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Industrial and Corporate Change, 2025, **00**, 1–26
DOI: https://doi.org/10.1093/icc/dtae043
Original Article

OXFORD

Economic benefits of new broadband network coverage and service adoption: evidence from OECD member states

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A broad-scale rollout and adoption of new broadband networks and services, respectively, are expected to generate innovative services for consumers and create a high potential for productivity increases and economic growth. However, there is no evidence available on the causal impact of both broadband coverage and adoption on economic outcomes, which we measure as gross domestic product (GDP). Moreover, no study has yet simultaneously considered the impact of both new wireline broadband based on fiber-optic technologies and wireless (mobile) broadband based on 3G+/4G technologies. Distinguishing these effects is of crucial relevance for the efficient design of broadband policies. To provide reliable evidence on causal effects, we utilize comprehensive panel data for 32 Organisation for Economic Co-operation and Development (OECD) countries for the years 2002–2020 and panel fixed-effects estimators including instrumental variables estimation. Our results show that both fixed and mobile broadband adoption exert a substantial and significant impact on GDP, while network deployment per se exhibits only minor multiplier-related effects on GDP per capita. Contemporaneous effects of a 1% increase in fixed broadband adoption impact GDP per capita growth in a range of 0.026–0.034%, while a 1% increase in mobile broadband adoption contributes between 0.092% and 0.102%. While the impact of contemporaneous mobile broadband adoption is substantially higher, fixed broadband adoption shows stronger dynamic and cumulative effects, as well as larger effects in later deployment periods. Generally, our results are consistent with the notion that the adoption of technologies to substantial proportions of the population is most important in driving economic growth.

JEL classification: L96, L98, O47

1. Introduction and motivation

In contrast to "old" networks, "new" broadband networks based on fiber-optic technology provide end customers access to much higher-quality connections and can account for the massively growing demand for bandwidth by both firms and private households. Such needs come from new services and applications, such as video streaming or online gaming, and business-specific applications, such as high-quality video conferencing or cloud computing services. In addition, wireline network operators are confronted with an increasing wholesale capacity demand from mobile (wireless) network operators due to the widespread usage of mobile broadband services ("apps").

Like the societal and economic benefits of older broadband networks, the importance of new broadband wireline and wireless networks and corresponding digital services relates to their general-purpose technology (GPT) character (Bresnahan and Trajtenberg, 1995), which promises significant productivity improvements and economic growth across all major economic sectors. Numerous studies exist that provide evidence of the positive impact of old broadband infrastructure on employment, productivity, and economic growth. In a similar vein, the adoption of new and innovative broadband services is expected to induce further process and product innovations. Regarding the latter, digital services already have a massive impact on the social lives of consumers and create substantial amounts of consumer surplus.

The deployment of new broadband networks has, however, also become a major challenge for public policy makers and network providers since the early 2000s. On the supply side, fiber-based broadband network deployment, in particular, is investment-intensive in terms of construction costs related to civil work for digging and laying down fiber-optic cables. Likewise, costs for the rollouts of new mobile broadband networks related to the radio frequency spectrum and network densification are very high. Given the significant costs of deployment, it is unlikely that private investment will be induced by market conditions on a nationwide scale, including areas exhibiting low population densities and hence high average deployment costs. Ubiquitous coverage targets thus typically require public funding that has run into billions of euros in many developed countries in the past (OECD, 2018; Bourreau *et al*. 2020; Briglauer and Grajek, 2024).

In contrast with "old" broadband networks, fiber-based broadband networks are not yet deployed on a nationwide scale; moreover, adoption by customers is even lower. In the case of old broadband, the distinction between coverage and adoption was much less relevant in view of rather high adoption rates (i.e., the ratio between adopted connections to all deployed connections).[1] Even 20 years after the very first deployments of fiber networks, fiber-based broadband connections appear to still be substantially underutilized, as on average the adoption rate in Organisation for Economic Co-operation and Development (OECD) countries is around 60% in 2020. While bad for the economy, these less than 100% adoption rates allow us to disentangle adoption-related effects from infrastructure deployment-related effects. This is important because we find that it is the broad-scale *adoption* and not the mere deployment of new broadband services by businesses and households that increases the welfare and income of consumers, and, on the firms' side, spurs product innovation and productivity in the use of labor and capital. In contrast, for mobile broadband, we observe adoption rates even above 100% in per capita terms since 2005.

Against this background, the aim of this paper is to address the following research questions: (i) What is the causal effect of new broadband network coverage on economic outcomes (gross domestic product, GDP)? (ii) What is the causal effect of the adoption of broadband services on GDP? (iii) What is the incremental role of mobile broadband on economic outcomes?

In answering these research questions, we employ OECD panel data for the years 2002–2020 and panel econometric estimation methods, including instrumental variables. Our results show that fixed and mobile broadband adoption exerts a substantial and significant impact on GDP when controlling for network deployment activities on the supply side, which exhibit only a minor direct effect on GDP. The average impact of mobile broadband appears to be substantially higher than that of fixed broadband during the entire analysis period. This result can be partly attributed to the much higher and faster adoption of mobile broadband services by the vast majority of the population, which translates into higher aggregate GDP effects. Fixed broadband appears, however, to be catching up in the adoption process, resulting in an increasing GDP effect in later adoption periods. These results are generally consistent with the notion that the adoption of technologies is at center stage in the growth process.

Our results entail important policy conclusions. Disentangling the various demand- and supply-side effects has not been analyzed yet in the literature; however, it is of central importance for any related public broadband policies. In particular, our results on broadband adoption versus deployment cast doubt on supply-side only policies that aim solely at increasing the deployment

[1] For instance, Czernich *et al*. (2011) employ a rather broad measure that defines broadband as a connection that enables download speed ≥ 256 kbit/s. As their data includes almost entirely old broadband connections (including only a small number of fiber-based connections at the very end of their period of analysis [1996–2007]), the underlying adoption rates were rather high. Due to such high adoption rates, some authors (e.g., Koutroumpis, 2009, 2019) equate broadband coverage with broadband adoption in their empirical specifications.

of broadband infrastructure, for example, via subsidizing the rollout of fiber-based broadband. Equally, or as we show, even more importantly for growth appears to be the adoption of the new technology—in other words, the eventual adoption by consumers.

The remainder of this article is organized as follows. The second section presents a review of the related empirical literature on the impact of wireline and wireless broadband networks on GDP. The third section outlines our estimation framework and identification strategy. The fourth section characterizes our OECD panel dataset, with a more detailed presentation of our main variables of interest measuring broadband coverage and adoption. The fifth section presents our main estimation results. The sixth and final section summarizes our main findings and outlines the key insights generated by our research for policy makers.

2. Literature review

The study of the economic impacts of broadband Internet has attracted a significant amount of empirical research. Acknowledging this large amount of prior research on the impact of old broadband networks (surveyed in Bertschek *et al.*, 2016), we limit our review to some of the most influential country-level studies that examine the impact on GDP. In view of our research questions, we focus on both the impact of broadband coverage and broadband adoption and then review the available studies using new broadband data in more detail.

The first seminal contribution with country-level data stems from Röller and Waverman (2001), who investigated the impact of telecommunications infrastructure for narrowband wireline connections (public switched telephone networks or PSTNs) on economic growth in 21 OECD countries from 1970 to 1990. Overall, telecommunications infrastructure is estimated to account for about one-third of the annual GDP growth between 1970 and 1990. Utilizing data for 22 OECD countries from 2002 to 2007, Koutroumpis (2009) was among the first authors to examine the relationship between broadband adoption and GDP growth. The author finds a significant positive impact of broadband adoption on GDP, with a 1% percent increase in broadband adoption generating a 0.023% increase in GDP growth. Using annual data from 192 countries over the period 1990–2007, Gruber and Koutroumpis (2011) investigated the contribution of mobile telecommunication infrastructure to economic growth. In low-income countries, the contribution of mobile telecommunications to annual GDP growth is 0.11%, while in high-income countries this contribution is significantly higher, around 0.20%. Thompson and Garbacz (2011) found that mobile broadband had a significant impact on GDP per household, based on cross-country data for 43 different countries from 2005 to 2009. In contrast to Gruber and Koutroumpis (2011), the authors found that the impact of mobile broadband was larger in low-income countries. Czernich *et al.* (2011) employ data for 25 OECD countries from 1996 to 2007 and find that the introduction of wireline broadband contributed between 2.7% and 3.9% to GDP per capita, and a 10.0% increase in the rate of broadband adoption led to a 0.9–1.5% increase in annual growth of GDP per capita. Koutroumpis (2019) utilized data on OECD countries between 2002 and 2016. The author finds that broadband adoption increased GDP by 4.34% on average in the OECD area if broadband adoption increased from 3.8 to 31.3 per 100 people.

Very few studies explicitly include data on new broadband networks (surveyed in Abrardi and Cambini, 2019, and more recently in Briglauer *et al.*, 2024). Briglauer and Gugler (2019) provide the first study assessing the causal impact of fiber-based broadband on GDP controlling for broadband adoption based on old legacy-based connections. The authors employ a panel dataset of EU27 member states for the period 2003–2015. The authors found coefficient estimates for old broadband adoption ranging from 0.015 to 0.026, and a small but significant incremental effect of fiber-based broadband adoption over and above the effects of old broadband adoption on GDP. Their estimates suggest that a 1% increase in fiber-based broadband adoption leads to an incremental increase of about 0.002–0.005% of GDP, which suggests diminishing returns to infrastructural upgrades. The authors, however, neither consider the simultaneous impact of network coverage and adoption nor the role of mobile broadband. In addition, the authors do not consider dynamic effects related to broadband adoption. Edquist *et al.* (2018) are the first to examine the impact of mobile broadband, including mobile technologies (4G/Long-Term Evolution [LTE]) at the end of their analysis period, using country-level data for the years 2002–2014. The authors find that a 1% increase in mobile adoption increases GDP by 0.08% for their entire country panel (90 countries).

