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## How is mobile broadband intensity affecting CO<sub>2</sub> emissions? – A macro analysis

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# **How is mobile broadband intensity affecting CO<sub>2</sub> emissions? – A macro analysis <sup>\*</sup>**

**By**

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## **Abstract**

This paper investigates the association between relative mobile broadband penetration and carbon dioxide (CO<sub>2</sub>) emissions globally. The study is based on 181 countries for the period 2002–2020. The results indicate an initial increase in CO<sub>2</sub> 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 kbps) and CO<sub>2</sub> is significantly negative, i.e. emissions at a country level significantly reduce as mobile broadband penetration increase. Based on a two-stage model and controlling for fixed broadband and four additional control variables (i.e. population density, electricity consumption from fossil fuel, industry as a share of GDP and a regulation index), we are able to conclude that on average a 10 percentage points increase in mobile broadband penetration causes a 7 percent reduction of CO<sub>2</sub> emissions per capita (given that the instrumental variable strategy, as assumed, identifies causal effects). Thus, the results show that investments in mobile infrastructure over longer periods of time can contribute to mitigating climate change.

**Keywords:** Mobile broadband, carbon dioxide (CO<sub>2</sub>), climate change

**JEL codes:** O13, O33, Q54

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## 1. Introduction

In 2022, it appears almost impossible to imagine a world without smartphones. Thus, mobile broadband arguably is one of the most important innovations of the early 21<sup>st</sup> century.<sup>1</sup> Mobile broadband has spread rapidly in most countries of the world and have had an important effect on how we lead our lives (see *figure 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 from mobile broadband on climate change and particularly carbon dioxide (CO<sub>2</sub>) at the macro level.

For a long time, CO<sub>2</sub> emissions and other greenhouse gases were neglected by politicians and policy makers. Many did not understand the problem that CO<sub>2</sub> emissions were causing climate change. Even though the effect on the climate was discussed already a century ago, climate change did not emerge as a political issue until the 1990s (Bodansky 2001).

The effects from CO<sub>2</sub> 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<sub>2</sub> 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<sub>2</sub> emissions as economic development has surged in most countries and the overall world population has increased substantially. *Figure 2* shows that CO<sub>2</sub> emissions accelerated during the second half of the 20<sup>th</sup> century. In 2020 total global CO<sub>2</sub> emissions reached 34.8 billion tonnes, somewhat below 2019 due to the pandemic (Our world in data 2022).

To avoid the most severe effects of global warming, global CO<sub>2</sub> 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. This

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<sup>1</sup> This paper defines mobile broadband as speeds of a least 256 kbps. 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.

is increasingly agreed by actors across nations, businesses and civil society and is demonstrated in the Paris Agreement (United Nations Framework Convention on Climate Change, 2015) and confirmed by the Glasgow Climate Pact (United Nations Framework Convention on Climate Change, 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). In the latest decades the economic impact of ICT has increased substantially with the spread of computers, smartphones and tablets, which has allowed a large part of the world population to be connected over the Internet.

From a climate perspective ICT can be associated with three orders of effects. In line with the International Telecommunication Union (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* 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<sub>2</sub> emissions, there is so far not much evidence of its aggregated impact at the macro level. Consequently, complementary approaches are needed to explore the resulting combined effect across the different orders of effects. Hence, this paper investigates the relationship between mobile broadband and CO<sub>2</sub> at the macrolevel to complement studies focusing on specific orders of effect. This paper focuses on CO<sub>2</sub> rather than overall greenhouse gases. At the first order level ICT is expected to have limited effects on other greenhouse gases, while overall effects are not known and could be a topic for future research. With regards to the assessment perspective this paper considers territorial or production-based CO<sub>2</sub> emissions which are associated with country reporting and without any modifications for trade. As consumption-based data sets evolve for more countries it would be of interest to explore also those.

The results of this study indicate an initial increase in territorial CO<sub>2</sub> 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<sub>2</sub> is significantly negative in a statistical meaning, i.e. emissions are significantly reduced as mobile broadband penetration increases.

Based on a two-stage model and controlling for fixed broadband and four additional control variables (i.e. population density, electricity consumption from fossil fuel, industry as a share of GDP and a regulation index), we are able to conclude that on average a 10 percentage points increase in mobile broadband penetration causes a 7 percent reduction of CO<sub>2</sub> emissions per capita (given that the instrumental variable strategy, as assumed, identifies causal 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.

## 2. Previous research

According to IPCC (2021) each of the last four decades has been successively warmer than any decade since 1850. Moreover, global surface temperature in 2000–2019 was 0.99 degrees higher compared to the period 1850–1900. IPCC (2021) concludes that human influence has warmed the atmosphere, ocean and land by increasing the emissions of greenhouse gas (GHG). Thus, one of the most important global questions of the 21<sup>st</sup> century will be to investigate how CO<sub>2</sub> and other greenhouse gases can be reduced without considerable decremental effects on the standard of living for billions of people.

