply side (*Fiber Broadband*), as there was still a large gap in the adoption and coverage of new fiber-based broadband connections, with adoption rates (i.e., the ratio of adopted connections to available connections) still averaging below 50% in many of the developed countries (European Commission, 2020). Hence, whereas we captured all direct effects related to the deployment of new fiber-based broadband infrastructures, we might not have considered all indirect effects related to the adoption of fiber-based broadband services.[9] In contrast, adoption rates of almost 100% for basic broadband were observed at the household level (European Commission, 2020), and hence coverage and adoption levels were largely correlated. For mobile broadband (*Mobile Broadband*), we observed adoption rates that were far above 100% in per capita terms due to the existence of multiple sim cards at a per capita level. For this reason, we also distinguished a supply-side measure of mobile broadband network coverage (*3G+ Coverage*), which could not exceed 100% of the population.

We further included variables measuring ICT imports (*ICT Imports*) and exports (*ICT Exports*) to capture ICT affinity and ICT-specific trade effects that complemented aggregate measures of trade, as suggested in Section 2.1. ICT affinity within a country might have been high, because many ICT hardware and software elements were produced in a certain country (such as in some of the fiber-leading East Asian countries) or consumers exhibited high demand for ICT imports (such as in most European countries where citizens use digital services, applications, and devices that are by and large produced outside Europe). To measure consumer´s taste for new broadband services, we also controlled for the market entrance of Netflix, *Netflix*, which is the most popular provider of online video-streaming services. Note that the latter, meanwhile, represents more than 80% of global Internet download traffic.[10] Finally, we included some of the most relevant end-user devices (*Laptop*; *Tablet*; *Smartphone*) to measure consumers´ Internet usage intensity.

Table 4 summarizes our measures of the ICT ecosystem.

Table 4: Core elements of the ICT ecosystem and expected net effects on CO_2 emissions

ICT networks	ICT affinity	ICT end-user devices
Fiber Broadband (+/-)	*ICT Exports* (+)	*Tablet* (+/-)
Basic Broadband (+/-)	*ICT Imports* (+/-)	*Smartphone* (+/-)
Mobile Broadband / 3G+ Coverage (+/-)	*Netflix (+)*	*Laptop* (+/-)

Notes: “+” refers to a CO_2 increasing effect; “-” refers to a CO_2 lowering effect; “+/-” indicates that one cannot derive unambiguous effects from theory and empirical evidence.

[9] In the midterm, however, most consumers will be migrated from traditional broadband networks to new fiber-based communications infrastructures and adopted fiber connections on the side of consumers will then largely correspond to the number of available connections on the supply side. At the end of this process, there will be a complete substitution of basic broadband with new fiber-based connections.

[10] Information available at: https://www.cisco.com/c/dam/m/en_us/solutions/service-provider/vni-forecast-highlights/pdf/Global_2021_Forecast_Highlights.pdf.

4.3.3 Control and instrumental variables

The vector $\boldsymbol{X}_{it}$ comprises various macroeconomic and institutional control variables, as identified in the relevant empirical literature and summarized in Table 1. The matrix of instrumental variables $\boldsymbol{Z}_{it}$, as outlined in Section 4.2, comprises measures for competition and public policies in broadband markets as well as spatial instruments measuring broadband deployment-related benchmarking effects. Detailed definitions of our control and instrumental variables are provided in Table A.1 in the Appendix.

5 Main estimation results

Table 5 contains the main results of our baseline estimating equation (1). In all the regression models, the country fixed effects (FE) were highly significant (the null hypothesis "all $\alpha_i = 0$" was rejected, with a probability of error < 0.001; the value is not reported in Table 5). At the same time, there was a high correlation between the fixed effects and the regressors, so that the simple pooled ordinal least squares (OLS) and random-effects panel estimators would lead to biased estimation coefficients.[11] For the FE models, in contrast, unbiased estimation coefficients requires the less restrictive assumption that idiosyncratic errors (ε_{it}) were not correlated with the explanatory variables. The α_i's can be viewed as nuisance parameters that do not need to be consistently estimated; in other words, $E(\alpha_i|\boldsymbol{ICT}_{it}, \boldsymbol{X}_{it},) = 0$ is no longer required. However, consistent estimates for the vector of coefficients, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, still require $E(\varepsilon_{it}|\boldsymbol{ICT}_{it}, \boldsymbol{X}_{it}, \alpha_i) = 0$ (Cameron & Trivedi, 2005). Strict exogeneity, in this sense, rules out any contemporaneous, past, and future correlation of regressors and idiosyncratic errors.

In addition to country-specific fixed effects, we further controlled for period effects (α_t), which affected all countries over time in the same way (similarly). The period effects were jointly significant in all regressions. The null hypothesis that the individual panels (countries) were contemporarily uncorrelated could not be rejected unless the period effects were taken into

[11] Robust Hausman tests clearly rejected the null hypothesis (with a probability of error < 0.001) that random effects models would lead to consistent estimation results. Next to the more restrictive identification assumption, we did not consider random effects models for conceptual reasons because the group of OECD countries did not represent a random draw from the population of all countries but by membership status, providing a rather homogenous and comprehensive group of developed countries.

account. Not accounting for period effects in the estimating equation would thus not only lead to biased estimation coefficients but also to inefficient ones.

