The Economic Significance of Modern Broadband Internet Infrastructures and Services

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Abstract

A broad-scale rollout and adoption of new high-speed broadband networks and services, respectively, is 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 high-speed 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 new wireless (mobile) broadband based on 3G+/4G technologies. Distinguishing these effects is of crucial relevance for the efficient design of broadband policies. In order to provide reliable evidence on causal effects, we utilize comprehensive panel data for 32 OECD countries for the years 2002–2020 and panel fixed-effects estimators including instrumental variables estimation. Exclusionary restrictions follow from micro-funded determinants of network coverage and consumer adoption decisions. 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 fixed broadband adoption impact GDP per capita growth in a range of 0.026% to 0.034%, while mobile broadband adoption contributes between 0.079% and 0.088%. 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 diffusion of technologies to substantial proportions of the population is most important in driving economic growth. Supporting policies should be technology neutral and should not neglect the demand side.

1 Introduction and motivation

In contrast to "old" networks, "new" high-speed 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 future high-speed 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 high-speed 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 high-speed 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 (Bourreau et al., 2020; OECD, 2018).

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). 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 OECD countries is still well below 100%.[1] While bad for the economy, these less than 100% adoption rates allow us to disentangle adoption-related effects from infrastructure deployment-related effects.[2] 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.

The aim of this paper was to analyze the following research questions: (i) What is the causal effect of high-speed broadband network coverage on economic outcomes (gross domestic product, GDP)? (ii) What is the causal effect of the adoption of high-speed broadband services on gross domestic product (GDP)? (iii) What is the incremental role of mobile broadband on economic outcomes?

In answering these research questions, we employ recent OECD panel data for the years 2002–2020 and panel econometric estimation methods, including instrumental variables, using a simple microeconomic model that outlines exclusionary restrictions. 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 attributed to the much higher and faster adoption of mobile broadband services by the vast majority

[1] In contrast, for mobile broadband, we observe adoption rates even above 100% in per capita terms since 2005.

[2] 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 amount 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 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 diffusion 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 many (supply-side) policies that aim solely at increasing the deployment 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 diffusion of the new technology—in other words, the eventual adoption by consumers. Moreover, in view of our results on the importance of mobile broadband adoption, policies should be technology neutral.

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 high-speed 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 "basic" 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 high-speed broadband data in more detail.

The first seminal contribution with country-level data comes 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 one percent increase in broadband adoption generating a 0.023 percent 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% to 3.9% to GDP per capita, and a 10.0% increase in the rate of broadband adoption led to a 0.9% to 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. The author further finds evidence of diminishing returns to scale and that broadband speed is a moderator of this effect.

Very few studies explicitly include high-speed broadband data (surveyed in Abrardi and Cambini, 2019). Briglauer and Gugler (2019) provide the first study assessing the causal impact of fiber-based broadband on GDP controlling for basic broadband adoption. 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 high-speed 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 macro level in the older broadband-related literature. However, there is still hardly any evidence available so far regarding the causal impact of high-speed broadband on GDP, which is at the core of the international policy debate in most developed countries. Our contribution further 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

3.1 Economic impacts of new broadband markets

Deployment of (high-speed) broadband networks affects GDP through different channels. First, there is a direct effect on GDP due to pure investment activities in the course of 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 socio-economic 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. While not included in GDP, 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.[3]

Third, we also have indirect adoption effects on the production side: information and communication technologies (ICT)[4] and (high-speed) broadband networks, in particular, the "C" in ICT, as an infrastructural basis for all applications and services enable 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. High-speed Internet 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

[3] There are very few empirical studies on this subject. Greenstein and McDevitt (2011) provide evidence on old broadband services using US data, Lee (2022) examines the consumer benefits in smartphone use based on survey data from South Korea.

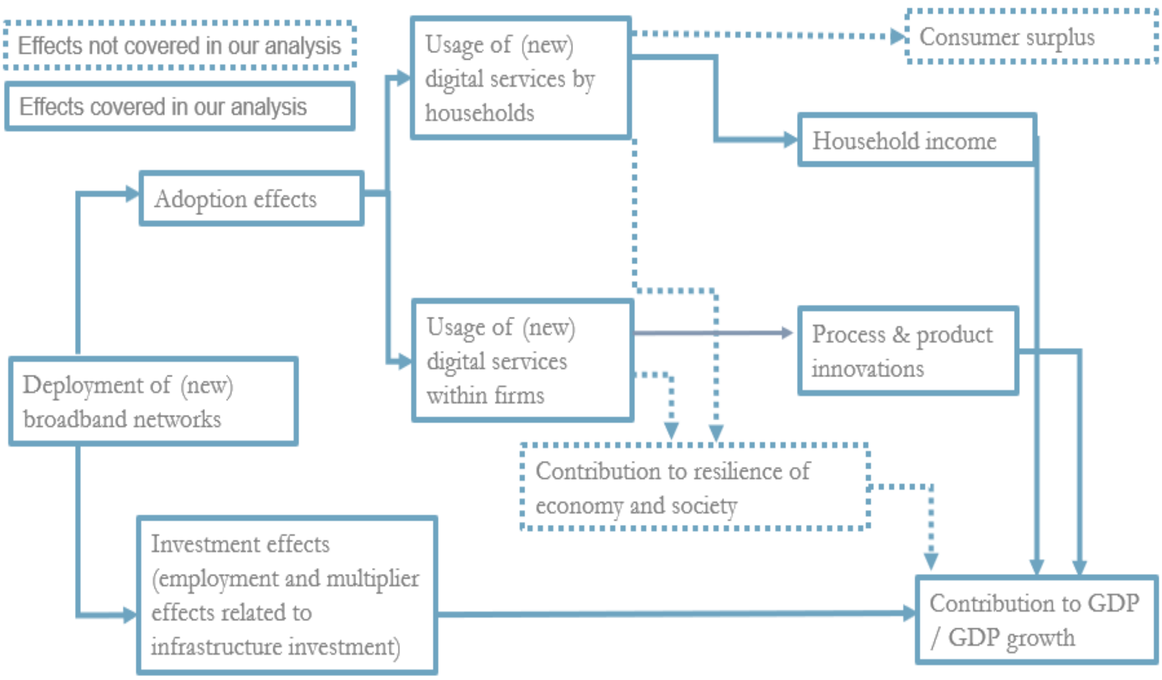
[4] The ICT sector includes relevant broadband network infrastructure, as well as ICT hardware and ICT software and other information services, and forms the infrastructural basis for digitization across all sectors of the economy.

