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How is mobile broadband intensity affecting CO_2 emissions? – A macro analysis

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ABSTRACT

This paper investigates the association between relative mobile broadband penetration (i.e. mobile broadband connections in total mobile connections) and carbon dioxide (CO_2) emissions globally. The study is based on 181 countries for the period 2002–2020. The results indicate an initial increase in CO_2 emissions for a country at an average emission level once mobile broadband is introduced. Possible explanations might be initial investment in network infrastructure and increased consumption of electricity. However, on average for the period 2002–2020 the continuous relationship between mobile broadband (defined as speeds of at least 256 kb/s) and CO_2 is significantly negative in a statistical sense, i.e. emissions at a country level significantly reduce as mobile broadband penetration increase. Based on a two-stage model and controlling for additional independent variables (i.e. GDP per capita, population density, the share of electricity consumption that comes from fossil fuel, industry as a share of GDP, a regulation index, fixed broadband penetration, working age population as a share of total population and a human capital index), we conclude that on average a 10 percentage points increase in relative mobile broadband penetration causes a 7 percent reduction of CO_2 emissions per capita (given that the instrumental variable strategy, as assumed, identifies causal effects). Thus, the results shows that investments in mobile infrastructure over longer periods of time can contribute to mitigating climate change. However, the relationship is only significant for high-income countries (i.e. countries with a GNI of $4096 or above). The results remain significant when mobile broadband is defined as mobile broadband connections per 100 inhabitants.

1. Introduction

In 2023, it appears almost impossible to imagine a world without smartphones. Thus, mobile broadband arguably is one of the most important innovations of the early 21st century.[1] Mobile broadband has spread rapidly in most countries of the world and have had an important effect on how we lead our lives (see Fig. 1, section 9). Moreover, mobile broadband has had large impact on economic development through faster distribution of information and new ideas, increased competition and distribution of services such as streamed music. Thus, mobile broadband has contributed substantially to GDP (Edquist et al. 2018). What is less known is the impact

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[1] This paper defines mobile broadband as speeds of a least 256 kb/s. Typically, average speeds have increased over the assessed period in parallel with penetration. This could be a contributing factor to the results, but such effects are outside the scope of this paper.

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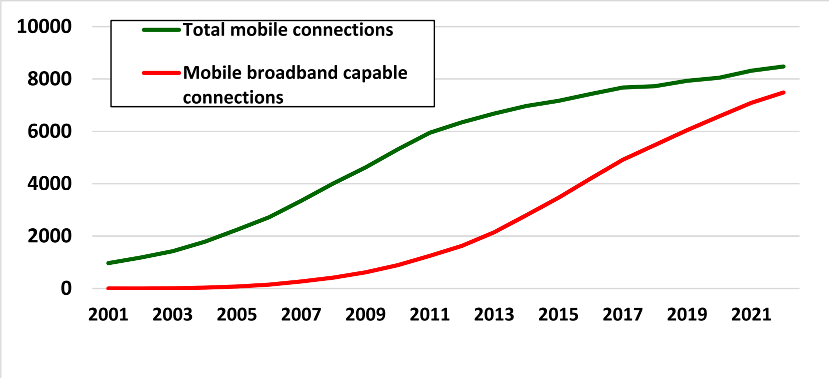

Fig. 1. Total global mobile and mobile broadband capable connections (in millions) 2001–2022
Note: Mobile broadband connections are defined as SIM cards that have been registered on the mobile network in a device capable of download speeds of 256 kb/s or greater. Total mobile connections are total unique SIM cards, excluding IoT connections, that have been registered on the mobile network. This implies that total mobile connections also include connections with download speeds of less than 256 kb/s.
Source: GSMA (2023).

from mobile broadband on climate change and particularly carbon dioxide (CO_2) at the macro level.

During most of the 20th century CO_2 emissions and other greenhouse gases were neglected by politicians and policy makers. The effects from CO_2 emissions became more evident as the Intergovernmental Panel of Climate Change (IPCC) started to issue its first assessments reports in 1990 (Houghton et al. 1990). It concluded that there is a greenhouse effect that keeps the earth warmer. It also concluded that CO_2 had been responsible for over half the enhanced greenhouse effect in the past and that it is likely to remain so in the future.

Despite the warnings from the IPCC, countries have not managed to keep down their CO_2 emissions as economic development has surged in most countries and the overall world population has increased substantially. Fig. 2 shows that CO_2 emissions accelerated during the second half of the 20th century. In 2021 total global CO_2 emissions reached 37.1 billion tonnes, which was the highest level ever so far (Our world in data 2023).

To avoid the most severe effects of global warming, global CO_2 emissions must be radically reduced already this decade and reach a net zero state by latest 2050 to keep world average temperatures well below 2 °C, preferably below 1.5 °C, above pre-industrialization levels (UN Framework Convention on Climate Change 2015; 2021). In this situation the role of technology in mitigating climate change is increasingly gaining attention. This is not least the case for Information and Communication Technologies (ICT).

From a climate perspective ICT can be associated with three orders of effects. In line with the International Telecommunication Union a k a ITU (2014) which refers back to research such as Berkhout and Hertin (2001) and Hilty et al. (2006), these could be referred to as i) *first order effects* associated with the life cycle impacts of ICT goods, networks and services through the need for energy and materials for different processes – their carbon footprints; ii) *second order effects* associated with the positive or negative impact induced in other sectors by the use of ICT; and iii) *other effects* (a k a higher order effects) such as behavioral changes and systemic effects at a societal level, including rebound (i.e. the changes in demand due to efficiency gains further explained in section 2.1).

Most studies focus on just one of these effects and although ICT is believed to have a great potential in reducing CO_2 emissions, there is so far not much evidence regarding its aggregated impact at the macro level. Hence, this paper investigates the relationship between mobile broadband and CO_2 at the macrolevel to complement studies focusing on specific orders of effect. The approach applied could only be used to study the aggregated effect of using ICT, hence it cannot distinguish between first order effects, second order effects and other effects. First, it estimates the effect from the introduction of mobile broadband based on a difference-in-difference specification. This does not control solely for first order effects, as effects of different orders cannot be distinguished in this study. Hypothetically, there might be a first order, second order and any other potential effect, but it is likely that it primarily assesses first order effects from the technology's own use of energy and materials. Second, it estimates a continuous relationship over time which includes both first, second and other effects.

The results of this study indicate an initial increase in production-based CO_2 emissions once mobile broadband is introduced. Possible explanations might be initial investment in network infrastructure and increased consumption of electricity. However, on average for the period 2002–2020 the continuous relationship between mobile broadband and CO_2 is significantly negative in a statistical meaning, i.e. emissions are significantly reduced as mobile broadband penetration increases. These results also hold once controlling for simultaneity, but the relationship is only significant for high-income countries. One possible explanation could be that the speed in the mobile broadband networks generally is higher in high income countries. Moreover, industries in high income countries are often better prepared to benefit from mobile broadband. The paper is organized as follows. In section 2 we summarize findings from earlier research and position our study in current literature. In section 3 we present the methodological framework and describe the data. In section 4 and 5 we present our results based on both fixed effect and instrumental variable approach. Section 6 provides robustness checks. Section 7 discusses the results and provides concluding remarks.

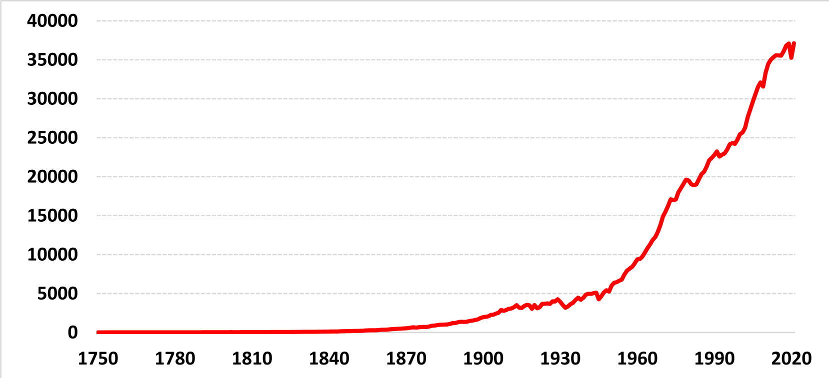

Fig. 2. Annual production-based CO_2 emissions in the world 1750–2021 (million tonnes per year).
Source: Our World in Data (2023).

2. Previous research

2.1. ICT and CO_2

ICT can have both positive and negative climate effects (Erdmann & Hilty, 2010). In this paper we divide the different effects into first order effects, second order effects and other effects (ITU, 2014).

Referring to one effect at a time, the first order effects are associated with and defined as the impacts of the lifecycle of ICT hardware and software. GeSI and BCG (2012) estimated that the ICT sector contribution to CO_2 equivalent emissions has remained quite stable since 2007 and even decreased somewhat despite growing data traffic. However, Malmodin and Lundén (2018) more recently and based on a higher degree of primary data, saw a considerable growth from 2007 to 2010, but a stabilization between 2010 and 2015. Thus, leading to a 2015 first order effect of an estimated 1.4 percent of total global CO_2 equivalents. This is also the level referred to by the ITU as a starting point of their decarbonization trajectory for the ICT sector (ITU, 2020). Malmodin et al. (2023) estimates a slight growth of emissions between 2015 and 2020, however the ICT sector's relative share of overall global emissions remains as those have increased proportionally. Overall, despite differences in approaches and quantifications (Bremer et al. 2023), estimates of the first order effect of the ICT sector, i.e. the life cycle carbon footprint, suggest that it represents a relatively small share of the overall GHG emissions (Andrae, 2020; GeSI and GeSIand Deloitte, 2019; ITU, 2020; Malmodin & Lundén, 2018; VHK and Viegand Maagoe, 2020).