### 2.1 ICT and CO<sub>2</sub>

ICT can have both positive and negative climate effects (Erdmann and Hilty 2010). In this paper we divide the different effects into first order effects, second order effects and other effects (ITU 2014). Salahuddin *et al.* (2016), using OECD panel data for 1991–2012 to derive the aggregated effect of these, find a significant long-run relationship between Internet usage and CO<sub>2</sub> emissions, but the coefficient is small and causality is unclear.

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<sub>2</sub> equivalent emissions remained quite stable since 2007 and even decreased somewhat despite growing data traffic. However, Malmmodin 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, leading to a 2015 first order effect of an estimated 1.4 percent of total global CO<sub>2</sub> 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). Overall, despite differences in approaches and quantifications, 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 (Malmmodin and Lundén 2018; Andrae 2020; GESI and Deloitte 2019; ITU 2020; 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<sub>2</sub> emissions. Decarbonization denotes a reduction of CO<sub>2</sub> 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.

Several studies have pointed out that ICT can reduce energy consumption (Moyer and 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 Malmudin 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 has a large impact on energy saving (GESI and BCG 2012). Moreover, 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. 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 (Malmudin and 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. Currently, organizations like the ITU and the European Green Digital Coalition are seeking to develop methodologies for assessment of the second order effect and the outcome of these processes is expected 2022.

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 19<sup>th</sup> 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<sub>2</sub>. For example, if increased productivity leads to lower prices of consumer electronics, there might be increased demand for cars: leading to higher CO<sub>2</sub> emissions. According to Coroamă and Mattern (2019) digitalization may have rebound effects that are negative for the environment. However, rebound effects might also foster environmentally friendly alternatives such as higher demand for electric cars, which might lead to decreased CO<sub>2</sub> 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 and 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 while the overall effect would be beyond reach since it would be impossible to know all possible usages of the technology (ITU 2014, Coroamă & Bergmark, 2020). In addition, traditional methods of estimating second order effects are always contrafactual by comparing to a baseline which cannot exist at the same time as the solution (Coroamă *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 preferred usages and estimating their effects.

There are a few studies at the macro level that have investigated the association between ICT and CO<sub>2</sub> emissions. Añón Higón *et al.* (2017) find that the relationship between ICT (measured as an index of fixed telephone subscriptions, mobile cellular telephone subscriptions, PC owners, Internet users and fixed broadband Internet subscriptions) and CO<sub>2</sub> emissions is characterized by an inverted U-shaped relationship based on a panel of 142 countries for the period 2010–2015. They find that at low levels of development additional ICT investment increase CO<sub>2</sub> emissions, but CO<sub>2</sub> emissions start to reduce after a threshold



level of ICT development has been reached. Hernnäs (2018) extends the analysis for the period 2000–2016 and finds 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<sub>2</sub> is based on the idea of an Environmental Kuznets Curve (EKC) (Grossman and Kreuger 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). 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.<sup>2</sup>

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<sub>2</sub>. The EKC framework predicts that CO<sub>2</sub> initially increases more rapidly during the first phase of mobile broadband investment when new infrastructure is installed and thus causes strong first 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) find evidence that an excessive level of digitalization causes 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 show different results and are 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, the EKC model is infeasible because the quadratic function of the variable would create values that are not theoretically possible to obtain.

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<sup>2</sup> Kuznets (1955) originally noted an inverted U relationship between income inequality and economic development.

There are also a number of studies using cointegration to investigate the relationship between ICT and CO<sub>2</sub>.<sup>3</sup> Lee and Brahmairene (2014) found a relationship showing that an increase in ICT was associated with an increase in CO<sub>2</sub> for Southeast Asian countries 1991–2009.<sup>4</sup> Salahuddin *et al.* (2016) found a corresponding relationship between the number of internet users per 100 inhabitants and CO<sub>2</sub> emissions in OECD-countries 1991–2012.<sup>5</sup> These studies suggest that there is little evidence so far that the positive second order effects from ICT on CO<sub>2</sub> have outperformed the combined effect of first order effects, any emission increasing second order effects of ICT and other effects such as rebound.

## 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 Oliner and Sichel 2000; Jorgenson *et al.* 2008; Goodridge *et al.* 2019). 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 environmental Kuznets curve, but no robust results were found between ICT and CO<sub>2</sub> emissions.

Añón Higón *et al.* (2017) measure 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<sub>2</sub>. Moreover, Hernnäs (2018) also focus on the impact of unique mobile subscriptions divided by population and found evidence of an inverted U-shaped curve. Hernnäs argues that the unique subscriptions measure can be a more accurate measure of the market penetration of ICT than number of subscriptions since e.g. in some markets subscribers may have more than one subscription just to ensure coverage. Moreover she suggests 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.