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. A recent study by ITU (2021) provides the first evidence on the impact of broadband and digitization during crises. The study 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.

Adoption-related effects regarding various business and residential usages thus impact on the level of household income, product innovation, and technological progress or total factor productivity and hence ultimately on GDP. Figure 1 illustrates the relevant effects and relationships induced by the deployment of new broadband networks as well as the impact channels that are (not) covered in our empirical analysis.

Figure 1: Economic impacts of (new) broadband networks



Source: Own presentation based on ITU (2012)

3.2 An augmented production function approach

Our methodological approach accounts for the *simultaneous* impacts on the GDP of (wireline and wireless) high-speed 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 high-speed 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 high-speed 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, …, *N*) in period *t* (*t* = 1, …, 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 high-speed 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 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, …, 3, represents the output elasticities of capital, labor, and (wireline or wireless) high-speed broadband infrastructure stocks, respectively.

[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).

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

As a separate channel, we further allowed 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 above and in the spirit of endogenous growth theory, we explain part of the growth residual A_{it} by assuming that the adoption of (high-speed) 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 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 (Figure 2 and 3).

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 (Koutroumpis, 2019; Briglauer & Gugler, 2019; Edquist et al., 2018). Taking logs and substituting for λ_{it} results in a linearized equation (2) that simultaneously captures both broadband channels, adoption and coverage, on GDP reads as follows (where $logA_0 + a_0 = \beta_0$):

$$logGDP_{it} = \beta_0 + \beta_1 logCAPITAL_{it} + \beta_2 logLABOR_{it} + \beta_3 logBB\_COV_{it}^{j} + \beta_{\mathrm{k}} logBB\_ADOP_{it}^{k} \tag{5}$$

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 related to basic and higher education and as ICT is a skill-intensive technology (Akerman et al., 2015).

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 (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 $years\_since\_cov_{it}^{j}$ and $years\_since\_adop_{it}^{k}$. 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:

$$logGDP_{it} = \beta_0 + \beta_1 logCAPITAL_{it} + \beta_2 logLABOUR_{it} + \beta_3 logBB\_COV_{it}^{j} + \beta_k logBB\_ADOP_{it}^{k} + \beta_h logEDUC_{it}^{h} + \beta_4 years\_adop_{it}^{k} + \alpha_i + \alpha_t + \epsilon_{it} \tag{6}$$

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

3.3 Coverage and adoption equations

Although fixed effects capture a substantial part of deployment and adoption decisions (Akerman et al., 2015), our broadband variables might still suffer from potential endogeneity due to simultaneity and omitted variable bias, which violates the strict exogeneity assumption underlying the fixed-effects estimator, in other words, $E(\varepsilon_{it}|X_{it}, \alpha_i, \alpha_t) \neq 0$ for $t = 1,\ldots T$, with $\boldsymbol{X}_{it}$ representing the vector of our explanatory variables in equation (6). In order to endogenize network coverage and consumer adoption decisions, we define simple micro models of both coverage (supply) and adoption (demand). Exclusionary restrictions then follow from these equations.

Determinants of network coverage

Coverage of high-speed broadband networks depends on (i) macroeconomic conditions, (ii) variables related to broadband market structure, (iii) broadband policies, and (iv) benchmarking variables. We extend the empirical specifications in Koutroumpis (2009, 2019) and Röller and Waverman (2001) by modeling a stylized representation of the supply side for fixed and mobile broadband deployment as follows:

$$log(BB\_COV_{it}^{j}) = f(ir_{it}, eco\_fr_{it}, Rev_{it-1}, P_{it}, \boldsymbol{W}_{it}, state\_aid_{it}, \frac{\sum_{l\neq i}^{n} BB\_COV^{j}}{n-1}, \boldsymbol{Z}_{it}, \alpha_i^{COV}), \tag{7}$$

where high-speed broadband network coverage in country i and in year t depends on a number of factors. First, macroeconomic investment conditions are proxied by the long-run interest rate (ir_{it}) and indices measuring the degree of economic freedom (eco_fr_{it}).

Second, there are market structural variables that include the firm's previous sales per connection, Rev_{it-1} (i.e., firm total revenues divided by the number of old broadband technology connections), to account for the traditional acceleration principle, which links the demand for capital goods to demand growth (Hubbard, 1988); the average fiber broadband price level (P_{it}), which captures expected revenues; and infrastructure-based competition in broadband markets measured by the vector $\boldsymbol{W}_{it}$ with two variables controlling for competition stemming from old mobile networks and old wireline broadband networks. We measure the former with the share of the total number of mobile-cellular subscriptions to the total number of mobile-cellular telephone subscriptions and the total number of active fixed broadband subscriptions offering ≥256 kbit/s. We measure the latter as the share of cable subscriptions relative to total basic broadband subscriptions offering ≥256 kbit/s. We argue that the market structure related to old broadband markets does affect new broadband market structures due to legacy-related path dependencies (Briglauer et al., 2018; Czernich et al., 2011) and hence also investment and adoption decisions of network operators and consumers, respectively. At the same time, the (old) broadband market structure is not impacted by variations in GDP.

Third, there are governmental policies aimed at enhancing new infrastructure deployments by funding policies to accrue externalities. Indeed, in most OECD countries, national and/or local governments have already provided substantial public funds in combination with setting broadband targets (Bourreau et al., 2020; OECD, 2018) to expand the fiber-based broadband infrastructure. The decision to provide public funds for new broadband networks might, however, depend on the past, current, or expected stock of fiber-based network coverage or on economic development levels. For this reason, we measure state aid for high-speed broadband network deployment by public funding for old broadband networks ($state\_aid_{it}$). Clearly, governments that were inclined to fund old broadband infrastructure should also be prone to fund new broadband networks.

Fourth, we add benchmarking variables that capture the state of broadband deployment and adoption in all other ("non-focal") OECD countries. It is 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 ($l \neq i$), denoted by $\frac{\sum_{l \neq i}^{n} BB\_COV^{j}}{n-1}$. 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). This institutional pressure is reinforced in cases where supra-national broadband targets in regards to 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 high-speed broadband networks (European Commission, 2016).[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 addition, $\boldsymbol{Z}_{it}$ represents a vector of cost-shifters that show some, albeit small, variation over time, such as housing structure variables. Deployment costs crucially depend on population or household density, as they exert a massive impact on average deployment costs ("economies of density"). The housing structure in terms of the number of households living in apartment dwellings divided by all households, denoted by $dwelling_{it}$, 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. 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) 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 (α_i^{COV}). 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.

