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The role of Video on Demand in stimulating broadband adoption[☆]

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A R T I C L E I N F O

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A B S T R A C T

In this paper we study the role of Video on Demand services (VOD) as drivers of broadband adoption. While the research literature has highlighted the importance of digital content, such as applications and Internet platforms, as a driver of broadband adoption, no studies have yet explored the specific contribution of VOD. We developed a worldwide database of VOD services launch by country since 2012 (including Netflix, Amazon Prime, Apple TV+, Disney+, Paramount+, and HBO Max) and explored their contribution as contributors to broadband adoption during the period. To do so, we relied on several empirical specifications including instrumental variables to control for reverse causality between broadband adoption and VOD services availability. Our results confirm that VOD services have been a key contributor to the increase of broadband connectivity, also helping to narrow down the digital divide especially in developing nations. In addition, VOD service offers have been associated with the gradual increase in the purchasing of broadband higher speed plans. Finally, there is a significant and positive increase in consumer surplus associated with the launch of VOD offers. This evidence points to the impact of VOD services on the digital economy as a stimulus for consumer acquisition of broadband services and therefore as a contributor to the revenues of broadband service providers.

1. Introduction

The debate around the contribution of Video on Demand (VOD) services to the broadband ecosystem has been so far primarily focused on their use of network infrastructure and therefore the need for them to participate in the funding of network deployment and/or operations (concept otherwise known as their “fair share”). According to this premise, the VOD services use of broadband network capacity is such that it should prompt the need for them to contribute to funding it.[1]

That said, little focus has been put so far on analyzing the contribution of VOD to stimulating broadband demand. In other words, there are no current studies that analyze the role of VOD content acting as a stimulus for consumer acquisition of broadband service

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[1] Several approaches have been proposed to fund the deployment costs, ranging from obliging VOD services to contribute to fund the Universal Service Fund (as the bill S. 3321 submitted in the US Senate “Lowering Broadband Costs for Consumers Act of 2023) to charging them for their use of network capacity, to taxing VOD services to subsidize ISPs.

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and therefore having also a concurrent contribution to the business of telecommunications operators. While this concept has already been raised in public fora,[2] the issue has not yet been analyzed empirically. This is an important gap in the research literature which this paper aims to address.

The question can be theoretically disaggregated into different areas of analysis. First, the direct contribution of VOD services availability to demand for broadband connectivity needs to be quantified. As is the case with other sources of content or internet platforms, the offering of audiovisual content can potentially drive broadband adoption. While fixed broadband adoption (especially in advanced economies) was relatively high at the time the VOD services were launched, one could hypothesize that the audiovisual content they offered was a driver of additional penetration, particularly among non-adopters. For example, Netflix launched video streaming in 2007, and started expanding internationally in 2010, while Amazon Prime Video was launched in 2006, and Hulu in 2008. In 2010, worldwide average fixed broadband adoption was 26.01% of households and by 2021 it had reached 57.84%.[3] Since broadband access has value only in terms of what it enables consumers to do (for example, download information from the Internet or provide distance education to children), it is reasonable to ask the question of what portion of the increase in broadband penetration since 2010 is associated with the offering of VOD content.

Moreover, if the previous argument is true, VOD should stimulate not only broadband adoption, but especially the migration to subscriptions of high-speed plans. This can be explained because offering of high-definition content in VOD services could prompt the need for some consumers to upgrade their broadband service from low-capacity bandwidth plans to services enabled by FTTx or DOCSIS 3.0 and above. While streaming a movie in standard definition requires 3 Mbps, the same content in 4K UHD requires 25 Mbps, and live broadcasts in 4K require approximately 30 Mbps (Lunn, 2022). As in the case above, we can also hypothesize that a portion of the migration from DSL service to FTTx (and DOCSIS 3.0) is driven by the need to gain access to high-quality video.

In addition, if VOD content contributes to stimulate adoption, then it could be playing a significant role in addressing the digital divide. Developing regions lag advanced economies in terms of fixed broadband adoption. As an example, in 2022 the share of households with fixed broadband connection in North America and Western Europe was above 95%, while the corresponding figures for Latin America and the Caribbean, Asia-Pacific and Sub-Saharan Africa were 67.69%, 68.77%, and 4.34%, respectively.[4] Even when considering mobile broadband, the difference between both groups of nations indicate that a portion of the world population is still unconnected. In a post-pandemic world, the International Telecommunications Union (ITU) has emphasized that countries cannot allow the digital divide to remain a social barrier. Recognizing that a large portion of the digital divide is driven by lack of coverage and affordability barriers, research has also shown that part of non-adoption behavior is also driven by lack of content relevance (Katz & Berry, 2014). The evidence consistently extends to both developed and developing countries. For instance, in a study conducted in the United Kingdom in 2011, more than 50% of households that did not adopt broadband mentioned "lack of relevance" as the reason for their decision (OFCOM, 2012). Similarly, in Colombia, a study conducted in the same year found that 20% of households without broadband justified their behavior by stating that they did not perceive the Internet as necessary (MITIC, 2011). In this context, it is relevant to raise the question whether the launch of VOD platform added “relevance” to the broadband value proposition, prompting some non-adopters to acquire the service. This last question could be very important for developing countries.

A different angle of analysis is that related to the consumer surplus that VOD availability generates to broadband adopters. Consumer surplus derived from broadband, as measured by the difference between the willingness to pay (WTP), as a measure of value, and what was actually paid for the service, is driven by the functionalities enabled in terms of access to information, platforms, and a host of applications ranging from e-commerce to communications and tele-medicine. Within this universe, acknowledging that broadband provides access to a whole suite of services and content, it is also relevant to inquire whether access to VOD content could be a driver of an increase in WTP, and therefore, consumer surplus.

The purpose of this study is to provide answers to the questions raised above and measure in quantitative terms the contribution of VOD in driving broadband uptake. The main contribution of this research is related to being the first study to quantitatively address this topic, to the best of our knowledge. The evidence provided in this research also accounts for a critical methodological problem that arises from the link between content and broadband adoption, which is that of endogeneity concerns.

The rest of the paper is organized as follows. Section 2 will present the relevant research literature. Section 3 will outline the dataset and review some of the descriptive statistics, while Section 4 will provide the main results of the empirical analysis. Section 5 develop some further robustness checks, while Section 6 provides some interpretation for the main results. Finally, Section 7 concludes by summarizing findings and outlining directions for further research.

2. Literature review

As predicted by microeconomic theory, broadband demand initially depends on the price of the services and income level of consumers. Multiple studies have found service price and income (consequently affordability) to be relevant in explaining broadband adoption. In the case of price, Rappoport et al. (2002), Garcia-Murillo (2005), Goolsbee (2006), Flamm and Chaudhuri (2007), Dutz et al. (2009), Galperin and Ruzzier (2013), Roycroft (2013), Katz and Berry (2014), and Lange (2017) provided explanatory evidence of its predictive value. Regarding income, Garcia-Murillo (2005), Grosso (2006), Prieger and Hu (2008), Vicente and Lopez (2010),

[2] See Netflix Co-CEO Greg Peters Keynote at the 2023 Mobile World Congress. Available in: https://about.netflix.com/en/news/co-ceo-greg-peters-keynote-address-to-the-2023-mobile-world-congress.

[3] Source: authors calculation with data from the International Telecommunications Union (ITU).

[4] Source: authors calculation with data from the ITU.

Roycroft (2013), and Lange (2017) also generated studies justifying the importance of this variable in driving adoption.

That said, in addition to conventional microeconomic variables, research also highlighted that differences in consumer preferences should also explain part of broadband adoption. This body of research linked disparity in preferences to socioeconomic variables, such as education (Vicente & Lopez, 2010; Galperin & Ruzzier, 2013; Roycroft, 2013; Srinuan & Bohlin, 2013; Quaglione et al., 2018); gender (Flamm & Chaudhuri, 2007; Srinuan & Bohlin, 2013; Roycroft, 2013); age (Vicente & Lopez, 2010; Galperin & Ruzzier, 2013; Srinuan & Bohlin, 2013; Quaglione et al., 2018); race (Prieger & Hu, 2008; Roycroft, 2013); household size/composition (Flamm & Chaudhuri, 2007; Vicente & Lopez, 2010; Roycroft, 2013; Quaglione et al., 2018); and demographic factors (Kim et al., 2003;Garcia-Murillo, 2005; Cava-Ferreruela & Alabau-Munoz, 2006; Quaglione et al., 2018).

Surprisingly, content availability has been rarely included as driver of broadband adoption in the empirical literature. However, several authors theoretically argued about its relevance along the following lines: given that broadband serves as a platform for accessing internet content, applications, and services, the value of the content itself should act as a motivating factor for individuals to purchase a subscription. For example, Srinuan and Bohlin (2013) argued that the availability of rich content is a crucial driver for broadband adoption and usage. Coincidentally, Yamakawa et al. (2012) stipulated that improved content is crucial for stimulating broadband demand. Likewise, Lee and Brown (2008) contended that, according to broadband users, the presence of captivating content, services, and applications plays a crucial role in driving the spread of broadband technology.

Counterfactually, some authors pointed that a potential lack of attractive content can be considered a barrier for broadband adoption. For example, according to Katz and Berry (2014), the lack of cultural relevance of available content could serve as a barrier to broadband adoption. Similarly, Galperin and Ruzzier (2013) argued that potential price reduction might not be enough to achieve penetration goals; therefore, complementary policy strategies that affect other determinants of broadband demand (including availability of relevant content) should also be considered. Along those lines, Irani et al. (2009) argue that cultural differences and dissimilarities in lifestyle between countries require specific strategies and tailored content to promote broadband adoption.