From our set of ICT variables, only the coefficient estimates for basic broadband adoption and fiber-based broadband coverage were statistically significant in all the regression models (including the robustness analysis reported in Tables 6 and 7). As our variable measuring basic broadband usage comprise all wireline broadband connections (with bandwidths ≥ 256 kbit/s, based on different broadband access technologies), the effect of deployed fiber-based broadband connections can be interpreted as measuring the incremental effect of new broadband connections while holding basic broadband connections constant. In terms of magnitude, the coefficient estimate for the variable *Fiber Broadband* was -0.055 in regression (1) and in fact was substantially lower than the respective coefficient estimate for the variable *Basic Broadband* (-0.175). Both the baseline effect of using wireline basic broadband and the incremental effect of fiber-based connections were significant at the 10% confidence level when included in regressions (1) to (5). The estimation coefficients have the interpretation of semi-elasticities according to the log-linear estimation specification in equation (1); in other words, if the value of the respective broadband variable increases by one unit (1 p.p. = 0.01), the level of the dependent variable (CO2 emissions) changes by approximately 100*β_i% for small changes in the independent variables, -0.055% and -0.175%, respectively. The exact percentage change in the dependent variable for larger changes in the independent variables over the period of analysis is given by the following:

$$\%\Delta\mathrm{CO2} \equiv \left({}^{\Delta\mathrm{CO2}}/_{\mathrm{CO2}}\right) \times 100 = \left[e^{(-0.175\times\Delta Basic\ Broadband)} - 1\right] \times 100$$

$$\%\Delta\mathrm{CO2} \equiv \left({}^{\Delta\mathrm{CO2}}/_{\mathrm{CO2}}\right) \times 100 = \left[e^{(-0.055\times\Delta Fiber\ Broadband)} - 1\right] \times 100 \qquad (3)$$

The average increase in household weighted basic broadband adoption in our OECD sample was 0.722 p.p. (=*Δ Basic Broadband*) over the entire analysis period (2002–2019). The observed increase in deployed fiber-based broadband connections per household was 1.635 p.p. (=*Δ Fiber Broadband*) over the entire analysis period. Evaluated at the grand mean of CO2 emissions (387.538 Mt of CO2, Table A.2), the total increase in basic broadband adoption and fiber-based broadband deployment yielded reductions in CO_2 emissions in the average OECD country in the amount of about 46 Mt and 33 Mt, respectively. Note that the implied reduction of fiber-based broadband connections was based on above 100% household coverage levels (*Δ Fiber Broadband* = 1.635) due to parallel coverage of multiple fiber infrastructures in (sub-)urban areas in most countries. Households, however, typically do not subscribe to more than one fiber-based broadband connection that offers sufficient bandwidth capacity, even if individual household members are using multiple services at the same time. If we therefore restrict the impact of fiber-based connections to a maximum household coverage level of 100%, (i.e., the change in p.p. was equal to one), we get a lower albeit still substantial average per country reduction of CO_2 emissions amounting to about 21 Mt caused by new broadband infrastructures (and 67 Mt in total). This was substantial in view of the 8.9 tons of CO_2 emitted per capita, on average, in OECD countries in 2018 (OECD, 2019). From a country-level perspective, aggregate CO_2 emissions of 67 Mt correspond approximately to the total CO_2 emissions of Greece in 2019 (67.18 Mt).

The effect of all the other ICT variables was insignificant in all the models. The consistently positive coefficient for the variable *Mobile Broadband* can be explained by the comparatively higher electricity consumption for the operation of mobile networks. The latter also held if we excluded wireline broadband technologies in our regression and additionally controlled for mobile broadband coverage (*3G+ coverage*) in model (6).

In view of the discussion in Section 2, we further tested for potential non-linear effects underlying the phenomenon of the tertiarization of the economy and the intermittent effect education might exert on inequality and indirectly on CO_2 emissions. According to regression models (2) and (3), in which the tertiarization of the industry was measured by the variable *Share tertiary*, tertiarization exhibited neither a direct nor an indirect effect (via GDP) on CO_2 emissions; this also held if we allowed for another interaction with the ICT variable *Basic Broadband*. Accordingly, we found no evidence that tertiarization led to significantly higher or lower CO_2 emissions. Regarding the intermitting role of education on the degree of income inequality and indirectly on CO_2 emissions, we found that higher levels of education significantly, albeit not substantially, lowered the CO_2 emission-reducing effects of the variable measuring income inequality, *Gini*. We also checked for potential non-linearities underlying our population variables, as found in some of the previous empirical contributions. In our data, we did not find any significant pattern underlying the linear and squared ("*_squared*") terms of the variable *Population density.* Likewise, we did not find any non-linear relationship for our other demographic control variables (*Urbanization*, *Age Dep. Ratio*). Linear terms of the variables *Urbanization* and *Age Dep. Ratio*, however, exhibited significant effects in several regression models. According to our results, both a higher share of the working-age population and people living in urban areas increased CO_2 emissions. Finally, we found evidence for a highly significant and non-linear impact of the variable *GDP pc,* suggesting that increases in GDP per capita increased CO_2 emissions, but with a diminishing effect according to an inverted U-shape pattern as predicted by the EKC hypothesis. All other macroeconomic, demographic, and institutional control variables were also in line with the results and predictions of the related literature (Section 2) when significant and showed the same coefficient signs in all the regression models, which further reaffirmed that our estimation equations were valid. In particular, the variables *Trade* and *Corruption* showed significant coefficient estimates in some regressions with expected signs. Including a large set of controls, along with country-fixed effects and period effects, our FE regression equations explained about 70% of the total within variation.

Table 6 reports the results of various FE robustness regressions. First, regression model (1) reports the baseline estimation results with the same set of control variables but with a modified dependent variable which was normalized with respect to a country´s total population, in other words, *ln(CO2 pc)* instead of *ln(CO2)*. Second, in view of the high heterogeneity in the development of the dependent variable over time (Table 4), country-specific individual period trends ($\alpha_{2i}\, t$) were allowed in regression model (2) (individual slopes, "IS"). In regression model (3), outlier values for the U.S., exhibiting by far the highest mean values of CO_2 emissions were excluded. Note that outlier values for Iceland and Luxembourg exhibiting the lowest mean values of CO_2 emissions were already excluded when we included all available ICT variables (for data availability reasons, given in footnote 5). In regression model (4), ICT-specific control variables that showed insignificant coefficient estimates in all regression specifications were excluded. Finally, in regression model (5), we excluded the years 2002 to 2004, as deployment of new fiber-based broadband did not noticeably start before the year 2005 in many OECD member states. Overall, regression models (1)–(5) underline that our baseline estimation results, as reported in Table 5, were by and large robust with respect to all significant explanatory variables. The latter also held with regard to the impact of basic and fiber-based broadband on CO2 emissions.

