THE CONTRIBUTION OF FIXED BROADBAND TO THE **ECONOMIC GROWTH** OF THE UNITED STATES BETWEEN 2010 AND 2020

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EXECUTIVE SUMMARY

What is the contribution of a robust broadband infrastructure to the growth of the US economy? Broadband high-speed internet is a general-purpose technology because it supports all types of economic activity, driving output growth beyond the impact of conventional capital goods. As such, broadband now constitutes a key component of the underlying infrastructure for development, like roads and electricity. Accordingly, it is possible to measure its contribution to the US economic growth over the last decade.

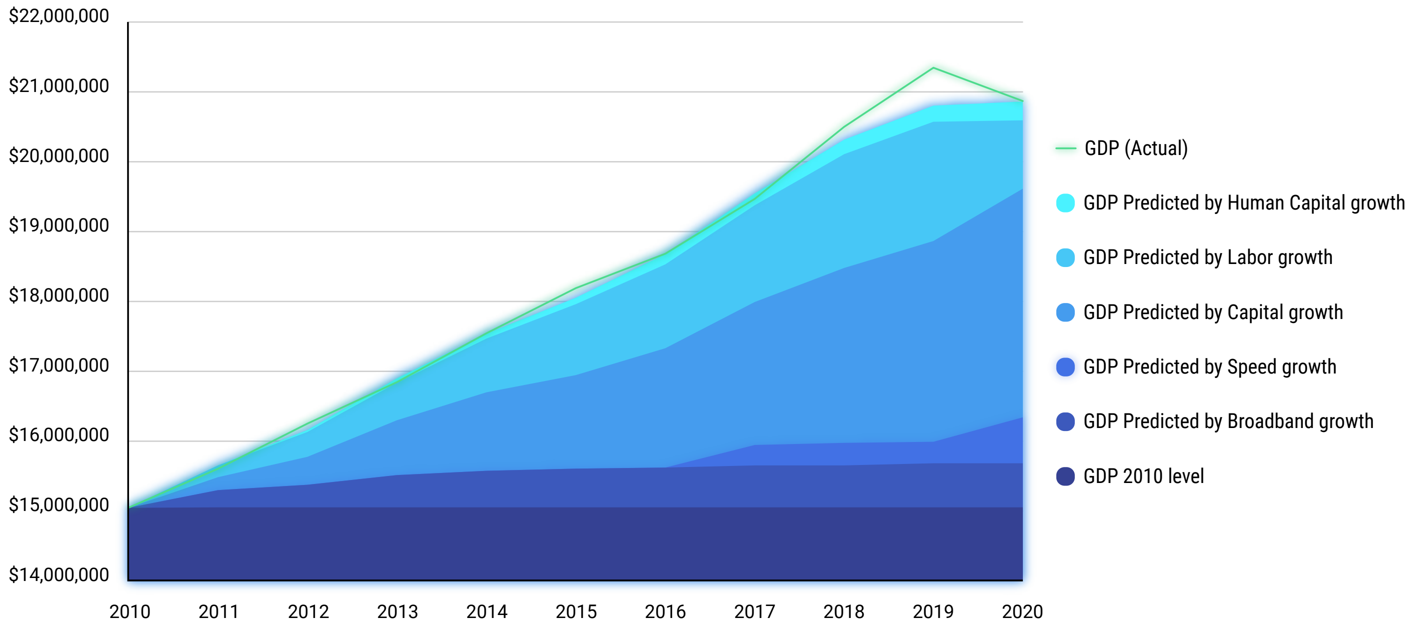
> If broadband adoption and speeds had remained at 2010 levels, in 2020 the US GDP would have been **$1.3 trillion lower** (**$19.6 trillion**, rather than **$20.9 trillion**).

Between 2010 and 2020, the US economy grew at an average rate of 3.3%. Adoption of fixed broadband connections of at least 25 Mbps download speed increased from 0.87% of households in 2010 to 65.69% in 2019[1], and, consequently, the fixed broadband average download speed grew from 10.03 Mbps in 2010 to 174.23 Mbps in 2020[2]. What is the contribution of this dramatic expansion to the country's economic growth? What would have been the economic gains if broadband had remained unchanged since 2010? Graphic A presents a high-level view of the sources of US GDP growth between 2010 and 2020.

1 The FCC Internet Access Services report mentions that there were 1,027,000 residential fixed internet connections in 2010 with download speed equal or above 25 Mbps (Internet Access Services Report 2010, Table 13, p.32). Considering that there were 117,671,000 households in 2010 (p, 35), this results in 0.87% penetration. Penetration for 2020, not yet provided by the FCC, was estimated based on fixed broadband penetration growth rate reported in the American Community Survey.

2 Ookla Speedtest

Graphic A. Sources of US GDP growth 2010-2020



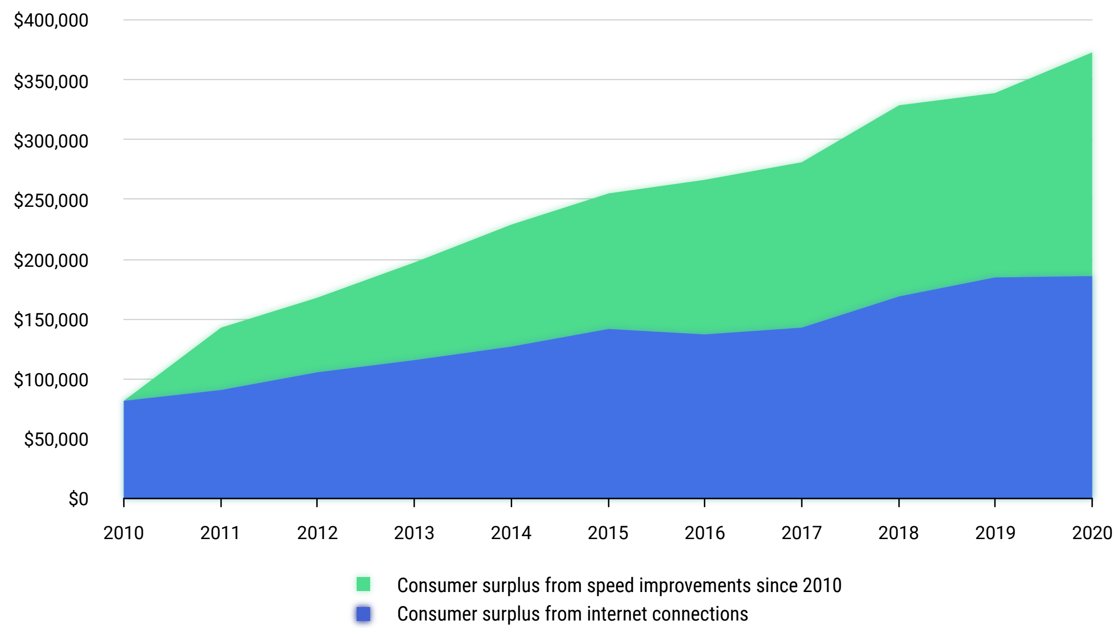
Source: Telecom Advisory Services analysis

As indicated in Graphic A, capital accumulation has been the main contributor to the US GDP growth (56.2% of cumulative GDP growth between 2010 and 2020), while labor and human capital have also been important contributors (21.3%). Beyond capital, labor, and human capital, the expansion of fixed broadband networks and their speed improvement emerge as crucial sources of growth. Fixed broadband adoption drove 10.9% of the accumulated growth, while speed improvement contributed to an additional 11.5%. Accordingly, if broadband adoption and speeds had remained at 2010 levels, in 2020 the US GDP would have been $1.3 trillion lower ($19.6 trillion, rather than $20.9 trillion). This is equivalent to almost $4,000 annual dollars less for the average American.

Beyond the GDP growth driven by broadband infrastructure, consumers receive a surplus linked to the fulfillment of a whole new range of applications in the areas of communications, entertainment and information. The gains in consumer surplus are associated with a wider portion of the population to communicate with as well as faster speed. Aggregated consumer surplus at the national level increased to over $186 billion in 2020 (up from $81.6 billion in 2010) as a result of increased connectivity. And an additional $186.2 billon of consumer surplus is realized, when considering the significant improvements in average broadband speeds (see Graphic B).

> Aggregated consumer surplus at the national level increased to over **$186 billion in 2020** (up from **$81.6 billion in 2010**) as a result of increased connectivity. And an additional **$186.2 billon** of consumer surplus is realized, when considering the significant improvements in average broadband speeds.

Graphic B. United States: consumer surplus generated since 2010 from broadband connections and speed increases



Source: Telecom Advisory Services analysis

It appears from the estimates that the relative weight of speed improvements over the total consumer surplus increases considerably. This may be explained by the decreasing network effects generated once a certain threshold of internet penetration is reached. With diminishing network effects, the larger source of consumer surplus is driven by faster connectivity speeds.

1. INTRODUCTION

The purpose of this study is to estimate the contribution of fixed broadband to the American economy during the period 2010-2020. This was a decade of exceptional economic performance for the country, averaging annual growth rates of 3.3%, driven by the strong recovery that followed the financial crisis of 2007-2009. That growth trend was only interrupted in 2020 due to the COVID-19 pandemic.

In this context, our objective is to analyze to what extent economic growth can be traced back in part to the massive fixed broadband diffusion that took place in the country during that period. In other words, how much economic growth would the economy have missed out on if broadband had remained at the 2010 level?

As demonstrated in the research literature conducted over the past twenty years, broadband diffusion is a key driver of economic growth (Koutroumpis, 2009; Czernich et al, 2011; Katz et al, 2012; Bertschek et al, 2013; Arvin and Pradhan, 2014; Katz and Callorda, 2018). This should be the case in the United States as well. In 2010, fixed broadband of more than 25 Mbps download speed had been adopted only by 0.87% of households[1]. By mid-2019, household penetration levels for that speed tier reached approximately 65.69%[2].

Beyond fixed broadband development, the country underwent significant economic changes during that period. For example, as an indication of capital deepening process[3], physical capital stocks grew at a yearly average of 4.1%. Similarly, labor contributed massively to economic growth: in 2019, there were nearly 29 million new jobs when compared with 2010 (a massive increase that came to a halt in 2020 due the COVID-19 recession). Jobs by 2019 had not only grown in quantity, but workers were also more skilled than before: while 39% of the population aged between 25 and 64 had tertiary education in 2010, that figure increased to 44% by 2020. Since the potential sources of economic growth were so diverse, it is necessary to disaggregate them into the different drivers to isolate the role of fixed broadband as a contributor.

A specific mention must be made to the role of fixed broadband in creating socioeconomic resiliency during 2020, as the outbreak created by the COVID-19 pandemic generated a major disruption in social and production processes. The role of broadband in providing resiliency during the pandemic will be analyzed in a separate study[4].

The study is structured as follows. Section 2 provides a review of the relevant empirical research conducted so far

1 Federal Communications Commission. Internet Access Services: Status of December 31, 2010
2 Federal Communications Commission. Internet Access Services: Status of June 30, 2019.
3 Capital deepening -or capital intensity- is an accumulation process where the capital stock per worker is increasing, resulting in a driver of economic growth.
4 Katz, R. and Jung, J. (2022). The role of America's robust broadband infrastructure in building economic resiliency during the Covid-19 pandemic.

to assess the economic contribution of broadband in the United States. Section 3 presents a descriptive analysis of the main trends in economic growth and broadband adoption during the decade under study. Section 4 proposes a theoretical framework that isolates the contribution of fixed broadband in explaining the economic growth at the national and state level. Section 5 describes the dataset built for conducting the econometric analyses, detailing the description of variables and their sources. Section 6 reports the econometric estimations for the models under different specifications and empirical approaches. Section 7 presents a growth accounting exercise to decompose the sources of growth to calculate the specific contribution attributable to broadband.

2. RESEARCH LITERATURE REVIEW

The impact of broadband has been widely studied in the economic growth literature, with an important part of that research conducted with United States data, due to the early network deployments and the extensive availability of datasets.