Summarizing, the general result of a positive and statistically significant effect of broadband coverage or adoption on either GDP or GDP growth is found at the macrolevel in the older broadband-related literature. However, there is still hardly any evidence available so far regarding the causal impact of fiber-based wireline and mobile broadband on GDP, which is at the core of the international policy debates which implicitly assume large externalities related to modern broadband networks. Our contribution aims to disentangle the underlying effects and mechanisms at the supply and demand sides, as well as contemporaneous and dynamic effects. We also analyze the role of mobile broadband as an alternative broadband technology that has not yet been considered simultaneously. We aim to fill these research gaps to inform the ongoing debate on the design of future policies at the European Union (EU) level and outside Europe.

3. Empirical specification and identification

Section 3.1 first outlines some of the main mechanisms through which broadband coverage and adoption can lead to higher GDP. Note, however, that we cannot test the individual channels, but rather the aggregate impact on GDP by estimating an augmented production function (Section 3.2). Section 3.3 outlines our identification strategy and the sources of exogenous variation we use in our instrumental variable approach.

3.1. Economic impacts of new broadband markets

Deployment of (new) broadband networks affects GDP through different channels.[2] First, there is a direct effect on GDP due to pure investment activities while supplying new network infrastructure as additional employment and economic production are generated and due to related multiplier effects in a way similar to other infrastructure projects without any further socioeconomic ramifications. Second, we expect indirect usage effects related to the actual adoption of new broadband services by residential consumers in their free time through various channels: consumers benefit from broadband adoption via easy and cheap access to, for example, e-health, public administration or banking services, and hotel booking or e-commerce platforms, which all offer great time savings. Moreover, broadband access makes people better informed and provides access to various online job search and education platforms, ultimately leading to higher human capital accumulation and household income. Broadband Internet also enables extensive price comparisons within the shortest possible time, leading to efficient consumption decisions and higher real income for households. The latter also benefit in terms of consumer surplus, defined as the difference between what they would be willing to pay for broadband access and all related digital services and the market price for broadband access. Though new measures of GDP could account for such technological changes as well as other social and economic dimensions of social welfare, they are typically not included in standard accounting measures of GDP.[3] Still, the use of a variety of digital services, such as highly popular search engines, online video content, or other enhanced multimedia applications, including social networks, have most likely led to massive consumer surplus in aggregate terms

[2] For a more detailed discussion of the individual channels, the reader is referred to the survey in Briglauer *et al.* (2024).

[3] As pointed out in Table A1, we use an accounting measure of GDP to proxy social welfare. It is important to acknowledge that a recent stream of the literature, inspired by and surveyed in Jorgenson (2018), supports the need to "go beyond" the standard accounting measures of GDP to really capture societal welfare. For example, Jorgenson (2018) highlights that standard GDP does not include measures of income distribution, such as poverty and inequality. Others, for example, the "High Level Expert Group on the Measurement of Economic Performance and Social Progress" at the OECD, has called for incorporating in a "beyond GDP measure" a comparison across a dashboard of different indicators of development beyond GDP (Stiglitz *et al.*, 2018).

Third, we also have indirect adoption effects on the production side: information and communication technologies (ICT)[4] and (new) broadband networks, in particular, the "C" in ICT, as an infrastructural basis for all applications and services enabling a faster distribution of high volumes of data (e.g., cloud storage and advanced computing) and big data analytics and consequently fosters the acceleration of new ideas, new products, and new business creation. The adoption of broadband technologies within firms also gives rise to productivity gains via more efficient business and information processes, for example, due to better logistics management; new distribution systems; online procurement and reduction in inventories; lower transaction and coordination costs; or better access to labor pools, raw materials, and consumers. Online teleworking tools, such as videoconferencing or virtual private network (VPN) access, enable more flexible and effective ways of working for individual employees and the self-employed. Modern broadband access is also seen as a prerequisite for setting up and managing start-up companies in the digital economy. As broadband technology continuously develops (from xDSL to high-end fiber, from the Universal Mobile Telecommunications System [UMTS] to 5G) and the ecosystem around it grows, the positive impact on the overall economy is expected to be substantial and ongoing, and it is likeliest to further emerge in new fields of business, such as artificial intelligence (AI), machine-to-machine (M2M) communications, and the Internet of Things (IoT). Against this background, ICT is a pervasive technology with inherent potential for productivity gains and innovational complementarities, fulfilling all the essential characteristics of a GPT.

Fourth, another externality recently experienced during the COVID-19 pandemic exists in connection with the economic resilience of modern broadband infrastructure and services in times of a global crisis, when large parts of traditional economic sectors are affected or even shut down by governments. Digital services specifically contribute to maintaining social interaction, work, education, health, and entertainment, as well as the operation of numerous companies and market transactions. Some recent studies (ITU, 2021; Katz and Jung, 2022) provide first evidence on the impact of broadband and digitization during crises. The studies inter alia found that countries with better broadband infrastructure were able to mitigate part of the negative economic impact, allowing households, enterprises, and governments to continue functioning.

3.2. An augmented production function approach

Our methodological approach accounts for the *simultaneous* impacts on GDP of (wireline and wireless) broadband network coverage and service adoption and thus extends the previous literature by explicitly allowing for how different broadband channels impact national economic output (*GDP*).

GDP is first related to the input factors labor (*LABOR*) and capital (*CAPITAL*). Second, national economic output is affected directly by new broadband network coverage at a certain time (*BB_COV*), which, as a GPT, represents another crucial input factor for the whole economy. The growth of the stock of broadband connections during a year is explained by the annual capital investment in new broadband infrastructure in a certain country. Separating the stock of deployed broadband connections, the national production function for country i ($i = 1, \ldots, N$) in period t ($t = 1, \ldots, T$) reads as follows:

$$GDP_{it} = A_{it} F\left(CAPITAL_{it}; LABOR_{it}; BB\_COV_{it}^{j}\right), \tag{1}$$

where supraindex j indicates the type of new broadband (either fixed or mobile) technology ($j = fiber,\ 3G+$).[5] A_{it} represents total factor productivity given the levels of capital, labor, and installed new broadband infrastructure and is considered part of the economic growth that cannot be attributed to changes in observable production inputs but to several unobservable variables affecting overall efficiency. In a neoclassical interpretation, A_{it} is exogenously driven by technical change. In (1), it is assumed that the production function has the same functional form in each

[4] The ICT sector includes relevant broadband network infrastructure, as well as ICT hardware and ICT software and other information services and forms the infrastructural basis for digitization across all sectors of the economy.

[5] 3G+ indicates mobile broadband based on 3G (e.g., UMTS or high-speed downlink packet access [HSDPA]) or higher technology standards, such as 4G (e.g., LTE or WiMAX), see Table A1.

country and is separable in A_{it}. As another starting point, most empirical specifications assume a Cobb–Douglas-type production function (Cardona *et al.*, 2013), where all input factors are weighted by their constant output elasticities.[6] Rewriting equation (1) yields:

$$GDP_{it} = A_{it} CAPITAL_{it}^{\beta_1} LABOR_{it}^{\beta_2} BB\_COV_{it}^{j,\beta_3}, \tag{2}$$

where β_g, $g = 1, \ldots, 3$, represents the output elasticities of capital, labor, and (wireline or wireless) new broadband infrastructure stocks, respectively.

As a separate channel, we further allow for the impact of broadband adoption via total factor productivity. Following Czernich *et al.* (2011), we assume that the technological state evolves according to an exponential growth pattern:

$$A_{it} = A_0 e^{\lambda_i t}, \tag{3}$$

where λ_i is the growth parameter of technological progress in country i, and t is a yearly trend variable; hence, $\lambda_i t$ represents the compound growth rate. As motivated earlier and in the spirit of endogenous growth theory, we explain part of the growth residual A_{it} by assuming that the adoption of (new) broadband connections will impact the growth parameter λ_i by continuously spurring innovation and productivity across all major sectors of the economy. According to this view, the impact of new broadband on growth and productivity is beyond pure capital deepening and input substitution effects due to falling ICT prices and/or the increased quality of ICT products; rather, broadband adoption impacts the growth parameter λ_i via total factor productivity growth in view of the externality effects outlined in Section 3.1. We assume that this channel can be characterized by a simple linear functional form:

$$\lambda_i \mathrm{t} = \alpha_0 + \beta_{\mathrm{k}} \log BB\_ADOP_{it}^{k}, \tag{4}$$

where $BB\_ADOP_{it}^{k}$ represents the cumulative number of customers adopting new broadband connections under a commercial contract in country i in year t; and the supra-index k represents the *mobile* or *fixed* broadband adoption, which includes all old and new broadband technologies during our period of analysis. Note that although new investment activities were focused almost entirely on new wireline (fiber-based) and wireless (above standard 3G) technologies in the last two decades, consumer adoption was related to the use of all broadband technologies, with an increasing share of new broadband technologies during our observation period (Figures 1 and 2).