These theoretical arguments are supported by surveys carried out in multiple countries. In 2010, even in technologically advanced nations, the penetration of broadband was far from complete (71.96% of households in North America and 65.84% in Western Europe). When people were asked about their reasons for not adopting broadband, surveys consistently found that "lack of interest" or "lack of relevance" regarding the available content in advanced countries was a significant factor, often ranking higher than affordability. For instance, based on a survey conducted in the United States by Horrigan (2009), approximately 50% of households without broadband attributed their non-adoption to a "lack of relevance/interest." In this survey, the lack of relevance was driven by reasons like "no interest," "being busy with other tasks," or unspecified factors. Interestingly, the percentage of non-adopting households citing lack of relevance (50%) was higher than those citing affordability (35%). In another study conducted two years later in the United States, the proportion of non-adopting households explaining their decision with a "lack of relevance" answer only slightly decreased to 47%, while affordability dropped to 24% (NTIA, 2011). When examining non-broadband households with and without a computer separately, the percentage citing lack of relevance rose to 52%, while affordability decreased to 21%. Similarly, a study conducted in the United Kingdom in 2011, as mentioned in the introduction to this research (OFCOM, 2012), found that most non-adopting households attributed their decision to "lack of relevance." Again, this percentage was significantly higher than those indicating affordability as a barrier (16%). Interestingly, in a similar study conducted in 2010, the affordability barrier was mentioned by 23% of surveyed households. This suggests that as broadband prices declined from 2010 to 2011, the cultural relevance factor became more significant. In other words, when affordability becomes less influential in explaining non-adoption, the lack of relevance or interest becomes more prominent. However, this situation was not consistent across technologically advanced nations. For example, regarding Australia, the affordability variable held slightly more significance (26%) compared to lack of relevance (19%) (AGIMO, 2009).

As anticipated, the lack of relevance as a hindrance to broadband adoption is primarily observed within specific socio-demographic groups in developed nations. For example, in the United Kingdom, households that do not have broadband and mention lack of relevance as a reason are typically those with lower income and individuals aged over 65. Similarly, a study conducted in Spain (ONTSI, 2012) revealed that the perception of internet content's lack of relevance decreases as income levels rise.

Similar patterns were observed in developing nations, providing evidence that aligns with the findings in advanced economies. In Colombia, for instance, 20% of households without broadband justified their decision by stating that they did not perceive the Internet as a necessary tool (MITIC, 2011). The language barrier has also been identified as a factor in the emerging world. For example, in Peru, only 8% of individuals whose first language was not Spanish use the Internet, whereas among native Spanish speakers, this percentage increases to 40%. In the Middle East North Africa region, the limited availability of content in native languages is often cited as a significant hurdle for broadband demand.

In a study conducted in a developed nation, the lack of relevance was also influenced by linguistic factors. This was observed among the recently immigrated Hispanic population in the United States. It is crucial to note that the linguistic barrier is closely linked to economic and educational factors. Consequently, isolating the linguistic factors from socio-demographic variables remains challenging.

The lack of relevance variable introduces a level of complexity in its interpretation, and two possible explanations should be considered. The first straightforward option is that consumers have assessed the available applications, services, and content and have found them irrelevant to their needs. Under this scenario, adoption would likely increase if there were a wider range of offerings that better catered to consumer preferences. The second option is that consumers lack sufficient information to make an informed decision about adopting broadband.

The few empirical articles that have introduced some measure of content availability in explaining broadband demand found interesting results supporting its relevance. For example, using a worldwide sample of countries, Lee and Brown (2008) found content (measured as Internet hosts per 100 inhabitants) as a significant variable to explain broadband adoption. In a similar vein, Garcia-Murillo (2005) discovered that, based on a sample of 100 countries, there exists a positive correlation between the number of registered domain name servers and the number of broadband subscribers. This suggests that internet content plays a significant role in driving the adoption of broadband services. Additionally, Quaglione et al. (2018) found that video content serves as a crucial driver for broadband adoption in Italy. They observed that individuals who prefer premium content and are subscribers of pay TV services are more likely to adopt fixed broadband services, with a notable increase of 3.7%. In turn, Jayakar and Park (2020) argue about the complex interactions and mutual interdependence between OTT platforms such as Netflix and established industry incumbents as internet service providers. Conversely, Lenhart et al. (2003) found that the perceived lack of relevance of online content strongly predicts a decrease in online access. It is important to note that no research has been identified that analyzes the contribution of audiovisual content on the Internet as a driver of broadband demand.

In light of the reviewed research, there is a need for a deeper understanding of the role of audiovisual content in driving broadband adoption. From a theoretical perspective, several authors have highlighted the relevance of content in driving demand. However, very few studies have been able to conduct empirical estimates accounting for this effect, possibly because of lack of datasets. The (few) papers that have considered some measure of content in empirical estimates, have done so using metrics that are not suitable enough to consider the richness of audiovisual content over the internet. In summary, no study has analyzed empirically to date the specific relevance of audiovisual VOD services in driving broadband demand.

3. Data and descriptive statistics

The main hypothesis to test in this study is whether the increasing availability of VOD services has contributed to stimulate broadband adoption. For this purpose, we built a dataset of 149 countries between 2012 and 2022, a period characterized by the launch of several VOD services.

Table 1 presents the descriptive statistics of the full dataset. Main telecommunications sector variables were collected from the ITU statistics, while socioeconomic controls were extracted from well-known public databases such as the World Bank (World Development Indicators) and the UNESCO Institute for Statistics.

Since the variable quantifying the number of VOD services per country by year is not publicly available, the procedure to build it consisted in identifying from company databases and secondary sources the availability of the following services by country and year for 149 nations: Netflix, Amazon Prime, Apple TV+, Disney+, Paramount+, and HBO Max.[5] The dataset for estimating the VOD content contribution was constructed based on public information and inputting dummy variables to indicate that a VOD platform is being offered in a country in a given year.[6] Once that information was compiled, an ordinal scale was built taking values between 1 and 7 depending on the number of services being available by country in each year, where 1 means non-VOD platform available, 2 means only one available, and so on until 7 which reflects that all six platforms have been launched.[7]

A simple descriptive analysis of the variation in VOD services and broadband penetration variables appears to suggest, as expected, a close correlation between both: when the number of services increases, so does broadband penetration (Fig. 1).

Next, we constructed density functions to find out the differences in the distribution of the broadband penetration variable according to two different sample groups: those with VOD offers below and above the corresponding yearly mean (Fig. 2).

On the left of Fig. 2, we plotted the density functions for both groups for the first year of our dataset, 2012. There is not a clear distinction between both series in terms of broadband adoption, although the peak at the right of the continuous series and the concentration of values of the dotted one across low levels suggest a slightly higher penetration mean for the countries with more VOD services availability. However, in the figure on the right (2022) the differences are much more pronounced: the distribution of the continuous line (countries with VOD services above the mean) is clearly located at the right of the dotted line, indicating that countries with more VOD offers depict higher broadband penetration levels. In sum, between the left and right graphic there is a difference of 10 years, where VOD services strongly emerged, and the difference between both series increased notably.

While this descriptive analysis suggests a clear link between both variables, it is still not enough to determine if the effects are robust to the addition of controls, and if the causal direction is the one that has been hypothesized due to the potential presence of endogeneity arising from omitted variable bias or reverse causality. Therefore, the empirical strategy conducted from now on should concentrate on addressing these concerns and to disentangle the causal effect that takes place between VOD deployment and broadband adoption.

[5] We are cognizant that these six services do not cover the whole range of streaming services existing in each country, which include not only commercial VOD but also public service channels. The availability of these additional services is expected to be correlated with the six that were assessed. Additionally, YouTube premium was not included since at the time considered, it did not offer a comparable suite of streaming services as the others considered from the list, although nowadays it plays a relevant role.

[6] As suggested by one anonymous referee, it would have been desirable to get data on cases of mid-year entries of VOD platforms and to be able to treat this peculiarity in our empirical estimates. Similarly, it would have been interesting to enrich the VOD variable with further information on content languages, origin of productions, size of the catalogues, etc. This would have provided us with data to estimate how does popularity differ by country for the different services. Unfortunately, we were not able to incorporate those nuances in our analysis due to the heterogeneities in the information provided by the diverse data sources consulted.

[7] The scale initiates with 1 rather than 0 to avoid losing observations when converting to logarithms in the econometric models.

Table 1
Descriptive statistics.

Variable	Definition	Mean	Std. Dv.	Source
Main equation				
BB	Fixed-Broadband Subscriptions (per 100 inhabitants)	13.679	13.696	ITU
BB > 10 Mbps	Fixed-Broadband Subscriptions (per 100 inhabitants) with download speed above 10 Mbps	12.317	13.369	ITU
Price	Fixed broadband price (USD)	32.122	61.677	ITU
Income	Gross National Income per capita (USD)	14967.680	19750.340	World Bank
VOD services	Scale based on the number of audio-visual VOD services available (1–7)	2.647	1.485	Authors compilation
Additional controls				
Female population	Share of female individuals across population	48.874	3.459	World Bank
Population 15-64	Share of individuals aged 15–54 across population	64.025	6.380	World Bank
Human Capital	Mean school years (ISCED 1 or higher), population 25+ years	9.035	3.503	UNESCO, Telecom Advisory Services

Source: Prepared by the authors

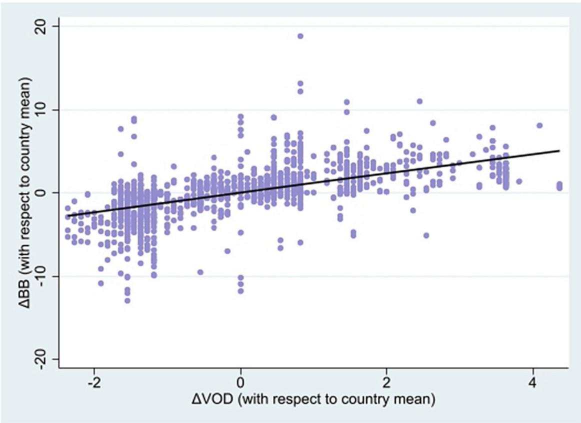

Fig. 1. Cross-country comparison of broadband penetration and VOD services (in deviation with respect to country mean).
Source: Prepared by the authors