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<sup>3</sup> Cointegration is used to establish if there is a correlation between several time series in the long term.

<sup>4</sup> 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.

<sup>5</sup> 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.

### 2.3 Mobile broadband and CO<sub>2</sub>

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).

*Figure 1* (Section 9) shows that mobile broadband has been adopted rapidly during the early 21<sup>st</sup> century. The first registered mobile broadband connections were registered in Japan in the 4<sup>th</sup> quarter in 2001.<sup>6</sup> In 2021, there were more than 7 billion mobile broadband capable connections in the world (GSMA 2022).

Mobile broadband networks allow people and businesses to receive and transfer data almost anywhere. This flexibility can drive CO<sub>2</sub> reductions. For example, less material will be used when people consume music online instead of buying CDs. Data transfer also allow mobile users to share, scooters and cars, which implies the opportunity for a smarter use of vehicles and thus reduces CO<sub>2</sub>.

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 also enables cellular IoT solutions in manufacturing, which may optimize production and reduce CO<sub>2</sub> emissions. Mobile devices can also be used to collect large amounts of data, that can be used to optimize traffic flows and thereby potentially reduce CO<sub>2</sub>. Thus, there appears to be a case for mobile broadband being able to drive CO<sub>2</sub> reductions over long time periods, even though the initial investments may be leading to CO<sub>2</sub> increases.

Currently mobile broadband data sets refers to data speeds of 256 kbps and above. For many applications that users expect to perform over mobile broadband today this speed is not

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<sup>6</sup> Since mobile broadband connections were only introduced in the last quarter of 2001, we consider 2002 as the first year that mobile broadband was introduced over a whole year. Thus, the relationship between mobile broadband and CO<sub>2</sub> is investigated for the period 2002–2019.

considered sufficient, for example watching youtube demands above 500 kbps.<sup>7</sup> It is also expected that many industrial applications, like real time regulation of systems, require particularly high data rates. 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.

### 3. Method and data

This paper will focus on mobile broadband measured as mobile broadband connections in total connections.<sup>8</sup>

#### 3.1 Model

The method used in this paper will be based on econometrics. To test if there is a first impact when mobile broadband is introduced a difference-in-differences specification is used:<sup>9</sup>

$$\ln CO_2cap_{i,t} = \beta_1 + \beta_2 D_{i,t} + \beta_3 \ln GDPcap_{i,t} + \theta T_t + (\alpha_i + \varepsilon_{i,t}) \quad (1)$$

where  $CO_2cap_{i,t}$  is territorial 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.  $GDPcap_{i,t}$  is real GDP per capita at constant 2017 national prices (in 2017 US\$).  $T_t$  is a set of year dummy variables that control for anomalies in  $CO_2$ . Finally,  $\alpha_i$  is a set of unobserved country specific effects and  $\varepsilon_{i,t}$  is the error term.<sup>10</sup>

<sup>7</sup> Google system requirements: <https://support.google.com/youtube/answer/78358?hl=en>

<sup>8</sup> According to GSMA (2022), mobile broadband connections represent SIM cards (or phone numbers, where SIM cards are not used) that have been registered on the mobile network in a device capable of download speeds of 256 kb/s or greater (agnostic of the device type) at the end of the period.

<sup>9</sup> 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.

<sup>10</sup> The error term models the deviation from the regression curve.

A first effect from mobile broadband on CO<sub>2</sub> 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 use of 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 thresholds when mobile broadband reaches 5 and 10 percent penetration levels are also included in the regressions.

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<sub>2</sub> in other sectors from energy savings, smarter transport etc. However, there might also be an impact leading to increasing levels of CO<sub>2</sub> from ICT due to potential other effects such as rebound. In reality second order effects may instead increase emissions, while rebound could sometimes lead to decreases. In order to capture the relationship over time between mobile broadband and CO<sub>2</sub>, the model is set up in the following way:

$$\ln CO_2cap_{i,t} = \beta_1 + \beta_2 MBBpen_{i,t} + \beta_3 \ln GDPcap_{i,t} + \delta X_{i,t} + \theta T_t + (\alpha_i + \varepsilon_{i,t}) \quad (2)$$

where  $MBBpen_{i,t}$  is mobile broadband penetration measured as the share of mobile broadband connections in 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<sub>2</sub> emissions per capita.  $X_{i,t}$  is additional control variables, which are introduced in the robustness section and  $T_t$  is a set of year dummy variables in order to control for common shocks. Moreover,  $\alpha_i$  is a set of unobserved country-specific effects and  $\varepsilon_{i,t}$  is the error term.<sup>11</sup>

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

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<sup>11</sup>  $\beta_1$  is a constant, which is not of interest to our analysis unless all our explanatory variables are equal to 0.

the regression and remove the country-specific effects is to take the first difference of the variables.

$$\Delta \ln CO_2cap_{i,t} = \beta_1 + \beta_2 \Delta MBBpen_{i,t} + \beta_3 \Delta \ln GDPcap_{i,t} + \delta_t + v_{i,t} \quad (3)$$

where  $\delta_t$  are year dummies which capture anomalies in  $CO_2$  and  $v_{i,t}$  is the differenced residual.