Lehr et al (2006) were among the first authors to study the impact of broadband on several economic variables in the US zip-code areas and states. Using regression analysis and matching estimators, they found a positive effect of broadband on employment, on the number of businesses, and on property values. However, they did not observe a significant effect on wages. The authors acknowledged that endogeneity was a concern, suggesting that future research should rely on instrumental variables techniques to better control for potential problems deriving from omitted variables and reverse causality[5]. Following this study, Crandall et al (2007) provided evidence on the economic contribution of broadband for a sample of 48 US states, highlighting that the number of accesses per 100 population stimulated employment and output growth between 2003 and 2005, although the positive effect was only found to be significant in the service industries. The authors argued that since broadband was at an early stage of the diffusion lifecycle, that could have prevented an accurate measurement of its overall impact on growth. The limited economic contribution of broadband in this study could also be explained by the lack of control for endogeneity of the broadband indicator.

Since the early 2010s, most researchers on the economic impact of broadband have attempted to address the problem of endogeneity. For example, Kandilov and Renkow (2010) used a difference-in-differences approach combined with a matching strategy to analyze the effect of a broadband deployment program in US rural areas, concluding that,

5 In econometrics, endogeneity broadly refers to situations in which an explanatory variable is correlated with the error term. It might lead to biased estimates. Instrumental variables are commonly used to address this problem.

between 2002 and 2003 the technology had not had yet a significant impact on their economic development (as measured by employment, payroll, and the number of business establishments) possibly because not enough time had elapsed for the impact to happen. A more spatially disaggregated analysis revealed, however, that a positive economic impact of rural broadband was identified in communities located closest to urban areas.

The comparison of the economic performance of geographies with different levels of broadband deployment but controlling for other characteristics, using the matching approach, has also been the strategy followed to estimate a causal link in the studies of Whitacre et al (2014) and Ford (2018). The first study used US county data between 2001 and 2010 and concluded that median household income, employment, and the number of firms increased faster in counties with higher broadband adoption, whereas they experienced lower unemployment. In addition, the study results suggested that higher download speed was associated with less poverty and more creative class employment. In turn, Ford (2018) also focused on the local economic effects of increasing broadband speed, although his results were less positive. Using US county-level data for the 2013-2015 period, his study showed that broadband services and upgrades were not randomly distributed in the territory, which could result in misleading conclusions about their economic impact. Once differences in observed characteristics between the counties were controlled, the study concluded that there was no significant effect of higher broadband speed on economic outcomes, including jobs, earnings, and total personal income.

Other recent studies conducted for the US at the subnational level have also dealt with the endogeneity of the broadband indicator in a regression framework. They included controls of the differences in observed and unobserved characteristics (fixed effects) of the spatial units under analysis to minimize the concern about the omitted variables bias. In addition, some of these studies used Instrumental Variables (IV) to deal with the potential problem of reverse causality. For example, Forman et al (2012) used the cost of internet deployment, local connections to older networks, and a proxy of demand, to identify a positive causal effect of investments in advanced internet technologies on wages and employment in the US counties from 1995 to 2000. A positive contribution was observed only for a reduced number of counties, characterized by intensive usage of IT and high skills, income, and population density. Similarly, Kolko (2012) assessed the impact of broadband availability on county employment using an IV estimator, based on the average slope of the terrain as an instrument of the broadband indicator. The results in this research suggest a positive causal effect of broadband on employment, although the author acknowledged that IV estimates might be upwardly biased. Mack and Rey (2014) showed that broadband availability in 2004 stimulated the number of knowledge-intensive firms in the counties of 49 of the 54 US metropolitan areas. The authors combined techniques to deal with spatial dependence with an IV estimator that used the lagged values of the broadband indicator and the county's household density. Finally, Mack and Faggian (2013) developed a series of spatial econometric models that examined the link between broadband provision and productivity for US counties. The developed models also evaluated the variability in broadband impact related to the quality of human capital. The results in this case suggested that in general, broadband has a positive impact on productivity only in territories with high levels of human capital and/or highly skilled occupations. Other studies suggest that the availability of high-speed broadband is an important determinant of rural firm location (Mack, 2014).

Research conducted recently has begun to provide evidence of a positive contribution of high-speed broadband, including in rural areas. Using a panel of counties in the state of Tennessee, Lobo et al (2020) found that unemployment rates are lower in counties where higher-speed services (above 100 Mbps) are available, and that effects are larger in rural counties. Using a similar panel data strategy, Deller et al (2021) found that broadband availability generally boosts new business formation in non-metro U.S. counties, and that the effect increases with faster broadband speeds (above 50 Mbps).

Overall, the review of the existing literature leads us to conclude that the evidence of the causal effect of broadband on the economic performance of subnational spatial units of the United States indicates results that tend to vary by geography, although the contribution appears to be greater in recent time periods (see Table 1).

Table 1. Summary of Prior Research Evidence

Time period	Research	Time frame	Effects of broadband
1995-2005	Lehr et al (2006)	2000-2002	Positive effect of on employment, on the number of businesses, and on property values No significant effect on wages
	Crandall et al (2007)	2003-2005	Positive effect on output and employment only in service industries
	Kandilov and Renkow (2010)	2002-2003	No significant economic development effect in rural areas (measured by employment, payroll, and the number of business establishments)
	Kolko (2012)	1999-2006	Positive effect of broadband on employment, although estimates might be upwardly biased
	Mack and Rey (2014)	2004	County broadband availability stimulated the number of knowledge-intensive firms
	Forman et al (2012)	1995-2000	Positive effect of Internet investment on wages and employment only for a reduced number of counties characterized by intensive usage of IT and high skills, income, and population density
2000-2010	Whitacre et al (2014)	2001-2010	Median household income, employment, and the number of firms increased faster in counties with higher broadband adoption, and lower unemployment Higher download speed is associated with less poverty and more creative class employment
	Mack and Faggian (2013)	2000–2007	Positive impact on productivity only in territories with high levels of human capital and/or highly skilled occupations
	Mack (2014)	2010	The availability of high-speed broadband is an important determinant of rural firm location
2010-2015	Ford (2018)	2013-2015	No significant effect of higher broadband speed on economic outcomes, including jobs, earnings, and total personal income
	Lobo et al (2020)	2011-2015	Unemployment rates are lower in counties where higher-speed services (above 100 Mbps) are available, and that effects are larger in rural counties
	Deller et al (2021)	2014	Broadband availability generally boosts new business formation in non-metro U.S. counties, and the effect increases with faster broadband speeds (above 50 Mbps)

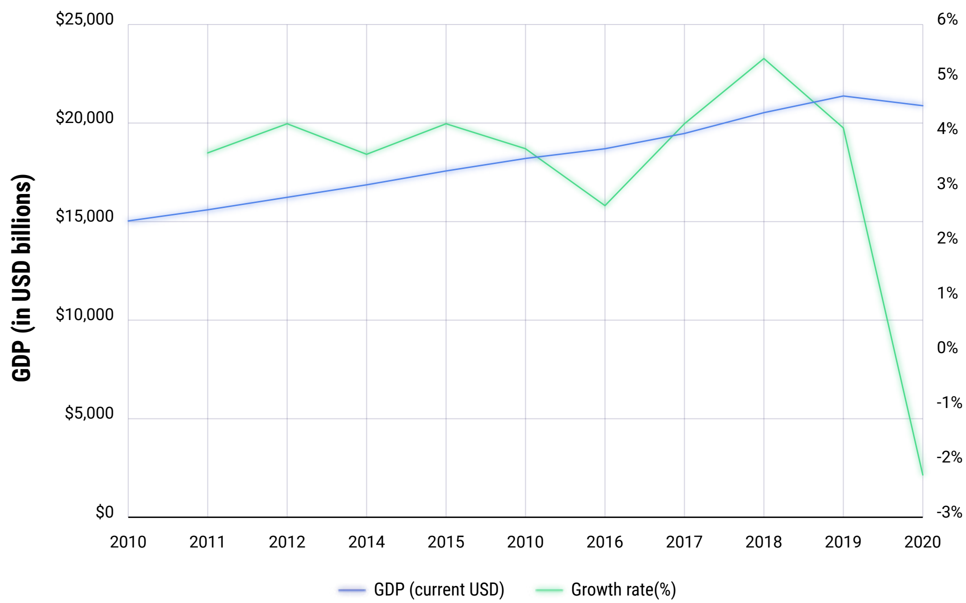
Source: Telecom Advisory Services analysis

As can be observed in Table 1, there is a lack of studies addressing the effects of broadband connectivity covering the most recent period, post 2015 which is a period in which massive deployment took place across the country. This is the area that we intend to focus on in this research. In addition, our effort will rely on econometric techniques used in recent research to control for endogeneity.

3. DESCRIPTIVE ANALYSIS: A CORRELATION BETWEEN BROADBAND DEVELOPMENT AND ECONOMIC GROWTH

Between 2010 and 2020, the US underwent significant economic growth. As noted in Graphic 1, the GDP of the United States grew at an average rate of 3.3%, even when factoring in the COVID-19 recession.

Graphic 1. GDP evolution in the United States (2010-2020)

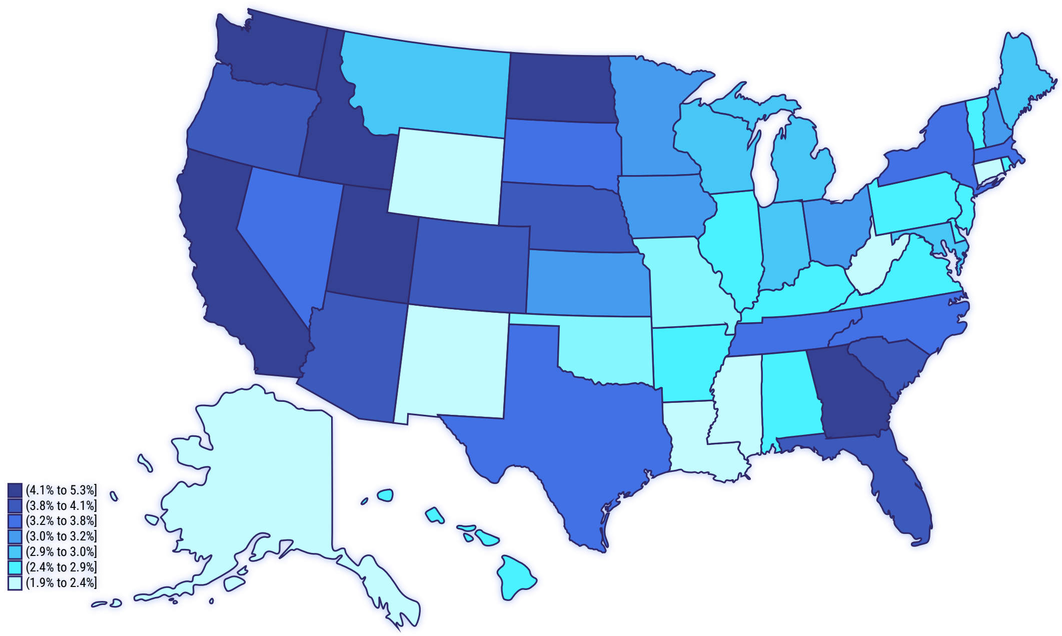


Source: International Monetary Fund; Telecom Advisory Services analysis

The steady growth until 2019 is the result of the country's recovery after the 2007-2009 financial crisis. This growth trend was interrupted in 2020, because of the crisis generated by the COVID-19 pandemic. At any rate, the GDP contraction occurred during 2020 (-2%) was relatively modest in comparison with that of other advanced economies such as the Euro zone (-6.3%), the United Kingdom (-9.8%) or Japan (-4.6%).

As for the evolution by state, Figure 1 presents each regional economy grouped by octiles according to their respective GDP's Compound Annual Growth Rate (CAGR), with the darker colors allocated to the faster growing states.