A potential source of endogeneity refers to the possibility of reciprocal causality (simultaneity bias). For this reason, we also conducted panel-specific Granger (1969) causality tests, although there was no plausible presumption of this on a priori grounds. In testing the directions of effects for the variables under consideration, Granger causality tests generally assume stationary data series to avoid spurious causalities. The starting point of the stationarity test was unit root tests. Different test specifications indicated that stationary time-series were present when taking the trend effects into account. We found that CO2 emissions were in fact not Granger causal for ICT variables under consideration.[12]

Regarding the identification of causal effects of ICT-related variables in our CO2 emission equation (1), we finally dealt with endogeneity concerns related to time-variant heterogeneity due to omitted variables (omitted variable bias) using several sets of exogenous instrumental variables (IV), as motivated in Section 4.2. Endogeneity, in that sense, might have been a concern in principle, as we could neither provide a comprehensive nor error-free measurement of the complex ICT ecosystem, even though we used a rather large set of explanatory ICT variables ($\boldsymbol{ICT}_{it}$). If instruments $\boldsymbol{Z}_{it}$ exist satisfying $E(\varepsilon_{it} | \boldsymbol{Z}_{it}, \boldsymbol{X}_{it}, \alpha_i) = 0$, then consistent estimation is feasible by IV regression. In Table 7, we report the corresponding results of FE-IV

[12] Tests were performed using the Stata command “xtgcause” which implemented a procedure proposed by Dumitrescu and Hurlin (2012) for testing Granger causality in panel data sets. We included a maximum number of two lags. Similarly, we conducted Granger causality tests which supported our presumption (Section 4.1) according to which electricity consumption was Granger-causal for CO2 emissions, but Granger causality did not also exist in the reverse direction from CO2 emissions to electricity consumption (at a significance level of < 1%). The estimation results are available from the authors upon request.

estimations where regressions (1) to (5) vary with respect to the included number of ICT control and instrumental variables, as well as the estimation method employed: two-stage least squares (2SLS) in regressions (1) to (4) and generalized methods of moments (GMM) in regression model (5). The 2SLS-IV estimators are special cases of the GMM-IV estimator; the latter produces more efficient estimates in the case of non-i.i.d. errors. While the IV estimator is less efficient than GMM-IV, it is also less subject to the overfitting problem (Roodman, 2009) and allows for additional post-estimation tests.

In view of the large number of ICT variables in our data set, we focused on the ICT network variables *Basic Broadband* and *Fiber Broadband,* which appeared significant in FE estimations in Tables 5 and 6, and ignored the other ICT variables that showed insignificant coefficient estimates throughout all the FE estimations. From Table 7 one can infer that all coefficient estimates of the broadband variables *Basic Broadband* and *Fiber Broadband* remained significant and negative, although the coefficient estimates were substantially higher than the respective FE estimates in Tables 5 and 6. The coefficient estimates of all the other explanatory variables appeared to be robust, as well, with respect to different FE, FE-IV, and GMM-IV estimations.

The table notes contain further information on the set of excluded instruments and our post-estimation analysis. According to Hansen *J* statistics of the overidentification test of all instruments, our instruments were jointly valid in all specifications in regressions (1) to (5). We also reported tests of subsets of our instruments related to (i) competition in broadband markets ($\boldsymbol{z}_1$), (ii) regulation and broadband polices ($\boldsymbol{z}_2$) and (iii) spatial instruments ($\boldsymbol{z}_3$). Respective *C* statistics (difference in Hansen-Sargan tests) informed us about the exogeneity of the susceptive set of instruments (see table notes) and indicated that our sets of instruments were also individually valid. The robust Kleibergen-Paap (KP) Lagrange multiplier (LM) test of underidentification clearly rejected the null hypothesis that the estimation equation was underidentified for all regressions at the 5% significance level, implying that the excluded instruments were correlated with the (potentially) endogenous regressors and were thus relevant. Testing for the strength of instruments in the case of multiple endogenous variables, the inspection of the individual first-stage F-statistics is no longer sufficient. We therefore reported Sanderson-Windmeijer (SW) multivariate tests of excluded instruments in our first stage results, which suggested that our instruments were not weak.[13] Durbin-Wu-Hausman (DWH) endogeneity tests, however, provided more ambiguous evidence on the null hypothesis of our wireline broadband variables being exogenous variables. For this reason, we considered the substantially lower coefficient estimates of the variables *Fiber Broadband* and *Basis Broadband* from the FE estimations in Tables 5 and 6 as the lower boundary for the actual effect on CO2 emissions and, in that sense, as conservative point estimates for our policy conclusions.

[13] Table A.3 in the Appendix reports two exemplary sets of first-stage results corresponding to regressions (1) and (3) in Table 7. The instruments were strong, as evidenced by the respective SW chi-squared and F tests of excluded instruments and the partial R^2 statistics, and the coefficients had economically meaningful signs when significant.

Table 5: FE baseline estimation results, dep. var.: *ln*(*CO2*)