In contrast with Czernich *et al.* (2011), who almost entirely employed data for old broadband, we use the log of adoption in equation (4), as the more recent broadband-related literature suggests diminishing marginal returns to technological upgrades (Edquist *et al.*, 2018; Briglauer and Gugler, 2019; Koutroumpis, 2019). Taking logs and substituting for $\lambda_i t$ results in a linearized equation (2) that simultaneously captures both broadband channels, adoption and coverage, on GDP and reads as follows (where $\log A_0 + \alpha_0 = \beta_0$):

$$\log GDP_{it} = \beta_0 + \beta_1 \log CAPITAL_{it} + \beta_2 \log LABOR_{it} + \beta_3 \log BB\_COV_{it}^{j} + \beta_{\mathrm{k}} \log BB\_ADOP_{it}^{k} \tag{5}$$

In view of our above discussion, we expect $\beta_{\mathrm{k}} \gg \beta_3$ for all k and j (“adoption hypothesis”). Estimating the impact of coverage and adoption of mobile and fixed broadband technologies separately allows us to examine the individual effects of fixed and mobile broadband technologies. As suggested by Aghion and Howitt (1998, 2009), in order to account for important externalities among input factors in terms of knowledge spillovers from high-skilled individuals (Sianesi and Van Reenen, 2003), we further control for the level of human capital (*EDUC*). The impact of adoption may differ across countries due to different levels of ICT skills, which are partly related to basic and higher education as ICT is a skill-intensive technology (Akerman *et al.*, 2015).

[6] We do not, however, impose any assumptions on returns to scale.

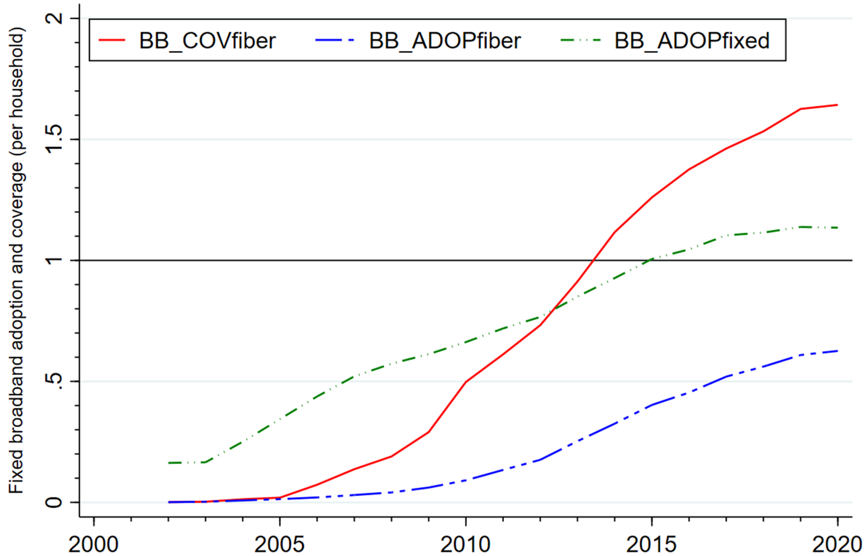

Figure 1. Household-weighted fixed broadband coverage and adoption (OECD mean values).

Finally, GPTs, such as broadband networks, might exert cumulative effects on total factor productivity over time, as well as affect productivity with a lag until, for example, relevant complementary investments in information technologies, organizational resources, or human capital are made. Given this cumulative and lagged impact of ICT (Brynjolfssen and Hitt, 2003), spillover and network effects might also take time to unfold. Following Czernich *et al.* (2011), Edquist *et al.* (2018), and Briglauer *et al.* (2021), we therefore add variables that measure the number of years since broadband has been introduced in a country, denoted by $years\_since\_adop_{it}^{k}$. Specifically, they measure the number of years since new fixed and mobile broadband technologies have been deployed or adopted, respectively, beyond a certain threshold level. The "years since" variables allow us to test the "cumulative hypothesis," as countries at later deployment and adoption stages should experience more product innovations, higher productivity gains, and ultimately, more widespread usage of innovative services by firms and residentials. As an alternative test for the cumulative hypothesis, we also included lags of broadband adoption in equation (4).

Our empirical baseline estimating equation further includes country-fixed effects, α_i, to capture any time-invariant heterogeneity at the country level, as well as year-fixed effects, α_t, to cover common macroeconomic shocks, such as business cycles. The supraindex h distinguishes different levels of education ($h = secondary; higher$), which allows us to test whether ICT skills related to education exhibit increasing or decreasing returns. Our augmented estimating equation finally reads as follows:

$$\log GDP_{it} = \beta_0 + \beta_1 \log CAPITAL_{it} + \beta_2 \log LABOUR_{it} + \beta_3 \log BB\_COV_{it}^{j} + \beta_{\mathrm{k}} \log BB\_ADOP_{it}^{k} + \beta_{\mathrm{h}} \log EDUC_{it}^{h} + \beta_4 years\_adop_{it}^{k} + \alpha_i + \alpha_t + \epsilon_{it} \tag{6}$$

In view of our earlier discussion on the cumulative hypothesis, we expect $\beta_4 > 0$ for all k. The additive error term, ε_{it}, is capturing residual variations between countries and time.

3.3. Identification strategy

Although fixed effects capture unobservable time-invariant heterogeneity in GDP per-capita and absorb a substantial part of deployment and adoption decisions (Akerman *et al.*, 2015), our main variables of interest might still suffer from endogeneity due to simultaneity and omitted variable bias, violating the strict exogeneity assumption underlying the fixed-effects estimator. We identify two sets of potentially endogenous variables. The first set includes capital and labour. As they are the main components of GDP, time-varying unobservable shocks in the labour and capital markets will affect country GDP. The second set of potentially endogenous variables involves our measures of broadband coverage and adoption. Both investment in broadband infrastructure and the demand of broadband services are expected to depend on economic development. Moreover, regulatory interventions in the telecommunication sectors, which would drive both coverage and adoption, may be driven by unobservable shocks related to GDP. The sign of such a potential bias is unknown ex-ante. On the one hand, we expect that positive shocks on aggregate income should foster both investment and adoption, as higher income shifts the demand for broadband services upward. However, regulatory intervention can be countercyclical, acting as an economic stimulus following an economic crisis such as the COVID-19 pandemic. We deal with the endogeneity issue through an instrumental variable approach based on relevant instruments that are not correlated with time-varying shocks affecting GDP. That is, exogenous variables which can be excluded from our augmented production function (equation 6).

In particular, we employ the following sources of exogenous variation: Our first source of plausibly exogenous variation exploits cross-sectional dependence across OECD countries. For each endogenous variable, we construct Hausman-type of instruments, which are a popular choice for identification in industrial economics since the seminal work by Hausman *et al*. (1994). These instruments exploit variation in the respective endogenous variable in "neighborhood" countries. Their relevance comes from the path dependence between closely related countries with similar economies. For instance, a reform of the labor market in country A may provide incentives for a similar intervention in country B. This would affect the labor market in country B without a direct effect on its GDP, thus ensuring validity of the instrument. A similar argument applies for the broadband variables. For instance, the average deployment level in countries with similar economic development exerts pressure on the national politicians of a focal country not to fall too far behind the average development in all other countries (Briglauer and Gugler, 2019).[7] Due to such benchmarking effects, we expect that national broadband deployment is strongly and positively influenced by average broadband coverage and adoption in all other OECD states, and the latter are not impacted by yearly variations in GDP in a focal country. To construct the instruments, we proceed in two steps. First, for each country, we define a set of countries that share similar features from a geographic and development point of view. In particular, we split countries among two broad macro-areas, namely Europe and outside Europe. Within these two macro-areas, we identify countries characterized by a similar level of development by exploiting the distribution of (log-) per-capita GDP in the base year (2002). We allocate countries according to the quartiles of such a distribution, generating additional cross-sectional variation for the construction of the instruments. In essence, we define 4×2 sub-regions of comparable countries. Then, for each endogenous covariate, we construct an instrumental variable as the average of the endogenous covariate in the ("nonfocal") countries that belong to the same sub-region. For instance, the instrument associated with broadband coverage will be defined as the ratio of deployed connections (in the case of fixed broadband) or all active mobile–cellular telephone subscriptions (in the case of mobile broadband) in all other countries (i.e., other than focal country i) to the total number of other countries ($l \neq i$) within the sub-region, denoted by $z = \frac{\sum_{j \neq i}^{n_s} BB\_COV^j}{n_s - 1}$, where n_s is the number of countries in the sub-region.

We complement the aforementioned set of instruments with an additional plausibly exogenous variable related to broadband deployment costs. Such costs crucially depend on population or household density as they exert a massive impact ("economies of density") on average deployment costs. The housing structure in terms of apartments as a share of family homes crucially determines average deployment costs and thus household broadband coverage. The housing structure in terms of the number of households living in apartment dwellings, denoted by

[7] This institutional pressure is reinforced in cases where supra-national broadband targets regarding coverage and adoption exist. In fact, ambitious broadband targets have been implemented in most developed countries and at the EU level. Similar or even more ambitious targets have been defined outside the EU in some East Asian countries and in Australia and New Zealand. Following the Digital Agenda Europe (DAE) objectives for 2020 (European Commission, 2010), the European Commission expressed more ambitious and specific long-term objectives for 2025 in its "gigabit strategy," which shows a strong emphasis on the promotion of modern broadband networks (European Commission, 2016).

Dwelling$_{it}$, determines average deployment costs (Briglauer *et al*., 2021); the more households live in apartments instead of detached houses, the lower the average deployment costs. We argue that housing structure might be impacted by average income levels but not by yearly variations in GDP. In particular, we argue that the housing structure in a given country is predetermined by various path dependencies related to many factors, often determined decades ago, and thus unrelated to GDP or other determinants of broadband coverage or adoption.

Other major cost determinants of broadband deployment, such as costs for civil engineering and network construction, and the costs related to the acquisition of mobile frequencies, are strongly impacted by topographical factors, such as ground conditions and regulations, including rights of way and provisions on network cooperation (FTTH Council Europe, 2012, 2016; Briglauer and Cambini, 2019; Briglauer, et al., 2018) or institutional factors, such as spectrum auction design. These factors either show no or only very low variation over time and are thus largely captured by the fixed effects specific to the investment decision. Furthermore, wireline and wireless broadband infrastructures are subject to rather long investment horizons. Therefore, wireline and wireless broadband infrastructures represent a long-run investment decision based on the expectation of stable market conditions. In view of the above, broadband coverage, while subject to regional fixed effects, may plausibly be considered exogenous. Akerman *et al*. (2015: 1796–1797) conclude as follows: "We find that 84% of the variation in broadband availability can be attributed to time-invariant municipality characteristics and common time effects, while 1% of the variation in broadband availability can be attributed to a large set of time-varying variables."