Figure 1. GDP growth by US state (CAGR 2010-2020)

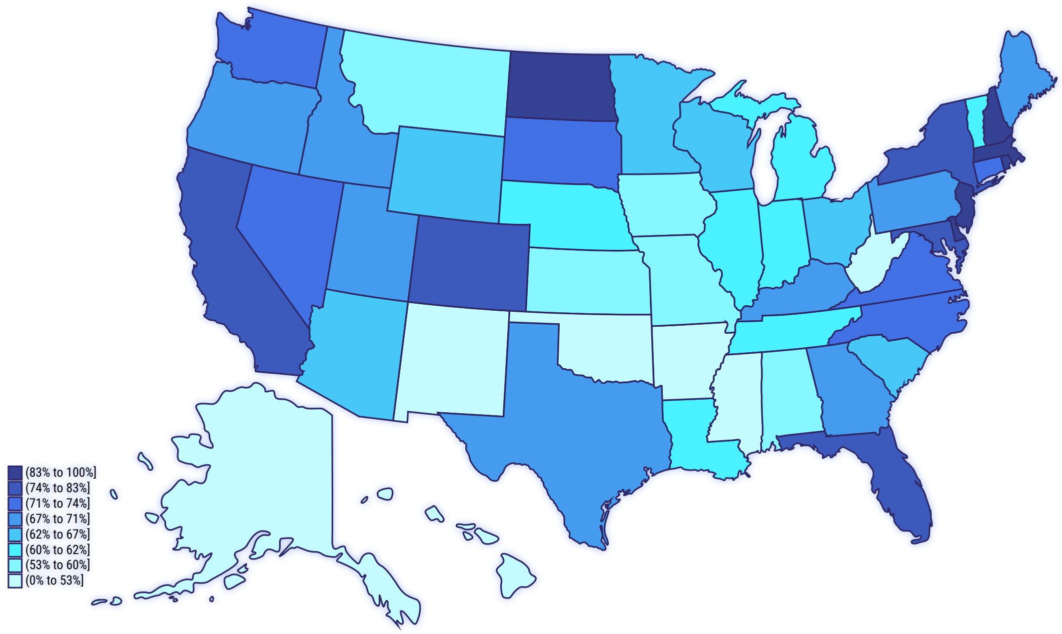


Source: Bureau of Economic Analysis; Telecom Advisory Services analysis

Utah, Washington, California, North Dakota, Idaho, and Georgia were the states with the largest growth rates - over 4% in all cases - well above the national average of 3.3%. Other states were found to be in a worse relative position at the end of the decade, as they grew below 2% on average. Such is the case of Oklahoma, Mississippi, Connecticut, New Mexico, West Virginia, Louisiana, Wyoming, and Alaska. This means that the economic evolution has not been homogeneous during the past decade, and one possible reason behind these variations may be related to different adoption pace of high-speed broadband. Another important aspect derived from Figure 2 is the presence of certain spatial correlations, where the economic evolution of some states may be linked with that of their neighbors.

In the case of broadband penetration, we report data for 2020 based on connections of at least 25 Mbps download speed per every 100 households[6].

Figure 2. Fixed broadband penetration by US state (2020)



Source: FCC; Telecom Advisory Services analysis

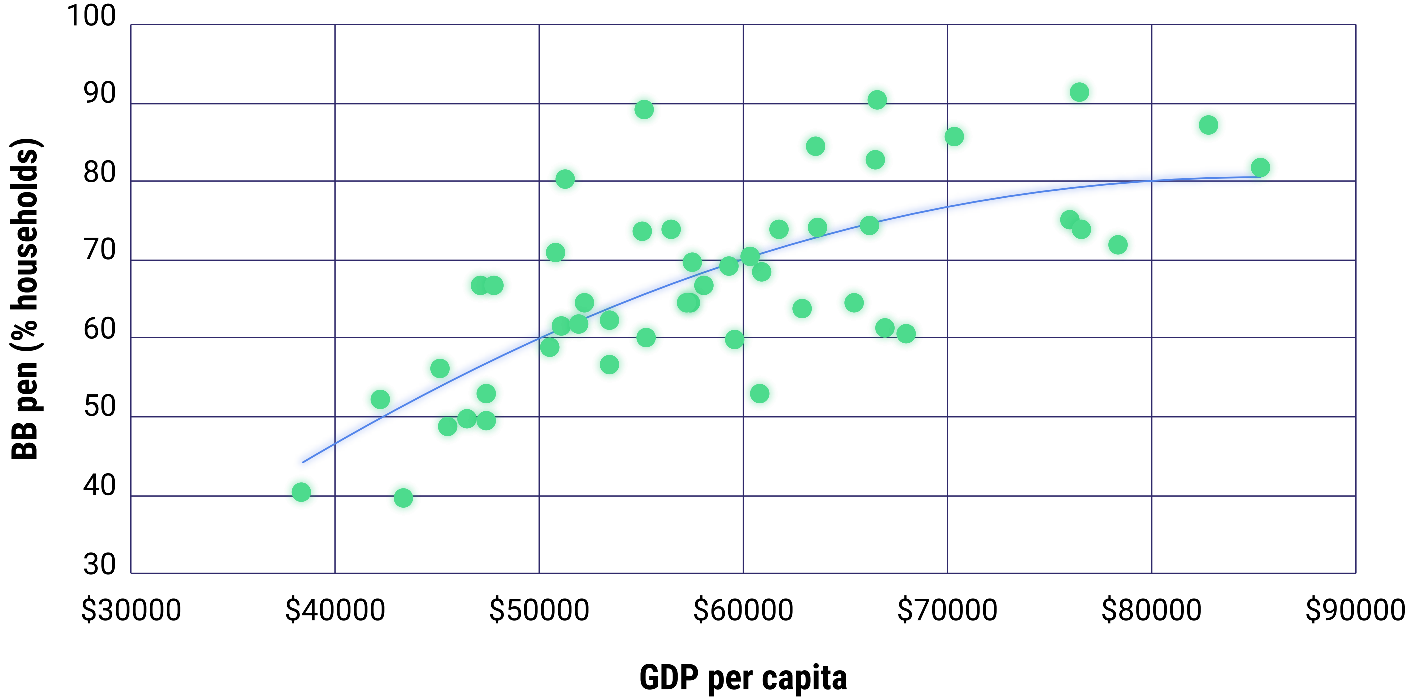
6 For 2010 the FCC has not reported as of now state-level data for 25/3 Mbps

As indicated in Figure 2, broadband penetration is also uneven, with more connected states mostly situated at the north-east of the country (New Hampshire, Massachusetts, New Jersey, Delaware, or Maryland), exhibiting well above 80% penetration figures. On the other extreme, broadband penetration in New Mexico, Oklahoma, Idaho, Mississippi, and Arkansas did not reach 50% of households. In sum, important regional disparities also arise in terms of broadband diffusion.

In order to explore the correlation links between economic output and internet adoption, a plot linking current levels of GDP per capita[7] and broadband penetration is presented in Graphic 2, indicating the presence of a specific descriptive pattern. When plotting each state with a fractional polynomial fit, there seems to be a positive relation, where the more connected states are also the richer ones. On the other end, Mississippi exhibits the lower figures for GDP per capita ($38,445), and the second-lower broadband penetration level (40.5%, only above Arkansas).

7 Here we use GDP per capita, rather than GDP, for comparison purposes across states.

Graphic 2. GDP per capita and fixed broadband penetration by US state (2020)



Note: Washington, DC is not included because it is an outlier.

Source: FCC; Bureau of Economic Analysis; Telecom Advisory Services analysis

In sum, the results of the descriptive analysis consistently point to a positive link between broadband penetration and economic performance. However, it remains to be seen if this is link is merely a correlation, or if this relation represents a causal direction, and if it remains robust when adding control variables which also affect output. This will be explored in the next section.

4. THEORETICAL MODELS, METHODOLOGIES, AND EMPIRICAL SPECIFICATION

As stated in the introduction, the objective of the research is to estimate the unique contribution of fixed broadband to the American economy during the period 2010-2020. The methodology to be followed is composed of four models:

1. An empirical Ordinary Least-Squares (OLS) model derived from Solow's exogenous model of long-run economic growth as driven by capital accumulation, labor, and increases in productivity resulting from technological progress.
2. A Spatial Error Model (SEM) estimated through Maximum Likelihood (ML), to account for spatial correlation across neighboring states.
3. A single - equation IV estimator to control for potential reverse causality where rather than being a driver of economic growth, broadband adoption results from higher level of development.
4. A structural four equation model also used to control for potential endogeneity but developed only as a robustness test because it covers only the 2016-2020 subperiod.

Each model will be presented in turn.

4.1. Long-run economic growth model

The empirical model to estimate the impact of broadband on regional output in the United States is based on an augmented Solow (1956) framework, where economies are supposed to produce according to a Cobb-Douglas production function with various input factors[8]:

$$GDP_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} HK_{it}^{\gamma} \quad [1]$$

where represents Gross Domestic Product, K is the non-telecom physical capital stock, L is labor and HK denotes human capital, approximated as $HK = e^{hk}$, where hk reflects the efficiency of a unit of labor, as in Hall and Jones (1999). Subscripts i and t denote respectively states and time periods. The term A represents Total Factor Productivity (TFP), which reflects differences in production efficiency across states over time. TFP is expressed as:

$$A_{it} = \Omega_i BB_{it}^{\Phi + \delta SPEED_{it}} \quad [2]$$

Accordingly, TFP is assumed to depend on some state-specific characteristics, represented by the fixed effect Ω_i, a term capturing time invariant idiosyncratic productivity effects, which may make some US states more productive per se because of unobserved characteristics[9]. As it is

8 This model was used by a previous study of Jung and López-Bazo (2020) to assess the impact of broadband on economic performance for a sample of Brazilian states.

9 For the empirical estimation, we have made some additional checks by incorporating further time-varying variables to the TFP term, such as R&D intensity, differences in industrial mix, and a time-trend to account for exogenous technological shocks. However, most of these variables were found to be not relevant from a statistical viewpoint. See the Appendix for a complete discussion.

supposed that internet connectivity contributes to increase productivity, A is assumed to depend positively on the level of broadband adoption, denoted by BB. Thus, it is expected a positive value for Φ, indicating the economic gains derived from broadband. Another important aspect that could shape the impact of broadband on state productivity is the existence of differentials in the quality of connections. To approximate quality, following Rohman and Bohlin (2013), the measure used is the download speed of connections within each state. The moderating effect of the quality of connections in a state is hypothesized to be positive, i.e., $\delta > 0$. In other words, for two US states with the same relative number of broadband connections, we expect to observe a larger economic impact for the region with the higher speed.

Inserting equation [2] in [1], we obtain:

$$GDP_{it} = \Omega_i BB_{it}^{\Phi+\delta SPEED_{it}} K_{it}^{\alpha} L_{it}^{\beta} HK_{it}^{\gamma}$$

Applying logarithms for linearization, and after some rearrangements, we derive the final empirical specification:

$$log(GDP_{it}) = \mu_i + \alpha\, log\ (K_{it}) + \beta log(L_{it}) + \gamma hk_{it} + \Phi \log(BB_{it}) + \delta SPEED_{it} log(BB_{it})$$

[3]

Where $\mu_i = log(\Omega_i)$ is a state-level fixed effect. Thus, we understand that the evolution of GDP depends on specific unobserved state-characteristics, on physical capital stock, on labor, on broadband adoption and on the speed of the connections. This baseline model will be estimated through Ordinary Least Squares (OLS).

4.2. Spatial Error Model

When working with regional data, a potential concern derived from models like the one presented in the previous section is that they neglect the possible spatial correlation across states. As seen before in Figure 2, there seems to be evidence of the presence of spatial correlation between the economic output of some states and that of their neighbors. Ignoring the potential spatial correlation may lead to biased and inefficient estimation results.

To incorporate border externalities to the theoretical framework derived in 4.1, we rely on the Spatial Error Model (SEM)[10], that allows the residuals to be spatially correlated (Anselin, 2001; Saavedra, 2000). Following the SEM model, the structure of the residuals is:

$$\varepsilon = \lambda W \varepsilon + \upsilon,$$

being W a spatial weights matrix. We used as spatial weights matrix a first-order contiguity matrix, row-normalized. The estimation is done through a Maximum Likelihood (ML) method.