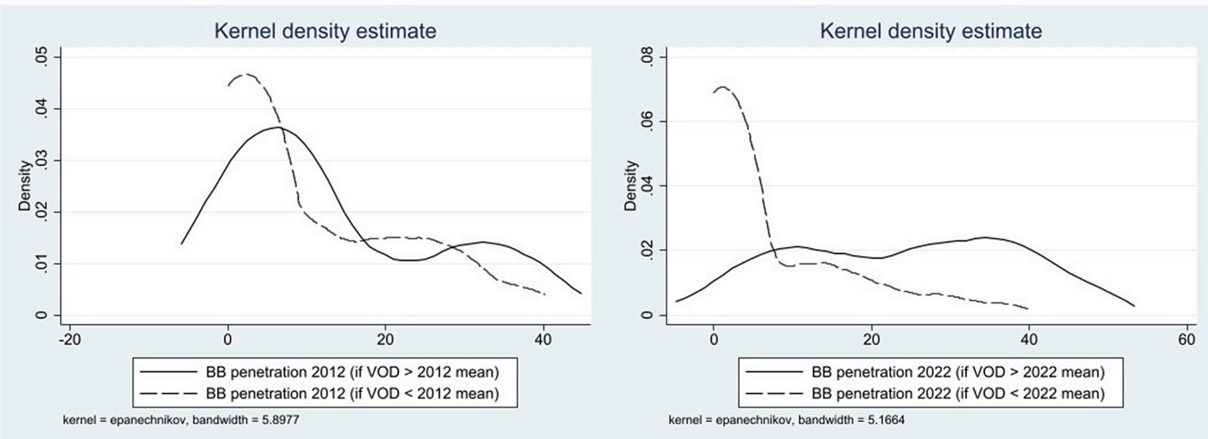

Fig. 2. Density functions for broadband penetration by sample groups, 2012 (left) and 2022 (right).
Source: Prepared by the authors

4. Estimation results

Our baseline empirical specification will consist of a demand function where broadband penetration depends on its price, on income levels, and on content availability, as denoted by the *VOD* variable:

$$\log(BB_{it}) = \alpha_i + \beta \log(Price_{it}) + \gamma \log(Income_{it}) + \delta \log(\text{VOD}_{it}) + \varepsilon_{it}$$

Where i and t denote respectively country and year. In the previous equation, α_i represents a country-level fixed effects to absorb all time-invariant unobservable factors that can be affecting broadband demand, such as culture, language, idiosyncrasies, and the like.

To estimate the demand function, we will follow three approaches. First, an estimation in levels, through a fixed effects panel (a *within*-model). Next, we will also estimate the model in first differences, to de-trend the variables, removing the temporal effects associated to the natural yearly growth of VOD and broadband adoption. Finally, as the dependent variable may depend on its own past realizations, we will also conduct estimates through a dynamic panel.

4.1. Estimation in levels

Table 2 presents the main estimates for the baseline model estimated in levels. Estimations are carried out through Ordinary Least Squares (OLS) and Instrumental Variables (IV) including country level fixed effects and robust standard errors (clustered by country). The period covered in the regressions is 2012–2021.[8]

The column (i) of Table 2 presents the results of OLS estimates. The results suggest that VOD services are positive and statistically significant (at the 1% level) to explain broadband penetration. As for the remaining variables, they behave as expected. Price is negatively linked to demand, while a higher income is associated with more broadband adoption, meaning that internet is a normal good.

A key methodological issue has to do with the expectation that the variables VOD services and broadband penetration influence each other. On the one hand, our main hypothesis assumes that VOD offers have driven broadband adoption, but on the other hand, it is still legitimate to expect that VOD services became available not randomly across countries, but first in those geographies where broadband adoption was higher. In other words, this seems to be a clear case of reverse causality, where both variables influence each other. To tackle this concern, in the columns (ii) and (iii) of Table 2 we present the results for a 2-step IV estimator using instruments that are expected to determine VOD availability but not the outcome variable in a direct way.

To select the set of instruments, we considered that current VOD content availability is explained not only by broadband adoption, but also relies on cultural population behavior that make some countries more prone to have stronger preference towards audiovisual content. Therefore, we looked for variables that must capture the latter (preference toward audiovisual content driving VOD offers), while not having a direct link with the broadband variable. In other words, a good instrument should be able to explain only the historical and cultural patterns that influence current content preferences, discarding the mechanisms linked to the technology through which this content is distributed.

With this in mind, we selected two alternative instruments to conduct the IV estimates. First, we considered an instrument based on free-to-air audiovisual content availability in past periods. This variable is represented by the number of broadcasting TV stations operating in each country during the period 1948–1958, according to data provided by ITU Historical Statistics.[9] This instrument is expected to explain current content availability, as cultural patterns are usually transferred intergenerationally. Furthermore, these free-to-air content was provided through other technologies (such as broadcasting) that were available way before current broadband networks were deployed.

More importantly, these older technologies are not related to current fixed broadband infrastructure, as their presence was not a requisite for their deployment (as can be the case of broadband networks dependent upon older fixed telephony lines). In addition, this instrument is lagged considerably to break any possibility of being affected by contemporary shocks that are also impacted by broadband, while they correlate with current VOD availability due to persistence of the cultural patterns of the population. In sum, we assume that this deeply lagged instrument satisfies the exclusion restriction, which implies that it does not affect in a direct way a country broadband adoption but only indirectly through its effect on VOD content.

This instrument, however, has a potential problem for the specific case of fixed effects models as the ones conducted in this section. The *within* nature of the model makes that the variation between broadband and VOD comes from year-to-year variation within a country. This means that identification comes from year-to-year variation in the number of broadcasting TV stations exactly 64 years earlier. Across all countries, the variation in TV stations from 1948 to 1949 causes a change in VOD from 2012 to 2013 and so on. This should not be a problem, as the period selected reflects a parallelism: TV stations were beginning to be deployed in the 50s, as VOD streaming platforms were in 2010s, thus the new trend may mirror previous ones. However, we recognize that this situation may generate skepticism, being then desirable to test an additional instrument that can be considered as contemporaneous to yearly

[8] As data for Gross National Income per capita is not yet available for 2022.

[9] Countries not reported by the ITU are assumed not to have broadcasting TV stations as that time, except for the United States, where the series was built from Jeff Miller compiled reports. As in the case of the VOD variable, we start the scale accounting for historical broadcasting TV stations with one when availability is zero (while the scale takes value of two then the number of stations is one, and so on), to avoid losing observations when converting the variable into logarithms.

Table 2
Broadband adoption drivers: estimation in levels.

Dep. variable: log(BB)	(i)	(ii)	(iii)
log(Price)	−0.148***	−0.162***	−0.095**
	[0.055]	[0.036]	[0.048]
log(Income)	0.395**	0.436***	0.830***
	[0.158]	[0.113]	[0.260]
log(VOD)	0.349***	0.220***	0.479***
	[0.039]	[0.021]	[0.136]
Country Fixed Effects	YES	YES	YES
Under identification test		60.732***	12.665***
Weak identification test		51.656$^{(\Upsilon)}$	15.074$^{(\Upsilon)}$
Hansen J test		0.192	1.660
Endogeneity test for log(VOD)		17.745***	3.209*
Observations	1408	1408	482
R-squared	0.249	0.222	0.002
Estimation Method	OLS	IV-LIML	IV-LIML
Instruments used		Broadcasting 1948–1958	National films

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets. $^{(\Upsilon)}$Stock-Yogo weak ID test critical values: 10% maximal LIML size: 8.68.
Source: Prepared by the authors

variations in VOD diffusion.[10]

Therefore, the second instrument selected is the number of national feature films produced. This is a metric that reflects the development of the media industry infrastructure, and also is related to cultural population patterns that explain why the public may be more prone in some countries towards consuming audiovisual content. It includes works of fiction, animation, and documentaries. As defined by UNESCO, these films are intended for commercial exhibition in cinemas, so there is not a direct link with current broadband deployment, as that is not the primary infrastructure selected for their distribution. This instrument complements perfectly the previous one, as it should be directly related to current VOD growth patterns, although it has as a disadvantage that some observations are missing, and the timeframe available is more limited, as latest data refers to year 2017. This means that when using this instrument, the estimates will rely on a shorter panel.

In column (ii) of Table 2 we present the results when using historical broadcasting TV stations as instrument, while on the other hand, in column (iii) we present the results for the case when national firms are considered. Estimates for our models are done using IV through the Limited Information Maximum Likelihood approach (LIML). All estimates include country-level fixed effects and robust standard errors.[11]

In both cases, IV estimates behave well, with under-identification being strongly rejected, while there is not a concern for weak instruments. Importantly, the Hansen J test does not reject the null hypothesis of exogeneity, providing support for the instrument selection. On the other hand, the endogeneity test rejects the null hypothesis of exogeneity of VOD, providing evidence on the accuracy of following this approach.

In the IV estimates, the link between VOD services and broadband penetration remains positive and highly significant, thus verifying our hypothesis of a causal link between the former and the latter. However, it is important to notice that in the estimate that uses historical broadcasting TV stations as instrument, the magnitude of the coefficients is smaller than in the respective OLS specification using a similar sample, suggesting again that it was critical to control for endogeneity, because if we ignore this concern, the resulting coefficients will be upward biased. On the other hand, when using national films produced as instrument, the VOD coefficient becomes larger than in the OLS estimation, although the sample is much different due to missing observations in this case (the sample is reduced from 1408 to only 482 observations), meaning that a direct comparison of the results may not be accurate.