[7] In the meantime, many EU member states have recently revised their national broadband targets accordingly. For instance, in its gigabit strategy, the European Commission explicitly acknowledges as a great success of the former broadband targets that "[a]t national level, setting objectives has become the cornerstone of broadband deployment public policy. … Many member states have indeed aligned their national or regional NGN [next generation networks] plans to the DAE speeds" (European Commission, 2016, p. 31).

Determinants of service adoption

The micro-founded determinants of demand for broadband connections are related to (i) prices, (ii) household communications budgets, (iii) ICT preferences of households, and (iv) available online content. Similar to the coverage equation, we also consider (v) variables measuring benchmarking effects:

$$BB\_ADOP_{it}^{k} = h\left(\boldsymbol{P}_{it}, EXP_{it}, \boldsymbol{Y}_{it}, \boldsymbol{C}_{it}, \frac{\sum_{j\neq i}^{n} BB\_ADOP^{k}}{n-1}, \alpha_{i}^{ADOP}\right) \tag{8}$$

The adoption of wireline and wireless broadband connections ($BB\_ADOP_{it}^{k}$) is a function of the average own price of broadband connections and related substitutes, measured by the vector $\boldsymbol{P}_{it}$ and consumer expenditure on communications services per household (EXP_{it}) capturing the income effects. The ICT affinity of people in a country is represented by the vector $\boldsymbol{Y}_{it}$, representing the consumer´s taste and preferences for ICT-related services. The vector $\boldsymbol{C}_{it}$ measures the online content provided to consumers. We control for the market entrance of Netflix, $netflix_{it}$. Video streaming services represent more than 70% of global Internet download traffic and are expected to grow to about 82% of annual global consumer Internet traffic by 2022 (Cisco, 2019). As one of the most well-known streaming services, Netflix had a market share of around 50% in streaming services at the end of our observation period.[8] We argue that although Netflix's initial market entrance decision might be impacted by average income levels, it is not impacted by yearly variations in GDP. Finally, equation (9) includes a variable measuring average broadband adoption in all other OECD countries ($\frac{\sum_{l\neq i}^{n} BB\_ADOP^{k}}{n-1}$), as well as country fixed effects (α_{i}^{ADOP}). The latter are meant to capture any time-invariant factors of consumer preferences within a country, such as determinants of ICT affinity, which show no or only slow-moving changes in consumers' preferences.

The system of equations (6)–(8) can be estimated jointly using three-stage least squares (3SLS), which provides more efficient estimates, in principle, by exploiting information on the contemporaneous correlation of error terms. In contrast to Röller and Waverman (2001) and Koutroumpis (2009), we do not

[8] Information available at: https://www.bloomberg.com/news/newsletters/2021-04-18/netflix-is-losing-market-share-but-is-it-losing-customers.

pursue this estimation strategy for the following reasons: first, in case of heteroscedastic errors,[9] 3SLS becomes inconsistent (Cameron and Trivedi, 2009, p. 207); second, we do not have OECD panel data on fiber-based or mobile broadband prices, as broadband markets are characterized by a very high degree of price differentiation and selecting individual data on tariff schedules appears to be arbitrary;[10] third, fiber-based broadband markets are not in equilibrium as fiber coverage clearly exceeds the adoption of fiber-based broadband services in almost all OECD states during the entire period of analysis (Figure 2).

Valid instruments come from exogenous variables in equations (7) and (8), which can be excluded from our augmented production function (equation 6). In view of the above discussion, we consider all variables related to broadband competition ($\boldsymbol{W}_{it}$) and policy ($state\_aid_{it}$), benchmarking variables, $\frac{\sum_{l \neq i}^{n} BB\_ADOP^{k}}{n-1}$ and $\frac{\sum_{l \neq i}^{n} BB\_COV^{j}}{n-1}$, as well as variables measuring average deployment costs and online content ($dwelling_{it}$; $netflix_{it}$) as excluded instruments, which can be expected to exert no other impact on national GDP and are also not affected directly by changes in GDP. This results in an overidentifying set of instruments $\boldsymbol{Z}_{it}$ also 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).[11]

[9] Tests for cross-sectional correlation in the fixed effects model indicate the presence of heteroscedasticity.

[10] Due to this data limitation, some authors, including Röller and Waverman (2001) and Koutoumpis (2009), refer to measures of average revenues per user (ARPU) as a proxy variable. Relating average revenues to fiber connections, however, introduces other methodological concerns as regards simultaneity bias and the interpretation of marginal effects.

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

4 Data

We employ panel data from 32 OECD member states for the period 2002–2020 for dependent and independent variables with a maximum number of observations of 608.[12] Note that this period of analysis covers the entire period of fiber and 3G+ broadband deployment, which started in developed countries in the early 2000s. 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 A.1, and the summary statistics of all variables are provided in Table A.2 in the Appendix.

4.1 Dependent variable: GDP per capita

Average economic outcome in a particular OECD member state is measured by gross domestic product (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. Most likely, it underestimates the true effects of broadband networks (Figure 1). GDP is, however, established in the empirical analysis of political relevance and positively correlated with other non-GDP-effective benefits of broadband networks.

[12] 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 percent of all the raw data was calculated using linear interpolation.

4.2 Main explanatory variables: Broadband coverage and adoption

Whereas the variable BB_COV^{fiber} measures the real stock of broadband capacity in terms of physical fiber connections deployed, BB_ADOP^{fixed} measures the number of actual adopting households and businesses that show sufficient willingness to pay for access to old or new broadband services. 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 A.1 in the Appendix contains further details on relevant fiberization scenarios that enable at least 100 Mbit/s as requested by the EU and 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. The variables BB_COV^{3G+} and BB_ADOP^{mobile} measure the percentage of the population covered by at least a 3G mobile network (3G+) 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).[13]

Figure 2 shows household-weighted OECD mean values for fiber coverage, BB_COV^{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 even still in 2021 exhibit low household coverage in rural areas (European Commission, 2022) where average deployment costs are much higher. One can further infer from Figure 2

[13] Note that 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).

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 they move to fiber-based connections and adopt the new technology. Although fiber adoption rates have been slightly increasing in the last ten 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 3 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;[14] 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.

[14] Note that 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, pre-paid and post-paid SIM cards (Table A.1).