Model no.	(1)	(2)	(3)	(4)	(5)	(6)
Model name	**Baseline**	**Tertiary_1**	**Tertiary_2**	**Inequality**	**Fixed**	**Mobile**
ICT networks						
Fiber Broadband	-0.055**	-0.053**	-0.056**	-0.050**	-0.050**	
	(-2.22)	(-2.25)	(-2.48)	(-2.07)	(-2.44)	
Basic Broadband	-0.175*	-0.184*	-0.260**	-0.204**	-0.180*	
	(-1.71)	(-1.77)	(-2.48)	(-2.55)	(-1.75)	
Mobile Broadband	0.008	0.007	0.001	-0.003		0.067
	(0.15)	(0.12)	(0.01)	(-0.05)		(1.17)
3G+ Coverage						-0.001
						(-1.19)
ICT affinity & devices						
ICT imports	-0.001	-0.001	-0.000	0.001	0.001	0.002
	(-0.13)	(-0.19)	(-0.04)	(0.19)	(0.18)	(0.31)
ICT exports	0.005	0.005	0.004	0.004	0.004	0.004
	(1.06)	(1.05)	(0.89)	(0.94)	(0.98)	(0.93)
Netflix	0.003	0.002	0.001	0.010	0.001	-0.008
	(0.17)	(0.16)	(0.05)	(0.64)	(0.07)	(-0.50)
Laptop	0.001	0.001	0.001	0.001		
	(0.40)	(0.48)	(0.34)	(0.70)		
Tablet	-0.000	-0.000	-0.000	-0.001		
	(-0.10)	(-0.15)	(-0.07)	(-0.70)		
Smartphone	0.001	0.001	0.000	0.001		
	(0.57)	(0.66)	(0.03)	(0.59)		
Macroeconomic controls						
GDP pc US$	0.000***	0.000**	0.000***	0.000***	0.000***	0.000***
	(4.00)	(2.22)	(4.42)	(3.58)	(3.23)	(3.15)
GDP pc US$_squared	-0.000***	-0.000***	-0.000***	-0.000**	-0.000*	-0.000**
	(-2.92)	(-2.92)	(-3.45)	(-2.70)	(-2.02)	(-2.10)
Share tertiary		-0.005	-0.004			
		(-0.56)	(-0.89)			
GDP pc US$#Share tertiary		0.000				
		(0.12)				
GDP pc US$#Share tertiary #Basic broadband			0.000			
			(0.98)			

Table 5 (continued)

Model nr.	(1)	(2)	(3)	(4)	(5)	(6)
Gini	-0.009**	-0.010**	-0.010**	-0.033***	-0.011**	-0.012***
	(-2.53)	(-2.58)	(-2.59)	(-3.51)	(-2.55)	(-2.78)
Gini #Education				0.001***		
				(2.97)		
Trade	-0.002*	-0.002**	-0.001*	-0.001	-0.001	-0.001
	(-2.02)	(-2.11)	(-1.89)	(-1.56)	(-0.80)	(-1.11)
R&D	0.062	0.059	0.057	0.072**	0.025	0.035
	(1.62)	(1.59)	(1.52)	(2.37)	(0.71)	(0.98)
Demographic controls						
Age Dep. Ratio	-0.012***	-0.011***	-0.011***	(-2.53)	-0.013***	-0.017***
	(-3.33)	(-3.25)	(-3.19)	-0.005	(-3.52)	(-4.66)
Population dens	-0.003	-0.003	-0.002	(-0.97)	-0.003	-0.003
	(-0.53)	(-0.58)	(-0.43)	0.000	(-0.78)	(-0.75)
Population dens_squared	0.000	0.000	0.000	(1.18)	0.000	0.000
	(0.64)	(0.70)	(0.54)	0.012	(1.05)	(0.76)
Urbanization	0.020**	0.019**	0.020**	(1.51)	0.015	0.017*
	(2.39)	(2.48)	(2.52)	-0.022*	(1.67)	(1.74)
Education	0.006	0.007	0.006	(-2.04)	0.007**	0.007*
	(1.30)	(1.44)	(1.38)	(-2.53)	(2.15)	(1.85)
Institutional controls						
Corruption	0.383**	0.399**	0.357**	0.466***	0.466**	0.444*
	(2.35)	(2.48)	(2.08)	(3.09)	(2.59)	(2.02)
Left-wing gov	-0.000	0.000	0.000	0.000	-0.000	-0.000
	(-0.00)	(0.12)	(0.14)	(0.22)	(-0.22)	(-0.28)
Constant (α_o)	3.419***	3.863***	3.613***	4.761***	3.896***	3.971***
	(2.89)	(3.01)	(3.16)	(3.95)	(3.30)	(3.13)
Country fixed effects (α_i)	Yes	Yes	Yes	Yes	Yes	Yes
Year effects (α_t)	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.702	0.704	0.706	0.727	0.664	0.653
AIC	-1516.001	-1518.871	-1523.030	-1564.795	-1557.678	-1537.746
RMSE	0.061	0.061	0.060	0.058	0.063	0.064
#Countries	32	32	32	32	34	34
#Observations	556	556	556	556	592	592

Notes: Year effects were jointly significant and therefore included in all regressions, as well as OECD member state fixed effects. The *t*-statistics in parentheses were robust and allowed for heteroscedasticity and correlation within countries; tests for the presence of cross-sectional dependence were based on the Stata command “xtcsd” (De Hoyos & Sarafidis, 2006). When controlling for year effects, the test did not reject the null hypothesis of cross-sectional independence. Note that in models (5) and (6), the number of groups (countries) was 34 (with 592 observations), as ICT variables with missing values for countries Iceland and Luxembourg were excluded. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: FE robustness results, dep. var.: *ln(CO2 pc)* in model (1), *ln(CO2)* in models (2)–(5))