4.2. Estimation in first differences

In some empirical estimates, researchers introduce temporal effects to account for unobservable factors affecting all observations in a same period. As an example, time-trends are usually used when it is believed that the outcome variable in the model tends to grow linearly over time. In our case, broadband penetration is expected to respond to certain natural growth tendency, that may well be captured by a time-trend. Similarly, introducing year fixed effects will account for any unobservable factors that affect all countries in a given year.[12]

However, in our empirical specification when introducing a time-trend or year fixed effects the coefficients and standard errors associated with the VOD variable are largely affected. Specifically, the coefficients become insignificant.[13]

In a first stance, one could say that because of this, VOD is not relevant to explain broadband adoption. Still, we believe that this

10 We thank an anonymous referee for bringing this fact to our attention.
11 In Table A1 in Appendix 1 we present the first stage estimations, under different specifications.
12 Although macroeconomic or cyclical shocks are less of a concern in this case, as our specification is already controlling for income levels.
13 See results and estimates in Appendix 2.

interpretation is not correct. A closer look at the analysis allows us to conclude that the insignificance of the coefficient associated with VOD in such situations is the result of a multicollinearity problem, and not because we could conclude that VOD had no effect on driving broadband adoption. The multicollinearity problem is verified with the analysis of the VIF test and is explained because the correlation index between the time-trend and the logged VOD variable is 0.858, significant at a 1% level. This is because the launch of new VOD platforms typically happens simultaneously in many countries. Thus, the VOD variable registers a gradual growth over the years, with increases being shared across a large groups of countries. That correlation also generates similar problems in the case of year fixed effects because a time-trend is just a perfect linear combination of both of them.

In sum, the VOD variable confounds with the temporal effects, creating the collinearity problem. Multicollinearity problems have been largely studied in the specialized literature. The effects generated by this problem, according to Greene (2003), include coefficients with high standard errors and low significance levels, as well as the presence of coefficients with the "wrong" sign or implausible magnitudes. These symptoms can be appreciated in our case.

However, when we take some alternative measures to overcome this collinearity limitation, we prove that results pointing to the positive effects of VOD on broadband penetration become robust to the presence of temporal effects. We identified four different empirical strategies to overcome this collinearity problem, that are explained in detail in Appendix 2. Here, we will just focus on the approach that is most widely used to deal with these situations, which is also the one that we believe to produce the more accurate results.

A common assumption in many time series techniques is that the data is stationary. This is defined as a process in which the mean, variance and autocorrelation structure do not vary over time. While this is not usually considered a serious problem in short panels as ours, with $N > T$ (larger cross section than temporal dimension), it is equally worth to say that our dependent variable, broadband penetration, is not expected to be stationary, as it reflects a natural positive evolution over time.

The research literature typically applies transformations to achieve stationarity to remove the presence of these natural temporal tendencies. The most common technique to achieve stationarity is to difference the data. This technique is intended to generate series with constant location and scale. The regression using differenced data will contain one less year than the original one, because the first year of the panel is lost in the process, although on the positive side, it will remove any effect associated to a time-trend pattern, providing more accurate results.

Relying on our baseline specification, differencing with respect to the previous period means that the equation can be estimated as follows:

$$\Delta\log(BB_{it}) = \beta\Delta\log(Price_{it}) + \gamma\Delta\log(Income_{it}) + \delta\Delta\log(VOD_{it}) + \Delta\varepsilon_{it}$$

As a result, the regression will be calculated for growth rates rather than levels as initially done. Results following the OLS and IV approaches are presented in Table 3.

The OLS results are reported in column (i). They indicate that after removing the temporal effects by differencing, the coefficient associated with the differenced VOD variable is positive and significant, although smaller than in the estimation in levels, proving the presence of some omitted variable bias when we ignore the temporal effects. In other words, the coefficients associated with VOD in Table 2 where larger than their "real" value, as they were capturing the effects of other things *beyond* the VOD availability. In light of this, removing the temporal effects was necessary to estimate a more accurate approximation of the effects of VOD on broadband adoption.[14]

Next, in column (ii) we present the IV estimation for the differenced specification. In this case, the critique reported above regarding that the yearly variation in TV stations 64 years ago causes a change in VOD since 2012 is no longer valid. This is because first differences models are no longer *within*-models, as the differencing procedure necessarily consists in getting rid of the country-level fixed effects. We are still introducing the instruments in levels, but now to explain differences. This means that it is the stock of past TV stations what drives the growth in VOD offers in the first years in which these services where launched. It is completely reasonable to expect countries with a higher stock of TV stations during the decade of the 1940s to be those that are the first to receive the VOD offers, meaning that the growth rate is faster, at least in these initial years of the sample.[15] This means that it is no longer necessary to rely on the second instrument (number of films produced), since it presented disadvantages due to missing observations.

The results presented in column (ii) of Table 3 indicate that the instruments prove to be very accurate, as they are found to be strong (as denoted by the under identification and weak identification tests) and exogenous (as reflected by the Hansen J-test), and the results verify again the positive effect of VOD on broadband adoption. In any case, the endogeneity test does not reject the null hypothesis of VOD exogeneity, meaning that it was not necessary to control for endogeneity under the differenced specification. In other words, when differencing, endogeneity seems to be no longer a problem, meaning that the estimate presented in column (i) of Table 3 can be considered as a valid reference.

4.3. *Estimation as dynamic panel*

To further consider the time series properties of the data, it can be expected that broadband adoption is driven by its past levels. This would mean that a dynamic panel estimation in which lagged broadband adoption is added as right-hand side regressor may be necessary. Therefore, we will estimate the model for different lag structures of the dependent variable, following the generalized

[14] We are especially grateful to an anonymous referee for raising up this point.

[15] This has been verified in the first-stage estimate (see Table A2 in Appendix 1).

Table 3
Broadband adoption drivers: estimation in differences.

Dep. variable: Δlog(BB)	(i)	(ii)
Δlog(Price)	−0.058**	−0.058**
	[0.026]	[0.026]
Δlog(Income)	0.260**	0.248**
	[0.114]	[0.113]
Δlog(VOD)	0.139***	0.112***
	[0.035]	[0.028]
Under identification test		39.616***
Weak identification test		24.220$^{(\Upsilon)}$
Hansen J test		0.590
Endogeneity test for Δlog(VOD)		0.224
Observations	1250	1250
R-squared	0.028	0.027
Estimation Method	OLS	IV-LIML
Instruments used		Broadcasting 1948–1958

Note: **p<5%, ***p<1%. Robust standard errors in brackets. $^{(\Upsilon)}$Stock-Yogo weak ID test critical values: 10% maximal LIML size: 8.68.
Source: Prepared by the authors

Table 4
Broadband adoption drivers: dynamic panel estimation.

Dep. variable: log(BB)	(i)	(ii)	(iii)	(iv)
log(BB) $_{t-1}$	0.410*	0.298	0.221	0.110
	[0.222]	[0.223]	[0.194]	[0.191]
log(BB) $_{t-2}$		0.017	0.009	0.040
		[0.042]	[0.069]	[0.033]
log(BB) $_{t-3}$			0.038	−0.031
			[0.052]	[0.052]
log(BB) $_{t-4}$				0.076
				[0.060]
log(Price)	−0.008	−0.053	−0.007	0.000
	[0.033]	[0.042]	[0.040]	[0.054]
log(Income)	0.123	0.120	0.124	0.032
	[0.111]	[0.107]	[0.117]	[0.140]
log(VOD)	0.068**	0.099***	0.112***	0.147***
	[0.030]	[0.032]	[0.034]	[0.043]
Observations	1125	983	838	691

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

method of moments (GMM) approach proposed by Arellano and Bond (1991) to conduct consistent dynamic panel estimations.

Results are presented in Table 4, incorporating the dependent variable as regressor using the first lag in column (i), adding a second lag in column (ii), and so on. Instruments used for the differenced equation are those normally proposed under this approach: from second lag onwards of the dependent variable to instrument its first lagged regressor, and differenced values for the remaining explanatory variables.

Results presented in Table 4 indicate that the lagged dependent variable is mostly insignificant. Only in the estimate reported in column (i) it presents a weak significance level of 10%. With this evidence, we understand that it might not be necessary to carry on the analysis with a dynamic panel specification.

5. Further checks

The estimations reported in Section 4 appear to suggest a critical role of VOD in stimulating broadband adoption. In this section we aim to expand the analysis by checking the robustness of the results by adding further controls, in terms of the possible existence of country-level heterogeneities in the effect associated with VOD, and finally to analyze the results for the specific case of high-speed broadband connections.

5.1. Additional controls

While the previous specifications represent the natural application of microeconomic theory, it can still be argued that further control variables are needed to account for disparities in preferences.[16] If that is the case, this can reflect a situation of omitted variable bias. To minimize this bias, we perform additional estimates including in the specification a set of further time-varying country controls (Gender, Population age, Human Capital) that could be associated with broadband adoption and, at the same time, correlate them with VOD availability. On a side note, to allay any concerns that the VOD offer variable is capturing the impact of other content services, it should be noted that most well-known social networks and messaging services had already launched by the first year of our panel, and had been available worldwide for some years, so we do not expect the VOD variable to capture those effects.[17]

In Table 5 we replicate the estimations of Table 2, but now adding the further controls. Results for VOD are mostly unchanged. This suggest that omitted variable bias related to socioeconomic factors should not be a concern affecting the link between VOD services and broadband penetration in our model.

As for the controls, in the IV estimate conducted in column (ii) human capital presents a positive and significant coefficient, which is an expected result. Also, the higher presence of female population seems to be relevant to explain broadband adoption according to the results presented in columns (ii) and (iii). As for the working-age population, the coefficient is positive and significant in the results presented in columns (i) and (ii).

On the other hand, it is interesting to note that the coefficient for income is reduced with respect to Table 2. This may be resulting from the fact that some of the controls (human capital, female population, population in working age) are capturing some of the effects associated with income. Another interesting result is that, when adding controls, the price coefficient increases in absolute value, meaning that under those estimations average individuals are more sensitive to price changes. This can be related to differences in price sensitivity by different population groups, which means that controlling for these groups affects the price coefficient.

Next, we replicate the estimation in first differences but now adding further controls (Table 6). As the IV estimations conducted for the differenced specification provided evidence that it was no longer necessary to consider VOD growth as endogenous (in Table 3), we only report the OLS results. As in the levels estimation, results for VOD are mostly unchanged, suggesting that omitted variable bias related to socioeconomic factors should not be a concern in our model.

5.2. Heterogeneities by country

In the introduction, we raised the question as to whether the launch of VOD services could be a stimulus for driving broadband adoption in developing regions, thereby contributing to the reduction of the digital divide. To test the hypothesis of whether VOD is effectively contributing to drive broadband adoption in richer or in poorer countries, we relax the assumption of homogeneous effect associated with the increase of VOD services of the analyses presented above. For this purpose, we assume that the impact of audiovisual content on broadband penetration may depend on a country's level of economic development, and we further introduce the VOD variable in interaction with the income indicator, first in the estimation conducted in levels.