### 3.2 Data

The purpose of this paper is primarily to investigate the association between  $CO_2$  and mobile broadband penetration. Data on  $CO_2$  emissions has been taken from Our World in Data (2022), which is an open-source database founded 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 as 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.<sup>12</sup> The  $CO_2$  is measured from the territorial perspective i.e. in the countries where  $CO_2$  are emitted. Thus, it may not reflect where the consumption of goods and services take place. 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.

Mobile broadband penetration is based on the GSMA Intelligence database (GSMA 2022). It is measured as the share of mobile broadband connections in total mobile connections for a particular country.<sup>13</sup> Mobile broadband connections are defined as SIM cards that have been registered on the mobile network in a device capable download speeds of 256 kb/s or greater. 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.

Data on GDP is based on World Bank (2022). GDP is based on 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

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<sup>12</sup> Population is defined as de facto population in a country, area or region as of July 1 of the year indicated.

<sup>13</sup> IoT connections are excluded from mobile connections.

GDP as the U.S. dollar has in the United States. Moreover, GDP per capita has been calculated based on population data from GSMA (2022).

This paper is primarily focused on mobile broadband, which is not the only ICT investment that may have an impact on CO<sub>2</sub>. Añón Higón (2017) uses a broad index over ICT to investigate the general ICT impact on CO<sub>2</sub>. Their index includes fixed telephone subscriptions, mobile cellular telephone subscriptions, PC owners, Internet users and fixed broadband Internet subscriptions. This paper primarily control 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 the robustness section additional control variables are included that are important for CO<sub>2</sub> emissions according to the literature. According to Borghesi (2000) the higher population density, the higher pressure on the environmental resources available in that area. Moreover, traffic congestions in highly populated areas may also affect CO<sub>2</sub> 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<sub>2</sub> and the share of industry in GDP. Their findings suggest that industrial production is the driving force of CO<sub>2</sub> emissions in G7 countries. Thus, industry share including construction as a share of GDP based on World Bank (2022) is included as a control variable. A large share of CO<sub>2</sub> emissions are emitted from electricity generation through the combustion of fossil fuels to generate heat needed to power steam turbines (Abdallah and El-Shennawy 2013). Therefore, the share of electricity production from fossil fuel in total electricity production based on Our World in Data (2022) is included in the regressions.

Gani (2012) argues that good governance and stability reduce CO<sub>2</sub> 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.

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 regression, have been dropped. *Table 1* shows a list of the countries that have been included in the regressions based on CO<sub>2</sub> per capita, GDP per capita and mobile broadband penetration i.e. the broadest specification of the model.<sup>14</sup> Moreover, *table 2* shows some descriptive statistics. It shows that, not unexpectedly, both CO<sub>2</sub> 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 is most appropriate.<sup>15</sup> 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<sub>2</sub> 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 (CO<sub>2</sub>) and the independent variables in the model.

As described in section 3.1 there might be two effects from mobile broadband on CO<sub>2</sub>. The first effect is that there might be an initial shift in the level of CO<sub>2</sub> once mobile broadband is introduced. *Table 3* shows the results from the difference in difference regression measuring the effect from mobile broadband introduction. This paper uses different thresholds of introduction defined as mobile broadband penetration of 1%, 5% and 10%.

The results shows that there is a highly significant association between the introduction of mobile broadband and CO<sub>2</sub> based on 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 are still significant, but the coefficients is smaller. However, when the

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<sup>14</sup> 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.

<sup>15</sup> The random effects model assumes is 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 including time specific effects gives a statistic of 161.15 with a  $Prob > \chi^2 = 0.0000$ . Thus, the hypothesis that the random effects model is most appropriate is rejected.



threshold is defined as 10 percent the results are considerably less significant (only significant at the 10 percent level). Moreover, the pooled effects estimations (based on OLS) are all insignificant, which might be due to bias when country specific effects are not taken into account.