The second order effects are the potential for ICT to induce lower or higher emissions by other sectors when used. For example, ICT supports more efficient use of energy, better industrial processes and reduced demand for transportation which is considered a source of emission reductions. This implies that ICT may drive decarbonization and dematerialization and productivity resulting in less resources being used and thus resulting in lower CO_2 emissions. Decarbonization denotes a reduction of CO_2 emissions through the use of low carbon power sources. Similarly, dematerialization refers to the absolute or relative reduction in the quantity of materials used in an economy, thus it implies doing more with less material inputs (McAfee, 2019). Productivity is connected to dematerialization and defined as the ratio of output to inputs. Inputs of capital and labor are used to produce output. Thus, increased productivity does not necessarily lead to less material being used, as labor is also considered an input. Higher productivity makes it possible either to produce more with the same resources or to maintain the same level of production with less resources. At the same time, ICT can be used in products and services that maintain carbon intensive lifestyles and industries (Falk and Gaffney et al. 2020). This dual nature of the second order effects, together with the other two orders of effects, implies the need for macro-methods to understand the aggregated impact of these technologies across their different effects.

Several studies have pointed out that ICT can reduce energy consumption (Moyer & Hughes, 2012; Salahuddin et al. 2016). Smart grids are energy infrastructures that use ICT continuously to monitor the use of electricity and thus optimize the energy performance. Moreover, ICT dependent systems controlling ventilation, lightning, power system, fire system and security system could also have substantial impact on energy savings in the buildings sector (GeSI and BCG, 2012).

ICT can also have a large impact on transportation. For example, logistics can be optimized through eco-driving, real time traffic alerts, truck and route planning and intelligent traffic management (GeSI and BCG, 2012). According to Malmodin and Bergmark (2015) smart work solutions such as video- and teleconference solutions can reduce business travel and commuting. Moreover, when the pandemic struck the world in early 2020 working from home became a new reality for many of the world's office workers (Ericsson, 2020). Automation and optimization of manufacturing processes by using ICT equipment have also been suggested to have a large impact on energy saving (GeSI and BCG, 2012). Furthermore, investment in IoT will help optimize the use of resources in production and contribute to productivity and dematerialization (Edquist et al. 2021).

There appear to be large opportunities for positive environmental effects based on second effects from ICT, although solutions with adverse effects exist as well. A major problem however is to estimate second order effects correctly and two recent papers conclude that research on its effects is so far inconclusive (Bieser et al. 2023; Bremer et al. 2023). GeSI and BCG (2012) estimate that ICT has the potential to abate 16.5 percent of the world's total GHG emissions in 2020, while the more recent GeSI and Deloitte study (2019) sees a potential of 9 percent until 2030 for selected solutions. Another study suggest that ICT solutions could have a potential of reducing greenhouse gas emissions by 6–15 percent in 2030 for selected solutions referring to two different scenarios (Malmodin & Bergmark, 2015). Moreover, Bieser et al. (2020), looking at 5G only, are more careful in their conclusions, saying that the overall reduction potential of the investigated use cases is clearly larger than the GHG footprint of 5G networks plus the GHG footprint of ICT equipment required for enabling the use cases. As pointed out by Bremer et al. (2023) one reason for variation in results is the diverse methodologies applied. As standards emerge this may change. Recently, the ITU published a methodology for assessing the second order effects (ITU, 2022). Also, the European Green Digital Coalition is working to support organizations in assessing these effects.

One problem that arises is how to evaluate these estimates even ex-post, due to rebound effects. The rebound effects are the changes in demand that is the result of productivity gains. Already in the 19th century, the English economist William Stanley Jevons observed that the consumption of coal soared, despite the improvement of the steam engine by James Watt (Jevons, 1865). He concluded that: "It is a confusion of ideas to suppose that the economical use of fuel is equivalent to diminished consumption. The very contrary is the truth".

The findings by Jevons suggest that increased productivity leads to increased demand that may increase the total consumption in the economy. These effects are known as rebound effects and may have both positive and negative impacts on CO_2. For example, if increased productivity leads to lower prices of consumer electronics, the savings may be used for other consumption and there might be an increase in demand for other goods, such as gasoline cars: leading to higher CO_2 emissions. According to Coroamă and Mattern (2019) digitalization may have rebound effects that are negative for the environment. However, rebound effects might also foster increased demand for low-carbon alternatives such as electric cars, which might lead to decreased CO_2 emissions as more people shift to an electric car. Thus, rebound effects may be driving alternatives with lower emissions when they have a smaller footprint or resource consumption than the original activities (Coroamă & Mattern, 2019).

First and second order effects as well as other effects are often addressed using bottom-up or hybrid approaches. For first order effects such approaches may be used to derive an overall first order effect at a sector level if data for different types of products are combined with sales statistics and typical life spans, as described by ITU (2019). However, for second order effects, and even more so for other effects, such approaches could only be used to estimate the effect of specific use cases. Thus, the overall effect would be beyond reach since it would be impossible to know all possible usages of the technology (ITU, 2014, Coroamă and Bergmark et al. 2020). In addition, traditional methods of estimating second order effects are always contrafactual by comparing emissions to a baseline which cannot exist at the same time as the solution (Coroamă and Bergmark et al. 2020). Hence, such effects can only be estimated, not measured. For this reason, macro methods are considered complementary approaches that could help increasing the understanding of the overall impact on emissions across all usages and all orders of effects by providing a different perspective. However, bottom-up and hybrid approaches are still relevant to identify and estimating the effects of preferred usages of ICT.

There are a few studies at the macro level that have investigated the association between ICT and CO_2 emissions. Añón Higón et al. (2017) found that the relationship between ICT and CO_2 emissions was characterized by an inverted U-shaped relationship based on a panel of 142 countries for the period 2010–2015. [2] They found that at low levels of development, additional ICT investment increase CO_2 emissions, but CO_2 emissions start to reduce after a threshold level of ICT development has been reached. Hernnäs (2018) extended the analysis for the period 2000–2016 and found similar evidence when studying unique mobile subscriptions per capita, referring to the share of population that has at least one mobile connection.

The findings of an inverted relationship between ICT and CO_2 is based on the idea of an Environmental Kuznets Curve (EKC) (Grossman & Krueger, 1991; Dasgupta et al. 2002). The environmental Kuznets Curve is a hypothesized relationship between different indicators of environmental degradation and income per capita (Stern, 2004). It suggests that at the early stages of economic development environmental degradation increases, but beyond a certain level of income per capita the trend is reversed, because high income levels are expected to lead to environmental improvements in a country.[3]

An additional important factor for environmental improvements might be investment in mobile broadband. Thus, it is also possible that there is an inverted U-shape relationship between mobile broadband intensity and CO_2. The EKC framework predicts that CO_2 initially increases more rapidly during the first phase of mobile broadband investment when new infrastructure is installed and thus causes strong first order effects. However, when mobile broadband capabilities have been expanded in a country, the technology can be used to optimize production and reduce transports and increase energy efficiency.

There is also evidence that questions the EKC framework. According to Stern (2004) there is little evidence for a common inverted U-shaped pathway that countries follow as their income rises. Ahmadova et al. (2022) found evidence that an excessive level of digitalization caused a "rebound effect" leading to increasing use of resources with the risk of a surge in pollution. According to Salahuddin et al. (2016), the empirical findings of the EKC showed different results and were inconclusive. Moreover, from an econometric point of view the EKC model might face problems of simultaneity and omitted variable bias. In this paper we investigate the mobile broadband based on mobile broadband connections in total connections. Since the maximum value of our variable is 100,

[2] ICT is measured as an index of fixed telephone subscriptions, mobile cellular telephone subscriptions, PC owners, Internet users and fixed broadband Internet subscriptions.

[3] Kuznets (1955) originally noted an inverted U relationship between income inequality and economic development.

the EKC model is infeasible because the quadratic function of the variable would create values that are not theoretically possible to obtain. Furthermore, the pollution haven hypothesis (PHH) argues that firms will try to avoid cost of stringent environmental regulations by locating production in countries where environmental norms are laxer, which is often countries with lower incomes (see Gill et al. 2018; Koźluk & Timiliotis, 2016; Levinson & Taylor, 2004). This implies that emissions are exported rather than reduced.

There are also a number of studies using cointegration to investigate if there is a long run relationship between ICT and CO_2. Lee and Brahmasrene (2014) found a relationship showing that an increase in ICT was associated with an increase in CO_2 for nine Southeast Asian countries 1991–2009 when studying the aggregated effects of different kinds of subscriptions.[4] Salahuddin et al. (2016) found a corresponding relationship between the number of Internet users per 100 inhabitants and CO_2 emissions in OECD countries 1991–2012.[5] However, there are a number of studies that find that ICT reduces CO_2 emissions in OECD countries (Briglauer, Köpple-Turyna, et al., 2023). These studies suggest that there is little evidence so far that, in relation to the indicators used, the positive second order effects from ICT on CO_2 have outperformed the combined effect of first order effects, any emission increasing second order effects of ICT and other effects such as rebound. However, it is noted that none of the studies mentioned above have investigated specifically the impact from mobile broadband on CO_2 emissions.

2.2. Measuring ICT development

Many different approaches have been used to measure ICT development. Several research articles in economics use ICT capital stocks and services to capture the impact of ICT (see Goodridge et al. 2019; Jorgenson et al. 2008; Oliner & Sichel, 2000). These studies have primarily been focusing on the role of ICT for economic and productivity growth. Hernnäs (2018) used estimates of ICT capital stocks to investigate the environmental Kuznets curve, but no robust results were found between ICT and CO_2 emissions.

Añón Higón et al. (2017) measured ICT as an index based on fixed telephone subscriptions, mobile cellular telephone subscriptions, PC owners, Internet users and fixed broadband Internet subscriptions all measured per 100 inhabitants. They found evidence of an inverted U-shaped relationship between ICT and CO_2. Moreover, Hernnäs (2018) also focused on the impact of unique mobile subscriptions divided by population and found evidence of an inverted U-shaped curve. Hernnäs argued that the unique subscriptions measure can be a more accurate measure of the market penetration of ICT than number of subscriptions, since subscribers may have more than one subscription e.g. to ensure coverage in some markets. Moreover, she suggested that there are probably diminishing returns to number of connections per person; meaning that the first connection will create greater behavioral or organizational changes than the second or third one.

Briglauer, Köppl-Turyna, and Schwarzbauer (2023) found a reducing impact (i.e. lowering CO_2 emissions) from new fiber-based broadband and basic broadband connections on CO_2 emissions based on 34 OECD countries for the period 2002–2019. However, there was no significant impact from mobile broadband. Thus, the main findings suggest that fixed broadband networks can give rise to positive environmental effects for society. Danish et al. (2019) found that fixed and mobile telephone subscriptions long-term reduced the level of CO_2 emissions across high- and middle-income countries, but increased CO_2 emissions in low-income countries (based on 73 countries in 1990–2015).