Model no.	(1)	(2)	(3)	(4)	(5)
Model name	**Dep_var**	**IS**	**USA_excl**	**ICT_excl**	**_2005_2019_**
Fiber Broadband	-0.037*	-0.054**	-0.057**	-0.058**	-0.041*
	(-1.75)	(-2.21)	(-2.17)	(-2.54)	(-1.86)
Basic Broadband	-0.155*	-0.183*	-0.178*	-0.131	-0.236**
	(-1.78)	(-1.78)	(-1.72)	(-1.35)	(-2.39)
Mobile Broadband	0.022	0.002	0.007	0.019	-0.001
	(0.51)	(0.04)	(0.10)	(0.26)	(-0.03)
ICT imports	0.002	-0.001	-0.001		0.004
	(0.33)	(-0.18)	(-0.20)		(0.56)
ICT exports	0.003	0.005	0.005		0.004
	(0.96)	(1.10)	(1.13)		(0.98)
Netflix	0.007	0.003	-0.001		0.009
	(0.50)	(0.21)	(-0.05)		(0.68)
Laptop	0.001	0.001	0.001		0.002
	(0.71)	(0.52)	(0.43)		(1.18)
Tablet	-0.000	-0.000	-0.000		-0.001
	(-0.22)	(-0.06)	(-0.12)		(-0.86)
Smartphone	0.000	0.001	0.001		0.002
	(0.12)	(0.63)	(0.59)		(1.63)
GDP pc US$	0.000***	0.000***	0.000***	0.000***	0.000***
	(5.11)	(4.05)	(3.96)	(3.29)	(4.67)
GDP pc US$_squared	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***
	(-4.61)	(-2.94)	(-2.90)	(-2.27)	(-4.19)
Gini	-0.001	-0.009**	-0.009**	-0.010*	0.000
	(-0.34)	(-2.46)	(-2.39)	(-2.00)	(0.07)
Trade	-0.000	-0.002*	-0.002*	-0.001	-0.000
	(-0.43)	(-1.96)	(-2.02)	(-1.16)	(-0.00)
R&D	0.055*	0.063	0.062	0.050	0.010
	(1.70)	(1.67)	(1.62)	(1.33)	(0.25)
Age Dep. Ratio	-0.009**	-0.011***	-0.011***	-0.014***	-0.014***
	(-2.46)	(-3.28)	(-3.27)	(-3.98)	(-3.37)
Population dens	-0.009*	-0.002	-0.003	-0.001	-0.006
	(-2.03)	(-0.44)	(-0.55)	(-0.15)	(-1.26)
Population dens_squared	0.000*	0.000	0.000	0.000	0.000
	(1.74)	(0.58)	(0.66)	(0.43)	(1.44)
Urbanization	0.018*	0.020**	0.020**	0.016*	0.012
	(1.91)	(2.46)	(2.39)	(1.84)	(1.03)
Education	0.006	0.006	0.006	0.005	0.009**
	(1.51)	(1.26)	(1.26)	(1.13)	(2.27)
Corruption	0.200	0.368**	0.407**	0.295	0.375**
	(1.46)	(2.33)	(2.46)	(1.48)	(2.25)
Left-wing gov	-0.001	0.000	-0.000	-0.001	-0.000
	(-0.69)	(0.01)	(-0.02)	(-0.78)	(-0.46)
Constant (α_0)	-13.079***		3.322***	3.563**	3.917***
	(-10.79)		(2.82)	(2.73)	(2.76)
Country fixed effects (α_i)	Yes	Yes	Yes	Yes	Yes
Year fixed effects (α_t)	Yes	No	Yes	Yes	Yes
Individual year effects ($\alpha_{2i}t$)	No	Yes	No	No	No
R^2 (within)	0.798	0.737	0.702	0.673	0.715
AIC	-1472.588	n.a.	-1453.171	-1456.551	-1362.736
RMSE	0.054	n.a.	0.062	0.064	0.055
#Countries	32	32	31	32	32
#Observations	556	556	538	592	466

Notes: All regression models were based on the set of explanatory variables in regression model (1) in Table 1. Year effects were jointly significant and therefore included in all regressions as well as OECD member state fixed effects. The *t*-statistics in parentheses were robust and allowed for heteroscedasticity and correlation within countries. The specification reported in model (2) allowed for “individual slopes” (IS) for period effects and was based on a user-written (Ludwig, 2019) Stata command (“xtfeis”), which did not provide an estimation coefficient for the constant (α_0) and likewise no values for the goodness-of-fit measures AIC and RMSE. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: FE-IV robustness results, dep. var.: *ln(CO2)*

Model nr.	(1)	(2)	(3)	(4)	(5)
Estimator	**2SLS**	**2SLS**	**2SLS**	**2SLS**	**GMM-IV**
Fiber Broadband	-0.151***	-0.163***	-0.173***	-0.160***	-0.151***
	(-2.76)	(-3.10)	(-3.52)	(-2.69)	(-2.80)
Basic Broadband	-0.541**	-0.254*	-0.252**	-0.439	-0.424*
	(-2.16)	(-1.76)	(-2.20)	(-1.61)	(-1.85)
Mobile Broadband	-0.061	-0.032			-0.052
	(-0.87)	(-0.46)			(-0.82)
ICT imports	-0.002	0.001			-0.003
	(-0.32)	(0.15)			(-0.49)
ICT exports	0.005	0.002			0.006
	(1.15)	(0.55)			(1.42)
Netflix	0.015	0.015			0.017
	(0.93)	(0.84)			(1.16)
Laptop	0.003	0.003			0.003
	(1.42)	(1.37)			(1.20)
Tablet	0.000	0.000			0.000
	(0.04)	(0.33)			(0.01)
Smartphone	0.001	0.001			0.001
	(0.51)	(0.60)			(0.59)
GDP pc	0.000***	0.000***	0.000***	0.000***	0.000***
	(2.79)	(4.63)	(4.12)	(2.90)	(3.40)
GDP pc US$_squared	-0.000**	-0.000***	-0.000**	-0.000*	-0.000**
	(-1.98)	(-2.84)	(-2.55)	(-1.93)	(-2.46)
Gini	-0.006	-0.006	-0.005	-0.005	-0.005
	(-1.47)	(-1.44)	(-1.13)	(-0.86)	(-1.37)
Trade	-0.001	-0.001	0.000	0.000	-0.001
	(-0.81)	(-0.81)	(0.36)	(0.18)	(-1.27)
R&D	0.053	0.052	0.007	0.013	0.060
	(1.26)	(1.33)	(0.17)	(0.31)	(1.47)
Age Dep. Ratio	-0.008**	-0.009***	-0.011***	-0.012***	-0.007**
	(-2.30)	(-2.68)	(-2.81)	(-3.26)	(-2.16)
Population dens.	-0.002	-0.001	-0.001	-0.001	-0.001
	(-0.41)	(-0.31)	(-0.32)	(-0.25)	(-0.24)
Population dens_squared	0.000	0.000	0.000	0.000	0.000
	(0.86)	(0.87)	(0.99)	(0.82)	(0.71)
Urbanization	0.020***	0.021***	0.012	0.013	0.022***
	(2.66)	(2.71)	(1.43)	(1.61)	(3.20)
Education	0.006	0.003	0.004	0.005	0.005
	(1.12)	(0.65)	(0.91)	(1.09)	(1.11)
Corruption	0.500***	0.425***	0.422**	0.363**	0.474***
	(3.31)	(2.69)	(2.44)	(2.21)	(3.63)
Left-wing gov	0.000	0.000	0.000	0.000	-0.000
	(0.15)	(0.28)	(0.10)	(0.05)	(-0.14)
Trend		-0.009	0.008		
		(-1.00)	(0.91)		
Country fixed effects (α_i)	Yes	Yes	Yes	Yes	Yes
Year fixed effects (α_t)	Yes	No	No	Yes	Yes
R^2 (uncentered)	0.480	0.621	0.547	0.401	0.496
F-statistic	14.605	144.034	15.005	6.879	25.121
KP test (*p*-value)	0.004	0.049	0.008	0.023	0.004
Hansen J test (*p*-value)	0.683	0.585	0.297	0.760	0.683
Diff-in-Hansen (*p*-value)	0.827	0.581	0.279	0.733	0.421
DWH test (*p*-value)	0.084	0.194	0.165	0.047	0.084
#Instruments	5	7	7	5	5
#Countries	32	32	34	34	32
#Observations	556	556	592	592	556