Figure 2: Household weighted fixed broadband coverage and adoption (OECD mean values)

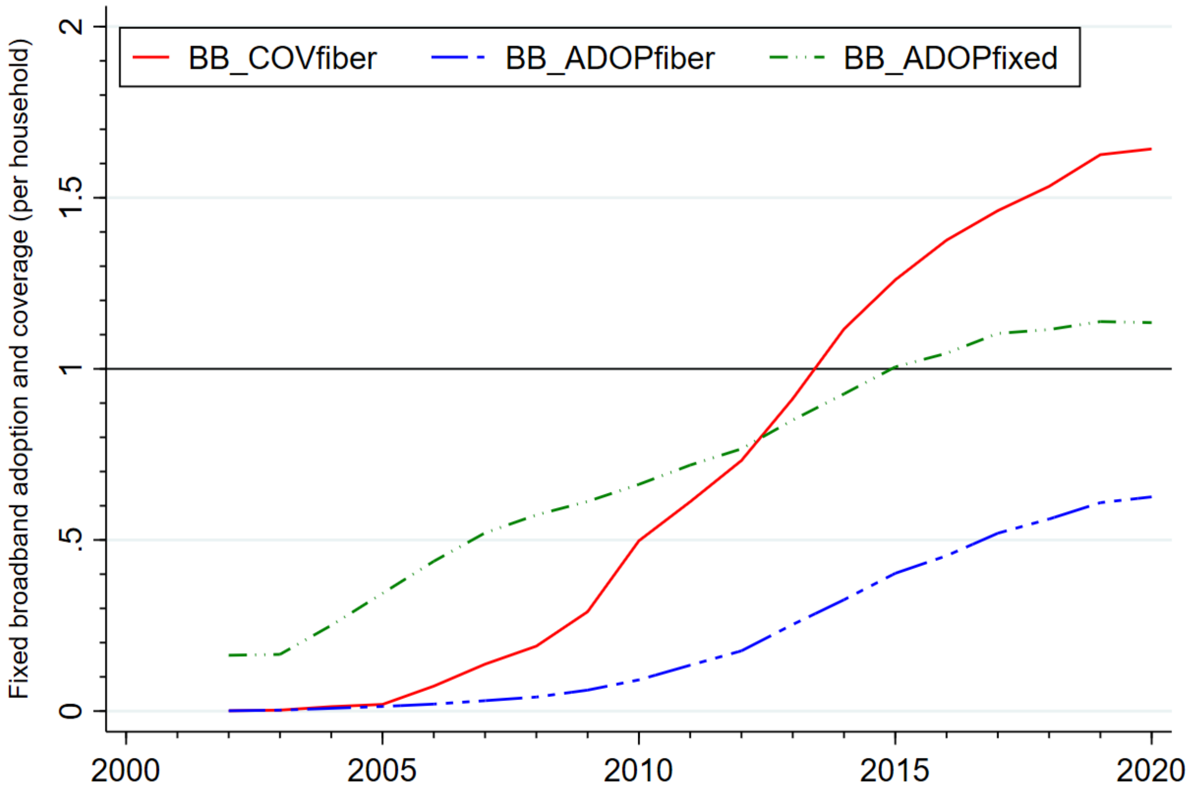
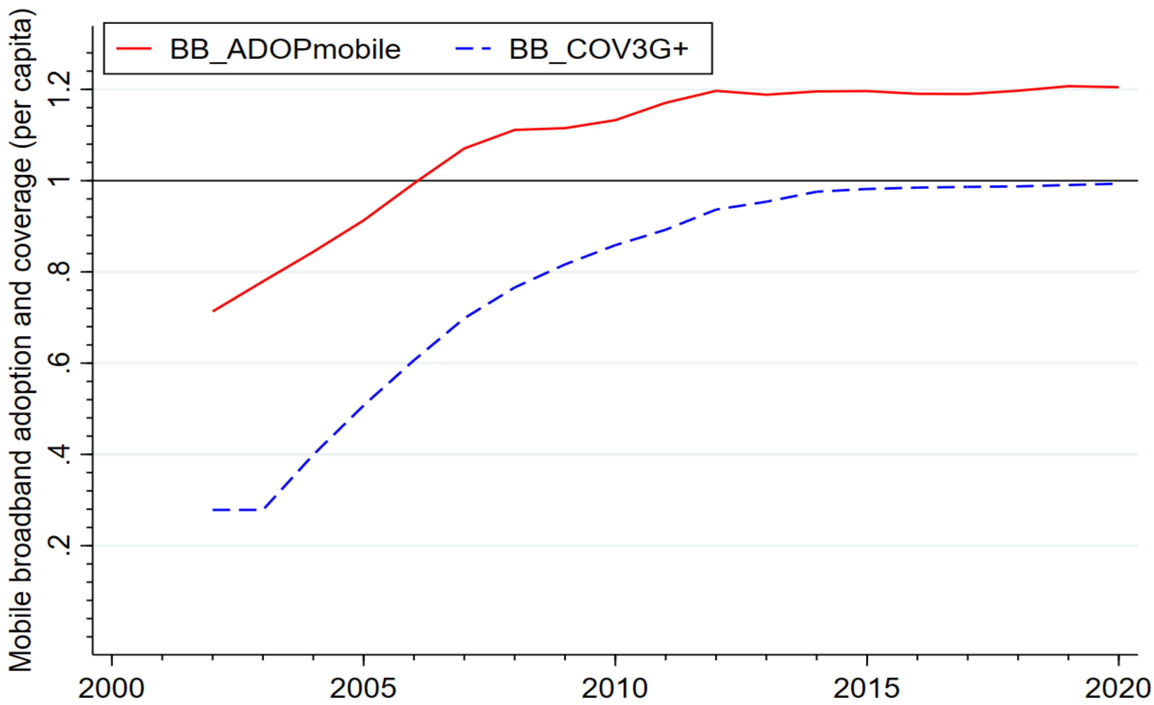


Figure 3: Per capita mobile broadband coverage and adoption (OECD mean values)



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 (Czernich et al., 2011; Koutroumpis, 2009, 2019). 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+ with secondary or higher education. The labor variable (*LABOR*) is defined as the labor force participation rate, which is calculated by dividing the labor force aged 15–64 years by the total working age (15–64 years) population.