4.3. Instrumental Variable model

A common critique of the estimation based on models such as those presented in 4.1 and 4.2 is that the results for the broadband effect could determine correlation rather

10 We have also tested empirically the alternative Spatial Autocorrelation Model (SAR) but reported lower likelihood.

than causality because investments in broadband may be considered as a driver, but also a result of productivity and economic growth (e.g., Cardona et al, 2013). This means that both broadband penetration and broadband speed may be potentially endogenous. This likely reverse causality may arise due to three factors: (i) individuals and firms in high-income states may also have higher resources to pay for broadband, (ii) policy interventions are aimed to stimulate deployment and (iii) use of broadband might depend on the level of development of each region, and because adoption of broadband can run in parallel to other technological advances (Czernich, 2011).

To address these reverse-causality concerns, we will apply a single-equation IV estimator using instruments that are expected to determine broadband but not the outcome variable in a direct way (this was the strategy followed by authors such as Czernich et al, 2011; Rohman and Bohlin, 2012; Forman et al, 2012; Kolko, 2012, Czernich, 2014; Mack and Rey, 2014; Ivus and Boland, 2015; and Castaldo et al, 2018).

4.4. Structural model

As a second measure to control endogeneity, we estimate the effect of interest from a structural multi-equation model, as other authors have previously done (Roller and Waverman, 2001; Koutroumpis, 2009; Katz and Callorda, 2018).

Following Koutroumpis (2009), a 4-equation model, as follows in Table 2, is adopted.

Table 2. System of equations for the structural model

Aggregate production equation	$GDP_{it} = f\left(K_{it},\ L_{it},\ HK_{it},\ BB_{it},\ SPEED_{it}\right)$
Demand equation	$BB_{it} = h\left(GDPpc_{it}, P_{it},\ HK_{it},\ URBAN_{it}\right)$
Supply equation	$REVENUE_{it} = g\left(P_{it},\ COMPETITION_{it}\right)$
Broadband infrastructure production equation	$BB_{it} - BB_{it-1} = k\left(REVENUE_{it}\right)$

Source: Telecom Advisory Services analysis

The aggregate production function is the same as that exposed in equation [3]. The demand equation endogenizes broadband penetration, stating that is a function of income (GDP per capita), the price of the service, education level (HK), and the percentage of the population that lives in densely populated areas (URBAN). The supply equation links the industry output with prices and the level of inter-platform competition in the broadband market (number of operators every 100,000 inhabitants). In our case, we will proxy sectorial output with revenue, rather than investment as done by Koutroumpis (2009). The reason is that there is not a reliable state-level broadband CAPEX series estimate for the US covering the considered period. Finally, the infrastructure production equation states that the annual change in broadband penetration is a function of the industry revenue[11].

In sum, as stated by Koutroumpis (2009), this system of equations effectively endogenizes broadband infrastructure[12] because they involve the supply and demand of broadband infrastructure. All equations include state-level fixed effects, and the empirical approach followed is three-stage least squares (3SLS) simultaneous equation estimate. Due to data limitations in most variables included in the secondary equations, the structural model could only be estimated for the subperiod 2016-2020. For this reason, it will be only used as a robustness test of the prior models.

11 Koutroumpis (2009) also adds R&D intensity and regulation (local loop unbundling) as determinants in the demand and supply equations, respectively. However, we understand that those regressors are suitable to explain demand and supply patterns in a cross-country context, but not for regional analysis as ours, as R&D is not necessarily a suitable indicator for regional disparities (see Appendix) and regulation is uniform for the whole country.

12 However, speed differentials remain exogenous, as the Koutroumpis (2009) framework does not account for it.

5. DATASET

To estimate the equations detailed in the previous section, we built a panel covering the US states during period 2010-2020. Table 3 details the sources and descriptive statistics for the variables compiled.

The main economic indicators collected at the state-level are sourced from the Bureau of Economic Analysis (BEA) dataset. That is the case for GDP and Labor. For physical capital stock, the BEA only reports national data. Therefore, to build state-level estimates we followed Garofalo and Yamarik (2002) who, for each economic sector, apportion the national estimate by the relative income generated by state. Each state capital stock is then the sum of the industry estimates, excluding the economic sector "Broadcasting and Telecommunications" to avoid overlapping information with the broadband penetration variable. As for human capital, defined as the share of population 25- to 64-year-olds with tertiary education, the data comes from the OECD regional database. As human capital data for 2020 is missing, we extrapolated the estimates for that year following each state annual compound growth rate in that indicator.

As for broadband variables, we rely on the official FCC broadband standard: household penetration levels for connections above 25 Mbps of download speed. However, data for this speed threshold at the state-level is only reported by the FCC since 2014, so for the years between 2010 and 2013 we imputed values based on the last observable data by state (2014) and national-level growth rates 2010-2013 for that speed tier. For 2020, the FCC has not yet reported state-level data, so we applied to 2019 figures the growth rate of overall fixed broadband for 2020 by state according to the American Community Survey (ACS). Considering that already in June 2019 nearly 80% of all fixed broadband connections are within the selected speed tier[13], this seems to be a feasible procedure to extrapolate 2020 state-level data.

13 78.4% of fixed broadband connections were of at least 25 Mbps downstream by June 2019, according to the Internet Access Service report.

Table 3. Variables and descriptive statistics

Code	Description	Mean	Obs.	Source
Main equation variables				
GDP	Gross Domestic Product in millions of current dollars	366,834.5 [453,797.3]	539	Bureau of Economic Analysis
K	Current-Cost Net Stock of Private Fixed Assets (excluding Broadcasting and Telecommunications) in billions of current dollars	826.304 [1,038.366]	539	Built with data from the Bureau of Economic Analysis
L	Total Full-Time and Part-Time Employment	3,812,162 [4,144,528]	539	Bureau of Economic Analysis
HK	Share of the population 25-64 with tertiary education	41.745 [6.664]	539	OECD Regional Statistics
BB	Fixed Broadband connections offering at least 25 Mbps down, every 100 households	38.987 [25.729]	539	FCC Internet Access Services reports/ American Community Survey (ACS)
Speed	Average maximum available download speed (Mbps)	607.388 [291.685]	294	Technology Policy Institute
Instruments for IV estimate				
Telephone penetration 1912-1922	Number of telephones, for all systems and lines, per person from 1912 to 1922	0.107 [0.049]	539	Census of telephones, Department of Commerce
Wire per km2 1912-1922	Miles of wire, for all systems and lines, per km2 from 1912 to 1922.	33.120 [177.018]	539	Census of telephones, Department of Commerce
Daily telephone calls 1912-1922	Daily calls by telephone from 1912 to 1922	6.428 [1.712]	539	Census of telephones, Department of Commerce
Additional variables for the structural model				
Price	Average price for commercial plans offering at least 25 Mbps down	89.584 [17.010]	220	FCC
Operators	Number of fixed broadband operators every 100,000 inhabitants	2.570 [1.929]	343	FCC form 477
Revenue	Calculated as: average price*total broadband connections (in million USD)	168.460 [178.351]	227	Built from FCC and ACS data
Urban	Percentage of population living in urban areas.	0.749 [0.147]	539	U.S. Census Bureau

Source: Telecom Advisory Services analysis

As for broadband speed, the FCC does not report average levels by state, only penetration levels by speed intervals, which in turn, vary over time. Therefore, we relied in the variable of average maximum available download speed (Mbps), provided by the Technology Policy Institute (TPI). It is important to consider that this is not real data of average speeds. First, because it is based only on advertised speeds (from the FCC form 477). Second, because it is an average calculated over maximum values. For that reason, this indicator should be better interpreted as the availability of high-speed offers. Since this data is only available from 2015 onwards, by transforming it into dummy variables by speed tiers we were able to expand the data set to the whole period 2010-2020. As presented in the Table 4, for the first year of data availability (2015), the mean speed was 194.408 Mbps, while the maximum value reached was 352 Mbps (Utah). For the following years, the average, minimum and maximum values always increase, which means that for the previous years (2010-2014) those figures must have reached smaller values than in 2015. This is reasonable, as broadband speed is ever increasing due to the introduction of FTTx and DOCSIS advancements in the distribution. As a result, for years before 2015, we can safely expect that no state reached an average maximum available download speed of 400 Mbps (as the maximum value in 2015 is 352 Mbps). Thus, we can build a dummy dataset taking values of 1 when a state reaches a speed ranging from 400 Mbps to 850 Mbps (something that only happens after 2015), and another dummy variable for states reaching speeds of 850 Mbps, or above. Both dummy variables take the value of zero for the period 2010-2014.

Table 4. Descriptive statistics for Speed variable (Mbps)

Year	Mean	Min	Max	States reaching 400-850	States reaching > 850
2015	195.408	58	352	0	0
2016	392.796	80	797	20	0
2017	588.000	184	980	31	6
2018	774.102	395	982	30	18
2019	833.408	537	986	25	24
2020	860.612	611	995	17	32

Source: Technology Policy Institute

The threshold of 400 Mbps was chosen as it is the first "safe" round value that allows us to extrapolate the data back to 2010. The threshold of 850 was chosen as it represents the top quartile of the sample available by the TPI data. Only 6 states reached that high-speed figure in 2017, a number that progressively increased to 18, 24 and 32 in 2018, 2019 and 2020, respectively.

6. ESTIMATION RESULTS

The estimation results are reported according to the models reviewed in sections 4.1, 4.2, 4.3, and 4.4.

Table 5 reports the estimated results for the empirical specification presented in equation [3], following the OLS method. The data sample includes 49 states between 2010 and 2020. We exclude from the analysis the states of Alaska and Hawaii for which there is no complete information on the broadband variable. All estimates include state-level fixed effects and robust standard errors, clustered by state.

We start by estimating a baseline model without considering the differential effect from speed (that is to say, assuming the restriction $\delta = 0$). Results presented in column (i) exhibit the expected results: positive and significant coefficients for Capital, Labor, and Human Capital. This means that all three factor inputs have contributed to the growth of US states during the period 2010-2020. As for broadband penetration, the coefficient is positive and highly significant, meaning that a 10% increase in broadband penetration is associated with 0.04% growth in GDP.

In column (ii), we present the estimates by considering differentials in broadband speed, relying on dummy variables for speed thresholds of 400-850 Mbps and above 850 Mbps. In this case, the results present clearly different economic impact according to speed thresholds: for the cases of speed below 400 Mbps, the impact of increasing in 10% the broadband penetration is 0.06%; for those states reaching speeds between 400 and 850 Mbps, the impact is 0.08% (0.06% as for all connections, plus 0.02% for this specific speed tier), while for those states enjoying the larger speeds (above 850), the economic impact is 0.11% (0.06%+0.05%). The increasing economic impact of broadband speed has been identified in prior research and labeled "return to speed" (Briglauer and Gugler, 2018; Carew et al, 2018; Kongaut and Bohlin, 2014; Lobo et al, 2019; Hasbi, 2017; Katz and Callorda, 2020).

To minimize any potential concern related to omitted variable bias, in addition to the production inputs we included in the specification a set of time-varying regional controls (R&D intensity, industrial mix) as well as temporal effects. The reason to consider these additional variables is that they could be associated to each region's output and, at the same time, correlate with broadband use. These additional variables were found to be non-significant in most estimates (see detailed discussion in Appendix). Furthermore, the panel structure of the data set for the US states allows us to control for time-invariant unobserved regional characteristics, by the inclusion of state fixed effects. As a result, the pernicious influence of confounding factors omitted in the specification (e.g., the effect of geography and differences across regions in managerial talent that evolves smoothly over time) is less of a concern in our empirical exercise.