Finally, we include year-fixed effects to capture common market or relevant industry shocks, such as falling ICT and network equipment prices, which affect all network operators in a similar way. Similarly, adoption can be affected by common shocks such as the introduction of popular online content such as video-on-demand or online games, which are typically available at the same time in most developed countries. Employing the above sets of instruments results in an overidentifying set of instruments $\boldsymbol{Z}_{it}$, which allows us to test the validity of our (subsets of) instruments. If $E(\varepsilon_{it}|\boldsymbol{Z}_{it},\alpha_i)=0$ holds for $t=1,\ldots T$, we can estimate equation (6) consistently with two-stage least squares (2SLS).[8]

4. Data

We employ panel data from 32 OECD member states for the period 2002–2020 for dependent and independent variables with a total number of 608 observations.[9] Note that this period of analysis covers most of the period of fiber deployment and the entire 3G–4G broadband deployment. Mobile broadband started in developed countries in the early 2000s and is now being gradually replaced by the new 5G technology, which was initially introduced in most of the developed countries for the first time in 2020. In constructing our dataset, we use the following sources: first, for our dependent variable, real GDP per capita, we use data from the World Bank (Section 4.1). Second, for the main explanatory independent broadband variables (Section 4.2), we use the database of the FTTH Council Europe, which includes annual numbers of newly deployed and adopted fiber-based broadband connections. Data for old broadband are retrieved from the OECD and Euromonitor. Third, we use the OECD databases "Digital Economy Outlook" and "Economic Outlook," as well as several other datasets, to construct our control and instrumental variables (Sections 4.3 and 4.4). All variable definitions and sources are provided in Table A1, and the summary statistics of all variables are provided in Table A2 in the Appendix.

[8] For the sake of clarity, we drop the subindices in the remainder of the paper.

[9] We do not include all current 37 OECD member states, as we do not have data for Columbia, Lithuania, and Latvia, which joined the OECD in 2020, 2018, and 2016, respectively. Data for variables measuring education are not available for Luxembourg and Iceland, yielding ultimately a total number of 32 countries. We argue that these missing values are not related in any apparent pattern to our dependent or independent variables of interest, but rather to political and institutional decisions. Finally, some 0.85% of all the raw data was calculated using linear interpolation.

4.1. Dependent variable: GDP per capita

Average economic outcome in a particular OECD member state is measured by GDP in constant 2015 USD, which is normalized to total population and denoted by *GDP_pc*. Following our baseline specification in equation (6), GDP per capita is logarithmized, log*(GDP_pc)*.

We acknowledge the imperfect nature of GDP as a measure of the overall benefits of broadband networks considering—for example—that environmental aspects are not factored in. Most likely, it underestimates the true economic effects of broadband networks. GDP is, however, established in the empirical analysis of political relevance and positively correlated with other non-GDP-effective benefits of broadband networks.

4.2. Main explanatory variables: broadband coverage and adoption

Whereas the variable BB_COV^{fiber} measures the cumulative stock of broadband capacity in terms of physical fiber-based connections deployed, BB_ADOP^{fixed} measures the cumulative number of adopting households and businesses that show sufficient willingness to pay for access to old or new broadband services under a commercial contract. Note that in constructing these variables, we include all relevant fiber-based broadband technologies, which either deploy fiber-optic cables directly to the premises of consumers (homes or offices) or partly rely on old copper wire and coaxial cable connections in the remaining segment of the access network ("hybrid fiber"); Table A1 in the Appendix contains further details on relevant fiberization scenarios that fulfill most national targets (OECD, 2018). In contrast to new fiber-based broadband networks, old broadband networks rely on copper or coaxial cable and DSL or cable modem technologies in the entire access network—in other words, from the local exchange to the customer premises. As customers were using both old and new broadband technologies during our period of analysis, the variable BB_ADOP^{fixed} includes all types of old and new wireline broadband technologies. Similarly, the variables BB_COV^{3G+} and BB_ADOP^{mobile} measure the percentage of the population covered by at least a 3G mobile network (3G to 4G) and the number of mobile–cellular telephone subscriptions, respectively. Analogously to wireline broadband variables, our mobile adoption variable includes all relevant mobile broadband technologies (2G to 4G), whereas our mobile coverage variable only includes new investment activities during our period of analysis (3G to 4G).[10] Note that while our fixed broadband variables are household weighted, our mobile broadband variables are expressed on a per capita basis.

Figure 1 shows household-weighted OECD mean values for fiber coverage, BB_COV^{fiber}, fiber adoption, BB_ADO^{fiber}, and wireline broadband adoption, BB_ADOP^{fixed}. Since 2013, for most countries, the parallel household coverage of various fiber-based broadband infrastructures in (sub-)urban areas shows that on average more than one fiber connection is available per household (horizontal line at value one). Despite this fact, ubiquitous coverage of all individual households, as foreseen in (supra-)national broadband targets, is not reached in most countries, which still exhibit low household coverage in rural areas (European Commission, 2022) where average deployment costs are much higher. One can further infer from Figure 1 that the share of fiber-based broadband adoptions in total broadband adoptions increased from 0.0234 at the beginning of broad-scale fiber deployment in 2005 to 0.552 at the end of our period of analysis in 2020. Finally, a comparison of fiber-based adoption, denoted by BB_ADOP^{fiber}, with fiber-based broadband coverage (BB_COV^{fiber}) shows that, on average, far more fiber-based broadband is provided on the supply side than is actually used on the demand side, which gives rise to substantial overcapacities. Only if consumers consider fiber-based broadband services attractive enough in terms of innovations or quality improvements compared with old broadband services will

[10] Note that our mobile broadband coverage and adoption variables also include—next to 2G, 3G, and 4G/LTE technologies—WiMAX (Worldwide Interoperability for Microwave Access), which is another popular wireless communication technology. During our period of analysis, WiMAX provided broadband speeds comparable to old and hybrid-fiber-wired broadband access technologies, making it suitable for popular activities such as streaming video, online gaming, and large file downloads. In contrast, 5G network rollouts are not considered in our analysis, since the first commercial 5G rollouts did not start until 2020 (information available at: http://5gobservatory.eu/wp-content/uploads/2021/01/90013-5G-Observatory-Quarterly-report-10.pdf). Furthermore, we also acknowledge the growing availability and affordability of low-earth-orbit satellite networks for broadband communications. Yet, satellite broadband represented a niche application during our period of analysis and was therefore also not considered in this study.

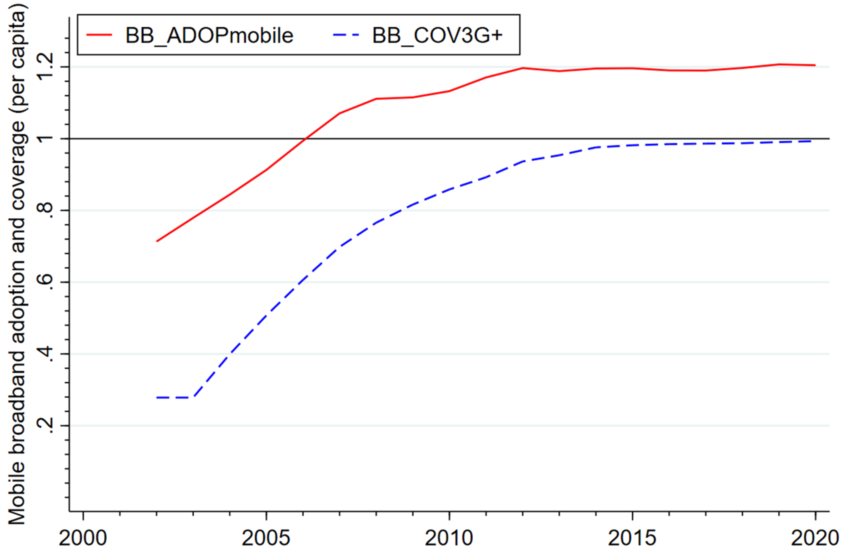

Figure 2. Per capita mobile broadband coverage and adoption (OECD mean values).

they move to fiber-based connections and adopt the new technology. Although fiber adoption rates have been slightly increasing in the last 10 years, they are still below 50% on average with respect to all deployed fiber connections. Adoption rates, however, typically cannot exceed 100%, as households usually do not subscribe to more than one fiber connection, which provides enough bandwidth capacity even in the case of concurrent usage of multiple electronic devices within households. Assuming an upper limit of 100%, the average OECD adoption rate at the end of the observation period was about 63%.

Figure 2 shows the per capita weighted OECD mean values for 3G+ mobile broadband coverage, BB_COV^{3G+}, and mobile broadband adoption, BB_ADOP^{mobile}. When comparing both developments, it appears that—in contrast to fixed broadband—mobile adoption is consistently higher than mobile coverage: first, this observation is due to the existence of multiple (subscriber identity module) SIM cards at a per capita level;[11] second, during the deployment of 3G networks (until 2009/2010), some consumers still used 2G(+) mobile services primarily for narrowband voice and SMS services. Since 2014, almost 100% of consumers have been covered with 3G+ networks on average; above 100% adoption rates in the 2014–2020 period are therefore due to the existence of multiple SIM cards. This relationship appears to be rather constant during the last quarter of our analysis period.