Results based on the ASEAN countries, from 1996 to 2019, found that both fixed Internet subscriptions and mobile phone subscriptions are correlated with reduced CO_2 emissions (Haini, 2021). Moreover, the magnitude of the reduction in CO_2 is larger for mobile phone subscriptions than fixed Internet penetration. Another study presents evidence based on different regions in China, suggesting that a larger ICT industry contributed to reducing CO_2 emissions (Zhang & Liu, 2015).

2.3. Mobile broadband and CO_2

Mobile broadband enables faster distribution of information and new ideas. This has enabled applications such as streamed music and film into mobile devices. Thus, mobile broadband may be a substitute for fixed broadband, while fixed broadband is not a substitute for mobile broadband (Stork et al. 2014).

Fig. 1 (Section 10) shows that mobile broadband has been adopted rapidly during the early 21st century. The first registered mobile broadband connections were registered in Japan in the 4th quarter in 2001. In 2022, there were more than 7 billion mobile broadband capable connections in the world (GSMA, 2023).

Mobile broadband networks allow people and businesses to receive and transfer data almost anywhere. This flexibility can drive CO_2 reductions. For example, less material may be used when people consume music online instead of buying CDs. Data transfer also allow mobile users to share goods, e.g. scooters and cars, which implies the opportunity for a smarter use of such goods and thus a CO_2 reduction potential.

Mobile broadband also allows for smart metering from a mobile device, which implies that you can control heating and lightning in your home from your device. Moreover, mobile broadband enables cellular IoT solutions in manufacturing, which may optimize production and reduce CO_2 emissions. Mobile devices can also be used to collect large amounts of data, that can be used to optimize

[4] ICT was measured as an index of telephone lines, mobile phone subscriptions, Internet users and fixed broadband Internet subscribers per 100 inhabitants. The following countries are included in the investigation: Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand and Vietnam.

[5] Internet users are defined as individuals who have worldwide access to and used the Internet from any location in the three months prior to the time of data collection.

traffic flows and thereby potentially reduce CO_2.

All these new services are driving data use in the mobile networks. According to Ericsson (2023) the global data consumption has increased by over 50 percent annually since 2017, which clearly shows that mobile services play an important role in people's lives. Increasing data use in the future might have negative effect on first order effects as this implies more investment in energy-using telecommunication equipment, including those used for industrial applications and real time regulation of systems. At the same time, energy performance of mobile broadband equipment improves over time.

3. Method and data

3.1. Model

To test if there is a first impact when mobile broadband is introduced a difference-in-differences specification is used[6]

$$\ln CO_2cap_{i,t} = \beta_1 + \beta_2 D_{i,t} + \delta X^{'}_{i,t} + \gamma_t + \left(\alpha_i + \varepsilon_{i,t}\right) \tag{1}$$

where $CO_2cap_{i,t}$ is production-based carbon dioxide per capita measured in tonnes per inhabitant at time t in each country i. $D_{i,t}$ is a dummy variable used to identify differences in a before and after situation. Thus, it takes the value 0 before mobile broadband is introduced and 1 when mobile broadband is introduced. $X^{'}_{i,t}$ is an K × 1 vector that represent other country level control variables that are further discussed in section 3.2 and γ_t is a set of year dummy variables that control for anomalies in CO_2. Finally, α_i is a set of unobserved country specific effects and $\varepsilon_{i,t}$ is the error term, which models the deviation from the regression curve.

A first effect from mobile broadband on CO_2 might be explained by the fact that a lot of investment in network infrastructure is necessary to introduce mobile broadband. These investments are associated with goods that use energy and materials. This effect is captured based on the methodology by Czernich et al. (2011) and implies that a dummy variable should be included in the specification. The dummy variable equals one when mobile broadband reaches a penetration level that is greater or equal to 1 percent. Using a one percent threshold might seem arbitrary and therefore a threshold when mobile broadband reaches 5 percent penetration level is also included in the regressions. Although the introduction of mobile broadband measures the total effect (including first order, second order and any other potential effect), it is likely that it primarily assesses first order effects from the technology's own use of energy and materials. Hence, it is most plausible that the impact from second order and any other effects are limited especially considering mobile broadband penetration level at 1 percent.

Mobile broadband may also have a continuous impact over time. As argued in the literature section, ICT needs electricity for its operation, but ICT could also have a reducing impact on CO_2 in other sectors from energy savings, smarter transport etc. There might also be an impact leading to increasing levels of CO_2 from ICT due to potential other effects such as rebound. However, in reality, second order effects may also increase emissions, while rebound could sometimes also lead to decreases. In order to capture the relationship over time between mobile broadband and CO_2, the model is set up in the following way:

$$\ln CO_2cap_{i,t} = \lambda_1 + \lambda_2 MBBpen_{i,t} + \rho X^{'}_{i,t} + \gamma_t + \left(\alpha_i + \mu_{i,t}\right) \tag{2}$$

where $MBBpen_{i,t}$ is mobile broadband penetration expressed as a percentage of total connections for a particular country i at time t. The specification implies that we assume constant returns to scale, i.e. all connections have the same marginal importance for CO_2 emissions per capita. $X^{'}_{i,t}$ is a K × 1 vector that represents other country level control variables that are further discussed in section 3.2, and γ_t is a set of year dummy variables in order to control for common shocks. Moreover, α_i is a set of unobserved country-specific effects and $\mu_{i,t}$ is the error term.[7]

Equation (2) measures the continuous effect over time from mobile broadband penetration. This includes both first, second and other effects. Moreover, equation (2) controls for country specific effects by using within-groups regression, where the mean values of the variables in the observations of a given country are calculated and subtracted from the data of that country. Thus, the model explains the variation around the mean of the dependent variable in terms of variation around the means of the explanatory variables for the group of observations for a given country. An alternative way of estimating the regression and remove the country-specific effects is to take the first difference of the variables.

$$\Delta \ln CO_2cap_{i,t} = \varphi_1 + \varphi_2 \Delta MBBpen_{i,t} + \sigma \Delta X^{'}_{i,t} + \gamma_t + v_{i,t} \tag{3}$$

where γ_t are year dummies which capture anomalies in CO_2 which are common to all countries and $v_{i,t}$ is the differenced residual.[8]

[6] Difference-in-differences is a statistical technique that attempts to mimic an experimental research design using observational study data, by studying the differential effect of a treatment on a 'treatment group' versus a 'control group' in a natural experiment. It calculates the effect of a treatment (i.e., an explanatory variable or an independent variable) on an outcome (i.e., a response variable or dependent variable) by comparing the average change over time in the outcome variable for the treatment group to the average change over time for the control group.

[7] β_1 is a constant, which is not of interest to our analysis unless all our explanatory variables are equal to 0.

[8] According to Wooldridge (2013) if you first difference the year-dummies the intercept will disappear in the regression which is inconvenient for the computation of R-square. Wooldridge (2013) instead recommends to estimate the first difference equation with an intercept and include a time dummy variable for each time period.

3.2. Data

3.2.1. Dependent variable

The purpose of this paper is primarily to investigate the association between CO_2 and mobile broadband penetration. Data on the dependent variable CO_2 emissions has been taken from Our World in Data (2022), which is an open-source database funded through grants and donations. The CO_2 and greenhouse gas emissions datasets are a collection of key metrics maintained by Our World in Data and is updated on a regular basis. CO_2 is measured in tonnes. Data on population from the GSM Association a k a GSMA (2022) based on UN data, has been used to calculate CO_2 per capita.[9] The CO_2 is measured from the territorial perspective i.e. in the countries where CO_2 are emitted. Thus, it does not reflect emissions embodied in imported goods and services. Moreover, the emissions occurring during use of products are associated with the using country. According to Our World in Data (2022) it includes all emissions from energy production (from coal, oil, gas and flaring) plus direct industrial emissions from cement and steel production, but it does not include emissions from land use change.

In addition to the production-based (or territorial) CO_2 emissions, there are also estimates of consumption-based CO_2 emissions provided by Our World in Data (2022). Consumption-based emissions are national emissions that have been adjusted for trade (i.e. production-based emissions minus emissions embedded in exports plus emissions embedded in imports). Thus, the consumption-based emissions reflect the consumption and lifestyle choices of a country's citizens and avoid exclusion of outsourced emissions and burdening export intensive countries unproportionally. However, the total emissions in the world will be the same based on both consumption and production emissions figures. Production-based and consumption-based emissions estimates should be seen as complementary as they give different perspectives of a country's association with CO_2 emissions.

Estimating consumption-based emissions implies tracking traded goods across the world and include all CO_2 emissions that were emitted in the production of a specific good that is imported. Vice versa the emissions that are emitted in an exported good are subtracted. There might of course be measurement errors involved in these estimations. In the database the trade adjustments have been made for 117 countries in the dataset for the period 2000–2020 (see Our World in data 2022; 2023). Thus, not all countries are included in the database.

According to the pollution haven hypothesis (PHH) firms will try to avoid cost of stringent environmental regulations by locating production in countries where environmental norms are laxer, which is often countries with lower incomes. One way of controlling for such effects would be by using consumption-based CO_2-emissions as it takes the consumption lifestyle choices of a country's citizens into account. Moreover, when environmental regulations can be viewed as country specific effects which are fixed over time, another way for controlling for different policy preferences is to use fixed effects estimation, which will control for different policy effects between countries.

When possible, it is preferred to study effects from both consumption-based and production-based perspectives to establish a more comprehensive understanding of emission patterns. However, traditionally consumption-based data sets are scarcer.

In table A2 (appendix A) we present results based on consumption-based emissions. The results remain robust also with consumption-based CO_2 emissions, even though the sample size is reduced. However, it is possible that the smaller sample may be biased towards certain types of countries (i.e. large countries and high-income countries).