Table 5. Economic Impact of Broadband – Fixed Effects OLS estimate

Dep. variable: $log(GDP)$	Complete sample 2010-2020		Excluding DC 2010-2020		Complete sample 2014-2019	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$log(K)$	0.516***	0.481***	0.512***	0.478***	0.596***	0.557***
	[0.030]	[0.028]	[0.029]	[0.028]	[0.067]	[0.065]
$log(L)$	0.641***	0.644***	0.644***	0.648***	0.605***	0.587***
	[0.052]	[0.053]	[0.052]	[0.054]	[0.123]	[0.115]
HK	0.005***	0.003*	0.005***	0.003*	0.003	0.001
	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]
$log(BB)$	0.004***	0.006***	0.004***	0.006***	0.010**	0.009**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.005]	[0.004]
$log\left(BB\right) * Speed(400-850)$		0.002***		0.002**		0.002
		[0.001]		[0.001]		[0.001]
$log\left(BB\right) * Speed > 850$		0.005***		0.005***		0.004*
		[0.002]		[0.002]		[0.002]
Fixed effects by State	YES	YES	YES	YES	YES	YES
R2 (within)	0.97	0.97	0.97	0.97	0.94	0.95
Observations	539	539	528	528	294	294
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS

*Note: Robust standard errors in parentheses. *p<10%, **p<5%, ***p<1%.*

Source: Telecom Advisory Services analysis

Next, to check if our results are influenced by the outlier nature of Washington, DC, we replicated the previous estimates excluding this spatial unit from the sample. The results, represented in columns (iii) and (iv) of Table 5, are almost identical to those of the complete sample. This means that the inclusion of the District of Columbia does not bias the results; consequently, we will include these observations in the remaining analyses. In addition, another potential concern could be that a subset of the broadband dataset was extrapolated (estimated) from real data (broadband penetration figures for 2010-2013 and for 2020), as explained above in section 5. Thus, to check if these extrapolation techniques are biasing the results, we replicated the previous estimates but only for the period of "real" data available, 2014-2019. Results for broadband penetration coefficients (0.010 in (v) and 0.009 in (vi)) are larger than for the complete sample showing that using extrapolated data to cover the whole period is not artificially inflating the economic impact. In fact, if any bias is generated by including extrapolated observations, it might be a downward one. Nevertheless, this may be a hasty interpretation, as it is reasonable to expect a larger economic impact for the subperiod estimated, given that 25 Mbps broadband penetration figures for 2010-2013 were modest. To sum up, we do not foresee any methodological problem in continuing the analysis for the complete period 2010-2020.

For the remaining estimates (reported in Table 6), we rely on different empirical strategies beyond OLS, as described above in section 4.

Table 6. Economic Impact of Broadband – Fixed Effects additional estimates

Dep. variable: $log(GDP)$	**Spatial Error Model (2010-2020)**		**Instrumental Variables (2010-2020)**		**Structural model (2016-2020)**	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$log(K)$	0.488***	0.479***	0.462***	0.387***	0.444***	0.399***
	[0.045]	[0.043]	[0.029]	[0.041]	[0.028]	[0.032]
$log(L)$	0.699***	0.694***	0.511***	0.609***	0.633***	0.606***
	[0.080]	[0.080]	[0.054]	[0.052]	[0.038]	[0.038]
HK	0.004***	0.004**	0.001	-0.003	0.001	-0.000
	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
$log(BB)$	0.005**	0.005**	0.022***	0.016***	0.125***	0.139***
	[0.003]	[0.003]	[0.005]	[0.003]	[0.014]	[0.015]
$log\,(BB) * Speed(400-850)$		0.001*		0.009*		
		[0.001]		[0.005]		
$log\,(BB) * Speed(400-850)$		0.002*		0.017***		0.002***
		[0.001]		[0.005]		[0.001]
Dep. variable: $log(BB)$						
$log(P)$					-0.082**	-0.070*
					[0.038]	[0.038]
$log(HK)$					0.979***	0.987***
					[0.324]	[0.323]
$log(GDP\ pc)$					2.001***	2.022***
					[0.187]	[0.185]
$log(URBAN)$					3.846***	3.709***
					[1.336]	[1.311]

Dep. variable: $log(REVENUE)$						
$log(P)$					0.370***	0.372***
					[0.068]	[0.068]
$Operators$					0.077	0.076
					[0.072]	[0.072]
Dep. variable: $log\left[\frac{BB_t}{BB_{t-1}}\right]$						
$log(REVENUE)$					-0.295***	-0.295***
					[0.060]	[0.060]
Lambda	0.554*** [0.054]	0.532*** [0.049]				
Under identification test			36.994***	6.782***		
Hansen J statistic			0.761	Exactly identified		
Fixed effects by State	YES	YES	YES	YES	YES (⊠)	YES (⊠)
R2 (within)	0.97	0.97	0.95	0.96	0.99	0.99
Observations	539	539	539	539	219	219
Estimation method	ML	ML	2SLS	2SLS	3SLS	3SLS

*Note: Robust standard errors in parentheses for estimates (i) to (iv). Standard errors in parenthesis for estimates (v) and (vi). *p<10%, **p<5%, ***p<1%. (⊠) State-level fixed effects included in all the equations of the model.*

Source: Telecom Advisory Services analysis

In columns (i) and (ii) of Table 6 we consider the possible presence of border externalities, something that was already pointed out above when analyzing spatial correlation. As described above, ignoring the potential spatial correlation may conduct to biased and inefficient estimation results. For that purpose, we rely on the Spatial Error Model, estimated through the Maximum Likelihood approach. Results are similar as in the OLS estimate, although the higher-speed interaction seems to reach a smaller coefficient than in the former, and its significance is only 10%.

As in previous studies of the impact of ICT in general, and broadband in particular, reverse causality can be considered as a potential concern. To take into account this source of endogeneity, we estimate the IV model in columns (iii) and (iv) of Table 6. To select the instrument set for the IV model, we followed the IV selection rationale provided by Czernich et al (2011) and Bertschek et al (2013), which state that a large portion of broadband deployments rely on the wire of pre-existing networks. The required access to an existing infrastructure built for other purposes, makes it a suitable instrument for this estimation strategy. In our study, the instrument for broadband penetration is the number of voice-telephony fixed access lines per inhabitant and the miles of wire per square kilometer in each US state during period 1912-1922 (data extracted from historical census of telephones by the Department of Commerce). Our assumption is that the infrastructure of previous telecommunication technologies determines the spatial diffusion of current technologies because legacy networks made the deployment of broadband less costly. Although it was not deployed with this aim, traditional voice fixed access lines in the US states can condition the current broadband connections.

As a result, we are using two variables (lagged voice telephony access lines and miles of wire per square km) to instrument one potential endogenous variable (broadband penetration). Even if it is not strictly necessary to have more instruments than endogenous variables (using only one instrument might have been enough), we preferred to use two (as in Czernich et al, 2011), considering that this allows the possibility of checking the exogeneity of the instrument set, through the overidentification test. If we were using only one instrument, the system would have been exactly identified, thus not being possible to confirm its exogeneity, as we have done.

However, when including speed differences in column (vi), the previous instrument set is not enough. Even if the information provided by both instruments cited above is suited to explain current speed differentials, the model cannot be estimated empirically because the system is under-identified (as we have a smaller number of instruments -2- than that of endogenous variables -3-). Therefore, for the system to be specified, we needed to include a third instrument. For this purpose, we decided to choose a metric potentially linked to speed variations, relying on an intensity-of-use indicator for the same lagged period (1912-1922): the average daily telephone calls.

To sum up, the assumption is that conditioned to the included set of time-variant and time-invariant state characteristics, the lag of traditional technologies in the state does not affect current economic output in a direct way, but only through its influence on the deployment of the newer technology. The instruments are lagged considerably (almost 100 years) to break any possibility of being affected by contemporary shocks that also impacted economic output. Results, reported in columns (iii) and (iv) of Table 6, confirm the direction of the economic impact estimated in the previous approaches. Moreover, the coefficients associated with broadband penetration and speed increase considerably, suggesting that the potential presence of endogeneity may be biasing down the economic effect of this technology. In addition, the overidentification test carried out for the estimate of column (iii) verifies the exogeneity of the instruments.

Finally, columns (v) and (vi) of Table 6 present the results for the structural model. The results for coefficients associated to capital and labor are like those from the previous estimates, while human capital loses significance. However, the economic impact for broadband in this case yields in a higher coefficient, suggesting that a 10% increase in broadband penetration drives a 1.25% increase in output (as indicated in column (v)). The reasons behind this increased effect can be, at least, three. First, the estimates refer to a subperiod of wider deployment of 25 Mbps networks. These connections were very limited in 2010, as it was its economic impact at the beginning of the period. Second, this is a subperiod of much higher internet speeds. As the impact of this technology depends on its speed level, it seems reasonable to estimate a higher effect when the average speed is much larger. Finally, as seen before in the IV model, estimation strategies conducted to control for endogeneity sometimes result in increased coefficients, as neglecting this concern usually leads to bias down the results.

As for the secondary equations, the estimated coefficients are in line with the expected results. Broadband demand depends negatively on service price, while taking larger values for more educated, urban, and richer states. On the other hand, sector output (Revenue) is positively influenced by prices, although the competition intensity (number of operators for every 100,000 inhabitants) is not significant

In column (vi) of Table 6 we replicate the previous estimate but allowing for different impact according to speed level. Considering that in the subperiod 2016-2020 nearly 83% of the observations already presented average maximum speeds above 400 Mbps, we include only the dummy associated to the 850 Mbps threshold, that identifies the top quartile of the speed distribution. Results are in line with the expected ones: a positive impact of broadband on GDP, that increases for those cases of average speeds above 850 Mbps.

7. ESTIMATING FIXED BROADBAND CONTRIBUTION TO ECONOMIC GROWTH

To estimate the contribution of each factor to economic growth, we first need to select the coefficient set from the estimated regressions presented in Tables 5 and 6. For that purpose, we will compare the results only of those regressions that include speed differentials and cover the complete period 2010-2020 (to generate a complete picture of what happened over the whole period): Column (ii) from Table 5 (OLS), Column (ii) from Table 6 (SEM), and Column (iv) from Table 6 (IV). These coefficients are summarized in Table 7.

Table 7. Coefficients considered for growth accounting estimation

Model	OLS	SEM	IV	Average
Reference	Column (ii) Table 5	Column (ii) Table 6	Column (iv) Table 6	
α	0.481	0.479	0.387	0.449
β	0.644	0.694	0.609	0.649
γ	0.003	0.004	0.000	0.002
Φ	0.006	0.005	0.016	0.009
$\delta_{400-850}$	0.002	0.001	0.009	0.004
δ_{850}	0.005	0.002	0.017	0.008
Advantages	Better fit (R-sq=0.972)	Accounts for spatial correlation	Accounts for endogeneity	
Disadvantages	Does not account for endogeneity or spatial correlation	Does not account for endogeneity	Does not account for spatial correlation	

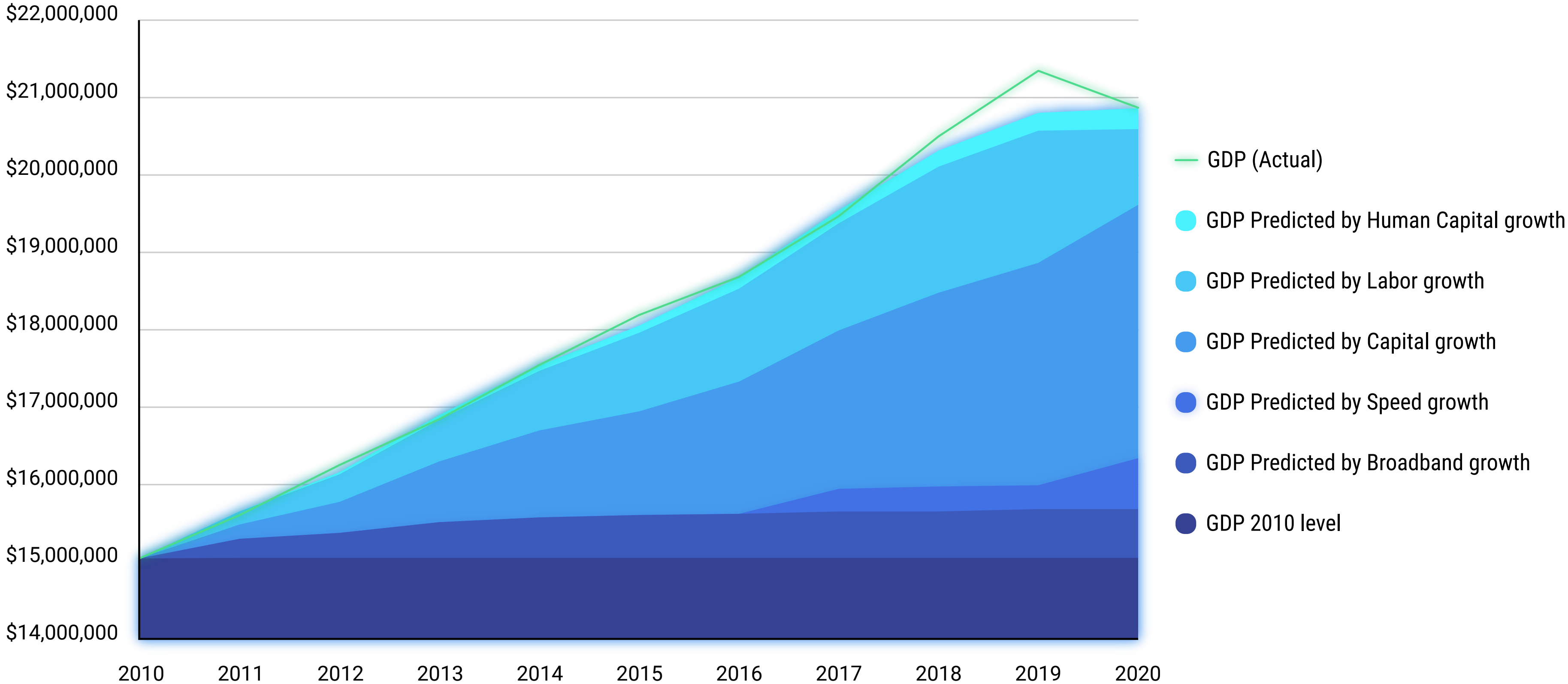
Source: Telecom Advisory Services analysis