Notes: Regressions (1)–(4) were based on a 2SLS estimator, the coefficient estimates in regression (5) were based on GMM estimation. The regressions differed with respect to the internal and external instruments employed: external instruments in regressions (1), (4), and (5) included broadband competition and policy variables (*Mobile Comp, DSL **Notes** (continued) Comp, Cable Comp, Net Neutr, State Aid*); regressions (2) and (3) additionally included Hausman-type internal instruments (*Basic Broadband*$_{j\neq l}$ and *Fiber Broadband*$_{j\neq i}$). Diff-in-Hansen-Sargan tests refer to varying subsets of instruments: $\boldsymbol{z_1}$ in regressions (1) and (4), $\boldsymbol{z_2}$ in regressions (2) and (5), and $\boldsymbol{z_3}$ in regression (3). Whereas country fixed effects were included in all regressions, we had to exclude year-period effects in regressions (2) and (3) due to very high collinearity with the Hausman-type instrumental variables, which results as a logical consequence of the underlying construction of our spatial instruments. In regressions (2) and (3), we included instead a linear trend variable (*Trend*). Note that the “xtivreg2” Stata command included no constant with a fixed-effects model. As a goodness-of-fit measure, we report the uncentered R^2 (because there was no constant). The *t*-statistics in parentheses were robust and allowed for heteroscedasticity and correlation within countries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Summary and policy conclusions

Environmental externalities in terms of CO2 emissions associated with the production and use of digital services and applications have become increasingly relevant in the public policy debate in recent years. Our analysis aims to inform policy decision-makers about the actual climate relevance of the ICT ecosystem by providing sound empirical evidence on the net effect of ICT core elements based on recent OECD panel data. We employed various panel econometric estimation methods that were a prerequisite for adequately considering heterogeneity regarding the level and development of CO2 emissions across countries and for the identification of causal effects. Our estimation results proved to be robust in a series of alternative regression specifications, including instrumental-variables regression analysis.

We found evidence of heterogeneity underlying our set of explanatory ICT variables. First, variables measuring wireline new fiber-based broadband and basic broadband connections showed a statistically significant and negative effect in almost all regression specifications. This result indicates a lowering total effect of wireline broadband networks on CO2 emissions. Specifically, we found that according to conservative estimates, basic, and fiber-based broadband connections induced a substantial reduction of CO2 emissions in the average OECD country amounting to at least 67 Mt CO2 during our period of analysis (2002–2019). This roughly corresponded to the total annual CO2 emissions of an OECD country with the size of Greece. Our findings thus suggest that broadband networks give rise to positive environmental effects for society next to the positive effects of general-purpose technologies that have already been clearly demonstrated in the empirical literature in numerous contributions.

Our main results are largely in line with previous empirical studies, according to which the CO2-lowering indirect effects seemed to outweigh the CO2-increasing direct and indirect effects on average, particularly when using data from developed countries. This finding therefore provides evidence for the pollution haven hypothesis suggesting that environmentally intense production of ICT network equipment and end-user devices, the extraction of rare earth elements and disposal of ICT waste is allocated to some major non-OECD member states such as India, China and some East-Asian countries (other than OECD member states Japan and South Korea). Whereas in OECD countries the value added from ICT services has been rising, the value added from ICT manufacturing has been falling. In contrast, ICT manufacturing has become the dominant ICT subsector in China. Although the ICT sector as a whole is growing worldwide, the growth of energy-intense ICT production and manufacturing differs substantially between regions (Lange et al., 2020; OECD, 2019).

Second, our variables measuring the effect of mobile broadband networks, ICT affinity, and the diffusion of ICT end-user devices exhibited a statistically insignificant net effect on CO2 emissions. This result points to potentially opposing and, by, and large, offsetting effects at an aggregate level and/or to the dominant role of the other macroeconomic, demographic, and institutional control variables—next to country and period fixed effects—in explaining total CO2 emissions at the country-year level.

From our empirical analysis, it can first be concluded that undifferentiated climate policy measures imposed on the ICT ecosystem, such as some sort of a sector-wide emissions cap or carbon tax, would not do justice to the identified heterogeneity with numerous and in part opposing effects which are also subject to regional heterogeneity but would likely be accompanied by inefficiencies and market distortions. Second, any regulatory interventions in the complex ICT ecosystem would also have to be considered against the background of the many and varied sectoral interactions and related policy measures, such as existing industry self-regulations or technical regulations and standards (Madlener et al., 2021). Third, in addition to interventions aimed at reducing particularly resource-intensive digital services with evidentially high CO2 emissions (such as online video streaming or bitcoin mining), it might also be conceivable to promote specific ICT elements that evidentially exhibit CO2-reducing effects (such as wireline broadband networks).