3.2.2. Main variable of interest

This paper focuses on mobile broadband penetration measured as mobile broadband connections in total mobile connections for a particular country. Mobile broadband penetration is based on the GSMA Intelligence database (GSMA, 2022). Mobile broadband connections are defined as SIM cards (or phone numbers where SIM cards are not used) that have been registered on the mobile network in a device with capable download speeds of 256 kb/s or greater (agnostic of the device type) at the end of the period[10]. Total mobile connections are total unique SIM cards, excluding IoT connections, that have been registered on the mobile network at the end of the period. This implies that total mobile connections also include connections with download speeds of <256 kb/s. IoT connections are excluded from mobile connections as those are hard to analyze due to large variations in data rate and frequency.

For many applications that users expect to perform over mobile broadband today the speed of 256 kb/s is not considered sufficient, for example watching YouTube demands above 500 kb/s.[11] Hence, the definition of mobile broadband, doesn't distinguish between relatively low speeds and state-of-the art, despite those being associated with different levels of opportunities. To understand the implications of this, complementary studies would be needed to investigate the robustness of the results with regards to different data speeds and to understand if additional effects occur at higher speeds.

3.2.3. Other independent variables

It is generally acknowledged that there is a link between CO_2 emissions and economic development (Grossman & Krueger, 1991; Stern, 2007). Thus, data on GDP is based on World Bank (2022) real GDP in 2017 international dollars. Purchasing Power Parities have been used to convert national currency GDP into international dollars. An international dollar has the same purchasing power over GDP as the U.S. dollar has in the United States. Moreover, GDP per capita has been calculated based on population data from GSMA

[9] Population is defined as de facto population in a country, area or region as of July 1 of the year indicated.

[10] The first country to register mobile broadband connections was Japan in the fourth quarter of 2001. However, since it only accounts for the last quarter of 2001, it is considered that 2002 was the first year that mobile broadband had an impact over a whole year.

[11] Google system requirements: https://support.google.com/youtube/answer/78358?hl=en.

(2022).

According to the literature there are also other control variables that are important for CO_2 emissions that we include in our base case regression. Borghesi (2000) finds that the higher population density, the higher pressure on the resources that an individual uses and consumes from the environment available in that area. Moreover, traffic congestions in highly populated areas may also affect CO_2 emissions. Population density is defined as number of persons per square kilometers and provided by World Bank (2022).

Hocaoglu and Karanfil (2011) examine the link between CO_2 and the share of selected industries in GDP.[12] Their findings suggest that industrial production is the driving force of CO_2 emissions in G7 countries. Thus, industry as a share of GDP based on World Bank (2022) is included as a control variable. A large share of CO_2 emissions are emitted from electricity generation through the combustion of fossil fuels to generate heat needed to power steam turbines (Abdallah & El-Shennawy, 2013). Therefore, the share of electricity production that comes from fossil fuel in total electricity production based on Our World in Data (2022) is included in the regressions. This variable controls for the energy mix of fossil fuel used to produce electricity for a particular country over time. If a country decides to increase its relative electricity production based on fossil fuel it will affect CO_2 emissions directly.

Gani (2012) argues that good governance and stability reduce CO_2 emissions. Thus, a regulation index from the Worldwide Governance Indicators (WGI, 2021) is included as a robustness measure. The index reflects the perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

3.2.4. *Additional robustness variables*

In the robustness section, we introduce three additional robustness variables. This paper primarily focuses on mobile broadband, which is not the only ICT investment that may have an impact on CO_2. For example, Briglauer, Köppl-Turyna, and Schwarzbauer (2023) found that fixed broadband has reduced CO_2 emissions in 34 OECD countries. Thus, this paper also controls for fixed broadband as it may be a complement to mobile broadband. Data on fixed broadband per 100 inhabitants is based on the World Telecommunication/ICT Indicators (WTI) database (ITU, 2021).

In addition to fixed broadband, we also try to control for the share of the working age population. According to (Wulandari, 2021) working age population causes an increase in consumption which in turn will have an impact on increasing CO_2 emission. Working age population is based on data from the World Bank (2023) and is defined as total population between the ages 15 to 64 as a percentage of the total population.

A number of studies has shown that there is a relationship between human capital and CO_2 emissions (see Yao, Ivanovski, Inekwe, & Smyth, 2014; Wang & Xu, 2021; Sart et al. 2022). Therefore, we also include a human capital index variable. The index of human capital is based on Penn World Tables, 10.01 (see Feenstra et al. 2015). The index is based on the average years of schooling and an assumed rate of return for primary, secondary and tertiary education. Data is available for the period 2002–2019. Thus, regressions that includes the human capital index exclude datapoints for the year 2020.

3.2.5. *Balanced panel*

In total, data for 181 countries are used in the regression analysis for the period 2002–2020. The analysis is based on a balanced panel for all variables included in the respective regressions. Thus, all countries with missing data for a specific variable that is included in the specific regression analysis, have been dropped.[13] Table 1 shows a list of the countries that have been included in the regressions based on CO_2 per capita, GDP per capita and mobile broadband penetration i.e. the most parsimonious specification of the model.[14] Moreover, Table 2 shows some descriptive statistics. It shows that, not unexpectedly, both CO_2 and mobile broadband penetration vary considerably between countries.

4. Results

Based on a Hausman test, we reject the hypothesis that the random effects (RE) model is most appropriate and conclude that the fixed effect (FE) model should be used.[15] Thus, this paper applies the FE model that partials out the effects of the country specific components i. e institutional variables that are fixed over time and assumed correlated with CO_2 or the explanatory variables but vary between countries. The RE model is instead usually applied when variation across countries is assumed to be random and not correlated with the dependent variable (CO_2) and the independent variables in the model.

As described in section 3.1 there might be different effects from mobile broadband on CO_2. The first effect is that there might be an initial shift in the level of CO_2 once mobile broadband is introduced. Table 3 shows the results from the difference-in-differences regression measuring the effect from mobile broadband introduction. This paper uses different thresholds of introduction defined

[12] The industry data include manufacturing, mining and quarrying, electricity, gas and water supply and construction.

[13] For example, the countries with missing data for fixed broadband per 100 inhabitants will be dropped when the variable fixed broadband per 100 inhabitants is included in a regression.

[14] In 2020, the number of mobile broadband capable connections are higher than the number of total connections for Macao. Thus, there appear to be a measurement error for Macao. We therefore decided to drop Macao and Hong Kong as they are not independent countries.

[15] The random effects model assumes that the individual-specific effects are uncorrelated with the independent variables, while the fixed effects model assumes that the individual-specific effects are correlated with the independent variables. The Hausman test for the fixed and random effects model based on our base case specification including time specific effects gives a statistic of 359.37 with a $Prob > chi2 = 0.0000$. Thus, the hypothesis that the random effects model is most appropriate is rejected.

Table 1
Countries included in the regressions.

Low-income countries (75)	Afghanistan*, Algeria*, Angola, Bangladesh, Belize, Benin, Bhutan*, Bolivia, Burkina Faso, Burundi*, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Comoros*, Congo, Cote d'Ivoire, Democratic Republic of Congo, Egypt*, El Salvador, Eswatini, Ethiopia, Gambia*, Ghana*, Guinea, Guinea-Bissau*, Haiti, Honduras, India, Indonesia, Iran, Kenya*, Kiribati, Kyrgyzstan, Laos, Lesotho, Liberia*, Madagascar, Malawi, Mali*, Mauritania, Micronesia, Mongolia, Morocco, Mozambique*, Myanmar*, Nepal, Nicaragua, Niger, Nigeria, Pakistan*, Palestine, Papua New Guinea*, Philippines, Rwanda, Samoa, Sao Tome and Principe, Senegal, Sierra Leone*, Solomon Islands, Sri Lanka, Sudan*, Tajikistan, Tanzania, Timor*, Togo, Tunisia, Uganda, Ukraine, Uzbekistan, Vanuatu, Vietnam, Zambia, Zimbabwe
High-income countries (106)	Albania, Antigua and Barbuda*, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Barbados*, Belarus, Belgium, Bermuda*, Bosnia and Herzegovina, Botswana*, Brazil*, Brunei, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Curacao*, Cyprus, Czechia, Denmark, Dominica, Dominican Republic, Ecuador, Equatorial Guinea, Estonia, Fiji, Finland, France, Gabon, Georgia, Germany, Greece, Grenada, Guatemala*, Guyana, Hungary, Iceland*, Iraq, Ireland, Israel, Italy*, Jamaica*, Japan, Jordan, Kazakhstan*, Kuwait*, Latvia, Lebanon, Libya*, Lithuania, Luxembourg, Malaysia, Maldives, Malta, Marshall Islands, Mauritius, Mexico, Moldova, Montenegro*, Namibia, Netherlands, New Zealand, North Macedonia*, Norway, Oman, Palau, Panama, Paraguay, Peru, Poland, Portugal, Qatar, Romania*, Russia, Saint Kitts and Nevis, Saint Lucia*, Saint Vincent and the Grenadines, Saudi Arabia, Serbia*, Seychelles, Singapore, Slovakia, Slovenia*, South Africa, South Korea, Spain, Suriname, Sweden, Switzerland, Thailand*, Tonga, Trinidad and Tobago, Turkey*, Tuvalu*, United Arab Emirates, United Kingdom*, United States*, Uruguay*

Note: * indicates that the country will be dropped on our two-stage model as there is missing data for either mobile-cellular telephone subscriptions per 100 inhabitants or fixed Internet subscriptions per 100 inhabitants. In 2020, the number of mobile broadband capable connections is higher than the number of total connections for Macao. Thus, there appears to be a measurement error for Macao. We therefore decided to drop Macao and Hong Kong as they are not independent countries.

Table 2
Descriptive statistics.

Variable	Mean	St. Dev.	Min	Max	No. obs
CO_2 per capita (in tonnes per inhabitant)	5	7	0.02	62	3439
Mobile broadband penetration (as percent of total connections)	25	31	0	100	3439
GDP per capita in constant 2017 $US	18570	20009	704	120606	3439
Mobile broadband connection per 100 inhabitants	30	39	0	166	3439
Fixed broadband per 100 inhabitants	14	13	0.0002	56	1634
Population density (persons per square kilometers of land area)	194	577	2	8045	3439
Share of electricity consumption from fossil fuel (in percent)	61	34	0	100	3287
Industry (including construction) as a share of GDP (in percent)	26	11	3	74	2983
Regulation index	0.004	0.93	−3	2	3344
Working age as a share of population (in percent)	63	7	47	86	3439
Human capital index	3	0.7	1	4	2502
Mobile broadband introduction (1%)	0.6	0.5	0	1	3439
Mobile broadband introduction (5%)	0.5	0.5	0	1	3439

Note: Data on human capital index is only available for the period 2002–2019.