At the threshold of 1 percent, the results imply that after a country has introduced mobile broadband, CO<sub>2</sub> levels per capita are on average approximately 9 percent higher than before its introduction. For higher thresholds the results become less significant and the coefficients become smaller, thus there is evidence of an initial increase from mobile broadband on CO<sub>2</sub> at low threshold levels. This could be explained by the fact that the introduction of mobile broadband requires large investments in mobile infrastructure that also drives increased consumption of electricity. 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 second impact from mobile broadband is the effect over time. *Table 4* shows the association between the continuous mobile broadband penetration variable and CO<sub>2</sub> emissions per capita. The coefficient is insignificant based on both pooled OLS estimations and when country fixed effects are introduced. The coefficient is negative which implies that the relationship between mobile broadband penetration and CO<sub>2</sub> emission per capita is negative over time, i.e. higher relative penetration is associated with lower CO<sub>2</sub> emissions per capita.

In *table 4*, an additional control variable measuring the years since mobile broadband introduction is also included in two of the regressions.<sup>16</sup> This controls for the catching-up in the mobile broadband diffusion in countries that introduce mobile broadband later.<sup>17</sup> *Table 4* shows that the association between relative mobile broadband and CO<sub>2</sub> is not significant once years since introduction are included. Thus, once controlling for catching-up effects our results are not robust.

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<sup>16</sup> Introduction is defined as relative mobile broadband penetration of 1 percent i.e. the year the share of mobile broadband connections in total connections reach 1 percent.

<sup>17</sup> When years since mobile broadband introduction is included, year dummy variables are excluded. According to Wooldridge (2009) it is not possible to estimate the effect of any variable whose change across time is constant if year dummy variables are included.

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<sub>2</sub> per capita at the five percent level, i.e. an increase in the relative mobile broadband penetration is associated with a decrease in CO<sub>2</sub> per capita.. According to Griliches and Mairesse (1999) longer differences reduce measurement error. Once longer differences based on 3 and 5 years are introduced the magnitude of the coefficient becomes larger and more significant. One explanation could be that the impact from MBB on CO<sub>2</sub> 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 Simultaneity

The methods used thus far have determined a correlation rather than a causal effect from mobile broadband introduction and diffusion on CO<sub>2</sub>. Simultaneity, on the other hand, would imply that mobile broadband can be considered both a driver and a result of CO<sub>2</sub> emissions. It can be argued that it is unlikely that CO<sub>2</sub> emissions per capita in themselves affect the penetration of mobile broadband. However, it is not unlikely that policy response by governments to reduce CO<sub>2</sub> 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.

Simultaneous equation bias occurs when a regression is used to estimate an individual equation that is actually part of a simultaneous system of equations. It implies that the explanatory variable is correlated with the error term, which gives biased regression results. Advanced methods, designed to eliminate simultaneous equation bias, use instrumental variables in the first stage of a two-stage procedure.<sup>18</sup> One way of addressing the simultaneity bias is hence to use instruments that are correlated with the explanatory variable, but not with the error term. In this paper we will use an approach to identify mobile broadband

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<sup>18</sup> 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.

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 saturation point among individuals and the construction of mobile phone infrastructure 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 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 can be modeled as a linear function of cell phone penetration and diffusion of computers before the diffusion of mobile broadband:

$$\delta_i = \theta_0 + \theta_1 \text{Mobilephone}_{i0} + \theta_2 \text{Internet}_{i0} \quad (4)$$

where  $\delta_i$  is the maximum penetration level in country  $i$ .  $\text{MobilePhone}_{i,0}$  is cell phone penetration, measured as mobile-cellular telephone subscriptions per 100 inhabitants in 2002 and  $\text{Internet}_{i,0}$  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:

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

where  $MobileBroadband_{it}$  is mobile broadband penetration rate in country  $i$  at year  $t$ .  $\delta_i$  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  $\beta$  and  $\tau$  are invariable across countries and determine the diffusion speed and the inflection point of the diffusion process, respectively. At the inflection point  $\tau$ , the diffusion curve has its maximum growth rate  $\beta/2$ .  $\varepsilon_t$  is the error term.

## 5.2 First stage results

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.<sup>19</sup> 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  $\delta_i$  in the mobile broadband diffusion curve. The inflection point is determined to be around 2014. 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<sub>2</sub>.

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<sup>19</sup> 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.

Standard errors in the second stage are bootstrapped (500 repetitions) since the independent variable was predicted by the first stage estimation.<sup>20</sup>

*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<sub>2</sub> per capita. Thus, a 10 percentage points increase in mobile broadband intensity causes (if the IV strategy identifies causal effects) the level of CO<sub>2</sub> per capita to decrease by approximately 10 percent. This implies that investing in mobile broadband equipment has important long term negative effects on CO<sub>2</sub> emissions.

It could be argued that countries in similar stages of economic development should be compared. Therefore, *Table 7* also shows the results for high- and low-income countries. The countries have been classified based on gross national income (GNI) (World Bank 2022). Low-income countries have a GNI of \$4095 or below, while high-income countries have a GNI of \$4096 or above.