The selection of a specific estimation is not an easy task, as each of the estimates reported in Table 7 has pros and cons. The OLS estimate does not control for spatial correlation or for endogeneity between broadband and GDP, but it remains the estimate that provides the better fit. On the other hand, the SEM model accounts for spatial correlation, but neglects the potential endogeneity as discussed above. Finally, the IV estimate controls for endogeneity, but does not address the spatial correlation concerns. Considering that there is not a single obvious choice, we will choose to carry on relying on the average coefficients estimated (last column of Table 7). Thus, the average coefficients are then: $\alpha = 0.449, \beta = 0.649, \gamma = 0.002, \Phi = 0.009, \delta_{400-850} = 0.004,$ and $\delta_{850} = 0.008$. By relying on these average coefficients, and in the empirical specification represented in equation [3], we get, after some rearrangements:

$$\frac{\Delta \text{GDP}}{GDP} = 0.449\frac{\Delta \text{K}}{K} + 0.649\frac{\Delta \text{L}}{L} + 0.002\Delta \text{hk} + 0.009\frac{\Delta \text{BB}}{BB} + 0.004\Delta(SPEED_{400-850}log(BB)) + 0.008\Delta(SPEED_{850}log(BB))$$

where the growth rate of GDP can be decomposed in different terms, to estimate the relative contribution of each item to economic growth. Graphic 3 presents the accumulated growth since 2010, as explained by the different sources.

Graphic 3. Sources of GDP growth 2010-2020



Source: Telecom Advisory Services analysis

The starting point is the US 2010 GDP: $15,048,970 million. As observed in Graphic 5, the main contributor to GDP growth since that year has been the capital deepening process, with important investment levels that increased considerably the physical capital stock of the economy. Labor has also been an important contributor, as reflected in the evolution of the unemployment rate, from 9.6% in 2010 to 3.7% in 2019[14]. On the other hand, the change in skills level of the workforce was not among the main contributors, possibly because the American population had already reached a high educational level by 2010. After capital and labor, the expansion of fixed broadband networks and the speed improvement emerge as crucial sources of growth.

Table 8 presents the accumulated growth by source, explaining the GDP gap from 2010 to 2020 values (all figures in current dollars). Again, physical capital is the main contributor, explaining 56.2% of the accumulated growth occurred during the period. Following capital, labor drives 16.8% of the growth. Fixed broadband expansion explains 10.9%, while speed improvements drives an additional 11.5%.

Table 8. United States: Decomposition of GDP growth 2010-2020

Segment		USD (million)	As % of accumulated growth	As % of 2020 GDP
GDP 2010		15,048,970		
Accumulated growth 2010-2020	Explained by Physical Capital (K)	3,287,035	56.2%	15.7%
	Explained by Labor (L)	981,928	16.8%	4.7%
	Explained by Human Capital (hk)	260,316	4.5%	1.2%
	Explained by Broadband (BB)	635,402	10.9%	3.0%
	Explained by Broadband Speed Increases	673,722	11.5%	3.2%
	Residual (not explained by model)	6,373	0.1%	0.0%
GDP 2020		20,893,746		

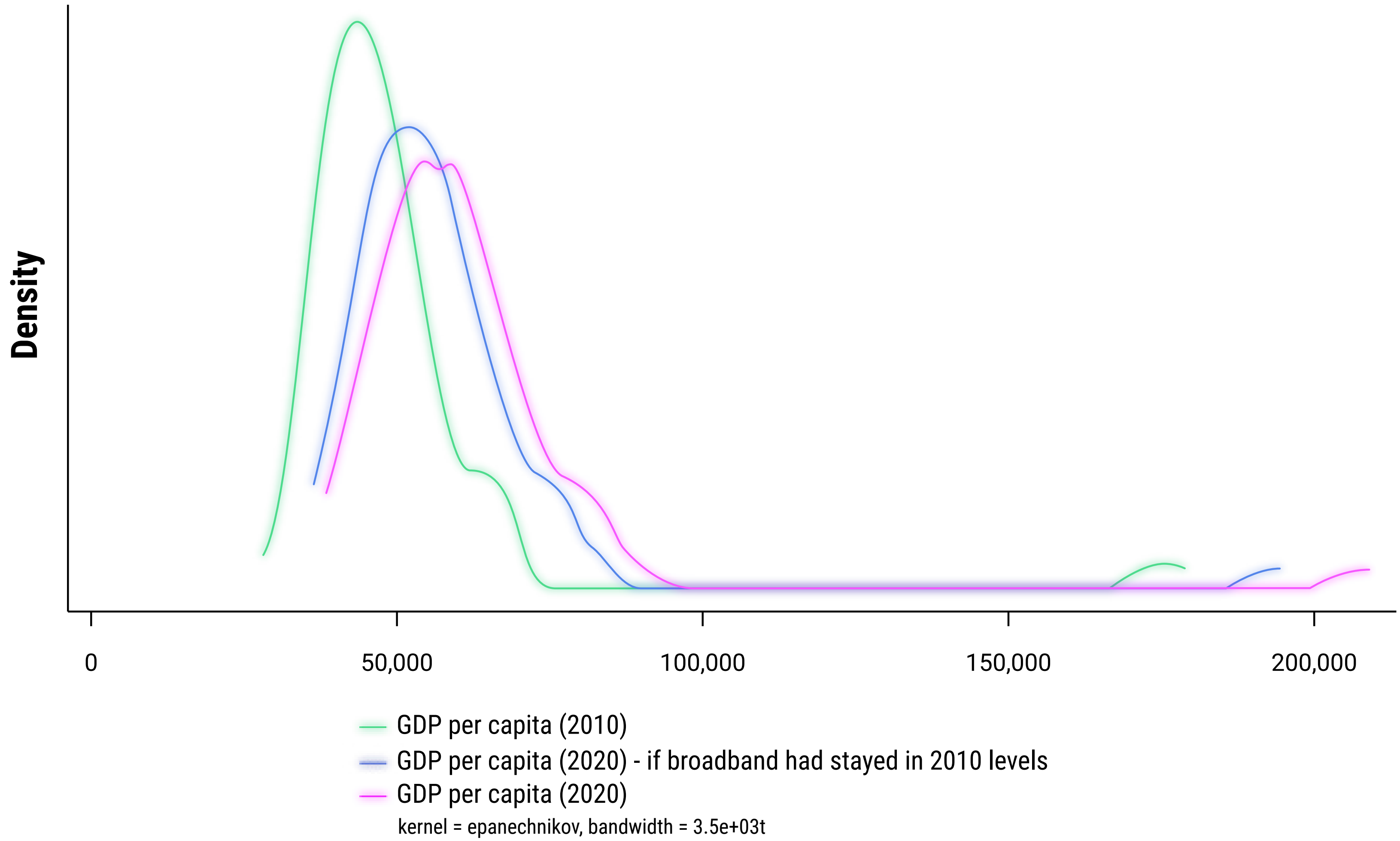
Source: Telecom Advisory Services analysis

14 Source: IMF

According to Table 8, if broadband adoption and speed had stayed unchanged since 2010, the GDP of the United States in 2020 would have been $19,584,622 millions, rather than the current level of $20,893,746 millions. The difference between both figures is what can be called the broadband contribution: $1,309,124 millions, a figure equivalent to 6.27% of 2020 GDP. In per capita terms, GDP would have been $59,481 rather than $63,457, almost $4,000 annual dollars less for the average American.

The same growth accounting exercise was done by state. Graphic 4 represents the kernel density function for three state-level series: the GDP per capita in 2010, the GDP per capita in 2020 (actual), and the GDP per capita in 2020 had broadband stayed in 2010 levels (in terms of adoption and speed). The GDP per capita growth would have been much lower without broadband improvement, as the distribution of the 2020 counterfactual series is clearly situated at the left of the actual one.

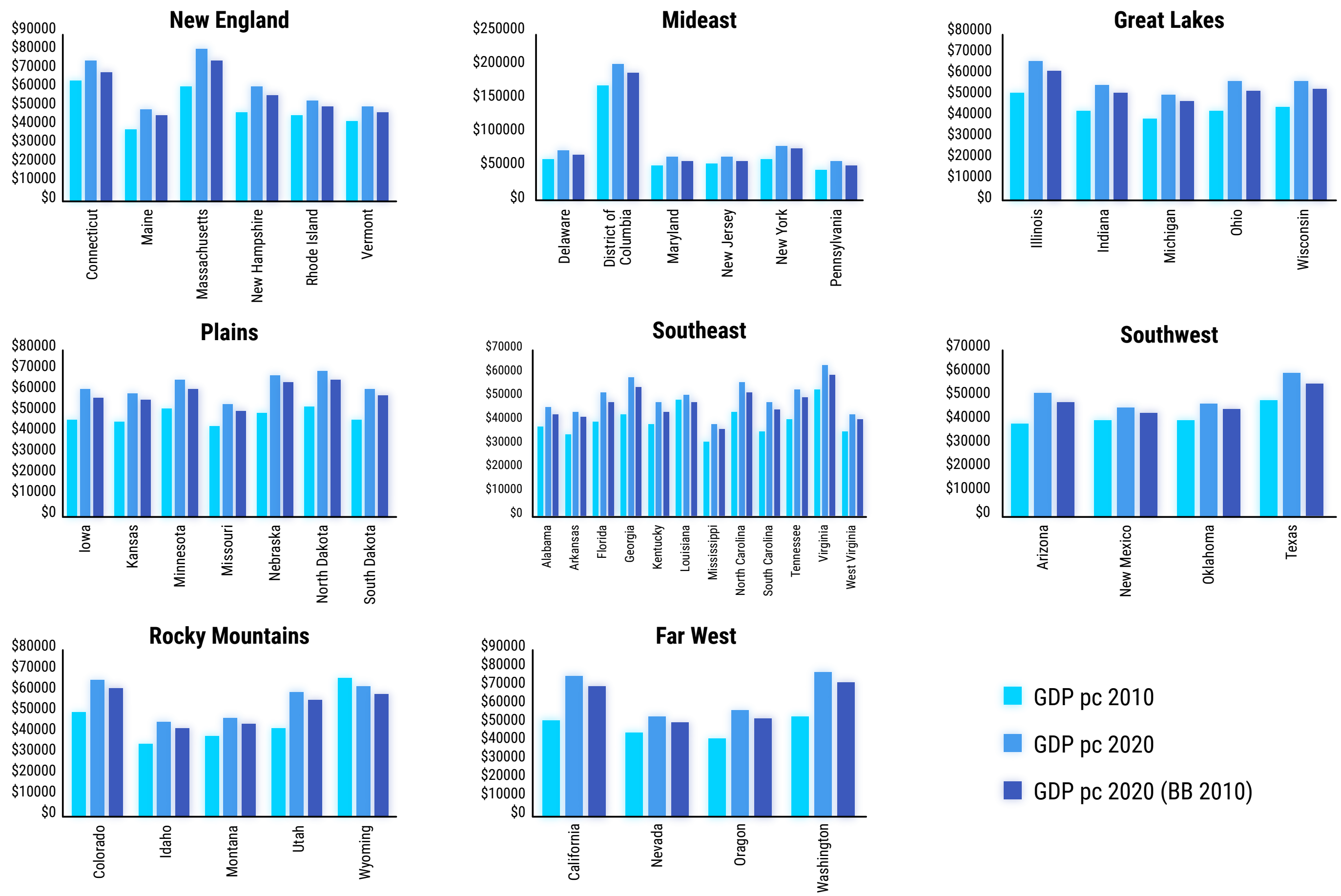
Graphic 4. Kernel Density function for GDP per capita scenarios



Source: Telecom Advisory Services analysis

Finally, Graphic 5 depicts the average GDP per capita by state according to the three scenarios: 2010, 2020 (actual), 2020 had broadband stayed at 2010 levels (in terms of adoption and speed). While broadband has generated a positive economic contribution in all states, some differences emerge.