Table 3
Regressions investigating the introduction of mobile broadband penetration and carbon dioxide (CO_2) per capita.

	Dependent variable: log CO_2 per capita			
	Pooled regressions		Fixed effects	
Mobile broadband introduction (1%)	0.14** (0.052)		0.05** (0.019)	
Mobile broadband introduction (5%)		0.10** (0.050)		0.03 (0.019)
Log of GDP per inhabitant (*lnGDPcap*)	1.31*** (0.067)	1.31*** (0.067)	0.89*** (0.150)	0.91*** (0.149)
Log of population density (*lnpopden*)	−0.06 (0.036)	−0.05 (0.036)	0.83*** (0.161)	0.84*** (0.160)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)	0.007*** (0.001)	0.007*** (0.001)	0.005*** (0.002)	0.006*** (0.002)
Industry (including construction) as a share of GDP (in percent) (*indushare*)	0.008** (0.004)	0.008** (0.004)	0.003 (0.003)	0.003 (0.003)
Regulation index (*regind*)	−0.19** (0.078)	−0.19** (0.078)	−0.001 (0.047)	−0.004 (0.047)
Constant	−11.71*** (0.613)	−11.71*** (0.615)	−11.42*** (1.704)	−11.58*** (1.690)
Country fixed effects	No	No	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2 (overall)	0.90	0.89		
R^2 (within)			0.42	0.42
Number of observations	2869	2869	2869	2869

Note: The estimates are based on pooled Ordinary Least Squares (OLS) and fixed effects estimations. Cluster robust standard errors are presented in parenthesis. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

as mobile broadband penetration of 1% and 5%.

The results shows that there is a highly significant association between the introduction of mobile broadband and CO_2 per capita based on both pooled and fixed effects estimation when the relative mobile broadband penetration threshold is defined as one percent. When the threshold is defined as five percent the results becomes insignificant when population density, the electricity generated from fossil fuel, the share of industry in total GDP and a regulation index is included (see Table 3). When the threshold is defined at 10 percent the magnitude of our estimated introduction coefficients becomes smaller (results available upon request). Moreover, the pooled effects estimations (based on Ordinary Least Square (OLS)) are all significant but becomes less significant for the 5 percent threshold. OLS estimates do not take country specific effects into account.

At the threshold of 1 percent, the results, based on fixed effects estimations, imply that after a country has introduced mobile broadband, CO_2 levels per capita are on average approximately 5 percent higher than before its introduction. For higher thresholds (i.e. 5 percent) the results become less significant and the coefficients become smaller, thus there is evidence of an initial increase from mobile broadband on CO_2 at low threshold levels. This could primarily be explained by first order effects as the introduction of mobile broadband requires large investments in mobile infrastructure that also drives increased consumption of electricity. If additional electricity is fossil-based, there will be increasing CO_2 emissions. Typically, networks are built for an intended capacity and not only for the initial users, hence, emissions associated with the deployment and initial operation is shared by only a few subscriptions (Lundén et al. 2022).

The estimates are considerably higher than studies investigating the first order effects based on the carbon footprint from ICT (see Malmodin & Lundén, 2018). One reason could be that our investigation estimates the correlation, where each country has the same weight, while the impact of the total footprint from ICT is an aggregate estimate that take the weight of each country into account. Moreover, traditional carbon footprint studies investigate the emission level for specific years meaning that the broadband maturity level will vary between countries.

The second impact from mobile broadband is the effect over time. Table 4 shows the association between the continuous mobile broadband penetration variable and CO_2 emissions per capita. Based on fixed effects estimations, the coefficient is highly significant for all different specifications The coefficient is negative which implies that the relationship between mobile broadband penetration and CO_2 emission per capita is negative over time in a statistical sense, i.e. higher relative penetration is associated with lower CO_2 emissions per capita. The pooled mobile broadband coefficient becomes insignificant when all variables are included, thus it is likely that our results would be biased if fixed effects are not taken into account. Moreover, based on fixed effects estimation, the magnitude of the estimated mobile broadband coefficient is smaller once controlling for the share of electricity consumption emerging from fossil fuel.[16]

Table 5 shows the regressions based on first differences. It shows that the change in relative mobile broadband penetration is negatively associated with the change in log CO_2 per capita at the one percent level, i.e. an increase in the relative change of mobile broadband penetration is associated with a decrease in the change of CO_2 per capita. According to Griliches and Jacques (1999) longer differences reduce measurement error. Once longer differences based on 3 and 5 years are introduced, the magnitude of the coefficient becomes larger. One explanation could be that the impact from mobile broadband on CO_2 materialize with a lag because additional innovation is required to take advantage of the increased diffusion and use of mobile broadband applications. Another explanation is that longer differences decrease the measurement errors over time (Edquist et al. 2021).

5. Instrumental variable approach

5.1. Endogeneity

Endogeneity implies that the independent variable is correlated with the error term, which gives biased regression results. Endogeneity may occur due to a number of different reasons e.g. measurement errors, omitted variable bias and simultaneity. One way of dealing with endogeneity is to use an instrumental variable approach. This implies using instruments that are correlated with the independent variable, but not with the error term.[17]

The methods used thus far have determined a correlation rather than a causal effect from mobile broadband introduction and diffusion on CO_2 per capita. Simultaneity, on the other hand, would imply that mobile broadband can be considered both a driver and a result of CO_2 emissions. It can be argued that it is unlikely that CO_2 emissions per capita in themselves affect the penetration of mobile broadband. Nevertheless, there are several studies that have recommended investment in ICT as an important policy response to

[16] In addition, we included a variable testing for the years since introduction to control for faster adoption in countries introducing mobile broadband later. The results were insignificant suggesting that our results are not robust once controlling for faster adoption in countries introducing mobile broadband later.

[17] Instrumental variables are used when an explanatory variable of interest is correlated with the error term. A valid instrument induces changes in the explanatory variable but has no independent effect on the dependent variable. Thus, it allows a researcher to uncover the causal effect of the explanatory variable on the dependent variable.

Table 4
Regressions investigating the relationship between mobile broadband penetration and carbon dioxide (CO_2) per capita.

	Dependent variable: log CO_2 per capita					
	Pooled Regressions			Fixed effects		
Mobile broadband penetration (as percent of total connections) (*MBBpen*)	−0.007*** (0.002)	−0.004** (0.002)	−0.001 (0.002)	−0.004*** (0.0007)	−0.004*** (0.0008)	−0.003*** (0.0008)
Log GDP per inhabitant (*lnGDPcap*)	1.31*** (0.044)	1.43*** (0.070)	1.32*** (0.069)	0.74*** (0.117)	0.90*** (0.142)	0.87*** (0.145)
Log of population density (*lnpopden*)		−0.003 (0.038)	−0.05 (0.036)		0.79*** (0.141)	0.73*** (0.147)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)			0.007*** (0.001)			0.005*** (0.002)
Industry (including construction) as a share of GDP (in percent) (*indushare*)		0.006 (0.004)	0.009** (0.004)		0.002 (0.003)	0.002 (0.003)
Regulation index (*regind*)		−0.27*** (0.085)	−0.17** (0.079)		0.02 (0.047)	0.01 (0.045)
Constant	−11.34*** (0.398)	−12.56*** (0.609)	−11.84*** (0.622)	−6.16*** (1.064)	−10.93*** (1.610)	−10.79*** (1.654)
Country fixed effects	No	No	No	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (overall)	0.86	0.87	0.89			
R^2 (within)				0.32	0.40	0.43
Number of observations	3439	2907	2869	3439	2907	2869

Note: The estimates are based on pooled OLS and fixed effects estimations. Cluster robust standard errors are presented in parenthesis. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5
Regressions investigating the relationship between the change in the log of CO_2 per capita ($\Delta lnCO_2cap$) and the change in mobile broadband penetration based on first, three and five years differences.

	Dependent variable: $\Delta lnCO_2$ per capita		
	First differences	Three years differences	Five years differences
ΔMobile broadband penetration (as percent of total connections) (Δ*MBBpen*)	−0.0011*** (0.0004)	−0.0012*** (0.0004)	−0.0012** (0.0005)
Δlog of GDP per inhabitant (Δln*GDPcap*)	0.47*** (0.080)	0.71*** (0.123)	0.76*** (0.144)
Δlog of population density (Δ ln*popden*)	0.35*** (0.124)	0.64*** (0.132)	0.72*** (0.148)
ΔShare of electricity consumption from fossil fuel (Δ*elffshare*)	0.003*** (0.0008)	0.004*** (0.001)	0.005*** (0.002)
ΔIndustry (including construction) as a share of GDP (Δ*indushare*)	0.0003 (0.001)	0.002 (0.001)	0.004* (0.002)
ΔRegulation index (Δ*regind*)	0.03* (0.016)	0.03 (0.024)	0.03 (0.036)
Constant	0.02** (0.009)	−0.03 (0.020)	−0.08** (0.033)
Year dummies	Yes	Yes	Yes
R^2 (overall)	0.14	0.21	0.27
Number of observations	2718	2416	2114

Note: Cluster robust standard errors are presented in parenthesis. Long differences include n-period growth rates of each variable. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

reduce CO_2 emissions (Charfeddine & Umlai, 2023; GeSI, 2015; Sun & Kim, 2021; Wang et al. 2021). Thus, it is not unlikely that policy response by governments to reduce CO_2 emissions per capita might lead to subsidies of investment in mobile broadband infrastructure, hence simultaneity (i.e. a bidirectional relationship) cannot be excluded but needs further investigation. [18]

In this paper we will use an approach to identify mobile broadband instruments based on the nature of mobile broadband. Czernich et al. (2011) pioneered this method by investigating the impact of fixed broadband on economic growth and it was later used by Edquist et al. (2018) to investigate the economic impact of mobile broadband.

The method is based on the idea that mobile broadband networks are designed for accessing the Internet on mobile phones or computers anywhere. This implies that the number of mobile broadband connections are related to the number of mobile phone and computer users. Prior to the introduction of mobile broadband, the penetration of computers had already reached a market saturation point and the construction of mobile phone infrastructure (e.g. 2G) had been completed in many countries.