4.3. Production function variables

As our dependent variable is the logarithm of GDP per capita, we also use a logarithmic form for independent variables, as suggested by our baseline specification in equation (6), as well as normalization to have consistent scales (Koutroumpis, 2009, 2019; Czernich *et al.*, 2011). Accordingly, the propensity to accumulate physical capital (*CAPITAL*) is measured by the ratio of the gross fixed capital formation net of telecommunications investment to real GDP. Human capital (*EDUC*) is proxied by the percentage of the population aged ≥15 years with secondary or higher education. The labor variable (*LABOR*) is defined as the total working age (15–64 years) population.[12]

[11] Whereas fixed broadband connections are household related typically providing sufficient bandwidth capacity for all household members, mobile contracts, and SIM cards are related to individuals, typically with multiple SIM cards per household. Note the variable BB_ADOP^{mobile} includes both, prepaid and postpaid SIM cards (Table A1).

[12] As part of our robustness analysis, we also estimate our empirical model using the employment rate instead of the working age population.

4.4. Instrumental variables

The set of instrumental variables $\mathbf{Z}$, as outlined in Section 3.3, comprises internal Hausman-type variables such as $\frac{\sum_{k \neq i}^{n_s} BB\_ADOP^k}{n_s - 1}$ and $\frac{\sum_{j \neq i}^{n_s} BB\_COV^j}{n_s - 1}$, as well as an external instrumental variable measuring average deployment costs (*Dwelling*). Definitions of instrumental variables are provided in Table A1 in the Appendix.

5. Estimation results

Table 1 reports the main regression results for the fixed-effects (FE) specification without mobile adoption and coverage variables, whereas Table 2 includes mobile broadband. Columns (1)–(4) in Table 1 estimates the model *via* OLS, while columns (5)–(8) refer to 2SLS estimates in which log*(LABOR)* and log*(CAPITAL)* are instrumented with their corresponding Hausman-type instrument. Coefficient estimates for the production function input factors labor and capital, log*(LABOR*) and log*(CAPITAL)*, are significant in all regressions and with the expected sign. The magnitude of the coefficients is not significantly affected by the estimation method, thus suggesting that fixed effects absorb most of the heterogeneity across countries and time. Both the first-stage *F*-test and the first-stage results (Table A3) show that our instruments are strong. Moreover, the correlation between the endogenous variables and the Hausman-type of instruments is positive, as one would expect. The Hansen *J*-test reported in Tables 1 and 2 suggest that our instruments are valid. Human capital variables log$(EDUC^{secondary})$ and log$(EDUC^{higher})$ also exhibit a strong and positive correlation with GDP.

The coefficient estimates for our broadband adoption and fiber coverage variables, log(BB_ADOP^{fixed}) and log(BB_COV^{fiber}), respectively, confirm the adoption hypothesis, according to which new broadband investment in terms of fiber deployment on the supply side only exerts a comparatively negligible impact on GDP per capita, whereas the coefficient estimates on broadband adoption not only point to significant but also to substantial effects which are much higher than respective coverage effects. Coefficient estimates of the variable log(BB_ADOP^{fixed}) range from 0.026 to 0.033. Our coefficient estimates thus suggest that a 1% increase in household weighted wireline broadband adoption leads to an increase of GDP per capita by 0.026–0.033%, which corresponds well with the estimates identified in the empirical literature. Briglauer and Gugler (2019) identify adoption-related effects ranging from 0.0152 to 0.0265, but their analysis does not include the years 2016–2020 at a later adoption stage with presumably higher GDP effects.

The regressions in Table 1 vary regarding different specifications to assess dynamic effects related to the cumulative hypothesis. When we include "years since" variables based on a 10% or 20% household adoption threshold, $(years\_since\_adop^{fiber\ 10\%}, years\_since\_adop^{fiber\ 20\%})$, in regressions (2)–(3) and (6)–(7), respectively, we observe that coefficient estimates of our years-since variables are positive and significant.[13] In regressions (4) and (8), adding the years-since variable modestly increases the estimated coefficient from contemporaneous adoption rate.

Table 2 presents the estimation results, including the mobile broadband coverage and adoption variables, log(BB_COV^{3G+}) and log(BB_ADOP^{mobile}), respectively. Regressions (1) and (4) first present the results including only the mobile broadband variables, whereas regressions (2)–(3) and (5)–(6) contain all the wireline and wireless broadband variables. When comparing regression (1) and (2), one can infer that omitting wireline broadband variables yields a slightly overestimated coefficient for mobile broadband adoption (0.092 vs. 0.084). All the regressions point to substantial effects of mobile broadband adoption, log(BB_ADOP^{mobile}), on GDP, which appears to be about three times higher than the effect of wireline broadband adoption and significant at the 1% level in all regressions. Coefficient estimates in Table 2 suggest that a 1% increase in per capita weighted mobile broadband adoption leads to an increase of GDP per capita by 0.084–0.113%, which is in line with Edquist *et al.* (2018), who identify an elasticity value in the amount of 0.08%. The variable measuring mobile network deployment during our period of analysis, log(BB_COV^{3G+}), is often insignificant and with an estimated coefficient close to zero. Both

[13] We further examined alternative threshold values (40%, 50%), finding consistent positive effects that are statistically different from zero, although lower in magnitude.

Table 1. Two-way FE regression results

Dependent variable:	Log of real GDP per capita, log(*GDP_pc*)							
Estimation method:	**OLS**	**OLS**	**OLS**	**OLS**	**IV**	**IV**	**IV**	**IV**
Regression #:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(*CAPITAL*)	0.241***	0.215***	0.207***	0.224***	0.279***	0.192***	0.233***	0.225***
	(0.021)	(0.027)	(0.030)	(0.023)	(0.042)	(0.035)	(0.034)	(0.030)
log(*LABOR*)	0.409***	0.374***	0.417***	0.386***	0.293***	0.396***	0.325***	0.340***
	(0.031)	(0.032)	(0.029)	(0.030)	(0.065)	(0.027)	(0.040)	(0.028)
log(BB_COV^{fiber})	−0.002	0.001*	0.000	0.001	−0.002	0.001*	0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
log(BB_ADOP^{fixed})	0.026***			0.033***	0.026***			0.033***
	(0.009)			(0.010)	(0.007)			(0.010)
$years\_since\_adop^{fiber\ 10\%}$		0.013***		0.015***		0.013***		0.015***
		(0.003)		(0.004)		(0.003)		(0.004)
$years\_since\_adop^{fiber\ 20\%}$			0.009**				0.008**	
			(0.004)				(0.003)	
log($EDUC^{secondary}$)	0.212***	0.364***	0.321***	0.297***	0.236***	0.361***	0.339***	0.309***
	(0.037)	(0.049)	(0.038)	(0.045)	(0.037)	(0.047)	(0.038)	(0.050)
log($EDUC^{high}$)	0.189***	0.272***	0.276***	0.225***	0.201***	0.266***	0.283***	0.226***
	(0.031)	(0.042)	(0.050)	(0.034)	(0.037)	(0.049)	(0.056)	(0.038)
First-stage *F*-test					35.62	34.70	31.65	34.60
P-value Hansen J stat					0.115	0.126	0.130	0.123
Within R^2	0.440	0.465	0.441	0.495	0.436	0.465	0.438	0.494
Observations	608	608	608	608	608	608	608	608

OECD member state-fixed effects and year-fixed effects are included in all regressions. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of spatial dependence (Driscoll and Kraay, 1998).
*$P < 0.10$;
**$P < 0.05$;
***$P < 0.01$.

Table 2. Two-way FE regression results, including mobile broadband

Log of real GDP per capita						
Dependent variable	log(*GDP_pc*)					
Estimation method Regression#	OLS (1)	OLS (2)	OLS (3)	IV (4)	IV (5)	IV (6)
log(*CAPITAL*)	0.237***	0.243***	0.214***	0.241***	0.273***	0.170***
	(0.030)	(0.025)	(0.029)	(0.020)	(0.028)	(0.050)
log(*LABOR*)	0.334***	0.362***	0.356***	0.237***	0.201***	0.314***
	(0.040)	(0.038)	(0.033)	(0.051)	(0.049)	(0.066)
log(BB_COV^{fiber})		−0.002	0.002**		−0.001	0.003***
		(0.002)	(0.001)		(0.002)	(0.001)
log(BB_ADOP^{fixed})		0.025**	0.034***		0.024***	0.032***
		(0.009)	(0.011)		(0.008)	(0.010)
log(*COV_3 G+*)	−0.002***	−0.002***	−0.000	−0.002**	−0.002***	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
log(BB_ADOP^{mobile})	0.092***	0.084***	0.100***	0.102***	0.098***	0.113***
	(0.020)	(0.020)	(0.014)	(0.023)	(0.025)	(0.015)
$years\_since\_adop^{fiber\ 10\%}$			0.014***			0.015***
			(0.003)			(0.004)
$years\_since\_adop^{mobile\ 10\%}$			0.011***			0.012***
			(0.003)			(0.003)
log($EDUC^{secondary}$)	0.282***	0.229***	0.322***	0.296***	0.257***	0.328***
	(0.046)	(0.045)	(0.053)	(0.044)	(0.046)	(0.061)
log($EDUC^{high}$)	0.217***	0.181***	0.184***	0.217***	0.189***	0.171***
	(0.027)	(0.023)	(0.025)	(0.029)	(0.025)	(0.021)
First-stage F-test				11.72	12.08	11.11
P-value Hansen J stat				0.884	0.659	0.125
Within R^2	0.437	0.455	0.525	0.433	0.448	0.518
Observations	608	608	608	608	608	608

OECD member state-fixed effects and year-fixed effects are included in all regressions. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998).
*$P < 0.1$;
**$P < 0.05$;
***$P < 0.01$.

coefficients of wireline and wireless broadband variables thus point to a much larger impact on GDP from broadband adoption, again confirming our hypothesis that broadband induces much higher adoption-related welfare effects than pure investment-related multiplier effects.