Future research should therefore be targeted at examining the underlying heterogeneity of digital services and infrastructures and other ICT core elements at a more disaggregated level of analysis and considering that emission reducing and emission increasing effects are interrelated in multiple forms (Lange et al., 2020).

Appendix

Tables A.1, A.2, A.3

Table A.1: Variable descriptions and sources

Variable	Description	Source*
	Dependent variables	
CO2	The estimates of global and national fossil CO2 emissions include the combustion of fossil fuels through a wide range of activities (e.g., transport, heating and cooling, industry, fossil industry own use, and natural gas flaring), the production of cement, and other process emissions (e.g., the production of chemicals and fertilizers) and CO2 uptake during the cement carbonation process.	Global carbon atlas
CO2 pc	CO2 emissions divided by total population of a country.	Global carbon atlas/ WorldBank
	ICT related independent variables	
Fiber Broadband	Sum of homes passed by all relevant fiber access broadband technologies (fiber-to-the-home, fiber-to-the-building, fiber-to-the-cabinet, fiber-to-the-last amplifier) divided by the absolute number of households in a country. "Homes passed" is the total number of premises. Premise is a home or place of business; hence, it includes residential subscriptions and subscriptions for organizations.	FTTH Council Europe/IDATE/ Market Line Advantage
Basic Broadband	Number of subscriptions of basic broadband connections using copper-based DSL and coaxial cable-based technologies as well as other fixed (wired)-broadband connections such as satellite broadband divided by the absolute number of households. Basic broadband enables downstream speeds equal to or greater than 256 kbit/s. Basic broadband excludes subscriptions that have access to data communications (including the Internet) via mobile-cellular networks. However, it includes fixed WiMAX and any other fixed wireless technologies. It includes both residential subscriptions and subscriptions for organizations.	OECD/ Market Line Advantage
Mobile Broadband	Total number of wireless broadband adoption (subscribed commercial contracts) in thousands.	Euromonitor
3G+ Coverage	Percentage of population covered by at least a 3G mobile network.	Euromonitor
ICT Imports	ICT goods imports as percentage of total goods imports, including computers and peripheral equipment, communication equipment, consumer electronic equipment, electronic components, and other information and technology goods.	WorldBank
ICT Exports	ICT goods exports as percentage of total goods exports, including computers and peripheral equipment, communication equipment, consumer electronic equipment, electronic components, and other information and technology goods.	WorldBank
Laptop	Percentage of households possessing a laptop.	Euromonitor
Smartphone	Percentage of households possessing a smartphone.	Euromonitor
Tablet	Percentage of households possessing a tablet.	Euromonitor
Netflix	Dummy variable which takes on value one if Netflix streaming services were available (zero else).	Own research*)

Table A.1 (continued)

	Other independent variables (controls)	
Urbanization	Population of a country living in an urban environment as a percentage of total population.	WorldBank
Population dens.	Population density of a country in persons per square kilometer.	Market Line Advantage
GDP pc	GDP in constant 2010 USD per capita.	WorldBank
Share tertiary	Share of total services output in the country. Services include value added in wholesale and retail trade, transport, government, financial, professional, and personal services, such as education, health care, and real estate services. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. The data were given in current prices in USD.	Market Line Advantage
Age dep. ratio	Ratio of dependents (people younger than 15 or older than 65) per 100 working-age individuals.	WorldBank
Education	Percentage of working age population (ages 15–64) with educational attainment of tertiary education.	OECD
Trade	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product.	WorldBank
Gini	Gini coefficient is a measure of income inequality, based on a Lorenz Curve. A society that scores zero on the Gini index has perfect equality, where every inhabitant has the same income. A score of 100 indicates total inequality, in which only one person receives all the income.	Euromonitor
R&D	Expenditure on R&D is total expenditure on R&D performed on the national territory during a given period. It includes R&D performed within a country and funded from abroad but excludes payments made abroad for R&D.	Euromonitor
Corruption	Corruption index ranking countries based on how corrupt their public sector is perceived to be. Scores range from zero (highly corrupt) to 10 (very clean). It is a composite index, a combination of polls, drawing on corruption-related data collected by a variety of institutions. The relevant subindex measures how pervasive a country is to political corruption.	QoG OECD Data
Elecon	Electricity consumption refers to the net consumption of electricity computed as generation, plus imports, minus exports, minus transmission and distribution losses.	Market Line Advantage
	Instrumental variables	
Mobile Comp	Fixed-mobile substitution defined as the share of the total number of mobile-cellular telephone subscriptions to the total number of mobile-cellular telephone subscriptions and total number of active fixed landlines.	Market Line Advantage
Cable Comp	Number of coaxial cable based broadband subscriptions to the total number of fixed broadband subscriptions enabling downstream speeds ≥256 kbit/s.	OECD
DSL Comp	Number of copper cable xDSL broadband subscriptions to the total number of fixed broadband subscriptions enabling downstream speeds ≥256 kbit/s.	OECD
State Aid	Dummy variable which takes on value zero if new fiber-based broadband deployment has been subsidized in country *i* in a certain year *t* (zero else).	Own research**)
Net Neutr.	Dummy variable which takes on value one if mandatory net neutrality regulations exist under a formal policy instrument, such as sector-specific regulation, legislation, administrative order, etc. in country *i* in year *t* (zero else).	Own research*)
Basic Broadband$_{j \neq i}$, *Fiber Broadband*$_{j \neq i}$	Hausman-type geographic instruments measuring average levels of basic (fiber-based) broadband deployment in all other (non-focal) OECD states in the sample. Both instruments were defined as the ratio of total basic (fiber-based) broadband adoption (deployment) in all other $j \neq i$ OECD states (i.e., other than the focal country *i*) to the total number of other countries.	Own***) calculation

Notes: [*)] For more detailed information, see Briglauer et al. (2020); [**)] for more detailed information, see Briglauer and Grajek (2021). [***)] calculation was based on basic and fiber-based broadband data and respective sources.