Mobile broadband networks (primarily 3G, 4G and 5G) were constructed along the existing base stations for mobile telephony by upgrading or modifying the pre-existing cellular infrastructure. Thus, a country with an advanced pre-existing network (e.g. 2G) is likely to have a higher adoption rate of next generation mobile broadband (e.g. 3G) than a country with a less advanced network. This

[18] We have run a panel specific Granger causality test based on Juodis et al. (2021) (using Stata command xtgrangert). The results show that we can reject the null hypothesis that CO_2 emissions does not Granger-cause mobile broadband intensity. This indicates that lagged values of CO_2 emissions contain information that predict mobile broadband intensity over and above the information contained in lagged values of mobile broadband intensity itself, which may be an indication of simultaneity.

implies that the pre-determined adoption rate of computers and mobile phones can be used to predict the diffusion trajectory of mobile broadband. Thus, the maximum penetration rate of mobile broadband per country can be modeled as a linear function of cell phone penetration and diffusion of computers before the diffusion of mobile broadband:

$$\delta_i = \theta_0 + \theta_1 Mobilephone_{i0} + \theta_2 Internet_{i0} \tag{4}$$

where δ_i is the maximum penetration level in country *i*. $MobilePhone_{i,0}$ is cell phone penetration, measured as mobile-cellular telephone subscriptions per 100 inhabitants in 2002 and $Internet_{i,0}$ is the diffusion of computers proxied by fixed Internet subscriptions per 100 inhabitants in 2002.

The diffusion model is based on a logistic form of S-shaped diffusion curve. The logistic function was first used as a model of population growth by mathematician Pierre Verhulst (Verhulst, 1845). The function finds applications in a range of fields such as ecology, chemistry, economics and statistics. It has also been used to analyze the economic impact of fixed and mobile broadband (Czernich et al. 2011; Edquist et al. 2018). Thus, in this paper we assume that relative mobile broadband penetration follows an S-shape and approaches its maximum level eventually, which can be described through a logistic curve of the following form:

$$MobileBroadband_{it} = \frac{\delta_i}{1 + \exp[-\beta(t - \tau)]} + \varepsilon_t \tag{5}$$

where $MobileBroadband_{it}$ is mobile broadband penetration rated in country *i* at year *t*. δ_i is the same as in equation (4) i.e. a country-specific and time-invariant parameter that determines the maximum penetration of mobile broadband when *t* approximates infinity. Both β and τ are invariable across countries and determine the diffusion speed and the inflection point of the diffusion process, respectively. At the inflection point τ, the diffusion curve has its maximum growth rate $\beta/2$. ε_t is the error term.

5.2. First stage results

The first stage least squares model includes data for all countries where data on cellphone and Internet penetration in 2002, CO_2 emissions per capita and GDP per capita is available. Non-linear least squares are used to estimate the first stage least squares model. Table 6 presents the results of the regressions. 44 countries that have missing values for either cellphone or fixed Internet penetration are excluded from the regressions.[19] The coefficients for cell phone and Internet penetration in 2002 are significant at the 1 percent level in all models. This implies that the pre-determined cell phone and Internet penetration have positive effects in a statistical sense on the saturation level δ_i in the mobile broadband diffusion curve. The inflection point is determined to be around 2014. Moreover, in model 3 we have run the F-test and are able to reject the hypothesis that our instruments are jointly equal to 0 at the 1% significance level. In total, the estimated model provides a very good fit of the broadband diffusion process across countries.

5.3. Second stage results

The first stage estimation predicted the diffusion process of mobile broadband based on cell phone and fixed Internet penetration in 2002 assuming a S-shaped diffusion curve. In the second stage the fitted values of the broadband penetration rate based on the first stage regression is applied in order to estimate the causal effects of mobile broadband on CO_2. Standard errors in the second stage are bootstrapped (500 repetitions) since the independent variable was predicted by the first stage estimation.[20]

Table 7 presents results based on the predicted mobile broadband penetration rates for each country. The results imply that predicted mobile broadband penetration has a statistically significant negative effect on the level of CO_2 per capita. Thus, a 10 percentage points increase in mobile broadband intensity causes (if the Instrumental Variable strategy identifies causal effects) the level of CO_2 per capita to decrease by approximately 8 percent. This implies that investing in mobile broadband equipment provides important reductions of CO_2 emissions.

It could be argued that countries in similar stages of economic development should be compared. One hypothesis might be that countries with higher GDP per capita have a larger opportunity to benefit from mobile broadband deployment because optimization gains are much larger in terms of CO_2 reductions as the level of CO_2 emissions is already considerably higher in high-income countries and as more advanced services may be enabled by better infrastructure. Therefore, Table 7 also shows the results for high- and low-income countries. The countries have been classified based on gross national income (GNI) in 2020 (World Bank, 2022). Low-income countries have a GNI per capita of $4095 or below, while high-income countries have a GNI per capita of $4096 or above.

The results show that, from a statistical perspective, there is a significant negative relationship between mobile broadband penetration and CO_2 per capita for high-income countries. For low-income countries the result based on fixed effects regressions is

[19] These countries are: Afghanistan, Algeria, Antigua and Barbuda, Barbados, Bermuda, Bhutan, Botswana, Brazil, Burundi, Comoros, Curacao, Egypt, Gambia, Ghana, Guatemala, Guinea-Bissau, Iceland, Italy, Jamaica, Kazakhstan, Kenya, Kuwait, Liberia, Libya, Mali, Montenegro, Mozambique, Myanmar, North Macedonia, Pakistan, Papua New Guinea, Romania, Saint Lucia, Serbia, Sierra Leone, Slovenia, Sudan, Thailand, Timor, Turkey, Tuvalu, United Kingdom, USA and Uruguay.

[20] Bootstrapping is any test or metric that uses random sampling with replacement. Bootstrapping provides a way of estimating standard errors when available formulas make inappropriate assumptions. It implies drawing N observations with replacement from the original data. Using the resampled dataset, it is possible to apply the estimator and collect the statistics. The process is repeated many times.

Table 6
Technology diffusion curve (first stage of the instrumental variable model).

	Dependent variable: Mobile broadband penetration rate		
	Model 1	Model 2	Model 3
Cell phone penetration rate	0.97*** (0.045)		0.83*** (0.049)
Fixed Internet pentration rate		2.42*** (0.181)	0.55*** (0.119)
Diffusion speed (β)	0.33*** (0.014)	0.32*** (0.016)	0.33*** (0.014)
Inflection point (τ)	2014.4*** (0.280)	2014.6*** (0.361)	2014.3*** (0.279)
Constant (θ)	53.78*** (2.057)	66.05*** (2.862)	53.61*** (2.029)
R^2 (overall)	0.88	0.84	0.88
Number of observations	2603	2603	2603

Note: Non-linear squares estimation. Robust standard errors are presented in parenthesis ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. In model 3 we have run the F-test and can reject the hypothesis that our instruments are jointly equal to 0 at the 1% significance level.

Table 7
The effect of mobile broadband on log CO_2 per capita in total sample and different country groups (second stage of the instrumental variable model).

	Dependent variable: log CO_2 per capita				
	Total sample	High-income	Low-income	OECD	Non-OECD
Mobile broadband penetration (as percent of total connections) (*MBBpen*)	−0.008*** (0.001)	−0.007*** (0.001)	0.009 (0.016)	−0.005*** (0.001)	−0.009*** (0.003)
Log GDP per inhabitant (*lnGDPcap*)	0.67*** (0.152)	0.29** (0.143)	1.12*** (0.273)	0.42*** (0.139)	0.70*** (0.180)
Log of population density (*lnpopden*)	0.26** (0.128)	−0.02 (0.129)	0.27 (0.439)	−0.08 (0.202)	0.23 (0.159)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)	0.004* (0.002)	0.005*** (0.001)	0.004 (0.003)	0.004** (0.002)	0.004 (0.003)
Industry (including construction) as a share of GDP (in percent) (*indushare*)	0.005* (0.003)	0.004* (0.002)	0.003 (0.005)	0.0005 (0.004)	0.005 (0.003)
Regulation index (*regind*)	0.016 (0.049)	0.11* (0.058)	−0.09 (0.100)	0.11** (0.052)	−0.001 (0.059)
Constant	−6.99*** (1.711)	−1.74 (1.707)	−11.26*** (2.381)	−2.34 (1.799)	−7.30*** (1.964)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.47	0.53	0.51	0.80	0.45
Number of observations	2242	1330	912	551	1691

Note: Fixed effects estimation. Bootstrapped standard errors in parenthesis ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. First stage regressions are based on the total sample.

insignificant. Thus, increase in relative mobile broadband penetration is associated with CO_2 per capita reductions, but this effect is only shown for high-income countries. Moreover, the results remain significant once the sample is divided into OECD and non-OECD countries (see Table 7).

6. Robustness

To further test the robustness of our findings regarding high- and low-income countries, the sample is split into four different country groups (i.e. high-income, upper middle-income, lower middle-income and low-income) based on GNI in 2020 provided by the World Bank (2022). [21] Table 8 shows that the results remain highly significant for high-income countries, but not for the other three groups (i.e. upper- and lower middle-income and low-income countries). Thus, it is primarily among the richest countries that there is a significant effect from mobile broadband on CO_2 emissions.

In addition, we divide our samples of high- and low-income countries into groups with above and below median mobile broadband penetration in 2020 (the final year of our sample). The results in Table 9 show that the mobile broadband penetration coefficient is only significant for high-income countries with above median mobile broadband penetration. Thus, the relationship is only robust for the high-income countries that had reached a high mobile broadband penetration in 2020. Moreover, the results remain insignificant for both groups in low-income countries.

This section also tests the robustness of our results by including additional data. In our paper mobile broadband intensity is measured as the share of relative mobile broadband connections in total connections. Another way of measuring would be to relate mobile broadband to the population in each country. Column (1) in Table 10 shows that our results remain robust once mobile broadband penetration is measured as mobile broadband connections per 100 inhabitants.

[21] The country groups are as follows in terms of GNI per capita: low income, $1045 or less; lower middle income, $1046 to $4095; upper middle income, $4096 to $12,695; and high income, $12,696 or more.