4.4 Instrumental variables

The set of instrumental variables $\boldsymbol{Z}$, as outlined in Section 3.3, comprises wireline and wireless broadband competition and policy variables (*comp_fixed; comp_mobile*; *state_aid*), benchmarking variables, $\frac{\sum_{l\neq i}^{n} BB\_ADOP^{k}}{n-1}$ and $\frac{\sum_{l\neq i}^{n} BB\_COV^{j}}{n-1}$, as well as variables measuring average deployment costs (*dwelling*) and online content (*netflix*). Note that our instrumental variables measuring competition and state aid policies are related to old broadband connections offering at least 256 kbit/s and hence represent a type of "low-tech" variable. Detailed definitions of instrumental variables are provided in Table A.1 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. Coefficient estimates for the production function input factors labor and capital, *log(LABOR)* and *log(CAPITAL)*, are significant in all regressions. Human capital variables *log*($EDUC^{secondary}$) and *log*($EDUC^{higher}$) also exhibit a strong impact on GDP, but it appears that secondary education is far more important for acquiring the necessary ICT skills for vast proportions of the population than higher education and hence more advanced ICT skills for a comparatively smaller population group. Taking into account all controls, along with country and year fixed effects, our two-way FE estimation specifications in Table 1 to Table 2 explain about 75%–81% of the total within variation.

The regressions in Table 1 vary with regard to different specifications to assess dynamic effects related to the cumulative hypothesis. Whereas we include different "years since" variables based on a 10% household adoption threshold, *years_since_adop*^{fiber}*(10%)*, in regressions (1) and (3), we allow for a 15% threshold, *years_since_adop*^{fiber}*(15%)*, in regression (4). As expected, all the coefficient estimates of our years-since variables are positive and significant. In regression (2), we add a lagged term, *L.log(BB_ADOP*^{fixed}*)*, and drop the years-since variable. The coefficient estimate of the lagged broadband variable is significant and shows the same magnitude as the contemporaneous effect in the other regressions; all specifications provide evidence for the cumulative hypothesis. In regression (5), we dropped the years-since variable, which does not impact the other coefficient estimates.

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 small impact on GDP per capita, whereas the coefficient estimates on broadband adoption not only point to significant but also to substantial effects. Coefficient estimates of the variable *log(BB_ADOP*^{fixed}*)* range from 0.027 to 0.033.[15] Our coefficient estimates thus suggest that a 1% increase in household weighted wireline broadband adoption leads to an increase of GDP per capita by 0.027% to 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 coefficient estimate on the years-since variable in regression (1) suggests that the contemporaneous GDP effect almost doubled in three years after broadband adoption passed the 10% household threshold, which points to very strong dynamic and cumulative adoption effects.

[15] In regression (2), we add coefficients for the contemporaneous and lagged effects.

Table 1: Two-way FE regression results

Dependent variable:	Log of real GDP per capita, *log(GDP_pc)*				
Regression #:	(1)	(2)	(3)	(4)	(5)
log(CAPITAL)	0.218***	0.215***	0.205***	0.216***	0.220***
	(9.22)	(7.83)	(9.13)	(8.97)	(8.11)
log(LABOR)	0.752***	0.817***	0.754***	0.794***	0.827***
	(10.14)	(7.77)	(10.48)	(9.30)	(8.08)
log(EDUC^secondary^)	0.334***	0.277***	0.394***	0.304***	0.270***
	(9.26)	(8.53)	(14.41)	(10.40)	(9.11)
log(EDUC^higher^)	0.078**	-0.000	0.122**	0.063*	0.033
	(2.49)	(-0.02)	(2.69)	(1.87)	(1.21)
log(BB_COV^fiber^)	0.002	0.001	0.001	0.002	0.002
	(1.21)	(1.18)	(0.53)	(1.25)	(1.15)
log(BB_ADOP^fixed^)	0.033***	-0.007		0.030***	0.027***
	(4.67)	(-0.81)		(5.24)	(6.47)
L.log(BB_ADOP^fixed^)		0.030***			
		(3.02)			
years_since_adop^fiber^(10%)	0.010***		0.008***		
	(3.29)		(4.05)		
years_since_adop^fiber^(15%)				0.006*	
				(1.91)	
constant	8.327***	0.000	7.922***	8.507***	8.718***
	(47.41)	(.)	(41.50)	(52.36)	(45.63)
R2 within	0.783	0.761	0.769	0.773	0.769
F-Test	584.034	12166.974	1119.990	370.104	776.309
#Countries	32	32	32	32	32
#Observations	608	576	608	608	608

Notes: 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 4, and are robust to very general forms of spatial dependence (Driscoll and Kraay, 1998). Inclusion of the lagged variable *L.log(BB_ADOP^fixed^)* in regression (2) reduces the sample size accordingly. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 2 presents the estimation results, including the mobile broadband coverage and adoption variables, *log(BB_COV^3G+^)* and *log(BB_ADOP^mobile^)*, respectively. Regression (1) first presents the results, including only the mobile broadband variables, whereas regressions (2) to (7) contain all the wireline and wireless broadband variables. When comparing regression (1) and (2), one can infer that omitting wireline broadband variables does not yield an overestimated coefficient for mobile broadband adoption. Economically, this result suggests that wireline and wireless broadband services are used complementarily by consumers. All the regressions, except for regression (3), which includes the lagged variable specification, *L.log(BB_ADOP^mobile^)*, point to substantial effects of mobile broadband adoption on GDP, which appears to be about three times higher than the effect of wireline broadband adoption. 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 0.079% to 0.088%, which is in line with Edquist et al. (2018), who identify an elasticity value in the amount of 0.08%. The variable measuring new mobile network deployment during our period of analysis, *log(BB_COV^3G+^)*, is either insignificant or much lower than the coefficient estimate of the variable measuring mobile broadband adoption, *log(BB_ADOP^mobile^)*. Both coefficients of wireline and wireless broadband coverage variables thus point to a much lower impact on GDP than the respective coefficients of broadband adoption variables, again confirming our hypothesis that broadband induces much higher adoption-related welfare effects than pure investment-related multiplier effects.

As shown in Table 1, regressions (1) to (7) vary regarding the specification of cumulative effects, including the lag of mobile adoption in regression (3) and variables measuring the number of years since wireline or wireless broadband has been deployed and adopted. As can be inferred from Table 2, our main estimation results remain robust with regard to these alternative specifications of dynamic and cumulative effects, and the years since variables again exhibit—when significant—a positive impact on GDP. The coefficient estimate of the years-since variable in regression (4), $years\_since\_cov^{mobile}(20\%)$, suggests that the contemporaneous GDP effect doubled about nine years after broadband introduction.

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 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 (0.040; 0.062) and thus indeed substantially higher than in the respective specifications in Table 1 and Table **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.