Table A.2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CO_2 (Mt)	612	387.538	961.965	2.986	6131.893
ln(CO_2)	612	4.759	1.509	1.094	8.721
Fiber Broadband (abs)	612	9490750.5	26018107	0	2.240e+08
Fiber Broadband	612	.67	.727	0	2.862
Basic Broadband (abs)	612	8323479.4	15739408	4083	1.165e+08
Basic Broadband	612	.586	.274	.001	1.097
Mobile Subscribers (000s)	612	20178.284	53195.922	11.9	494507.2
Mobile Broadband	612	.506	.431	0	1.955
3G+ Coverage	612	77.022	28.615	0	100
ICT imports	612	9.164	4.179	2.687	33.056
ICT exports	612	7.124	6.716	.067	33.703
Netflix	612	.337	.473	0	1
Laptop	576	44.517	24.282	.5	94
Tablet	576	20.929	19.893	0	74.4
Smartphone	576	31.798	29.695	0	93.8
GDP pc	612	39230.91	21871.34	8062.438	111968.35
Share tertiary	612	70.149	6.606	51.207	87.87
Gini	612	35.385	6.191	22.69	52
Trade	612	95.263	59.359	20.686	408.362
R&D	612	1.893	.978	.3	4.5
Age Dep. Ratio	612	50.272	5.574	36.214	68.28
Population dens.	612	141.395	135.406	2.53	530.74
Urbanization	612	77.279	11.373	50.857	98.041
Education	592	31.193	10.672	9.141	59.375
Corruption	612	.141	.17	.006	.781
Left-wing gov.	612	39.872	12.348	9.804	69.09
Mobile Comp	612	.588	.208	.019	.97
DSL Comp	612	.615	.229	.03	1
Cable Comp	612	.263	.167	0	.715
Net Neutr	612	.276	.447	0	1
State Aid	612	.456	.498	0	1
Basic Broadband$_{j\neq i}$,	612	.67	.601	0	1.669
Fiber Broadband$_{\neq i}$,	612	.586	.222	.092	.841

Table A.3: First stage results, dep. vars.: fiber broadband in model (1), basic broadband in model (2)

Model no.:	(1) **Fiber Broadband**	(2) **Basic Broadband**	(3) **Fiber Broadband**	(4) **Basic Broadband**
Excluded Instruments				
Basic Broadbandj≠i			0.319	0.012
			(1.52)	(0.35)
Fiber Broadbandj≠i			-0.607	0.837***
			(-1.42)	(7.40)
Cable Comp	-0.709*	0.218**	-0.077	0.099
	(-1.67)	(2.15)	(-0.20)	(1.29)
Mobile Comp	0.827***	-0.106***	0.619***	-0.143***
	(3.28)	(-2.74)	(3.09)	(-2.99)
DSL Comp	-0.421	0.149*	0.000	0.000
	(-1.57)	(1.81)	(0.13)	(1.54)
Net Neutr	0.131	-0.005	-0.004***	0.000
	(1.45)	(-0.45)	(-4.20)	(0.14)
State Aid	0.157**	0.032***	0.245***	0.044***
	(2.03)	(2.84)	(3.20)	(3.37)
Included Instruments				
Mobile Broadband	-0.541**	-0.029		
	(-2.55)	(-0.76)		
ICT imports	-0.026	0.002		
	(-1.53)	(0.51)		
ICT exports	0.010	0.001		
	(0.75)	(0.29)		
Netflix	-0.001	0.022***		
	(-0.02)	(2.94)		
Laptop	0.007	0.003**		
	(1.04)	(2.28)		
Tablet	0.010	-0.003***		
	(1.65)	(-3.39)		
Smartphone	-0.002	0.001		
	(-0.41)	(0.60)		
GDP pc	0.000	-0.000	0.000	-0.000
	(0.91)	(-1.07)	(1.49)	(-0.46)
GDP pc US$2	-0.000	0.000	-0.000	0.000
	(-0.56)	(0.95)	(-0.99)	(0.40)
Trade	0.005*	0.001	0.006***	0.000
	(1.96)	(1.47)	(3.91)	(0.92)
Age Dep. Ratio	0.050***	-0.004	0.031***	-0.004
	(5.74)	(-1.27)	(2.87)	(-1.04)
Population	-0.001	0.001	0.007	0.001
	(-0.07)	(0.51)	(0.45)	(0.27)
Population_squared	0.000	-0.000	0.000	-0.000
	(1.04)	(-0.45)	(0.60)	(-0.47)
Urbanization	0.040	0.010**	0.059*	0.012**
	(1.40)	(2.56)	(1.95)	(2.41)
Gini	0.007	0.003	0.016	0.002
	(0.51)	(0.68)	(1.02)	(0.28)
Education	-0.016	0.010***	0.004	0.001
	(-0.93)	(3.26)	(0.28)	(0.17)
R&D	0.092	0.011	0.024	0.034
	(0.89)	(0.50)	(0.23)	(1.17)
Corruption	1.325*	0.084	1.085*	-0.051
	(1.70)	(0.54)	(1.81)	(-0.25)

Left-wing gov	0.000	-0.000	0.002	-0.000
	(0.22)	(-0.14)	(0.85)	(-0.10)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	No	No
Linear trend	No	No	Yes	Yes
Table A.3 (continued)				
RMSE	.2305011	.0464469	.2325376	.0471685
Shea's partial R^2	.2000407	.1934296	.2199432	.429804
SW-F statistic	11.67729	10.2345	9.318092	16.15824
SW- chi-squared	65.07743	57.03674	70.77378	122.7268
#Instruments	5	5	7	7
#Countries	32	32	34	34
#Observations	556	556	592	592

Notes: First-stage regressions in models (1) and (2) pertained to the second stage model (1) reported in Table 7, and first-stage regressions in models (3) and (4) pertained to the second stage model (3) reported in Table 7. The Sanderson-Windmeijer first-stage chi-squared and F statistics were tests of underidentification and weak identification, respectively, of individual endogenous regressors. Shea's partial R^2 was reported as another weak instrument diagnostic. Standard errors in parentheses were clustered at the group (country) level and robust to arbitrary forms of heteroscedasticity and correlation within countries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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