Table 8
Robustness check of effect of mobile broadband on log CO_2 per capita in high-income, upper- and lower-middle income and low-income countries (second stage of the instrumental variable model).

	Dependent variable: log CO_2 per capita			
	High-income	Upper middle-income	Lower middle-income	Low-income
Mobile broadband penetration (as percent of total connections) (*MBBpen*)	−0.009*** (0.002)	−0.0003 (0.006)	0.004 (0.016)	−0.07 (0.362)
Log GDP per inhabitant (*lnGDPcap*)	0.04 (0.205)	0.44** (0.177)	1.33*** (0.305)	0.64** (0.306)
Log of population density (*lnpopden*)	−0.04 (0.146)	−0.12 (0.263)	0.56 (0.482)	1.07 (1.188)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)	0.005** (0.002)	0.007*** (0.002)	0.006 (0.004)	−0.002 (0.003)
Industry (including construction) as a share of GDP (in percent) (*indushare*)	0.008** (0.004)	0.0009 (0.003)	0.002 (0.007)	0.016*** (0.006)
Regulation index (*regind*)	0.107** (0.050)	0.11 (0.073)	−0.11 (0.113)	0.015 (0.177)
Constant	1.25 (2.467)	−3.17 (2.247)	−14.10*** (2.877)	−11.47** (5.292)
Country fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2 (within)	0.61	0.53	0.56	0.56
Number of observations	703	627	722	190

Note: Fixed effects estimation. Bootstrapped standard errors in parenthesis ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. First stage regressions are based on the total sample.

Table 9
Robustness check of effect of mobile broadband on log CO_2 per capita in high- and low-income countries with different mobile broadband penetration (second stage of the instrumental variable model).

	Dependent variable: log CO_2 per capita			
	High-income (Above median MBB penetration)	High-income (Below median MBB penetration)	Low-income (Above median MBB penetration)	Low-income (Above median MBB penetration)
Mobile broadband penetration (as percent of total connections) (*MBBpen*)	−0.009*** (0.002)	−0.003 (0.003)	0.009 (0.025)	0.002 (0.031)
Log GDP per inhabitant (*lnGDPcap*)	0.38** (0.187)	0.17 (0.204)	1.38*** (0.403)	0.76*** (0.287)
Log of population density (*lnpopden*)	0.08 (0.145)	−0.09 (0.250)	−0.20 (0.755)	−0.06 (0.870)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)	0.004** (0.002)	0.009*** (0.002)	0.005 (0.008)	0.002 (0.003)
Industry (including construction) as a share of GDP (in percent) (*indushare*)	0.005 (0.004)	0.004 (0.003)	0.01 (0.009)	−0.002*** (0.008)
Regulation index (*regind*)	0.07 (0.068)	0.14* (0.079)	0.01 (0.130)	−0.09 (0.140)
Constant	−2.72 (2.321)	−0.83 (2.234)	−11.30*** (4.016)	−7.33* (4.054)
Country fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2 (within)	0.65	0.45	0.56	0.54
Number of observations	665	665	456	456

Note: Fixed effects estimation. Bootstrapped standard errors in parenthesis ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. First stage regressions are based on the total sample.

Finally, we also in addition to the five independent variables in our base case (i.e. GDP per capita, population density, the share of electricity consumption that comes from fossil fuel, industry as a share of GDP and a regulation index)[22] introduce three additional variables to test the robustness of our regressions. We primarily also control for fixed broadband, the share of working age population and an index of human capital. According to the research literature, all these variables are considered important for CO_2 development (see Briglauer, Köppl-Turyna, & Schwarzbauer, 2023; Sart et al. 2022; Wang & Xu, 2021; Wulandari, 2021; Yao et al., 2014).

Column (2)–(4) in Table 10 shows that the results remain robust when each of the three control variables are included in the regressions separately. The results show that fixed broadband penetration also has a reducing effect on CO_2 emissions, while there is no significant effect from working age population and human capital. Finally, all control variables are included in the same regression.

[22] In line with section 3.2, higher population density implies higher pressure on the resources that an organism uses and consumes from the environment available in a specific area (Borghesi, 2000). Hocaoglu and Karanfil (2011) suggest that industrial production is the driving force of CO_2 emissions in G7 countries. Moreover, a large share of CO_2 emissions are emitted from electricity generation through the combustion of fossil fuels to generate heat needed to power steam turbines (Abdallah & El-Shennawy, 2013). Gani (2012) argues good governance and stability has a reducing impact on CO_2 emissions.

Table 10
Robustness check of the effect of mobile broadband on CO2 (alternative measure of mobile broadband intensity, fixed broadband and additional control variables (second stage of the instrumental variable model).

	Dependent variable: log CO_2 per capita				
	Other MBB measure	Fixed BB	Working age population	Human capital	All controls
Mobile broadband penetration (as percent of total connections) (*MBBpen*)		−0.007*** (0.001)	−0.007*** (0.001)	−0.008*** (0.001)	−0.007*** (0.001)
Mobile broadband connections per 100 inhabitants (*MBBcap*)	−0.005*** (0.0008)				
Fixed broadband per 100 inhabitant (*FBBcap*)		−0.008*** (0.002)			−0.009*** (0.002)
Working age as a share of population (*workageshare*)			0.02 (0.010)		0.005 (0.014)
Log of human capital index (*loghumcap*)				−0.12 (0.106)	−0.13 (0.146)
Log GDP per inhabitant (*lnGDPcap*)	0.65*** (0.153)	0.66*** (0.177)	0.66*** (0.151)	0.84*** (0.162)	0.64*** (0.214)
Log of population density (*lnpopden*)	0.24* (0.130)	0.23 (0.202)	0.18 (0.148)	0.44*** (0.157)	0.19 (0.319)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)	0.004* (0.002)	0.003 (0.002)	0.004* (0.002)	0.003 (0.002)	0.002 (0.002)
Industry (including construction) as a share of GDP (in percent) (*indushare*)	0.005* (0.003)	0.009** (0.003)	0.005* (0.003)	0.006 (0.004)	0.006* (0.004)
Regulation index (*regind*)	0.015 (0.049)	0.07 (0.053)	0.02 (0.047)	−0.01 (0.055)	0.06 (0.045)
Constant	−6.72*** (1.727)	−6.53*** (2.362)	−7.56*** (1.847)	−8.94*** (1.791)	−6.09** (2.635)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.47	0.63	0.48	0.54	0.64
Number of observations	2242	1292	2242	1800	1080

Note: The estimates are based on fixed effects estimations. Cluster robust standard errors are presented in parenthesis. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Column (5) shows that the magnitude of the mobile broadband coefficient is −0.007 and still significant at the 1 percent level. Thus, a 10 percentage points increase in mobile broadband penetration causes a 7 percent reduction of CO_2 emissions per capita (given that the instrumental variable strategy, as assumed, identifies causal effects).

7. Discussion and concluding remarks

7.1. Discussion

Despite that the Kuznets curve was found infeasible to use in the modelling of this study, the results of this paper support the view of an inverted U-shape relationship between mobile broadband and CO_2 which is also known as the environmental Kuznets curve (Dasgupta et al. 2002; Grossman & Krueger, 1991; Kuznets, 1955). The environmental Kuznets curve suggests that at the early stages of economic development, environmental degradation increases, but beyond a certain level of income per capita the trend is reversed, because high income levels are expected to lead to environmental improvements (Stern, 2004). An additional important factor for environmental improvements might be investment in mobile broadband.

In this paper we do not test directly for the inverted U-shape since taking the square of our mobile broadband intensity measure would lead to measures far beyond 100 which is not theoretically possible.[23] However, the findings clearly suggest that CO_2 emissions increases when mobile broadband is introduced, which most likely are driven by first order effects from the technology's use of material and energy. This is logical as new mobile broadband introduction often are designed for an intended capacity and not only for the initial users (Lundén et al. 2022). As mobile broadband is rolled out, the user intensity increases over time, which statistically has a long-term reducing impact on CO_2 per capita. The results indicate - that on average a 10 percentage points increase in mobile broadband penetration causes a 7 percent decrease in CO_2 emissions per capita (based on our instrumental variable strategy). Thus, our results are in accordance with similar studies investigating the impact from ICT on CO_2 based on a somewhat broader definition of ICT. Añón Higón et al. (2017) found that ICT, measured as a broad index, and CO_2 emissions are characterized by an inverted U-shaped relationship. Hernnäs (2018) found similar results based on unique mobile subscriptions per capita.

Based on our macro data it is not possible to determine exactly why increasing mobile broadband intensity leads to reduced CO_2 emissions. In this paper we have discussed the impact from first order, second order and other effects. First order effects usually lead to increased overall CO_2 emissions when new technology is deployed. Thus, one important conclusion based on our results is that the total impact from second order and other effects gradually outweighs the first order effects resulting in an aggregated impact associated with

[23] The data in this paper shows a strongly significant positive relationship between CO_2 emissions per capita and GDP per capita both in high and low-income countries, even though the magnitude of the estimated coefficient is considerably higher for low-income countries, i.e. increasing GDP per capita is associated with increasing CO_2 emissions per capita but to a varying extent.

reduction of CO_2. There are many examples of second order effects having a reducing impact on CO_2 such as more efficient use of energy, better industrial processes and reduced demand for transportation. However, also other effects such as rebound could have a reducing impact on CO_2. For example, environmentally friendly alternatives such as higher demand for electric cars. At the same time both second order effects and other effects may also be associated with increases in CO_2. This paper concludes that the total effect from different use cases reduces CO_2 emissions, but it is not possible to determine which ones that have the largest impact.

Table A2 (see appendix B) shows our results based on fixed effects estimations (without controlling for endogeneity) for different country groups. For high-income countries, there is a significant negative relationship in a statistical sense between CO_2 emissions per capita and both mobile and fixed broadband. The same holds for non-OECD countries. For OECD countries the statistical negative relationship is only significant between CO_2 emissions and fixed broadband. Moreover, the F-statistic for OECD countries show that it is possible to reject the null hypothesis that the two variables are jointly equal to zero at the 5 percent level. Thus, our results support the results by Briglauer, Köppl-Turyna, and Schwarzbauer (2023). Hence, it appears that fixed broadband is more strongly negatively correlated with CO_2 emissions per capita in OECD countries. One hypothesis is that OECD countries have invested more at an early stage in fixed broadband, which implies that the investment in mobile broadband infrastructure is less important for CO_2 emissions in these countries. However, the definition of mobile broadband starts at relatively low speeds where the additional features of mobility may not be used in an optimal way. Hence, studies that could differentiate speeds may reach another conclusion. At the current availability of data this cannot be investigated.