The rationale for expecting a differential impact of VOD depending on the development level of countries could be explained as the increase in content diversity resulting from the deployment of VOD services is much higher in developing countries than in developed nations. This is because prior to the entry of VOD, content diversity resulting from the offer of cable TV and free to the air channels was much higher in developed economies than in the developing world, where also pay TV penetration was much lower. Therefore, the magnitude of increase in diversity in developing countries triggered by the offer of VOD should be much higher than in the developed world.

In column (i) of Table 7 we report the OLS results for the estimate conducted in levels. The coefficient associated with the VOD variable is positive and significant, while the interacted variable of VOD with income has a negative and significant coefficient. This suggests that the lower the income level, the larger the impact of VOD on broadband adoption, which indicates that, while VOD services contribute to drive broadband adoption in all countries, the effect seems to be significantly stronger in the less developed ones.

Next, in column (ii) of Table 7 we apply the IV approach to the estimation that accounts for country heterogeneities. In this case, we instrumented both VOD and the interaction of VOD with income. The instruments in this case are the same as above for the case of the historical broadcasting TV stations, with the addition that the interaction between income and broadcasting is introduced as instrument. On the contrary, we could not use the second instrument of national films, as the model was unidentified due to the weakness of that instrument for the specification that includes the interaction.

According to the results presented in column (ii) of Table 7, the instruments proved to be suitable enough from the perspective of the under identification and Hansen J-tests, although they do not appear to present a strong explanatory power for the case of the interaction variable, as the weak instrument test statistic is slightly below the Stock-Yogo weak ID test of critical value (10% maximal LIML size). However, the endogeneity test in this case does not reject the null hypothesis of exogenous controls, thus suggesting that it was not necessary to approximate these regressions using IV. At any rate, results verify the conclusion linked to a stronger effect for less developed countries.

Next, we conduct the estimate allowing for country heterogeneities for the estimation in first differences (Table 8). In this case, the sign of the coefficients are the same as in the previous cases, although now the interacted variable loses significance.

Overall, these results provide some evidence on the VOD effect being stronger for less developing countries, although the lack of

[16] For example, countries with more educated individuals should present larger demand for broadband connectivity, while the opposite may happen in those with older population.

[17] Launch years of Facebook (2004), Twitter (2006), WhatsApp (2009), and Instagram (2010), most of them having reached already a critical mass in the first years of the period under analysis.

Table 5
Broadband adoption drivers: estimation in levels – further controls.

Dep. variable: log(BB)	(i)	(ii)	(iii)
log(Price)	−0.183**	−0.198***	−0.103**
	[0.078]	[0.047]	[0.049]
log(Income)	0.264	0.265***	0.512**
	[0.164]	[0.103]	[0.221]
log(VOD)	0.375***	0.267***	0.346**
	[0.058]	[0.043]	[0.146]
Human Capital	0.028	0.122**	0.167
	[0.111]	[0.060]	[0.105]
Female population	0.092	0.068**	0.313***
	[0.061]	[0.034]	[0.104]
Population 15-64	0.076**	0.062***	0.031
	[0.030]	[0.016]	[0.039]
Country Fixed Effects	YES	YES	YES
Under identification test		44.475***	6.800**
Weak identification test		25.614$^{(\Upsilon)}$	12.356$^{(\Upsilon)}$
Hansen J test		0.870	1.400
Endogeneity test for log(VOD)		5.695**	1.042
Observations	1211	1211	460
R-squared	0.287	0.274	0.199
Estimation Method	OLS	IV-LIML	IV-LIML
Instruments used		Broadcasting 1948–1958	National films

Note: **p<5%, ***p<1%. Robust standard errors in brackets. $^{(\Upsilon)}$Stock-Yogo weak ID test critical values: 10% maximal LIML size: 8.68.
Source: Prepared by the authors

Table 6
Broadband adoption drivers: estimation in differences – further controls.

Dep. variable: Δlog(BB)	
Δlog(Price)	−0.077*
	[0.045]
Δlog(Income)	0.152
	[0.113]
Δlog(VOD)	0.140***
	[0.040]
ΔHuman Capital	0.139***
	[0.047]
ΔFemale population	0.010
	[0.041]
ΔPopulation 15-64	0.048**
	[0.022]
Observations	1079
R-squared	0.050
Estimation Method	OLS

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

significance in the interacted term in the estimation in differences suggests that further research will have to be conducted to yield more robust results.

5.3. Effect on high-speed connections

As discussed above, we hypothesized that in addition to driving broadband uptake, VOD content might be associated with the migration of users to higher speed broadband plans. This is because the higher quality streaming content (UHD 4K) requires higher bandwidth throughput. To test this hypothesis, we consider as dependent variable broadband adoption for connections above 10 Mbps of speed.[18] This is relevant as this can be considered a bare minimum threshold of network performance to be able to handle bandwidth-intensive applications such as high-quality video streaming. If VOD was especially relevant to drive adoption of higher speed plans, then the relationship should be stronger for these connectivity plans than for overall broadband penetration, meaning that

[18] While we would have liked to additionally test the model for higher speed levels of the dependent variable, the ITU does not report this data.

Table 7
Broadband adoption drivers: estimation in levels – assuming country heterogeneity.

Dep. variable: log(BB)	(i)	(ii)
log(Price)	−0.110**	−0.112**
	[0.051]	[0.046]
log(Income)	0.375**	0.377***
	[0.146]	[0.103]
log(VOD)	1.148***	1.114**
	[0.291]	[0.541]
log(VOD)*log(Income)	−0.090***	−0.087*
	[0.030]	[0.051]
Country Fixed Effects	YES	YES
Under identification test		13.398***
Weak identification test		3.460$^{(\Upsilon)}$
Hansen J test		0.980
Endogeneity test for endogenous regressors		0.028
Observations	1408	1408
R-squared	0.273	0.273
Estimation Method	OLS	IV-LIML
Instruments used		Broadcasting TV 1948–1958

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets. $^{(\Upsilon)}$Stock-Yogo weak ID test critical values: 10% maximal LIML size: 5.44.
Source: Prepared by the authors

Table 8
Broadband adoption drivers: estimation in levels – assuming country heterogeneity.

Dep. variable: Δlog(BB)	
Δlog(Price)	−0.057**
	[0.026]
Δlog(Income)	0.313**
	[0.129]
Δlog(VOD)	0.133***
	[0.034]
Δlog(VOD)* Δlog(Income)	−0.312
	[0.480]
Observations	1250
R-squared	0.029
Estimation Method	OLS

Note: **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

Table 9
Broadband adoption drivers: estimation in levels – high speed broadband.

Dep. variable: log(BB > 10Mbps)	(i)	(ii)	(iii)
log(Price)	−0.231	−0.159	−0.681***
	[0.160]	[0.121]	[0.206]
log(Income)	−0.105	−0.015	2.298**
	[0.779]	[0.527]	[0.969]
log(VOD)	1.544***	0.814***	1.436***
	[0.149]	[0.104]	[0.424]
Country Fixed Effects	YES	YES	YES
Under identification test		52.929***	11.511***
Weak identification test		45.362$^{(\Upsilon)}$	14.212$^{(\Upsilon)}$
Hansen J test		0.614	0.070
Endogeneity test for log(VOD)		21.656***	1.788
Observations	1019	1017	399
R-squared	0.365	0.284	0.228
Estimation Method	OLS	IV-LIML	IV-LIML
Instruments used		Broadcasting 1948–1958	National films

Note: **p<5%, ***p<1%. Robust standard errors in brackets. $^{(\Upsilon)}$Stock-Yogo weak ID test critical values: 10% maximal LIML size: 8.68.
Source: Prepared by the authors

Table 10
Broadband adoption drivers: estimation in differences – high speed broadband.

Dep. variable: Δlog(BB > 10Mbps)	(i)	(ii)
Δlog(Price)	0.015	0.020
	[0.079]	[0.079]
Δlog(Income)	0.451	0.350
	[0.318]	[0.307]
Δlog(VOD)	0.727***	0.536***
	[0.113]	[0.113]
Under identification test		38.051***
Weak identification test		21.732$^{(\Upsilon)}$
Hansen J test		0.265
Endogeneity test for Δlog(VOD)		1.629
Observations	872	872
R-squared	0.071	0.066
Estimation Method	OLS	IV-LIML
Instruments used		Broadcasting 1948–1958

Note: ***p<1%. Robust standard errors in brackets. $^{(\Upsilon)}$Stock-Yogo weak ID test critical values: 10% maximal LIML size: 8.68.
Source: Prepared by the authors

the effects were mainly concentrated in the former ones.

Table 9 presents the results for the estimation conducted in levels, both under OLS and IV approaches. The results stand, with the main difference arising from the fact that the coefficient associated with VOD services is much larger in comparison with the model that included all broadband connections as dependent variable. This suggests that while VOD services have been relevant in driving broadband penetration, the effect seems to have been stronger in explaining higher speed connections.

Finally, we estimate the model for high-speed broadband under the first differenced specification. In this case, estimates will have to be conducted also on IV, as it may be the case that VOD is endogenous for higher speed broadband.

Results presented in column (i) of Table 10 (OLS) confirm a positive effect for VOD, with a much higher coefficient in comparison with the case of all broadband connections. A similar situation happens in the IV estimate reported in column (ii), although the endogeneity test suggests that, again, VOD can be treated as exogenous when conducting estimations in first differences.

6. Interpretation of results

From all the estimations conducted above, our preferred ones are those reported in column (i) of Table 3, as they remove the temporal effects, in a specification that does not require to account for endogeneity, as verified in the column (ii) of the same table. It also provides some of the most conservative magnitudes for the coefficients associated with VOD. Taking this result as a reference would mean that the value $\beta = 0.139$ will be considered the most accurate elasticity estimate. Thus, we can state that a 1% increase in the VOD content indicator will generate an increase of 0.139% in broadband adoption, being a positive but inelastic effect. We understand that this provides a reliable magnitude on the relevance of VOD video-streaming to drive broadband adoption.