The results show that, from a statistical perspective, there is a significant negative relationship between mobile broadband penetration and CO<sub>2</sub> per capita for high-income countries. For low-income countries the result based on fixed effects regressions is insignificant. Thus, increase in relative mobile broadband penetration is associated with CO<sub>2</sub> per capita reductions, but this effect is only shown for high-income countries.

## 6. Robustness

This section tests the robustness of our results by including additional data. In our paper mobile broadband intensity is measured as the share of relative mobile connections in total connections. Another way of measuring would be to relate mobile broadband to the population in each country. Column (1) in *table 8* shows that our results remain robust once mobile broadband penetration is measured as mobile broadband connections per 100 inhabitants.

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<sup>20</sup> 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.

The predicted value of mobile broadband penetration may also be correlated with fixed broadband diffusion. To control for this effect we also introduce a variable of fixed broadband. Fixed broadband penetration is measured as fixed broadband subscriptions per 100 inhabitants. According to column (2) in *table 8* the results remain robust at the one percent significance level also when fixed broadband per 100 inhabitants is introduced.

Finally, we also introduce additional variables to test the robustness of our regressions. The control variables are considered important for CO<sub>2</sub> development in the literature. We primarily focus on four different control variables related to CO<sub>2</sub>. These variables are: Population density, the electricity generated from fossil fuel, the share of industry in total GDP and an index measuring the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

Borghesi (2000) argues that the higher population density, the higher pressure on the environmental resources available in a specific area. Hocaoglu and Karanfil (2011) suggest that industrial production is the driving force of CO<sub>2</sub> emissions in G7 countries. Moreover, a large share of CO<sub>2</sub> emissions are emitted from electricity generation through the combustion of fossil fuels to generate heat needed to power steam turbines (Abdallah and El-Shennawy 2013). Gani (2012) argues good governance and stability has a reducing impact on CO<sub>2</sub> emissions.

Column (3) in *table 8* shows that the results remain robust once the four control variables are included in the regression. Finally, the four control variables and fixed broadband are included in the same regression. *Table 8* shows that the magnitude of the mobile broadband penetration variable is reduced to 0.007 and is still significant at the one percent level. Thus, a 10 percentage points increase in mobile broadband penetration causes a 7 percent reduction of CO<sub>2</sub> emissions per capita (given that the instrumental variable strategy, as assumed, identifies causal effects).

## 7. Conclusions

This paper investigates the relationship between relative mobile broadband penetration and carbon dioxide (CO<sub>2</sub>) emissions per capita. The results indicate increased emissions as an initial impact from relative mobile broadband penetration on CO<sub>2</sub> emissions per capita.

Possible explanations might be initial investment in network infrastructure shared by only few users initially and increased consumption of electricity.

As mobile broadband diffuses over time the continuous relationship between mobile broadband and CO<sub>2</sub> 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 fixed broadband and four additional control variables (i.e. population density, electricity consumption from fossil fuel, industry as a share of GDP and a regulation index), we are able to conclude that on average a 10 percentage points increase in mobile broadband penetration causes a 7 percent reduction of CO<sub>2</sub> emissions per capita (if the instrumental variable strategy identifies causal effects)

The results in this paper clearly support the finding that the initial first effects from mobile broadband is driving increments in CO<sub>2</sub> 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<sub>2</sub> emissions per capita. Thus, the results imply that investments in mobile infrastructure over longer periods of time are important in mitigating climate change.

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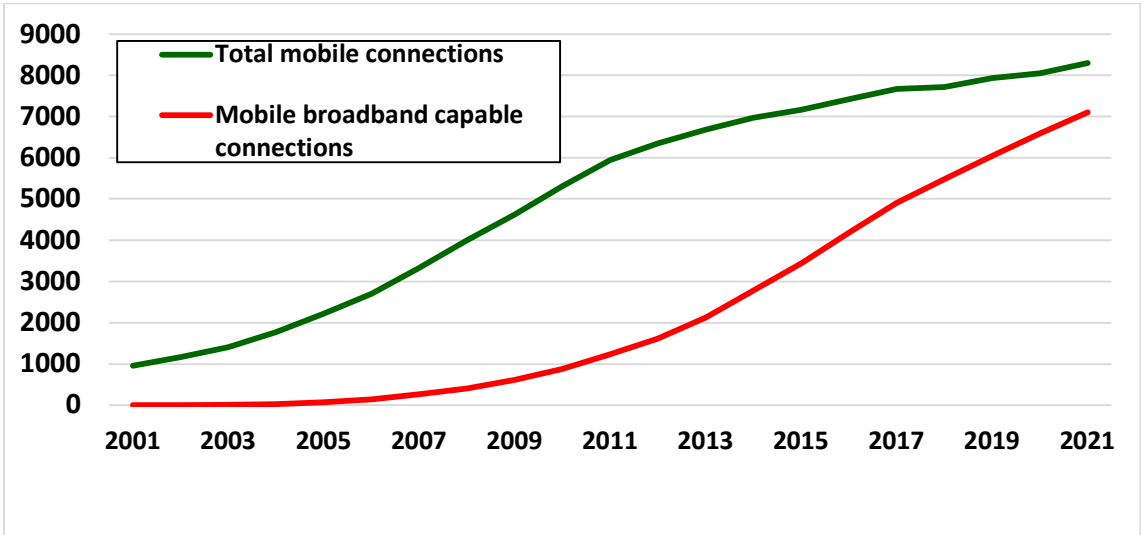
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9. Figures and tables