Based on the two-stage model, there is a significant decrease in CO_2 emissions for each of the following country groups: High-income countries, OECD and non-OECD countries (see Table 7). However, for low-income countries, there is no robust relationship between mobile broadband intensity and CO_2 emissions. One possible explanation could be that the size of the sample is limited due to excluding countries with data gaps (see Table 1). An additional explanation, in accordance with the pollution haven hypothesis (see Gill et al. 2018; Koźluk & Timiliotis, 2016; Levinson & Taylor, 2004), is that firms in high-income countries try to avoid cost of stringent environmental regulation by locating production in low-income countries where environmental norms are laxer. However, this would create even larger potential to use mobile broadband applications to reduce CO_2 in low-income countries. Thus, there must be additional explanations why there is no relationship between mobile broadband intensity and CO_2 emissions per capita in low-income countries. One such factor might be that the quality and speed of mobile broadband differs between countries. Another reason might be that mobile broadband may be used for different purposes in economies at different levels of development.

In the robustness section, we also find that there is only a significant effect from mobile broadband on CO_2 emissions in the richest countries of the world (i.e. a GNI per capita above $12 696 or above). Moreover, the results are only significant for high-income countries (i.e. a GNI above $4096) with a mobile broadband penetration above median in 2020. This is an indication that additional broadband investments are important also when high levels of mobile broadband have been reached (in high-income countries).

Mobile broadband connections are defined by the GSMA (2022) as SIM cards that have been registered on the mobile network in a device capable of download speeds of 256 kb/s or greater. When mobile broadband was introduced in 2001 this was considered a quite high speed, but as the mobile technology has improved many countries have a considerable higher download speed than 256 kb/s. According to Edquist (2022) the median download speed was 11 355 kb/s in 116 countries for the period 2014–2019. Thus, the download speed has increased considerably since mobile broadband was first introduced. Moreover, it is probable that download speed and other capabilities are considerably better in high-income countries. Due to data limitations, we are not able to control for the different quality aspects of mobile broadband in our regression analysis.

An additional analysis of the effect of speed would be needed in the future as many emerging technology applications, not least in industrial and infrastructure applications, would need the higher speeds associated with more advanced networks. In addition to speed, other parameters that might influence the difference between high- and low-income countries may be such as digital literacy, affordability and how the technology is used both in the private and the public sector.

7.2. Concluding remarks

This paper investigates the relationship between relative mobile broadband penetration and carbon dioxide (CO_2) emissions per capita. The results indicate increased emissions as an initial impact from relative mobile broadband penetration on CO_2 emissions per capita, which most likely are driven by first order effects from the technology's increased use of material and energy. A possible explanation might be that initial investment in network infrastructure and associated consumption of electricity is shared by only few users initially. Initial impacts indicated by this study are considerably higher than in studies investigating the first order effects based on the carbon footprint from ICT. However, these two types of studies cannot be compared. This paper investigates the correlation, where each country has the same weight, while the impact of the total footprint from ICT is an aggregated estimate that take the weight of each country into account. Moreover, traditional carbon footprint studies investigate the emission level for specific years meaning that the broadband maturity level will vary between countries for the investigated period.

As mobile broadband diffuses over time the continuous relationship between mobile broadband and CO_2 is significantly negative in a statistical sense i.e. emissions significantly reduce as mobile broadband penetration increases. Based on a two-stage model and controlling for additional independent variables (i.e. GDP per capita, population density, the share of electricity consumption that comes from fossil fuel, industry as a share of GDP, a regulation index. fixed broadband, working age as a share of population and a human capital index), we conclude that on average a 10 percentage points increase in mobile broadband penetration causes a 7 percent reduction of CO_2 emissions per capita (if the instrumental variable strategy identifies casual effects). However, the relationship is only significant for high-income countries. One possible explanation could be that the speed in the mobile broadband networks generally is higher in high-income countries. High-income countries might also have an industrial setup that allows them to benefit more from any

CO_2 emissions reduction opportunity associated with mobile broadband.

The results in this paper clearly support the finding that the initial first effects from mobile broadband is driving increments in CO_2 emissions per capita. However, the direction of the second and higher order effects from mobile broadband over time (including rebound) as well as sharing first order impacts between more users, appear to have a reducing effect on CO_2 emissions per capita. Thus, the results imply that investments in mobile infrastructure over longer periods of time are important tools in mitigating climate change.

Based on the results, policy makers in high-income countries may use mobile broadband as an integrated part of their decarbonization efforts. When doing so they need to consider how to best optimize the aggregated impact of first, second and other effects and seek to amplify any positive usages and suppress rebound and usages that maintain or increase emissions. As the results also indicate a reducing effect from fixed broadband on CO_2 emissions, policy makers should, as far as possible, facilitate investments in both mobile and fixed broadband equipment without distorting market competition. In contrast, policy makers in low-income countries need to establish further understanding of how their mobile broadband strategies should be defined to make use of the emission reduction effect of mobile broadband that seems to be present in high-income countries.

Finally, this paper has extended the analysis of the effect of ICT on CO_2 emissions by focusing primarily on mobile broadband. Earlier studies have investigated the effect on CO_2 emissions from ICT in general (i.e. Añón Higón et al. 2017), mobile phone subscriptions (i.e. Hernnäs, 2018; Danish et al. 2019; Haini, 2021) or fixed broadband (i.e. Briglauer, Köppl-Turyna, & Schwarzbauer, 2023). Since the findings of this paper shows that mobile broadband is only significant for high-income countries, further research is needed to understand why there is no reducing effect in low-income countries.

An additional area for future research is to understand how the speed of different networks effect CO_2 emissions. Moreover, future research should investigate how the use of mobile broadband differs between low-income countries and high-income countries, and how such as digital literacy, affordability and digitalization of industries and administration comes into play. Finally, it would be interesting to also investigate the impact from mobile broadband on CO_2 equivalents, which includes the impact from additional greenhouse gases (e.g. methane, nitrous oxide, hydrofluorocarbons).

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Appendices.

Appendix A

Table A1
Regressions investigating the relationship between mobile broadband penetration and consumption-based carbon dioxide (CO_2) per capita

	Dependent variable: log consumption-based CO_2 per capita			
	Pooled Regressions		Fixed effects	
Mobile broadband penetration (as percent of total connections) (*MBBpen*)	−0.002 (0.002)	−0.001 (0.002)	−0.003*** (0.0009)	−0.002*** (0.0009)
Log GDP per inhabitant (*lnGDPcap*)	1.23*** (0.085)	1.18*** (0.085)	1.10*** (0.167)	1.02*** (0.169)
Log of population density (*lnpopden*)	−0.04 (0.038)	−0.07** (0.034)	0.91*** (0.148)	0.77*** (0.148)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)		0.005*** (0.001)		0.006*** (0.002)
Industry (including construction) as a share of GDP (in percent) (*indushare*)	0.01** (0.004)	0.005 (0.005)	−0.0005 (0.004)	−0.00007 (0.004)
Regulation index (*regind*)	−0.07 (0.083)	−0.05 (0.083)	−0.004 (0.059)	−0.03 (0.054)
Constant	−10.54*** (0.780)	−10.11*** (0.776)	−13.09*** (1.796)	−12.09*** (1.847)
Country fixed effects	No	No	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2 (overall)	0.89	0.90		
R^2 (within)			0.43	0.46
Number of observations	1976	1976	1976	1976

Note: The estimates are based on pooled OLS and fixed effects estimations. Cluster robust standard errors are presented in parenthesis. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix B

Table A2

Regressions investigating the relationship between mobile broadband penetration and carbon dioxide (CO_2) per capita in total sample and different country groups (high and low income, OECD and non-OECD countries)

	Dependent variable: log CO_2 per capita				
	Fixed effects				
	Total sample	High-income	Low-income	OECD	Non-OECD
Mobile broadband penetration (as percent of total connections) (*MBBpen*)	−0.002*** (0.0007)	−0.002** (0.0008)	−0.003 (0.003)	−0.0003 (0.0007)	−0.003*** (0.001)
Fixed broadband per 100 inhabitant (*FBBcap*)	−0.01*** (0.003)	−0.008*** (0.003)	0.017 (0.019)	−0.006** (0.002)	−0.012*** (0.004)
Log GDP per inhabitant (*lnGDPcap*)	0.85*** (0.171)	0.52*** (0.161)	1.63*** (0.293)	0.67*** (0.145)	0.85*** (0.201)
Log of population density (*lnpopden*)	0.38** (0.182)	0.04 (0.157)	2.23** (0.844)	−0.05 (0.233)	0.33 (0.233)
Share of electricity consumption from fossil fuel (in percent) (*elffshare*)	0.006*** (0.002)	0.008*** (0.001)	−0.002 (0.002)	0.005*** (0.001)	0.004 (0.004)
Industry (including construction) as a share of GDP (in percent) (*indushare*)	0.008** (0.004)	0.005 (0.003)	0.005 (0.005)	−0.001 (0.005)	0.01*** (0.004)
Regulation index (*regind*)	0.02 (0.052)	0.04 (0.066)	−0.006 (0.102)	0.0005 (0.061)	0.04 (0.062)
Constant	−9.11*** (2.272)	−4.36** (2.094)	−22.46*** (4.565)	−4.98** (2.281)	−9.04*** (2.615)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.56	0.51	0.82	0.74	0.59
Number of observations	1444	1140	304	589	855
F-statistics: MBBpen = FBBcap = 0	20.04***	9.64***	1.94	4.01**	15.36***

Note: The estimates are based on fixed effects estimations. Cluster robust standard errors are presented in parenthesis. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The F-statistic is used to test the null hypothesis that some or all of the independent variables are jointly equal to zero. The critical value for F distribution at the 5 percent level for an F ratio with (2, 100) degrees of freedom is 3.09, while the critical value for F distribution at the 1 percent level with (2, 100) degrees of freedom is 4.82.

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