As in Table 1, our main estimation results remain robust with regard to alternative specifications of cumulative effects, as the years since variables exhibit a positive relationship with GDP which is significant at the 1% level in all regressions. As shown in Appendix Table A4, adding lagged variables of mobile broadband does not yield meaningful results, as both contemporaneous and lagged adoption are not statistically different from zero (columns [2] and [4]). For fixed broadband adoption (columns [1] and [3]), the lagged coefficient is slightly lower than the contemporaneous and significant only at the 10% level. Taken together, this evidence suggests that alternative specifications of dynamic effects do not bias the results and that the contemporaneous specification appears to be appropriate.[14]

[14] Our fixed effects baseline specification follows the relevant economic literature assessing the role of broadband adoption on economic growth (Koutroumpis, 2009, 2019; Czernich *et al.*, 2011; Briglauer *et al.*, 2021). An alternative empirical approach would be estimating a dynamic model in which the vector of independent variables includes the lag of GDP per capita, thus accounting for past realizations of the dependent variable as determinants of the current level. We performed this exercise by estimating a dynamic panel model with one lag using a two-step Arellano–Bond estimator (Arellano and Bond, 1991; Arellano and Bover, 1995) with endogenous variables. We find that the lagged GDP per capita captures all the variation in the contemporaneous GDP per capita, in such a way that even the main

Table 3. Two-way FE regressions, including mobile broadband for restricted samples

	Log of real GDP per capita							
Dependent variable	log(*GDP_pc*)							
Sample size	2005–2020	2009–2020	2005–2020	2009–2020	2005–2020	2009–2020	2005–2020	2009–2020
Estimation method	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Regression#	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(*CAPITAL*)	0.241***	0.266***	0.244***	0.268***	0.200***	0.303***	0.213***	0.314***
	(0.021)	(0.017)	(0.023)	(0.017)	(0.045)	(0.051)	(0.053)	(0.069)
log(*LABOR*)	0.375***	0.369***	0.343***	0.298***	0.427***	0.276***	0.298***	0.082
	(0.032)	(0.059)	(0.038)	(0.073)	(0.065)	(0.048)	(0.073)	(0.079)
log(BB_COV^{fiber})	−0.002	−0.002	−0.002	−0.003*	−0.002	−0.001**	−0.001	−0.002*
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
log(BB_ADOP^{fixed})	0.055**	0.085***	0.055**	0.095***	0.054**	0.086***	0.053**	0.102***
	(0.021)	(0.018)	(0.022)	(0.018)	(0.021)	(0.020)	(0.023)	(0.023)
log(*COV_3 G+*)			−0.001	0.032*			0.000	0.040*
			(0.001)	(0.016)			(0.001)	(0.019)
log(BB_ADOP^{mobile})			0.067***	0.076**			0.075***	0.086**
			(0.012)	(0.030)			(0.010)	(0.032)
$years\_since\_adop^{fiber}$	0.009***	0.005*	0.009***	0.004	0.010***	0.005**	0.010***	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
log($EDUC^{secondary}$)	0.402***	0.491***	0.417***	0.348***	0.384***	0.531***	0.419***	0.403***
	(0.040)	(0.014)	(0.033)	(0.044)	(0.052)	(0.026)	(0.054)	(0.055)
log($EDUC^{high}$)	0.159***	0.164***	0.165***	0.122***	0.139***	0.189***	0.153***	0.142**
	(0.018)	(0.016)	(0.018)	(0.016)	(0.008)	(0.034)	(0.011)	(0.048)
First-stage *F*-test					15.32	30.90	10.65	27.57
P-value Hansen J stat					0.136	0.191	0.170	0.313
Within R^2	0.516	0.564	0.524	0.580	0.513	0.560	0.519	0.569
Observations	512	384	512	384	512	384	512	384

OECD member state-fixed effects and year-fixed effects are included in all regressions. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998).
*$P < 0.10$;
**$P < 0.05$;
***$P < 0.01$.

Table 4. 2SLS regression results

Dependent variable	Log of real GDP per capita, log(*GDP_pc*)			
Estimation method Regression#	IV (1)	IV (2)	IV (3)	IV (4)
log(*CAPITAL*)	0.207***	0.227***	0.133*	0.203**
	(0.019)	(0.028)	(0.066)	(0.088)
log(*LABOR*)	0.570***	0.349***	0.416***	0.282***
	(0.080)	(0.045)	(0.110)	(0.038)
log(BB_COV^{fiber})	−0.012		−0.010	
	(0.008)		(0.007)	
log(BB_ADOP^{fixed})	0.173***		0.195***	
	(0.051)		(0.044)	
log(*COV_3 G+*)		0.004		0.007
		(0.005)		(0.010)
log(BB_ADOP^{mobile})		0.107***		0.112***
		(0.016)		(0.036)
log($EDUC^{secondary}$)	−0.132	0.159	−0.159	0.121
	(0.208)	(0.115)	(0.202)	(0.138)
log($EDUC^{high}$)	−0.060	0.193***	−0.130	0.176***
	(0.087)	(0.018)	(0.097)	(0.053)
Trend	−0.018	−0.003	−0.026***	−0.004***
	(0.011)	(0.002)	(0.008)	(0.001)
Trend squared	0.001	0.000**	0.001**	0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Instruments for BB variables	YES	YES	YES	YES
Instruments for inputs			YES	YES
First-stage *F*-test	3.565	5.691	12.26	1.174
P-value Hansen J stat	0.234	0.352	0.622	0.469
Within R^2	0.520	0.694	0.506	0.703
Observations	608	608	608	608

All regressions (1)–(4) were based on the 2SLS estimator and include country-fixed effects. However, we had to exclude year-fixed effects in the 2SLS regressions due to the large number of instruments and endogenous variables. However, we control for a linear and quadratic trend term in all regression models. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998).
*$P < 0.10$;
**$P < 0.05$;
***$P < 0.01$.

Table 3 shows the estimation results for restricted periods of analysis. Figure 1 shows that the rollout of fast fiber-based networks has essentially only begun since 2005. In mobile communications, there was also no significant leap in the quality of mobile broadband until 4G from 2009 onward. We therefore examine whether the rollout of new wireline and wireless broadband networks in later periods was accompanied by a larger marginal effect on GDP. For fixed broadband adoption, the estimation coefficients in Table 3 are in the interval (0.055; 0.102) and thus indeed substantially higher than in the respective specifications in Tables 1 and 2 based on the entire observation period 2002–2020. The period 2009–2020 shows higher-size effects than the period 2005–2020 for wireline broadband. Interestingly, we do not find similar results for mobile broadband adoption, which exhibits a similar magnitude for coefficient estimates for the full and restricted observation periods. A comparison of these developments reveals a certain catching-up process in the adoption of fixed broadband compared with mobile broadband services, which started at much higher adoption levels.

Finally, Table 4 reports FE 2SLS estimates that take into consideration the potential endogeneity underlying our broadband adoption and coverage variables. To deal with endogeneity,

determinants of GDP (capital and labor) are not statistically different from zero. Hence, this implies that in our setting, a dynamic specification is inappropriate and cannot lead to reliable results.

we employ geography-based instruments, as described in Section 4.4 as sources of exogenous variation in addition to our variable measuring economies of density in broadband deployment (*Dwelling*). Columns (1)–(2) treat capital and labor as exogenous, while in regressions (3) and (4) inputs are also endogenous variables. First-stage results are reported in Table A5. As can be seen, all instruments are strongly significant and with expected positive sign, with the only exception of log*(COV_3 G+)*. A simple comparison across specifications show that input coefficients are not significantly affected by the estimation method, again suggesting that country FE absorb most of the variation in GDP. Columns (1) and (3) include fixed broadband variables in Table 4. Compared with the results from Table 1, we observe larger point estimates for adoption (+0.13%). On the other hand, the effect from mobile broadband adoption is similar to the one observed in Table 2. A Durbin–Wu–Hausman (DWH) test on the endogeneity of broadband variables (including coverage and adoption, both fixed and mobile) shows that we cannot reject the null hypothesis that these variables can be treated as exogenous (*P*-value > 0.3, not reported for all broadband variables). A similar result is obtained when testing the joint exogeneity of both broadband and input variables (DWH *P*-value > 0.2). Hence, even though the 2SLS coefficient estimates point to a greater marginal impact of broadband on GDP—as in Czernich *et al.* (2011) and Edquist *et al.* (2018)—FE point estimates present consistent and conservative values to which we refer to as our main estimation results in our policy conclusions in the final section.