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

Dependent variable:	Log of real GDP per capita, *log(GDP_pc)*						
Regression #:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(CAPITAL)	0.199***	0.214***	0.213***	0.213***	0.218***	0.212***	0.208***
	(6.43)	(6.88)	(7.50)	(8.00)	(8.22)	(7.81)	(7.06)
log(LABOR)	0.780***	0.786***	0.671***	0.728***	0.683***	0.737***	0.803***
	(7.90)	(7.32)	(8.96)	(8.82)	(9.31)	(8.81)	(8.53)
$log(EDUC^{secondary})$	0.308***	0.267***	0.357***	0.300***	0.332***	0.299***	0.245***
	(8.41)	(6.04)	(7.85)	(7.32)	(6.35)	(6.26)	(9.62)
$log(EDUC^{higher})$	0.064*	0.025	0.053**	0.060*	0.072**	0.057*	0.020
	(2.03)	(1.00)	(2.32)	(1.92)	(2.46)	(1.92)	(0.83)
$log(BB\_COV^{fiber})$		0.002*	0.002*	0.003*	0.003*	0.003**	0.002*
		(2.02)	(2.09)	(2.07)	(1.97)	(2.10)	(1.99)
$log(BB\_ADOP^{fixed})$		0.026***	0.030***	0.030***	0.034***	0.031***	0.026***
		(5.82)	(4.15)	(4.97)	(4.74)	(5.15)	(5.54)
log(BB_COV3G+)	0.002	0.003	0.019**	0.014*	0.021**	0.015	-0.001
	(0.17)	(0.31)	(2.29)	(1.93)	(2.32)	(1.67)	(-0.15)
$log(BB\_ADOP^{mobile})$	0.086***	0.088***	0.003	0.083***	0.079***	0.085***	0.085***
	(5.12)	(4.62)	(0.04)	(4.71)	(5.39)	(4.71)	(4.31)
$L.log(BB\_ADOP^{mobile})$			0.065				
			(0.77)				
$years\_since\_cov^{mobile}(20\%)$	0.003	0.005	0.013*	0.009*			
	(0.45)	(0.90)	(2.06)	(1.90)			
$years\_since\_adop^{fiber}(10\%)$			0.011***		0.012***		
			(3.60)		(3.82)		
$years\_since\_adop^{fiber}\ (15\%)$				0.007**		0.007**	
				(2.29)		(2.33)	
$years\_since\_cov^{mobile}(30\%)$					0.011*	0.009	
					(1.82)	(1.44)	
constant	8.485***	8.778***	0.000	8.497***	8.286***	8.516***	8.918***
	(30.44)	(28.85)	(.)	(35.86)	(30.30)	(31.45)	(50.70)
R2 within	0.767	0.777	0.780	0.783	0.792	0.783	0.777
F-Test	934.596	2505.266	68049.031	1779.213	3058.796	2292.737	703.458
#Countries	32	32	32	32	32	32	32
#Observations	608	608	576	608	608	608	608

Notes: 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 4, and are robust to very general forms of cross-country spatial dependence (Driscoll and Kraay, 1998). Inclusion of the lagged variable $L.log(BB\_ADOP^{mobile})$ in regression (3) reduces the sample size accordingly. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Dependent variable:	Log of real GDP per capita, *log(GDP_pc)*			
Regression #:	(1)	(2)	(3)	(4)
Sample size:	2005–2020	2009–2020	2005–2020	2009–2020
Broadband (BB) tech.:	Fixed BB		Fixed & mobile BB	
log(CAPITAL)	0.219***	0.248***	0.219***	0.245***
	(7.47)	(9.73)	(7.39)	(9.31)
log(LABOR)	0.653***	0.609***	0.613***	0.574***
	(8.20)	(4.44)	(7.93)	(4.56)
$log(EDUC^{secondary})$	0.407***	0.482***	0.419***	0.306***
	(10.61)	(10.70)	(19.02)	(5.64)
$log(EDUC^{higher})$	0.030	0.041	0.026	-0.017
	(1.14)	(1.11)	(1.05)	(-0.51)
$log(BB\_COV^{fiber})$	0.001	0.001	0.002***	0.000
	(1.35)	(0.88)	(4.90)	(0.12)
$log(BB\_ADOP^{fixed})$	0.040***	0.053*	0.042***	0.062**
	(3.44)	(2.13)	(3.44)	(2.73)
log(BB_COV3G+)			0.032***	0.071**
			(3.77)	(3.00)
$log(BB\_ADOP^{mobile})$			0.070***	0.078**
			(3.98)	(2.32)
$years\_since\_adop^{fiber}(10\%)$	0.007***	0.004	0.009***	0.004
	(3.28)	(1.43)	(4.03)	(1.35)
$years\_since\_cov^{mobile}(30\%)$			0.022***	0.069***
			(4.44)	(3.24)
constant	8.118***	0.000	0.000	0.000
	(23.42)	(.)	(.)	(.)
R2 within	0.748	0.802	0.760	0.815
F-Test	661.750	5680.613	29019604.856	31865744.181
#Countries	32	32	32	32
#Observations	512	384	512	384

Notes: 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 4, 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

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, we employ external and internal (geography-based) instruments, as described in Section 4.4 as sources of exogenous variation. According to Hansen J tests, our sets of instruments are jointly valid in all specifications, and the regression estimates appear to be robust regarding different numbers of instrumental variables.[16] The Kleibergen-Paap (KP) test of under-identification rejects the null hypothesis that the respective estimating equation is under-identified for all regressions at the 10% significance level, implying that the excluded instruments are correlated with the endogenous regressors and thus relevant. Testing for the strength of instruments in the case of multiple endogenous variables, the inspection of individual first-stage F-statistics is no longer sufficient. Therefore, we additionally report Sanderson-Windmeijer (SWF) multivariate F-tests of excluded instruments in our first-stage results, which suggested that our instruments were not weak.[17] The Durbin-Wu-Hausman (DWH) tests do not reject the null hypothesis that broadband adoption is an exogenous variable in all regressions. Hence, the DWH tests suggest that our included fixed and mobile broadband variables can be considered exogenous, and the FE estimates reported in Tables 1 to 3 are consistent and more efficient. Hence, even though the 2SLS coefficient estimates point to a greater marginal impact of broadband on GDP—just as in Czernich et al. (2011) and Edquist et al. (2018)—in particular for wireless broadband technologies, FE point estimates present consistent and conservative values to which we refer in our policy conclusions in the final section.