Graphic 5. GDP per capita by state under different scenarios



Source: Telecom Advisory Services analysis

The contribution of broadband to GDP per capita has not been uniform by state, resulting in a higher impact in those states where adoption and speed evolved at a faster pace. The states where the biggest impact is achieved are Maine and Ohio, where 2020 GDP per capita would have been 7.9% and 7.8% (respectively) below 2020 levels had broadband stayed in 2010 levels. Beyond Ohio, other states also were big benefiters, such as North Carolina (7.6%), South Carolina (7.3%), Texas (7.2%) and Delaware (7.1%). On the other end, West Virginia was benefited less by broadband improvements, as the GDP per capita would "only" be 5% below current level had broadband stayed at 2010 level, followed by Montana (5.1%), Oklahoma (5.1%), and Wyoming (5.2%). The case of Wyoming is particularly interesting, as this state experienced a contraction in its GDP per capita during the period, being 2020 figures lower than 2010. Broadband contributed to mitigate this contraction, as 2020 GDP per capita would have been even lower have connectivity stayed in 2010 levels.

8. ESTIMATING FIXED BROADBAND CONTRIBUTION TO CONSUMER SURPLUS

To calculate the consumer surplus generated by broadband during the period 2010-2020 in the United States, we estimate a national-level linear demand function for broadband connectivity. With the coefficients estimated in the broadband impact equation, the demand function can be expressed as:

$$BB = -93300000 + 3652.20 * Income - 38555.6 * Price$$

Where BB represents the quantity of broadband connections[15], Income is measured through GDP per capita[16] and Price is the average annual cost of a fixed internet plan[17]. As expected, broadband demand depends positively on Income, and negatively on its own price, thus behaving as a normal good.

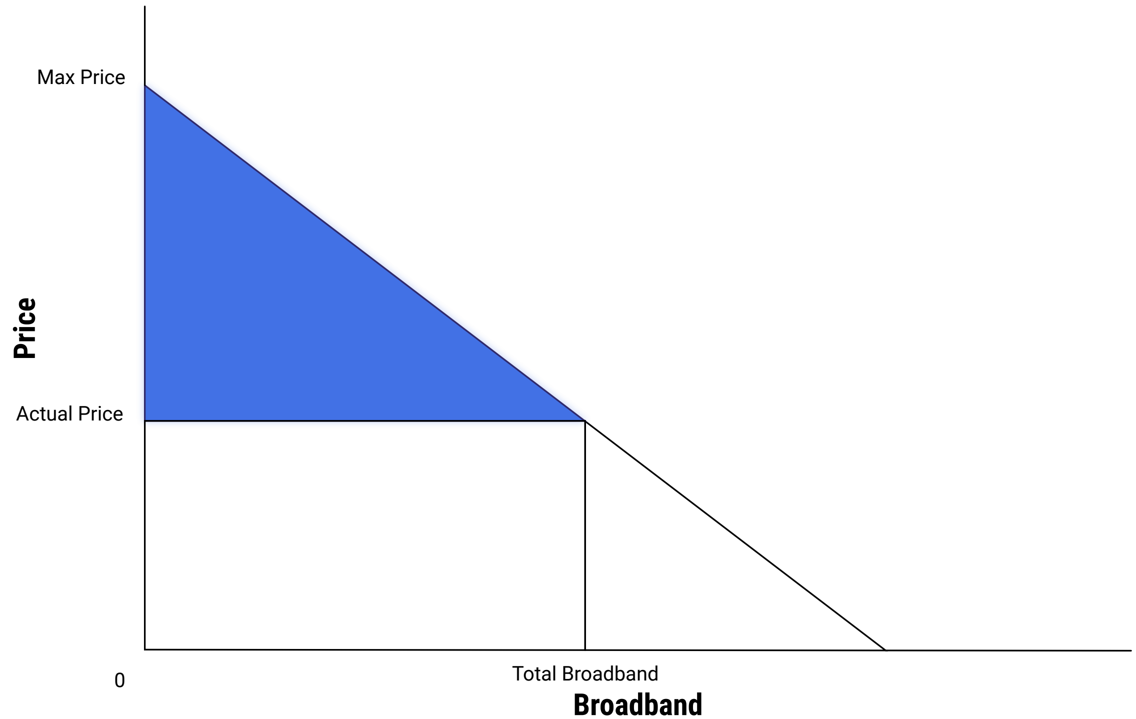
Rearranging, we can get the inverse of the demand function:

$$Price = \frac{-93300000 + 3652.20 * Income}{38555.6} - \frac{BB}{38555.6}$$

Where $Max\ Price = \frac{-93300000 + 3652.20 * Income}{38555.6}$ represents the maximum price that the market is willing to pay for a broadband connection. Above that maximum price, there is no demand for broadband. The consumer surplus is then calculated as the area below the demand function and above the actual price, as highlighted in Graphic 6.

15 Source: ITU
16 Source: World Bank
17 ITU reports data for a 5GB fixed broadband basket as percentage of Gross National Income per capita (GNI pc). By applying that percentage to annual GNI pc data provided for the US by the World Bank, we were able to estimate the annual price for a fixed internet connection.

Graphic 6. Calculation of consumer surplus from broadband



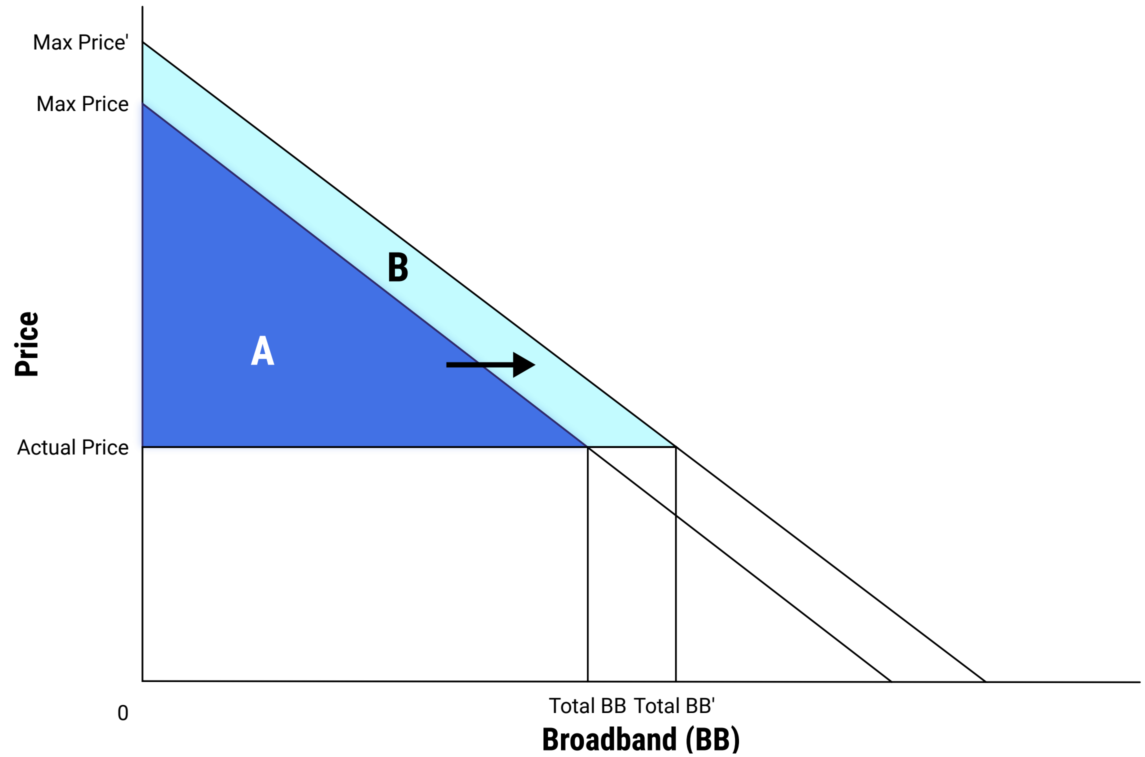
Source: Telecom Advisory Services

The consumer surplus is then calculated as the area of the highlighted area:

$$Consumer\ Surplus = \frac{(Max\ Price - Actual\ Price) * Total\ BB}{2}$$

The calculation must be made on a year-by-year basis, as the maximum price that consumers are willing to pay varies depending on income. Considering that a broadband subscription is a normal good, with higher income, the more the amount consumers will be willing to pay for it. In other words, the demand function exhibited shifts to the right every time the consumers income increases (Graphic 7), resulting in additional broadband demanded for a same price, and increasing the consumer surplus, now represented by the sum of areas A+B.

Graphic 7. Consumer surplus from broadband



Source: Telecom Advisory Services

Naturally, actual prices also vary over the time, again reinforcing the need to estimate consumer surplus on a yearly basis.

Table 8 summarizes the calculated surpluses for years 2010 to 2020. Income per capita increased for all the years of the sample (except for 2020), something that progressively shifted the demand curve to the right, resulting in bigger surplus. The difference between the maximum price the individuals are willing to pay, and the actual prices increases steadily during the period, thus increasing the consumer surplus.

Table 8. United States: consumer surplus for broadband connections

#	Concept	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Source
1	Max Price	$2,171.2	$2,305.3	$2,468.2	$2,610.7	$2,794.8	$2,966.5	$3,076.2	$3,274.0	$3,553.9	$3,763.8	$3,604.1	Demand function
2	Actual Price	$240.3	$244.2	$186.0	$201.2	$198.4	$203.6	$482.8	$630.2	$512.7	$529.0	$516.9	ITU
3	Internet connections (M)	84.52	88.32	92.51	96.03	97.81	102.21	105.71	108.20	110.76	114.27	120.53	ITU
5	Annual surplus ($ million)	$81,598	$91,015	$105,572	$115,692	$126,978	$141,201	$137,083	$143,031	$168,417	$184,820	$186,052	((1)-(2))*(3)/2

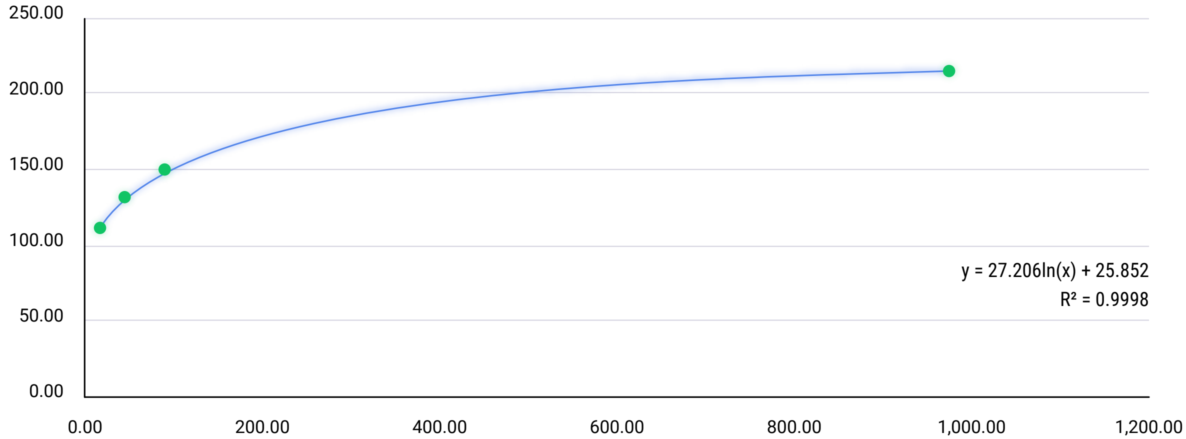
Source: Telecom Advisory Services

The number of broadband connections increased significantly during the period, from 84.5 million subscriptions in 2010 to 120.5 million in 2020. This increase yielded an aggregated consumer surplus at national level reached $81.6 billion in 2010, increasing to over $186 billion in 2020.