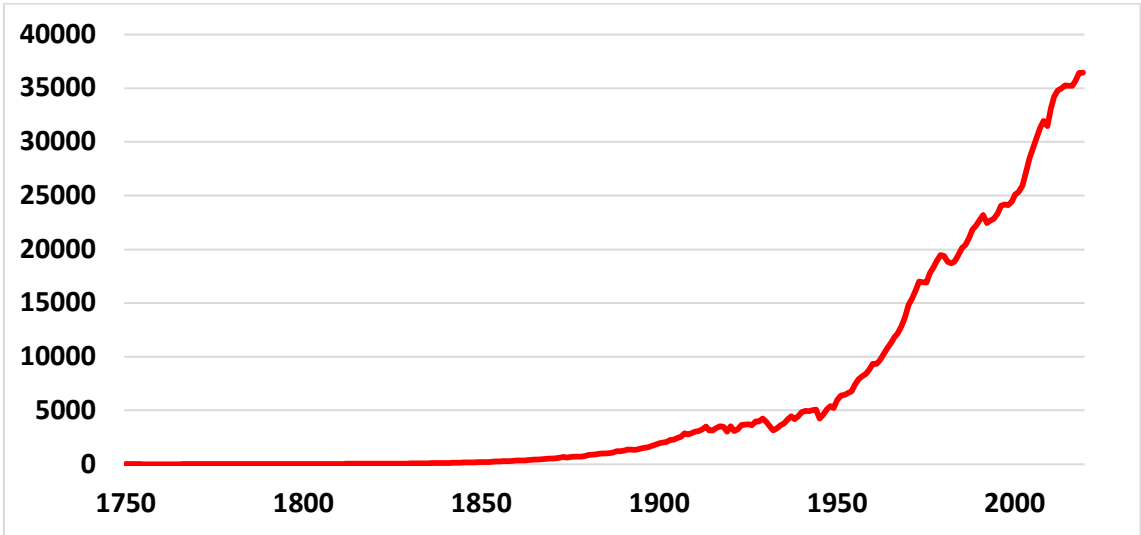
9.1 Figures

**Figure 1**      **Total global mobile and mobile broadband capable connections (in millions) 2001–2021**



Source: GSMA (2022).

**Figure 2**      **Annual production-based CO<sub>2</sub> emissions in the world 1750–2020 (million tonnes per year)**



Source: Our World in Data (2022).

## 9.2 Tables

**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: 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 <sub>2</sub> 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	194	577	2	8045	3439
Electricity consumption from fossil fuel (in percent)	61	34	0	100	3287
Industry (including construction) as a share of GDP	26	11	3	74	2983
Regulation index	0.004	0.93	-3	2	3344

**Table 3 Regressions investigating the introduction of mobile broadband penetration and carbon dioxide (CO<sub>2</sub>) per capita**

	Dependent variable: log CO <sub>2</sub> per capita					
	Pooled regressions			Fixed effects		
Mobile broadband introduction (1%)	-0.08 (0.070)			0.09*** (0.019)		
Mobile broadband introduction (5%)		-0.06 (0.070)			0.06*** (0.018)	
Mobile broadband introduction (10%)			-0.08 (0.066)			0.03* (0.017)
Log of GDP per inhabitant ( <i>lnGDPcap</i> )	1.26*** (0.040)	1.26*** (0.040)	1.26*** (0.040)	0.74*** (0.120)	0.75*** (0.120)	0.76*** (0.120)
Constant	-10.86*** (0.365)	-10.85*** (0.370)	-10.88*** (0.369)	-6.18*** (1.089)	-6.26*** (1.091)	-6.32*** (1.092)
Country fixed effects	No	No	No	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
R <sup>2</sup>	0.85	0.85	0.85	0.28	0.27	0.27
Number of observations	3439	3439	3439	3439	3439	3439

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.