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[16] Hausman-type internal instruments $(\frac{\sum_{l\neq i}^{n} BB\_COV^{j}}{n-1}, \frac{\sum_{l\neq i}^{n} BB\_ADOP^{k}}{n-1})$ and market competition-related instruments (*comp_mobile*; *comp_fixed)* are included in all regressions. Note that we also include squared terms for competition variables, as competition might impact investment in a non-linear form (Sacco and Schmutzler, 2011). Our instrument measuring deployment costs (*dwelling*) is included in regressions (1), (2), and (7), and the Netflix dummy (*netflix*) is included in regressions (1) to (7).

[17] Table A.3 in the Appendix reports these first-stage statistics for regressions (1) to (8) in Table 4. The instruments are strong and, in most cases, exceeding conventional threshold levels, as evidenced by the respective SWF and F tests of excluded instruments and Shea´s partial R^2 statistics.

Table 4: 2SLS regression results

Dependent variable:	**Log of real GDP per capita, *log(GDP_pc)***							
Regression #:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Broadband (BB) tech.:	Fixed BB	Fixed BB	Fixed BB	Mobile BB	Mobile BB	Mobile BB	Mobile BB	Mobile BB
log(CAPITAL)	0.211***	0.211***	0.211***	0.180**	0.180**	0.180**	0.174**	0.173**
	(3.20)	(3.19)	(3.19)	(2.49)	(2.48)	(2.48)	(2.22)	(2.20)
log(LABOR)	0.735***	0.739***	0.739***	0.820***	0.821***	0.821***	0.770***	0.772***
	(4.56)	(4.60)	(4.60)	(4.22)	(4.23)	(4.23)	(5.48)	(5.50)
log($EDUC^{secondary}$)	0.277***	0.273***	0.274***	0.292**	0.278**	0.276**	0.240**	0.236**
	(2.71)	(2.69)	(2.70)	(2.18)	(2.18)	(2.12)	(2.18)	(2.15)
log($EDUC^{higher}$)	0.059	0.052	0.053	0.029	0.023	0.021	0.002	-0.001
	(0.44)	(0.38)	(0.39)	(0.21)	(0.16)	(0.15)	(0.01)	(-0.01)
log(BB_COV^{fiber})	-0.004	-0.004	-0.004				0.002	0.002
	(-0.79)	(-0.75)	(-0.76)				(0.50)	(0.55)
log(BB_ADOP^{fixed})	0.041**	0.043**	0.043**				0.040*	0.041*
	(2.17)	(2.21)	(2.20)				(1.78)	(1.80)
log(BB_COV^{3G+})				-0.002	0.003	0.003	-0.008	-0.007
				(-0.09)	(0.11)	(0.13)	(-0.41)	(-0.39)
log(BB_ADOP^{mobile})				0.174*	0.165*	0.164*	0.164	0.166
				(1.78)	(1.69)	(1.67)	(1.64)	(1.64)
$years\_since\_adop^{fiber}$(10%)	0.007*	0.007*	0.007*				0.010**	0.010*
	(1.78)	(1.77)	(1.77)				(1.96)	(1.96)
$years\_since\_cov^{mobile}$(20%)				0.004	0.004	0.004	-0.005	-0.005
				(1.11)	(1.11)	(1.11)	(-0.98)	(-1.01)
R2 (uncentered)	0.758	0.758	0.758	0.751	0.752	0.752	0.770	0.769
F-statistic	37.110	37.282	37.348	36.382	36.403	36.488	32.729	32.847
KP test (p-value)	0.009	0.005	0.003	0.008	0.009	0.010	0.090	0.041
Hansen J test (p-value)	0.348	0.316	0.261	0.463	0.486	0.358	0.563	0.629
DWH test (p-value)	0.364	0.713	0.716	0.371	0.338	0.398	0.445	0.216
#Instruments	9	8	7	9	8	7	9	7
#Countries	32	32	32	32	32	32	32	32
#Observations	608	608	608	608	608	608	608	608

Notes: All regressions (1)–(8) 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 high collinearity with the Hausman-type instrumental variables. The "xtivreg2" Stata command includes no constant with a fixed-effects model. As a goodness-of-fit measure, we report the uncentered R2 (because there was no constant). The t-statistics in parentheses were robust and allowed for heteroscedasticity and correlation within countries.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Summary and conclusions

Our results show that both fixed and mobile broadband adoption by households and firms exerts 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 0.034%, while it ranges from 0.079% to 0.088% for mobile broadband adoption. When comparing both types of broadband technologies, the contemporaneous impact of mobile broadband adoption on GDP thus appears to be substantially higher. Fixed broadband adoption, however, 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 0.062%. 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. The 2SLS results point to (slightly) higher coefficient estimates for (fixed) mobile broadband adoption; thus, to remain conservative, we refer to FE estimates for our policy conclusions.

Our findings suggest the following policy implications: First, future public funding measures should no longer focus predominantly 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 be increasingly promoted in the future. Consumers with a limited willingness to pay for more expensive high-speed 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 broadband services. 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. Third, in addition to the benefits of broadband infrastructure and services, which are difficult to measure, particularly in the form of consumer surplus, our results indicate that the full economic benefits of broadband only unfold over time when companies have made 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.

Whereas almost all public funding programs in the past were based on supply-side stimuli, such as direct grants, 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 be directed toward quantifying the overall positive societal impact of broadband services.

Appendix: Tables A.1, A.2, and A.3

Table A.1: Variable descriptions and sources

Variable	Description	Source*)
	Dependent variable	
GDP_pc	GDP in constant 2015 USD per capita.	World Bank
	Independent variables	
LABOR	The variable is defined as labor force participation rate, which is calculated by dividing the labor force aged 15–64 years by the total working age (15–64) population.	Euromonitor(b)
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+ with secondary education	Euromonitor
$EDUC^{higher}$	Percentage of population aged 15+ with higher education	Euromonitor
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). 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(c)
BB_ADOP^{fixed}	Adoption in terms of the number of subscribed broadband connections under a commercial contract; 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(d)
BB_ADOP^{fiber}	Adoption in terms of number of actually subscribed broadband connections utilizing fiber-based FTTx technologies under a commercial contract.	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