However, it does not seem accurate to measure the effect of a 1% increase in VOD content when this variable was built as an ordinal scale. The relevant question to quantify, from our perspective, is to find out what happens when a new VOD platform becomes available. Therefore, we can calculate how much will be the percentage increase in broadband adoption after the launch of a new VOD platform, as depending on the current availability of VOD platforms. This is relevant because the impact of a new platform will decrease when the stock of content available becomes larger.[19]

We calculate the specific impact of an additional platform depending on the current stock of VOD offers, with results reflected in Fig. 3. When there are no VOD offers, the launch of a new one is associated with an increase in 13.9% of broadband adoption (e.g.: from 30% in broadband penetration to 34.2%). Further, if we add another VOD platform, the effect is positive but reduced to 7.0%, and so on. When we already have 6 platforms available, the hypothetical launch of a seventh one will only contribute to increase broadband in 2.0% (e.g.: from 30% to 30.6%). Therefore, we can conclude that the effect of VOD on broadband adoption is positive but diminishing with the number of platforms available.

Considering the positive effect of VOD availability as a broadband driver, we can estimate its overall effect on consumer surplus.[20] If broadband demand is expanded due to a richer audiovisual offer, we can expect that, all things being equal, consumer surplus will also increase, to reflect an additional benefit to connected users. Considering that, as shown above, VOD offerings are a key attribute in driving demand, the launch of successive services over the past decades has progressively been shifting the demand curve to the right (i.e.: for a certain price, now more people demand broadband services because of richer offer of VOD services being available). This has

[19] We thank an anonymous referee for highlighting this aspect.

[20] The consumer surplus calculation conducted in this section refers exclusively to the broadband market, and to find out how much it has changed because of VOD availability. The consumer surplus associated with the VOD market is not considered in our analysis, as it is not the focus of our research.

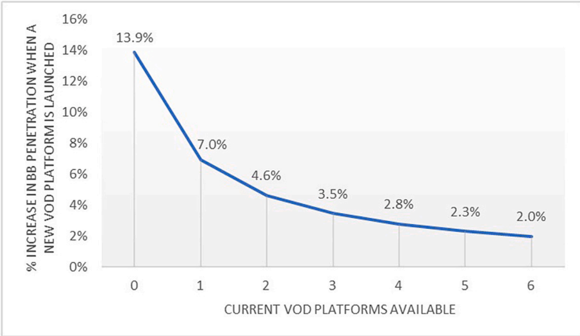

Fig. 3. Impact of a new VOD platform launch on broadband adoption.
Source: Prepared by the authors

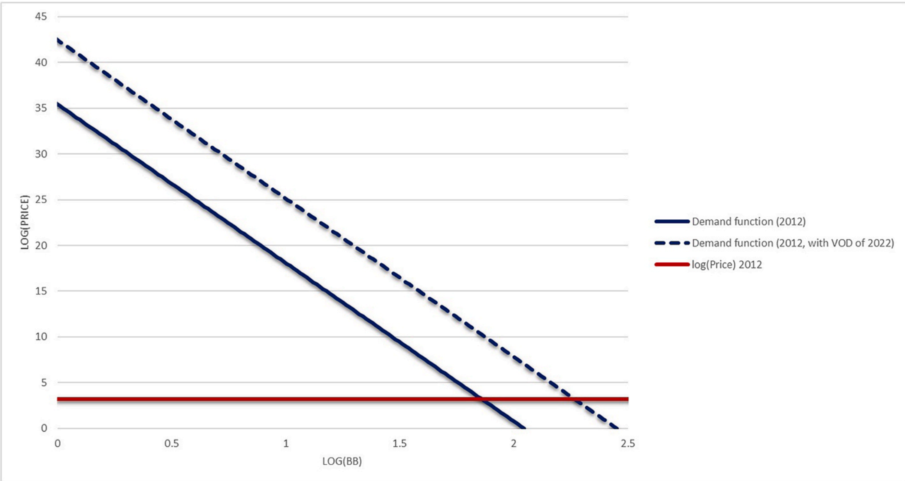

Fig. 4. Broadband demand before and after VOD growth 2012–2022.
Source: Prepared by the authors

contributed to an increase in consumer surplus, both because of the presence of new subscribers, and because the existing ones will be willing to pay more than before for broadband services.

To calculate this effect, we conservatively take as reference the parameters from the estimation highlighted before, that reported in column (i) of Table 3. With those coefficients, the following demand function is depicted, representing a hypothetical average country[21]

$$\log(BB) = -0.058\ \log(Price) + 0.260\ \log(Income) + 0.139\ \log(VOD)$$

From where the inverse-demand function can be easily obtained[22]

$$\log(Price) = \frac{0.260\ \log(Income) + 0.139\ \log(VOD) - \log(BB)}{0.058}$$

This inverse demand function shows the price the consumers are willing to pay for broadband services, and that figure depends positively on content availability through VOD services. Taking the sample average 2012 values for Income and VOD, we obtain our initial inverse-demand curve, for the first year of our panel:

[21] No constant term is introduced to remove any country-specific effect. This is supported by the fact that the common constant for all countries proved to be non-significant in our baseline estimation.

[22] Naturally, price was specified as a right-hand variable in our main empirical specification, so these inverse equations should not be interpreted as causal links where broadband adoption drives price changes.

$$\log(Price) = 35.424 - 17.324 \log(BB)$$

Naturally, as VOD available services progressively increased, the demand curve started shifting to the right, *ceteris paribus*. Leaving unchanged 2012 income levels, but updating the average VOD mean value for the last year covered in our sample (2022), we get a transformed version of the demand curve, where changes are exclusively attributed to a richer VOD platform offer after a decade:

$$\log(Price) = 42.468 - 17.324 \log(BB)$$

We leave the income level unchanged to isolate the shifting effects of VOD on the demand curve. In Fig. 4 we represent both demand functions, with the dotted one capturing the shift resulting from VOD development over the period. The area below each demand function, and above the price represent the consumer surplus. The difference between the respective consumer surplus for both figures can be assumed as the consumer surplus gain attributed to VOD services. In both cases we will use the average 2012 price as a reference (denoted in the red line in Fig. 4), to attend only for variations in surplus associated with VOD increases.

The area of both triangles reflecting the respective consumer surpluses in Fig. 4 can be easily calculated. After doing so, the difference between both measures of consumer surplus accounts for 48% of the initial value using VOD data from 2012. This would mean that over a period of 10 years, VOD content availability increased consumer surplus derived from broadband in 48%. This means that, over the course of the decade, we can conclude that the consumer surplus that subscribers get from broadband adoption increased annually at a compound annual growth rate of 4.03% exclusively because of the expanded quantity of VOD services available. This increased consumer surplus is what users can rely on to pay for the VOD services they subscribe.

7. Conclusions

While the research literature has highlighted the importance of content as a driver of broadband adoption, no studies have yet explored this link from an empirical standpoint. This study intended to fill this gap in the research literature by providing robust evidence on the role of VOD as a driver of broadband adoption, tackling omitted variable biases and endogeneity concerns that arise in this relationship.

We found that VOD services have played a significant role in enhancing the value of broadband and therefore contributing to drive broadband uptake: when controlling for service price, income, and temporal effects, every new VOD platform deployed in a given country is expected to increase average broadband penetration. However, the effect is decreasing, as the impact of a new platforms will decrease when the stock of content availability increases.

Further, we found evidence that the effect of VOD on broadband adoption seems to have been stronger for higher speed connections. In addition, these effects may have been even more important in terms of the reduction of the digital divide in disadvantaged countries, as our findings prove some evidence that the effect of VOD on broadband adoption is larger when income levels are lower. In a hypothetical average country, we calculated that after a decade of development in VOD offers, broadband consumer surplus, a measure of consumer benefit, increased in 48%, because of the launch of new VOD services. This is equivalent to an annual increase in consumer surplus of 4.03%.

The robust results of our study notwithstanding, future research will have to understand better the causal link between VOD and broadband adoption. For example, it would be interesting to enrich the VOD variable with further information on content languages, origin of productions, and size of the streaming sites' catalogues. Similarly, it would be useful to estimate potential variations in the magnitude of the VOD effects in the case of mid-year launch of streaming sites. We were not able to incorporate those nuances in our analysis due to the heterogeneities in the information provided by the diverse data sources consulted.

As a final reflection, our findings point to the impact of VOD services on the digital economy as a stimulus for consumer acquisition of broadband services and therefore as a contributor to the revenues of telecommunications operators. This conclusion raises the need to bring some balance to the debate around the contribution of VOD services to the broadband ecosystem.

CRediT authorship contribution statement

Raul Katz: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Juan Jung:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Fernando Callorda:** Data curation.

Appendix 1. First Stage IV estimates

In Table A1 we present the first stage for the IV model in the estimation conducted in levels, under different specifications. Clearly, historical broadcasting TV stations strongly influence current VOD content availability, as can be seen in column (i). However, estimations reported in column (ii) indicate that the link is nonlinear. A similar situation happens with the second instrument, the national films produced, as can be appreciated in columns (iii) and (iv). Therefore, the instruments will be included in levels and squares.

Table A1
First Stage estimation – VOD drivers

Dep. Variable: log(VOD)	(i)	(ii)	(iii)	(iv)
Log(Price)	−0.146***	−0.146***	0.021	0.031
	[0.044]	[0.044]	[0.081]	[0.082]
Log(Income)	0.324***	0.321***	−1.554***	−1.517***
	[0.121]	[0.121]	[0.262]	[0.262]
Log(Broadcasting TV stations 1948–1958)	0.444***	1.419***		
	[0.036]	[0.202]		
Log(Broadcasting TV stations 1948–1958) - squared		−0.504***		
		[0.104]		
National firms produced			0.004***	0.005***
			[0.001]	[0.001]
National firms produced - squared				−0.000**
				[0.000]
Country Fixed Effects	YES	YES	YES	YES
Observations	1408	1408	482	482

Note: **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

In Table A2 we present the first stage results for the IV estimate of the differenced model. Again, the instrument seems to behave well, showing a positive although non-linear effect.