**Table 4 Regressions investigating the relationship between mobile broadband penetration and carbon dioxide (CO<sub>2</sub>) per capita**

	Dependent variable: log CO <sub>2</sub> per capita			
	Pooled regressions		Fixed effects	
Mobile broadband penetration (as percent of total connections) ( <i>MBBpen</i> )	−0.007*** (0.002)	−0.001 (0.002)	−0.0045*** (0.0007)	−0.002 (0.001)
Years since mobile broadband introduction (1%)		−0.02 (0.017)		0.0007 (0.008)
Log GDP per inhabitant ( <i>lnGDPcap</i> )	1.31*** (0.044)	1.28*** (0.040)	0.74*** (0.117)	0.83*** (0.105)
Constant	−11.34*** (0.398)	−11.11*** (0.369)	−6.16*** (1.064)	−6.95*** (0.964)
Country fixed effects	No	No	Yes	Yes
Year dummies	Yes	No	Yes	No
<i>R</i> <sup>2</sup>	0.86	0.85	0.32	0.28
Number of observations	3439	3439	3439	3439

*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<sub>2</sub> per capita ( $\Delta \ln \text{CO}_2 \text{cap}$ ) and the change in mobile broadband penetration based on first, three and five years differences**

	Dependent variable: $\Delta \ln \text{CO}_2$ per capita		
	First differences	Three years differences	Five years differences
$\Delta$ Mobile broadband penetration (as percent of total connections) ( $\Delta \text{MBBpen}$ )	−0.0011** (0.0004)	−0.0017*** (0.0004)	−0.0022*** (0.0005)
$\Delta$ log of GDP per inhabitant ( $\Delta \ln \text{GDPcap}$ )	0.4*** (0.090)	0.60*** (0.094)	0.63*** (0.107)
Constant	0.03*** (0.007)	0.01 (0.013)	0.01 (0.020)
Year dummies	Yes	Yes	Yes
<i>R</i> <sup>2</sup>	0.09	0.13	0.16
Number of observations	3258	2896	2534

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



**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 penetration rate		2.42*** (0.181)	0.55*** (0.119)
Diffusion speed ( $\beta$ )	0.33*** (0.014)	0.32*** (0.016)	0.33*** (0.014)
Inflection point ( $\tau$ )	2014.4*** (0.280)	2014.6*** (0.361)	2014.3*** (0.279)
Constant ( $\theta$ )	53.78*** (2.057)	66.05*** (2.862)	53.61*** (2.029)
$R^2$	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<sub>2</sub> per capita (second stage of the instrumental variable model)**

	Dependent variable: log CO <sub>2</sub> per capita		
	Total sample	High-income	Low-income
Mobile broadband penetration (as percent of total connections) ( <i>MBBpen</i> )	-0.01*** (0.001)	-0.009*** (0.0008)	0.005 (0.014)
Log GDP per inhabitant ( <i>lnGDPcap</i> )	0.65*** (0.136)	0.39*** (0.096)	1.01*** (0.264)
Constant	-5.29*** (1.252)	-2.20** (0.958)	-8.97*** (2.103)
Country fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
$R^2$	0.41	0.43	0.46
Number of observations	2603	1539	1064

*Note:* Fixed effects estimation. Bootstrapped standard errors in parenthesis \*\*\*, \*\*, \* indicate statistical significance at the 1%, 5% and 10% levels, respectively.

**Table 8 Robustness check on the effect of mobile broadband on CO<sub>2</sub> (alternative measure of mobile broadband intensity, fixed broadband and additional control variables)**

	Dependent variable: log CO <sub>2</sub> per capita			
	Fixed effects			
	Other MBB measure	Fixed BB	Additional variables	Fixed BB and additional variables
Mobile broadband penetration (as percent of total connections) ( <i>MBBpen</i> )		−0.008*** (0.001)	−0.008*** (0.001)	−0.007*** (0.001)
Mobile broadband connections per 100 inhabitants ( <i>MBBcap</i> )	−0.006*** (0.0006)			
Log GDP per inhabitant ( <i>lnGDPcap</i> )		0.68*** (0.140)	0.67*** (0.152)	0.66*** (0.177)
Fixed broadband per 100 inhabitant ( <i>FBBcap</i> )		−0.009*** (0.002)		−0.008*** (0.002)
Log of population density ( <i>lnpopden</i> )			0.26** (0.128)	0.23 (0.202)
Electricity consumption from fossil fuel (in percent) ( <i>elffshare</i> )			0.004* (0.002)	0.003 (0.002)
Industry (including construction) as a share of GDP ( <i>indushare</i> )			0.005* (0.003)	0.009** (0.003)
Regulation index ( <i>regind</i> )			0.016 (0.049)	0.068 (0.053)
Constant	−5.16*** (1.248)	−5.21*** (1.348)	−6.99*** (1.711)	−6.53*** (2.362)
Country fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
<i>R</i> <sup>2</sup>	0.41	0.58	0.47	0.63
Number of observations	2603	1444	2242	1292

*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.