The previous calculation implicitly assumes that every internet connection is a homogeneous good, with only annual changes in demand being explained by income variations. That said, internet connections are not homogeneous, as the quality of the service increases over the time as consumers are able to enjoy more reliable and faster connections, which means that additional surplus is generated by the consumers when better connections are available.

To account for the additional surplus generated by speed increases, we surveyed existing research literature in this field. Most studies of consumer surplus derived from faster broadband speed are based on primary research, where users stipulate the amount they would be willing to pay for broadband service (Savage et al, 2004; Greenstein and McDewitt, 2011; Liu et al, 2017). Other studies of broadband speed consumer surplus focus the assessment on how consumers react to variations in price according to their data usage. For example, Nevo et al (2016) studied hour-by-hour Internet usage for 55,000 US subscribers facing different price schedules. They concluded that consumer surplus for speed is heterogeneous. Consumers will pay between $0 to $5 per month for a 1 Mbps increase in connection speed, with an average of $2[18]. In addition, they stipulated that, with the availability of more content and applications, consumers will likely increase their usage, implying greater time savings and a greater willingness to pay for speed. At the time of their research, the increase in willingness to pay at high speeds dropped by approximately $0.11 per Mbps[19]. The authors found that the valuation of bandwidth is highly concave, with lesser added value beyond 100 Mbps. As reported in this study, US households are willing to pay about US $2.34 per Mbps ($14 total) monthly to increase bandwidth from 4 Mbps to 10 Mbps, US $1.57 per Mbps ($24) to increase from 10 to 25 Mbps, and US $0.02 per Mbps (US $19) for an increase from 100 Mbps to 1000 Mbps (see Graphic 3).

Graphic 3. Log Curve of relationship between broadband speed and consumer surplus (based on Nevo et al, 2016)



Sources: Nevo et al (2016); Telecom Advisory Services analysis

Relying in the parameters estimated by Nevo et al (2016), we calculated the additional consumer surplus generated by the average speed improvements materialized since 2010 according to the data provided by Ookla/Speedtest. Table 9 summarizes the results.

18 Heterogeneity in willingness to pay for broadband was also highlighted by Rosston et al (2010).
19 This is confirmed by a more recent study. Liu et al (2017) administered two national, discrete choice surveys of US consumers to measure households' willingness-to-pay for changes in price, data caps, and speed.

Table 9. United States: consumer surplus for broadband speed increases since 2010

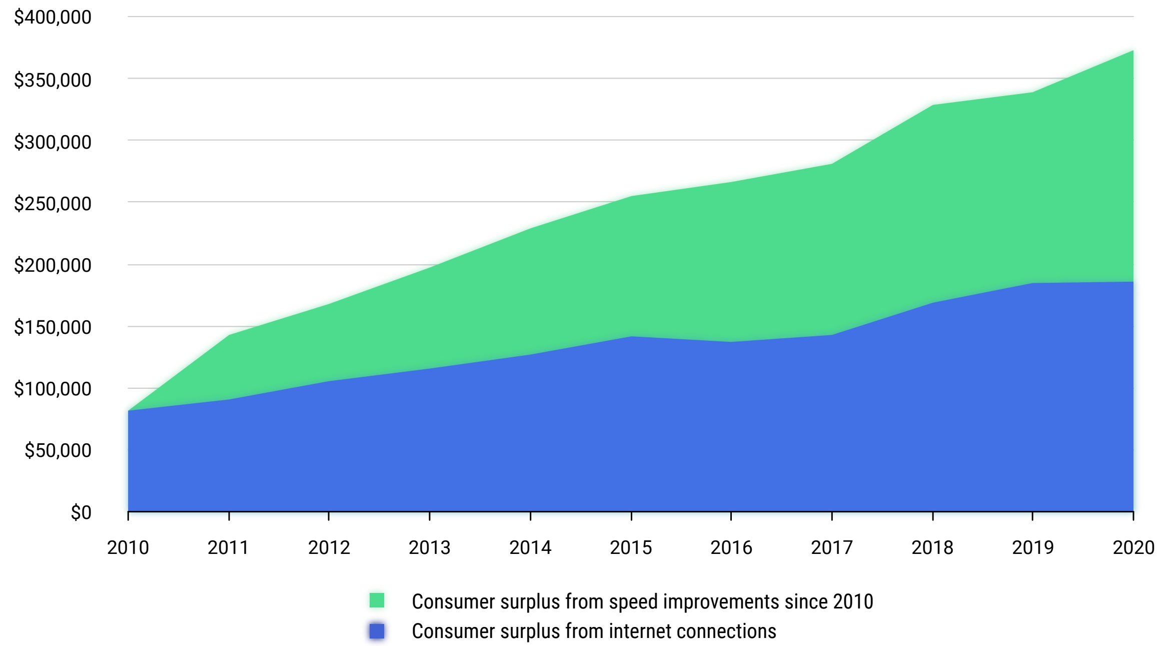
#	Concept	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Source
1	Fixed BB speed (Mbps)	10.03	12.37	15.41	20.62	29.96	41.74	58.15	77.48	109.63	133.93	177.84	Ookla
2	Delta		2.33	3.04	5.22	9.33	11.78	16.41	19.33	32.16	24.30	43.91	(1)-L.(1)
3	Additional Monthly Consumer surplus		$48.89	$56.11	$70.79	$86.62	$92.95	$101.97	$106.43	$120.27	$112.65	$128.75	Nevo Curve
4	Additional Yearly Consumer Surplus		$586.67	$673.38	$849.48	$1,039.44	$1,115.40	$1,223.66	$1,277.11	$1,443.29	$1,351.77	$1,544.98	(3)*12
5	Internet connections (M)		88.32	92.51	96.03	97.81	102.21	105.71	108.20	110.76	114.27	120.53	ITU
6	Annual surplus ($ million)		$51,813	$62,297	$81,577	$101,668	$114,008	$129,358	$138,183	$159,853	$154,466	$186,218	(4)*(5)

Source: Telecom Advisory Services

Considering the significant improvements in average speed (the average for fixed broadband evolved from 10.03 Mbps in 2010 to 177.84 Mbps in 2020), this increases in connection quality yielded important gains in terms of consumer surplus: from $51.8 billion in 2011 to $186.2 billion in 2020.

In Graphic 4 we compare the evolution of consumer surplus derived from both broadband connections and from speed gains, relying on the calculations presented in Tables 8 and 9.

Graphic 4. United States: consumer surplus generated since 2010 from broadband connections and speed increases (in USD million)



Source: Telecom Advisory Services

By considering the shape of both curves, it seems clear that the relative weight of speed improvements over the total consumer surplus increases considerably. This may be explained by the decreasing network effects generated once a certain threshold of internet penetration is reached. After that point, additional people connected yields lower surplus[20], and the larger source of consumer satisfaction comes from larger connectivity speeds.

20 For diminishing consumer surplus as determined by declining network effects, see Eisenmann et al (2006).

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APPENDIX – ADDITIONAL CONTROLS

In order to avoid the possibility of any omitted variable bias, we conducted further checks with additional controls. Beyond the variables that arise from the theoretical model presented above, we tested in the specification a set of time-varying regional controls, such as temporal effects, R&D intensity and industrial mix. To account for R&D intensity we include a variable of R&D spending as a share of GDP (data from the National Science Foundation). To control for differences in the productive structure, we introduce variables that account for share of agriculture and industry, respectively, in the regional GDP (data from BEA). Results are presented in Table A.1.

Table A.1. Economic Impact of Broadband – Fixed Effects OLS estimate with additional control variables

Dep. variable: $log(GDP)$	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$log(K)$	0.485***	0.539***	0.509***	0.492***	0.471***	0.512***
	[0.042]	[0.046]	[0.053]	[0.041]	[0.043]	[0.031]
$log(L)$	0.655***	0.586***	0.586***	0.682***	0.716***	0.651***
	[0.049]	[0.093]	[0.093]	[0.097]	[0.100]	[0.055]
HK	0.003**	0.005***	0.003**	0.003**	0.002*	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$log(BB)$	0.003**	0.004***	0.002*	0.006***	0.006***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Time-trend	0.003		0.003			
	[0.002]		[0.002]			
Year 2020 dummy		-0.009	-0.012			
		[0.007]	[0.007]			
$log(R\&D/GDP)$				0.010	0.013	
				[0.013]	[0.013]	

$log(Industry/GDP)$					-0.029*	-0.021
					[0.016]	[0.015]
$log(Agriculture/GDP)$					-0.014	
					[0.009]	
Fixed effects by State	YES	YES	YES	YES	YES	YES
R2 (within)	0.97	0.97	0.98	431	431	539
Observations	539	539	539	0.97	0.97	0.97
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS
Period covered	2010-2020	2010-2020	2010-2020	2010-2018	2010-2018	2010-2020

*Note: Robust standard errors in parentheses. *p<10%, **p<5%, ***p<1%.*

Source: Prepared by the authors

These additional variables were found to be non-significant in most estimates (see columns (i) to (vi) in Table A.1. This means that the selected variables introduced in Table 3 of the main text are suitable enough to explain the variance in output. In (i) we introduce a time-trend, to account for any exogenous technological growth affecting the country, however, it was found to be non-significant. The same when we introduce a 2020 dummy to absorb the exogenous shocks occurred that year, in column (ii). This may be explained as the COVID effects occurred during 2020 varied substantially by state. In (iii) we introduce both temporal variables together, again being no significant. In column (iv) we introduce the R&D intensity as regressor, being not significant. While it may seem surprising that R&D intensity was found to be non-significant, this may be explained by the fact that the region where the R&D investment is made (place of R&D facilities) is not necessarily the same to where the production of those innovations is carried out (usually production plants are translated to cheaper states, or either abroad). In columns (v) and (vi) we introduce the variables to account for industrial mix, being the share of industry over regional GDP significant, albeit only at 10%. In column (v) we replicate the previous regression, but including only the industry share on GDP, as it was found to be the only significant variable. The rationale for doing so is to avoid the constraint imposed by the variable of R&D (only available for 2010-2018) and to be able to perform an estimate covering the whole period (2010-2020). In this case, the industry intensity variable loses significance.

In Table A.2. we introduce the industry intensity control in both SEM and IV models, again being non-significant.

Table A.2. Economic Impact of Broadband – Fixed Effects SEM and IV estimates with additional control variables

Dep. variable: $log(GDP)$	Spatial Error Model	Instrumental Variable
	(i)	(ii)
$log(K)$	0.487***	0.462***
	[0.045]	[0.028]
$log(L)$	0.700***	0.509***
	[0.081]	[0.059]
HK	0.004***	0.001
	[0.001]	[0.001]
$log(BB)$	0.005**	0.022***
	[0.003]	[0.005]
$log(Industry/GDP)$	-0.009	0.003
	[0.013]	[0.016]
Lambda	0.552***	
	[0.054]	
Underidentification test		34.643***
Hansen J statistic		0.748
Fixed effects by State	YES	YES
R^2 (within)	0.97	0.95
Observations	539	539
Estimation method	ML	2SLS

*Note: Robust standard errors in parentheses. *p<10%, **p<5%, ***p<1%.*

Source: Prepared by the authors

In all the cases, broadband remains positive and significant. All in all, we can conclude that the selected set of variables used in the main text is suitable enough to explain output variations, without incurring in any omitted variable bias.

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