Table A2
First Stage estimation – VOD growth drivers

Dep. Variable: Δlog(VOD)	
ΔLog(Price)	−0.005
	[0.018]
ΔLog(Income)	−0.496***
	[0.104]
Log(Broadcasting TV stations 1948–1958)	0.683***
	[0.110]
Log(Broadcasting TV stations 1948–1958) - squared	−0.329***
	[0.056]
Observations	1250

Note: ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

Appendix 2. Temporal Effects

In some empirical estimates, researchers introduce temporal effects to account for unobservable factors affecting all observations in a same time period. As an example, time-trends are usually used when it is believed that the outcome variable in the model tends to grow linearly over time. In our case, broadband penetration is expected to respond to certain natural growth tendency, that may be captured by a time-trend. Similarly, introducing year fixed effects will account for any unobservable factors that affect all countries in a given year.

Therefore, the introduction as regressors of a time-trend or year fixed effects may be useful, for instance, when we want to remove temporal-related effects to isolate the impact of a certain variable on the cyclical variations of the outcome (typically in the case of non-stationary macroeconomic variables), or to absorb certain year-specific shocks (through year fixed effects).

However, in our empirical specification when introducing a time-trend or year fixed effects the coefficients and standard errors associated with the VOD variable are largely affected. Specifically, the coefficient becomes insignificant, as can be observed in Table A3.

Table A3
Fixed Effects estimation of broadband adoption – with temporal effects

Dep. variable:	log(BB)	log(BB)	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)	log(BB > 10Mbps)	log(BB > 10Mbps)
log(Price)	−0.117**	−0.153**	−0.135**	−0.171**	−0.243	−0.323**	−0.231	−0.338**
	[0.053]	[0.075]	[0.052]	[0.073]	[0.159]	[0.154]	[0.156]	[0.149]
log(Income)	0.282*	0.164	0.224	0.089	−0.787	−0.802	−0.785	−0.884
	[0.163]	[0.162]	[0.158]	[0.153]	[0.771]	[0.584]	[0.716]	[0.535]

(continued on next page)

Table A3 (*continued*)

Dep. variable:	log(BB)	log(BB)	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)	log(BB > 10Mbps)	log(BB > 10Mbps)
log(VOD)	−0.030	−0.008	0.005	0.016	0.015	0.054	0.122	0.115
	[0.048]	[0.049]	[0.052]	[0.055]	[0.184]	[0.159]	[0.174]	[0.153]
Human Capital		−0.095		−0.076		0.332		0.367
		[0.114]		[0.113]		[0.241]		[0.242]
Female population		0.132*		0.112*		0.810***		0.754***
		[0.069]		[0.066]		[0.221]		[0.221]
Population 15-64		0.079***		0.080***		0.415***		0.406***
		[0.029]		[0.029]		[0.078]		[0.077]
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	NO	NO	YES	YES	NO	NO
Time-trend	NO	NO	YES	YES	NO	NO	YES	YES
Observations	1408	1211	1408	1211	1019	939	1019	939
R-squared	0.312	0.361	0.297	0.347	0.45	0.548	0.447	0.543

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

One could assume that because of this, VOD is not relevant to explain broadband adoption. Still, we believe that this interpretation is not correct. A closer look to the analysis leads us to conclude that the coefficient's magnitude and lack of significance is the result of a multicollinearity problem. In fact, when we take some alternative measures to overcome this collinearity limitation, we prove that results are robust to the presence of temporal effects.

The origin of the problem

The introduction of the variables to account for temporal effects create severe multicollinearity, meaning that the estimates and p-values in the regression output become unreliable. To explain this problem, we will focus on the impact of introducing a time-trend as this is easier to visualize. That being said, the arguments are equally valid for year fixed effects, because the time-trend is just a perfect linear combination of the year fixed effects (meaning that both represent the same problem from the perspective of the multi-collinearity analysis).

The multicollinearity problem is verified with the analysis of the VIF test conducted after estimating the model than includes the time-trend as independent variable. The VIF associated with this estimation presents a value of 27.57 (with the time-trend variable presenting a massive 48.67), well above the level of 10 reflected in the very same model without the time-trend (10 is the threshold usually established in the literature above which the presence of collinearity arises).

The reason of this multicollinearity is straightforward to explain. When analyzing the correlation coefficient between the time-trend and the logged VOD variable, it can be observed that both variables experience a massive correlation (correlation index = 0.858, significant at a 1% level). This occurs because the launch of new VOD platforms typically happens simultaneously in many countries. Thus, the VOD variable registers a gradual growth over the years, with increases being shared across large groups of countries. As a result, this variable confounds with the temporal effects, creating the collinearity problem.

Multicollinearity problems have been largely studied in the specialized literature. According to Greene (2003):

> "The problem faced by applied researchers when regressors are highly, although not perfectly, correlated include the following symptoms:

- *Small changes in the data produce wide swings in the parameter estimates.*
- *Coefficients may have very high standard errors and low significance levels even though they are jointly significant and the R-squared of the regression is quite high.*
- *Coefficients may have the "wrong" sign or implausible magnitudes."*

This is exactly the situation in our case. Four approaches were implemented to overcome this problem and to be able to identify the effects associated with VOD regardless of the presence of temporal variables.

Solutions to the problem

The easiest solution proposed by Greene (2003) is to simply drop the "problematic" variable that causes the collinearity. In our case, this would mean to estimate the model without any temporal effects. This is the strategy that has been followed in Section 4 of the main text. However, this strategy may be generating omitted variable bias, as we can expect the VOD variable to capture all the temporal effects typically absorbed by a time-trend or the year fixed effects. In other words, the coefficients associated with VOD may be larger than their "real" value, as they are capturing the effects of other factors *beyond* the VOD availability.

Therefore, in order to find out if the effects of VOD over broadband are statistically significant in this context, we must prove that, if we solve or mitigate the collinearity problem, then the expected results will stand. As there is not a perfect solution to this concern, we explored four different -and complementary-alternatives.

- Differencing to remove temporal effects.
- Remove the overlapping information in the temporal variables.
- Using proxies to approximate the temporal effects not associated with VOD.
- Implement principal component analysis to build a new set of uncorrelated (orthogonal) regressors.

The first approach, differencing to remove temporal effects, is the one developed in the main text of the paper (Section 4.2), providing evidence of the positive effects of VOD on BB in such specification. The remaining proposals to be explored next are also successful in mitigating the omitted variable bias.

Remove the overlapping information in the temporal variables

Temporal effects are not measurable and observable variables such as the GDP or the employment. They are just a way to capture mostly unobservable factors that happen over time but are not typically able to be measured adequately. This means that, beyond the temporal effects, there are "real" economic phenomena that occur, which we may not be able to explain. Based on the collinearity analysis presented above, we understand that an important part of the temporal variables is capturing the effects associated with VOD, while there are other economic phenomena beyond VOD that should also be captured by these temporal effects. Therefore, we can decompose the temporal effects as follows:

$$Temporal\ effects = Effects_{VOD} + Effects_{no\ VOD}$$

This means that, if we can remove the overlapping pieces of information with VOD reflected in $Effects_{VOD}$, we would be able to isolate variables that capture only the temporal effects *other than* VOD, thus solving the collinearity problem.

To estimate the part of temporal effects explained by VOD, we will run regressions in which the temporal effects are the dependent variables (time-trend on the one hand, and year dummies on the other), with the logged VOD as regressor. This is reflected in Table A4, where as expected, the coefficient associated with VOD is always statistically significant. From the estimates conducted in Table A4, we will make predictions of the dependent variable, meaning that we will capture a measure $\widehat{Effects}_{VOD}$, that will reflect the part of the respective temporal effects that are associated with VOD.

Table A4
Estimation of VOD contribution to temporal variables

Dep. variable:	Time trend	Year 2012	Year 2013	Year 2014	Year 2015	Year 2016	Year 2017	Year 2018	Year 2019	Year 2020	Year 2021
log(VOD)	4.612***	−0.177***	−0.176***	−0.164***	−0.156***	−0.023***	0.066***	0.058***	0.100***	0.132***	0.157***
	[0.055]	[0.014]	[0.014]	[0.013]	[0.013]	[0.005]	[0.007]	[0.007]	[0.009]	[0.011]	[0.013]
Observations	1639	1639	1639	1639	1639	1639	1639	1639	1639	1639	1639
R-squared	0.735	0.131	0.129	0.113	0.102	0.002	0.018	0.014	0.042	0.072	0.104

Note: ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

After this, we will be able to estimate temporal variables that remove the overlapping information with VOD, as follows:

$$Effects_{no\ VOD} = Temporal\ effects - \widehat{Effects}_{VOD}$$

In sum, our created variable $Effects_{no\ VOD}$ will reflect only those temporal aspects *beyond* VOD. The correlation analysis presented in Table A5 for the example of the time-trend proves that now any overlapping information has been removed (null correlation between log(VOD) and the Time-trend $_{no\ VOD}$). This would mean that we have removed the multicollinearity problem.

Table A5
Correlation analysis of temporal effects with log(VOD)

	Log(VOD)	Time-trend	Time-trend $_{no\ VOD}$
Log(VOD)	1.000		
Time-trend	0.858	1.000	
Time-trend $_{no\ VOD}$	0.000	0.515	1.000

Source: Prepared by the authors

In Table A6 we present the estimations including the temporal trend after removing overlapping information with VOD. The coefficient associated with VOD is positive and significant, while the time trend is also positive and significant, meaning that we are effectively controlling for relevant temporal effects *beyond* VOD.