Table A.1 (continued)		
BB_ADOP^{mobile}	Absolute number of cellular mobile subscriptions; mobile-cellular telephone subscriptions refers 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 (i.e., those that have been used during the last three months).	OECD / ITU[(e)]
years_since_adop^{fiber}*(10%)*/ *years_since_adop*^{fiber}*(15%)*	Number of years passed since adoption of fiber-based (FTTx) connections exceeded 10%/15% of households	FTTH Council Europe / own calculation
years_since_cov^{fiber}*(10%)*	Number of years passed since coverage of fiber-based (FTTx) connections exceeded 10%/15% of households	FTTH Council Europe / own calculation
years_since_cov^{mobile}*(20%)*/ *years_since_cov*^{mobile}*(30%)*	Number of years passed since network coverage of 3G+mobile technologies exceeded 20%/30% of households	Euromonitor / own calculation
	Instrumental variables	
comp_mobile	Share of the total number of mobile-cellular subscriptions to the total number of mobile-cellular telephone subscriptions and total number of active fixed broadband subscriptions offering ≥256 kbit/s.	ITU / Euromonitor
comp_fixed	Share of cable subscriptions relative to total basic broadband subscriptions. Cable modem Internet subscriptions refer to the number of Internet subscriptions using a cable modem service to access the Internet at downstream speeds ≥ 256 kbit/s. A cable modem is a modem attached to a cable television network.	OECD
state_aid	A dummy variable that takes the value one if there is an active state aid program supporting basic broadband deployment in a given year in the respective country.	Own research, Briglauer & Grajek (2021)
dwelling	Total number of households by type of dwelling	Euromonitor
netflix	A dummy variable that takes on the value one if Netflix streaming services were available (otherwise, it is zero).	Own research
$\frac{\sum_{l\neq i}^{n} BB\_COV^{j}}{n-1}$	Hausman-type geographic instruments measuring average levels of new fiber-based (wireline and (wireless) broadband (3G+) deployment in all other (non-focal) OECD states in the sample. Defined as the ratio of total deployed connections based on technology *j* in all other (*l ≠ i)* OECD states (i.e., other than the focal country *i*) to the total number of other countries.	Own calculation
$\frac{\sum_{l\neq i}^{n} BB\_ADOP^{k}}{n-1}$	Hausman-type geographic instruments measuring average levels of wireline (wireless) adoption based on technology *k* in all other (non-focal) OECD states in the sample. Defined as the ratio of total adopted connections based on technology *j* in all other (*l ≠ i)* OECD states (i.e., other than the focal country *i*) to the total number in other countries.	Own calculation

Notes: [(a)] Data are publicly available at: https://data.worldbank.org/indicator/; [(b)] Data are commercially available at: https://www.euromonitor.com/our-expertise/passport; [(c)] The FTTH Council Europe is a non-profit industry organization, data are available to FTTH Council Europe members at: http://www.ftthcouncil.eu/resources?category_id=6; [(d)] Data are publicly available at: https://www.oecd-ilibrary.org/ [(e)] Data are publicly available at: https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx.

Table A.2: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
GDP pc	646	36834.434	21165.648	6373.132	105454.73
Gross fixed capital formation	646	2.835e+11	6.132e+11	2.159e+09	4.187e+12
CAPITAL	646	22.114	4.133	9.698	53.418
working age 15-64	646	15599208	25351681	151540.82	1.467e+08
LABOR	646	.662	.078	.415	.86
$EDUC^{secondary}$	608	58.129	11.921	28.1	87.3
$EDUC^{higher}$	608	22.814	7.563	8.2	45.3
$BB\_COV^{fiber}(abs)$	646	9975166.4	26357330	0	2.090e+08
BB_COV^{fiber}	646	.71	.729	0	2.935
$BB\_ADOP^{fixed}(abs)$	646	10309315	22815915	7699	1.936e+08
BB_ADOP^{fixed}	646	.712	.427	.002	2.282
BB_COV^{3G+}	646	.784	.283	0	1
BB_ADOP^{mobile}	646	1.085	.234	.255	1.721
$years\_since\_cov^{mobile}(30\%)$	646	8.441	5.637	0	19
$years\_since\_cov^{mobile}(20\%)$	646	9.036	5.65	0	19
$years\_since\_adop^{mobile}(10\%)$	646	6	5.241	0	19
$years\_since\_cov^{fiber}(15\%)$	646	4.283	4.426	0	16
$years\_since\_adop^{fiber}(15\%)$	646	2.161	3.269	0	16
$years\_since\_adop^{fiber}(10\%)$	646	2.703	3.66	0	17
$years\_since\_cov^{fiber}(10\%)$	646	4.503	4.546	0	17
comp_fixed	646	.322	.206	0	.882
comp_mobile	646	.828	.073	.691	1
state_aid(0/1)	646	.317	.466	0	1
dwelling	646	35.526	113.093	.066	437.401
netflix(0/1)	646	.372	.484	0	1
$log(\frac{\sum_{l\neq i}^{n} BB\_COV^{fiber}}{n-1})$	646	-.911	1.255	-3.494	.468
$log(\frac{\sum_{l\neq i}^{n} BB\_ADOP^{fixed}}{n-1})$	646	-.633	.766	-2.474	.099
$log(\frac{\sum_{l\neq i}^{n} BB\_ADOP^{mobile}}{n-1})$	646	.053	.169	-.398	.19
$log(\frac{\sum_{l\neq i}^{n} BB\_COV^{3G+}}{n-1})$	646	4.208	.513	3.028	4.599

Notes: Data for variables $EDUC^{secondary}$ and $EDUC^{shigher}$ are missing for Luxembourg and Iceland for the entire observation period 2002–2020.

Table A.3: First-stage estimation statistics of excluded instruments

	BB_COV^{fiber}	BB_ADOP^{fixed}	BB_COV^{3G+}	BB_ADOP^{mobile}
Regression (1)				
Shea's partial R2	1.478401	.3119588		
F	12.2662	13.26237		
SWF	11.54486	15.22181		
Regression (2)				
Shea's partial R2	.3255761	.5185564		
F	10.11175	10.72131		
SWF	9.380636	14.18167		
Regression (3)				
Shea's partial R2	.3252943	.5155926		
F	11.18657	11.64574		
SWF	10.61583	13.14534		
Regression (4)				
Shea's partial R2			.2480412	.3736413
F			35.92752	19.95078
SWF			12.59036	11.52998
Regression (5)				
Shea's partial R2			.2549246	.3792278
F			40.20831	18.58086
SWF			12.03451	10.78648
Regression (6)				
Shea's partial R2			.2468498	.3735591
F			30.85153	22.62416
SWF			13.0181	13.39763
Regression (7)				
Shea's partial R2	.2311803	.3480354	.2163302	.3795347
F	10.23258	7.298828	18.55573	16.82686
SWF	7.951637	5.236691	11.20368	14.05162
Regression (8)				
Shea's partial R2	.2272844	.3452084	.2142862	.3703964
F	10.87098	8.568992	22.89818	15.98021
SWF	7.306678	7.543811	9.693513	18.46629

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