All in all, both FE and IV estimation strategies point to a much more significant impact on GDP from broadband adoption than coverage and to the existence of dynamic effects as captured by the years since variable. These results are consistent across different specifications, holding true for both mobile and fixed broadband.[15]

6. Summary and conclusions

Our paper investigates the causal relationship between both the coverage and adoption of broadband infrastructures and their impact on economic performance, as assessed by GDP. To date, no empirical analysis has explored the effects of both old and new wireline and wireless broadband access technologies. Discriminating between these channels is, however, essential for crafting effective broadband policies. Our results show that both fixed and mobile broadband adoption by households and firms exert a substantial and significant impact on GDP when controlling for network deployment activities on the supply side. As expected, the latter only induced minor multiplier-related effects on GDP. Contemporaneous estimates for fixed broadband adoption show an impact on GDP per capita from 0.026% to 0.033%, while it ranges from 0.084% to 0.113% for mobile broadband adoption. Our main results regarding coefficient estimates for variables measuring broadband adoption and years since broadband adoption are significant at the 1% level in most regression models. When comparing both types of broadband technologies, the contemporaneous impact of mobile broadband adoption on GDP thus appears to be substantially higher. This result can be attributed to the much higher and faster adoption of mobile broadband services by the vast majority of the population over a much longer period of time, which translates into higher overall GDP effects. The coefficient estimate for mobile broadband adoption may also be influenced by WiMAX technology, which has become a widespread wireless broadband access alternative in several countries. However, only fixed broadband adoption shows increasing importance in later deployment periods (2005/2009–2020), as well as comparatively stronger cumulative and dynamic effects. Coefficient estimates for fixed broadband adoption in the 2009–2020 analysis period point out an impact on GDP per capita in a range between 0.053% and 0.102%. We have shown that our main results—including estimates for the other production function inputs (capital, labor, and human capital)—are robust to varying regression specifications and estimators including instrumental variables estimation. The 2SLS

[15] Another alternative specification would be to include the employment rate as a measure of labor in the empirical equation. We re-estimate the model using the employment rate and report the results in Appendix Table A6. We find no significant change in the coefficients associated with the broadband variables, which still indicate a significant effect of broadband adoption on GDP per capita (and a much smaller effect for broadband coverage). Applying the log transformation to the employment rate does not change the results either, although in this case, we obtain labor coefficients that are too high, especially when we instrument for them (data not reported).

FE results point to higher coefficient estimates for fixed broadband adoption; thus, to remain conservative, we refer to OLS FE estimates for our policy conclusions.

Our findings suggest the following policy implications: First, future public funding measures should not focus only on the supply-side provision of new broadband infrastructure. Because a far greater welfare effect in terms of GDP (and consumer surplus) is achieved through the large-scale demand-side adoption of broadband services, demand-side subsidy programs should also be increasingly promoted in the future. Consumers with a limited willingness to pay for more expensive new broadband connections could, for example, receive public support via vouchers or tax reliefs, closing the gap to the installed stock of fiber connections. Demand-side policies could also be targeted to increase "e-literacy," which indirectly increases the number of consumers ultimately adopting and using new and bandwidth-demanding broadband services. Second, in addition to the benefits of broadband infrastructure and services, which are difficult to measure, particularly in the form of consumer surplus, our results on the years since variable indicate that the full economic benefits of broadband unfold over time when companies have made e.g., complementary investments in organization and ICT skills and when consumers have become familiar with new services and have recognized their related benefits. Accordingly, demand-side policy measures should enhance these adoption processes, which simultaneously mitigate persistent overcapacities on the supply side. At this point, we would like to refer to the European Commission's recently revised guidelines on state aid for broadband networks (European Commission, 2023), which are broadly in line with our main findings and recommendations. In Chapter 6, the Commission discusses various "take-up measures" such as voucher systems. Indeed, dual policy objectives—as found in most (supra-)national broadband plans—recalling Tinbergen's maxim, typically require more than one policy instrument. The Commission guidelines also stipulate that, in addition to efficiency-based arguments related to the supply- and demand-side, other criteria could also be considered in the selection of broadband deployment technologies when granting state aid. For example, Member States could consider criteria pertaining to the climate and environmental performance of broadband networks (European Commission, 2023: para 122).[16] Second, due to the high impact of mobile broadband services on GDP, future funding measures should be designed in a technology-neutral manner and should no longer focus mainly on specific wireline fiber-optic rollout variants.

Whereas almost all public funding programs and related policy evaluations in the past were focused on supply-side stimuli, future research should investigate the effectiveness of different demand-side policies. This finding is further reinforced in view of other disregarded sources of major externalities of new broadband networks, which are difficult to measure and/or not yet considered in the empirical literature, for instance, resilience to shocks, such as the one caused by the COVID-19 pandemic policy measures, as well as consumer surplus related to the use of essential and popular broadband services and applications. Future research should therefore be directed toward quantifying the overall societal impact of broadband services, eventually accounting for a more comprehensive measure of the GDP beyond the standard accounting one. At the same time, it could be worth exploring also the compositional and heterogeneous effects unfolding at the microlevel of broadband coverage and adoption within firms, public administration and at the individual level, which was limited in our analysis due to aggregation.

Acknowledgments

The financial support from the Oesterreichische Nationalbank (Austrian Central Bank, Anniversary Fund, project number: 18736) is gratefully acknowledged. For valuable comments and discussions, the authors would like to thank the participants of the WIFO research seminar (Vienna), the Weizenbaum Institute for the Networked Society (Berlin), and the ITS 32nd European Conference (Madrid). Finally, the authors would like to thank Juan Jung and three

[16] In a recent report by the European Commission (2024: 16), it is reported that "the ICT sector accounts for between 7 and 9% of global electricity consumption (forecast to rise to 13% by 2030), around 3% of global greenhouse gas emissions, and increasing amounts of e-waste. Yet, if properly used and governed, digital technologies can also help cutting global emissions by 15%, outweighing the emissions caused by the sector".

anonymous referees for their valuable comments and insights. The views expressed in this article are those of the authors only and the authors have no competing interests to declare.

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Appendix

Table A1. Variable descriptions and sources

Variable	Description	Source
	Dependent variable	
GDP_pc	GDP in constant 2015 USD per capita. GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources.	World Bank
	Independent variables	
LABOR	The variable is defined as the labor force aged 15–64 years by the total working age (15–64 years) population.	Euromonitor
CAPITAL	Gross capital formation as percentage of GDP consisting of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories, minus capital investment in telecommunications.	World Bank
$EDUC^{secondary}$	Percentage of population aged ≥15 years with secondary education	Euromonitor
$EDUC^{higher}$	Percentage of population aged ≥15 years with higher education	Euromonitor

(continued)

Table A1. (Continued)

Variable	Description	Source
BB_COV^{fiber}	Total number of wireline connections passed by fiber-based technologies (FTTx, Fiber-to-the-x): fiber-to-the home (FTTH) and fiber-to-the building (FTTB), as well as the hybrid fiber technologies fiber-to-the cabinet (FTTC) and fiber-to-the last amplifier (FTTLA), divided by total number of households. One refers to FTTC when very high-speed digital subscriber line (VDSL) technologies are run on a hybrid fiber-based network, which extends to street cabinets and copper lines, which typically cover around several hundred meters from a street cabinet to the customers' premises. FTTLA refers to broadband access enabled by DOCSIS 3.0 technology on hybrid fiber-coaxial cables. "Homes passed" is the total number of premises (a home or place of business), i.e., connections deployed by operators (passed), but not necessarily subscribed by consumers (adopted).	FTTH Council Europe
BB_ADOP^{fixed}	Adoption in terms of the number of subscribed broadband connections under a commercial contract divided by total number of households; it includes connections utilizing fiber-based FTTx technologies, as well as old broadband using xDSL and coaxial cable technologies offering ≥256 kbit/s; it excludes other wired broadband technologies as broadband over powerline or leased lines.	FTTH Council Europe/ OECD
	Independent variables	
BB_ADOP^{fiber}	Adoption in terms of total number of actually subscribed broadband connections utilizing fiber-based FTTx technologies under a commercial contract, divided by total number of households.	FTTH Council Europe
BB_COV^{3G+}	Percentage of population covered by at least a 3G mobile network technology. This includes 3G technologies (e.g., UMTS or HSDPA) or higher technology standards, such as 4G (e.g., LTE/WiMAX).	Euromonitor
BB_ADOP^{mobile}	Total number of cellular mobile subscriptions divided by population; mobile–cellular telephone subscriptions refer to the number of subscriptions to a public mobile-telephone service that provides access to the PSTN using cellular 2G/3G technology. The indicator includes (and is split into) the number of postpaid subscriptions and the number of active prepaid accounts (those that have been used during the last 3 months).	OECD/ITU
$years\_since\_adop^{fiber}$	Number of years passed since adoption of fiber-based (FTTx) connections exceeded 10%/15% of households	FTTH Council Europe/own calculation
$years\_since\_adop^{mobile}$	Number of years passed since adoption of mobile broadband connections exceeded 10%/15% of households	
	Instrumental variables	
Dwelling (internal instrument)	Total number of households living in apartment dwellings.	Euromonitor
z (external instruments)	For each endogenous covariate, we construct an instrumental variable as the average of the endogenous variable in the ("nonfocal") countries that belong to the same sub-region. For instance, the instrument associated with broadband will be defined as the ratio of deployed connections (in the case of fixed broadband) or all active mobile–cellular telephone subscriptions (in the case of mobile broadband) in all other countries (i.e., other than focal country i) to the total number of other countries ($l \neq i$) within the sub-region, denoted by $z = \frac{\sum_{j \neq i}^{n_s} BB\_COV^{j}}{n_s - 1}$, where n_s is the number of countries in the sub-region.	Own calculation

Table A2. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
GDP	608	34,435.95	18,462.73	6,373.13	88,413.19
$CAPITAL$	608	22.26	4.09	9.70	53.42
$LABOR$	608	16,600,000	25,800,000	562.201	147,000 000
BB_COV^{fiber}	608	0.69	0.71	0	2.60
BB_ADOP^{fixed}	608	0.70	0.42	0	2.28
$years\_since\_adop^{fiber\ 10\%}$	608	2.71	3.68	0	17.00
$years\_since\_adop^{fiber\ 20\%}$	608	1.84	3.06	0	16.00
COV_3G+	608	78.25	28.49	0	100.00
BB_ADOP^{mobile}	608	1.08	0.24	0.25	1.72
$EDUC^{secondary}$	608	58.13	11.92	28.10	87.30
$EDUC^{high}$	608	22.81	7.56	8.20	45.30
$Dwelling$	608	51,079.64	235,004.40	170.10	1,577,976
$z^{capital}$	608	22.26	2.69	14.65	30.94
z^{labor}	608	16,600,000	23,700,000	2,422,831	147,000,000
$z^{BB\_ADOP\_fixed}$	608	0.70	0.39	0.01	1.66
$z^{BB\_COV\_fiber}$	608	0.69	0.65	0	2.53
z^{COV_3G+}	608	78.25	27.00	0	100
z^{ADOP_mobile}	608	1.08	0.20	0.31	1.44

Summary statistics of the main variables used in this study. Variables denoted by z refer to Hausman-type instruments as described in Section 4.4.

Table A3. First-stage estimation of Table 1

Endogenous variable:	log(*CAPITAL*) (1)	log(*LABOR*) (2)	log(*CAPITAL*) (3)	log(*LABOR*) (4)	log(*CAPITAL*) (5)	log(*LABOR*) (6)	log(*CAPITAL*) (7)	log(*LABOR*) (8)
$\log(z^{capital})$	0.443***	0.108***	0.422***	0.100***	0.376***	0.112**	0.408***	0.094**
	(0.034)	(0.034)	(0.042)	(0.039)	(0.049)	(0.049)	(0.041)	(0.039)
$\log(z^{labor})$	0.484***	0.521***	0.509***	0.528***	0.586***	0.505***	0.549***	0.546***
	(0.044)	(0.060)	(0.046)	(0.062)	(0.033)	(0.081)	(0.055)	(0.060)
Dwelling	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(BB\_COV^{fiber})$	−0.003**	0.002**	−0.001	0.002**	−0.001	0.002*	−0.001	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\log(BB\_ADOP^{fixed})$	−0.037***	−0.016***					−0.032***	−0.015***
	(0.006)	(0.004)					(0.006)	(0.003)
$years\_since\_adop^{fiber\ 10\%}$			0.013***	0.005***			0.011***	0.004**
			(0.002)	(0.002)			(0.002)	(0.002)
$years\_since\_adop^{fiber\ 20\%}$					0.014***	0.001		
					(0.003)	(0.002)		
$\log(EDUC^{secondary})$	0.100	0.221***	0.091	0.214***	0.078	0.191***	0.148*	0.239***
	(0.076)	(0.056)	(0.087)	(0.068)	(0.097)	(0.065)	(0.080)	(0.067)
$\log(EDUC^{high})$	−0.152	0.068***	−0.176**	0.056***	−0.147**	0.046***	−0.130	0.077***
	(0.106)	(0.017)	(0.088)	(0.013)	(0.073)	(0.011)	(0.100)	(0.014)
Observations	608	608	608	608	608	608	608	608

OECD member state-fixed effects and year-fixed effects are included in all regressions. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998).
*$P < 0.10$;
**$P < 0.05$;
***$P < 0.01$.

Table A4. Assessing dynamic effects

Dependent variable:	Log of real GDP per capita, log(*GDP_pc*)			
Estimation method:	**OLS**	**OLS**	**IV**	**IV**
Regression #:	(1)	(2)	(3)	(4)
log(*CAPITAL*)	0.241***	0.241***	0.271***	0.252***
	(0.020)	(0.031)	(0.047)	(0.024)
log(*LABOR*)	0.428***	0.345***	0.324***	0.241***
	(0.031)	(0.041)	(0.075)	(0.053)
log(BB_COV^{fiber})	−0.002		−0.001	
	(0.002)		(0.002)	
L.log(BB_COV^{fiber})	−0.001		−0.001	
	(0.001)		(0.001)	
log(BB_ADOP^{fixed})	−0.002		−0.001	
	(0.018)		(0.019)	
L.log(BB_ADOP^{fixed})	0.026*		0.024*	
	(0.014)		(0.014)	
log(*COV_3 G+*)		−0.002***		−0.002***
		(0.001)		(0.001)
L.log(*COV_3 G+*)		0.000		0.001
		(0.001)		(0.001)
log(BB_ADOP^{mobile})		0.040		0.037
		(0.059)		(0.062)
L.log(BB_ADOP^{mobile})		0.038		0.051
		(0.066)		(0.069)
log($EDUC^{secondary}$)	0.233***	0.309***	0.260***	0.327***
	(0.040)	(0.051)	(0.032)	(0.038)
log($EDUC^{high}$)	0.160***	0.194***	0.172***	0.196***
	(0.021)	(0.020)	(0.030)	(0.024)
First-stage *F*-test			51.56	13.89
P-value Hansen J stat			0.121	0.800
Within R^2	0.456	0.450	0.453	0.446
Observations	576	576	576	576

OECD member state-fixed effects and year-fixed effects are included in all regressions. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998). The inclusion of lagged variables changes the sample size accordingly.
*$P < 0.10$;
**$P < 0.05$;
***$P < 0.01$.

Table A5. First-stage estimation of Table 4

Endogenous variable:	log(*CAPITAL*) (1)	log(*LABOR*) (2)	log(*BB_COV*^{fiber}) (3)	log(*BB_ADOP*^{fixed}) (4)	log(*CAPITAL*) (5)	log(*LABOR*) (6)	log(*COV_3 G+*) (7)	log(*BB_ADOP*^{mobile}) (8)
log($z^{capital}$)	0.575***	0.131***	−2.724***	0.157	0.552***	0.096***	2.649***	0.021
	(0.028)	(0.032)	(0.841)	(0.187)	(0.023)	(0.024)	(0.858)	(0.071)
log(z^{labor})	0.244***	0.434***	4.861***	0.679***	0.261***	0.345***	5.082***	0.786***
	(0.061)	(0.072)	(1.384)	(0.114)	(0.071)	(0.122)	(1.939)	(0.059)
log($z^{BB\_ADOP\_fixed}$)	0.023	0.021***	−0.475	0.378***				
	(0.021)	(0.003)	(0.291)	(0.098)				
log($z^{BB\_COV\_fiber}$)	0.003**	0.004***	0.666***	0.012				
	(0.001)	(0.001)	(0.039)	(0.013)				
log(z^{COV_3G+})					−0.007***	0.003***	−0.096***	0.016***
					(0.003)	(0.001)	(0.008)	(0.004)
log(z^{ADOP_mobile})					0.123	0.164***	3.132***	0.418***
					(0.079)	(0.026)	(0.774)	(0.046)
Dwelling	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	−0.000*	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(*EDUC*^{secondary})	0.036	0.194***	1.533	2.252***	−0.021	0.092	15.849***	−0.050
	(0.080)	(0.051)	(0.965)	(0.438)	(0.123)	(0.074)	(1.197)	(0.097)
log(*EDUC*^{high})	−0.229**	0.014	1.002*	1.323***	−0.210**	0.037***	3.352***	0.163
	(0.111)	(0.015)	(0.604)	(0.414)	(0.094)	(0.013)	(0.499)	(0.107)
Trend	−0.009	−0.009***	0.550***	0.132***	−0.007	−0.012***	0.071**	0.033***
	(0.006)	(0.003)	(0.068)	(0.023)	(0.008)	(0.002)	(0.036)	(0.004)
Trend squared	0.000	0.000***	−0.018***	−0.006***	0.000	0.001***	−0.007***	−0.002***
	(0.000)	(0.000)	(0.003)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)
Observations	608	608	608	608	608	608	608	608

OECD member state-fixed effects are included in all regressions. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998).
*$P < 0.10$;
**$P < 0.05$;
***$P < 0.01$.

Table A6. Estimation using employment rate

Dependent variable:	**Log of real GDP per capita, log(GDP_pc)**					
Estimation method: **Regression #:**	**OLS (1)**	**OLS (2)**	**OLS (3)**	**IV (4)**	**IV (5)**	**IV (6)**
log(*CAPITAL*)	0.235*** (0.018)	0.203*** (0.021)	0.213*** (0.020)	0.118 (0.127)	0.012 (0.143)	0.063 (0.137)
Employment rate	0.010*** (0.001)	0.012*** (0.001)	0.010*** (0.001)	0.036*** (0.008)	0.039*** (0.008)	0.038*** (0.009)
log(BB_COV^{fiber})	0.001** (0.001)		0.003*** (0.000)	−0.003*** (0.001)		−0.002*** (0.001)
log(BB_ADOP^{fixed})	0.030*** (0.008)		0.031*** (0.008)	0.031*** (0.005)		0.032*** (0.003)
log(*COV_3G+*)		0.001 (0.001)	0.001 (0.001)		0.004* (0.002)	0.003* (0.002)
log(BB_ADOP^{mobile})		0.111*** (0.017)	0.107*** (0.015)		0.047** (0.021)	0.041 (0.028)
$years\_since\_adop^{fiber\ 10\%}$	0.011*** (0.003)		0.010*** (0.003)	−0.002 (0.003)		−0.003 (0.003)
$years\_since\_adop^{mobile\ 10\%}$		0.012*** (0.002)	0.012*** (0.003)		0.014*** (0.002)	0.015*** (0.002)
log($EDUC^{secondary}$)	0.357*** (0.039)	0.370*** (0.024)	0.356*** (0.038)	0.274*** (0.022)	0.345*** (0.047)	0.278*** (0.038)
log($EDUC^{high}$)	0.101*** (0.028)	0.054** (0.021)	0.053** (0.023)	−0.271** (0.102)	−0.311*** (0.100)	−0.346*** (0.114)
First-stage *F*-test				36.61	88.26	30.97
P-value Hansen J stat				0.468	0.412	0.464
Within R^2	0.528	0.519	0.563	0.039	−0.010	0.036
Observations	608	608	608	608	608	608

OECD member state-fixed effects and year-fixed effects are included in all regressions. The robust standard errors are heteroscedasticity consistent, allow for autocorrelation up to lag 10, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998).
*$P < 0.10$;
**$P < 0.05$;
***$P < 0.01$.

Industrial and Corporate Change, 2025, 00, 1–26, DOI: https://doi.org/10.1093/icc/dtae043, Original Article