Table A6
Fixed Effects estimation of broadband adoption– with temporal trend after removing overlapping information with log(VOD)

Dep. variable:	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)
log(Price)	−0.135**	−0.171**	−0.231	−0.338**
	[0.052]	[0.073]	[0.156]	[0.149]
log(Income)	0.224	0.089	−0.785	−0.884
	[0.158]	[0.153]	[0.716]	[0.535]
log(VOD)	0.341***	0.397***	1.554***	1.667***
	[0.039]	[0.058]	[0.148]	[0.164]
Human Capital		−0.076		0.367
		[0.113]		[0.242]
Female population		0.112*		0.754***
		[0.066]		[0.221]
Population 15-64		0.080***		0.406***
		[0.029]		[0.077]
Time-trend $_{\text{no VOD}}$	0.073***	0.083***	0.311***	0.336***
	[0.010]	[0.010]	[0.035]	[0.035]
Country Fixed Effects	YES	YES	YES	YES
Observations	1408	1211	1019	939
R-squared	0.297	0.347	0.447	0.543

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

Subsequently, in Table A7 we present the corresponding estimate for the case of year fixed effects after removing overlapping information with VOD, being year 2012 the baseline scenario (omitted). Again, the coefficient associated with VOD is positive and significant, while on the other hand, the year fixed effects are mostly significant, confirming the presence of temporal effects *beyond* VOD. It is worth mentioning that the coefficients are somewhat reduced, meaning that some omitted variable bias was effectively occurring when temporal effects were ignored.

Table A7
Fixed Effects estimation of broadband adoption – with year fixed effects after removing overlapping information with log(VOD)

Dep. variable:	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)
log(Price)	−0.117**	−0.153**	−0.243	−0.323**
	[0.053]	[0.075]	[0.159]	[0.154]
log(Income)	0.282*	0.164	−0.787	−0.802
	[0.163]	[0.162]	[0.771]	[0.584]
log(VOD)	0.188***	0.238***	0.936***	1.025***
	[0.036]	[0.050]	[0.137]	[0.136]
Human Capital		−0.095		0.332
		[0.114]		[0.241]
Female population		0.132*		0.810***
		[0.069]		[0.221]
Population 15-64		0.079***		0.415***
		[0.029]		[0.078]
Year 2013 $_{\text{no VOD}}$	0.041	0.026	0.464***	0.461***
	[0.040]	[0.031]	[0.109]	[0.097]
Year 2014 $_{\text{no VOD}}$	0.177***	0.185***	0.654***	0.809***
	[0.045]	[0.038]	[0.173]	[0.171]
Year 2015 $_{\text{no VOD}}$	0.294***	0.300***	0.928***	1.177***
	[0.047]	[0.046]	[0.201]	[0.193]
Year 2016 $_{\text{no VOD}}$	0.402***	0.407***	1.347***	1.593***
	[0.053]	[0.053]	[0.227]	[0.209]
Year 2017 $_{\text{no VOD}}$	0.505***	0.531***	1.786***	2.026***
	[0.057]	[0.064]	[0.255]	[0.251]
Year 2018 $_{\text{no VOD}}$	0.547***	0.584***	2.098***	2.350***
	[0.062]	[0.067]	[0.255]	[0.258]
Year 2019 $_{\text{no VOD}}$	0.582***	0.642***	2.394***	2.656***
	[0.071]	[0.076]	[0.282]	[0.289]
Year 2020 $_{\text{no VOD}}$	0.648***	0.706***	2.598***	2.807***
	[0.079]	[0.083]	[0.307]	[0.313]
Year 2021 $_{\text{no VOD}}$	0.641***	0.710***	2.960***	3.191***
	[0.084]	[0.087]	[0.330]	[0.326]
Country Fixed Effects	YES	YES	YES	YES
Observations	1408	1211	1019	939
R-squared	0.312	0.361	0.450	0.548

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

Overall, through this first methodology we can conclude that if we remove the overlapping information from the temporal variables we can solve the collinearity problem, verifying a positive effect from VOD on broadband adoption while at the same time controlling for temporal effects not linked to content availability.

Using proxies to approximate the temporal effects

Greene (2003) highlighted as a potential solution to multicollinearity problems to incorporate additional information in the model. In our specification, this would mean attempting to find proxy variables that can effectively account for those temporal effects *beyond* VOD.

Typically, the temporal effects in these situations are a reflection of some sort of technological enhancement over time. Therefore, it is worth exploring alternative variables than can effectively act as proxies of these temporal effects. Along these lines, it can be argued that broadband adoption may vary not only because of income, prices, and content availability; it can also be the case that it increases simply because networks have expanded over the time and now more people are served by the network. This means that it can be accurate to control for coverage levels. For this purpose, we will use the fixed broadband coverage variable (as share of households) elaborated by Telecom Advisory Services from data from regulatory agencies and operators reports. Contrary to the temporal effects, in this case the correlation between log(VOD) and broadband coverage is much lower (0.249), and thus less problematic. Another potential variable that can be associated with technological improvements over time that can matter in these situations is fixed broadband speed. In this case, the data on average speed comes from Ookla/Speedtest. The correlation between log(VOD) and speed is important (0.555) although lower than that of the time-trend. Following this, we introduced these additional regressors in the original models (Table A8).

Table A8
Fixed Effects estimation of broadband adoption – with additional controls to proxy the omitted temporal variables

Dep. variable:	log(BB)	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)	log(BB > 10Mbps)
log(Price)	−0.109	−0.101	−0.112	−0.084	−0.061	−0.117
	[0.073]	[0.071]	[0.071]	[0.153]	[0.156]	[0.154]
log(Income)	0.258	0.313	0.227	−0.737	−0.535	−0.711
	[0.179]	[0.196]	[0.169]	[0.724]	[0.771]	[0.619]
log(VOD)	0.172***	0.217***	0.218***	0.894***	1.040***	0.946***
	[0.036]	[0.059]	[0.067]	[0.101]	[0.155]	[0.164]
BB coverage	0.021***	0.021***	0.018***	0.089***	0.088***	0.078***
	[0.003]	[0.003]	[0.003]	[0.016]	[0.015]	[0.016]
BB speed		−0.001	0.000		−0.003	−0.001
		[0.001]	[0.001]		[0.002]	[0.002]
Human Capital			0.074			0.678***
			[0.087]			[0.223]
Female population			0.068			0.510***
			[0.063]			[0.153]
Population 15-64			0.065***			0.241***
			[0.023]			[0.078]
Country Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1030	1030	1030	832	832	832
R-squared	0.397	0.400	0.424	0.509	0.512	0.565

Note: ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

As denoted by the results presented in Table A8, the broadband coverage variable always presents a positive and significant coefficient, effectively proving that part of the variation in broadband adoption levels is explained by changes in coverage through the time. On the other hand, broadband speed is not significant. Importantly, in all estimates VOD services remain with a positive and significant coefficient, providing validity to the results presented in the main model.

Principal component analysis to build a new set of uncorrelated (orthogonal) regressors

Another alternative proposed by Greene (2003) is to carry out a principal component analysis using the set of correlated variables, and through this approach build a new set of uncorrelated (orthogonal) constructs. This effectively solves the collinearity problem, at the expense of making more difficult the interpretation of the coefficients as the newly created variables are built from the set of original ones.

First, we conduct the analysis by considering the time-trend and log(VOD) for the principal component analysis. As denoted by Table A9, a single construct is enough to keep 93% of the information provided by both variables.

Table A9
Principal components/correlation – log(VOD) and time-trend

Component	Eigenvalue	Difference	Proportion	Cumulative
Construct 1	1.857	1.715	0.929	0.929
Construct 2	0.143	.	0.071	1

Source: Prepared by the authors

Following the common criteria of selecting constructs with eigenvalue >1, we carry on with this newly built Construct 1, discarding Construct 2. The new construct is built from both original variables with equal weights (0.707), as represented in Table A10. This means that this new variable will contain information both from the temporal trend and from the VOD series.

Table A10
Principal components – log(VOD) and time-trend

Variable	Construct 1
Log(VOD)	0.707
Time-trend	0.707

Source: Prepared by the authors

When running the model using this construct containing both VOD and the time-trend related information, the associated coefficient is positive and highly significant (Table A11). Although the coefficient is not directly comparable with that of the previous estimates, a similar pattern appears to follow, as it takes a much higher value for the case of the estimates for broadband adoption above 10 Mbps of speed.

Table A11
Fixed Effects estimation of broadband adoption – using construct built from log(VOD) and time-trend

Dep. variable:	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)
log(Price)	−0.139***	−0.172**	−0.239	−0.339**
	[0.053]	[0.075]	[0.154]	[0.160]
log(Income)	0.303**	0.176	−0.472	−0.557
	[0.153]	[0.151]	[0.718]	[0.569]
Construct 1	0.163***	0.187***	0.730***	0.770***
	[0.017]	[0.026]	[0.066]	[0.075]
Human Capital		−0.052		0.438*
		[0.114]		[0.243]
Female population		0.110*		0.728***
		[0.065]		[0.230]
Population 15-64		0.082***		0.388***
		[0.029]		[0.077]
Country Fixed Effects	YES	YES	YES	YES
Observations	1408	1211	1019	939
R-squared	0.284	0.331	0.428	0.518

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

We also repeat the prior exercise, but considering now each year dummies, along with the logged VOD variable. As denoted by Table A12, up to the ninth construct 97.3% of the original information is kept.

Table A12
Principal components/correlation – log(VOD) and year fixed effects

Component	Eigenvalue	Difference	Proportion	Cumulative
Construct 1	1.899	0.799	0.173	0.173
Construct 2	1.1	0	0.1	0.273
Construct 3	1.1	0	0.1	0.373
Construct 4	1.1	0	0.1	0.473
Construct 5	1.1	0	0.1	0.573
Construct 6	1.1	0	0.1	0.673

(*continued on next page*)

Table A12 (*continued*)

Component	Eigenvalue	Difference	Proportion	Cumulative
Construct 7	1.1	0	0.1	0.773
Construct 8	1.1	0	0.1	0.873
Construct 9	1.1	0.848	0.1	0.973
Construct 10	0.252	0.205	0.023	0.996
Construct 11	0.049	.	0.004	1

Source: Prepared by the authors

Following the eigenvalue >1 criteria, we carry on with the first nine constructs, which by construction are orthogonal, effectively solving the collinearity problem. As represented in Table A13, the first construct is mainly built from VOD services (weight of 0.687), while the remaining ones do not rely at all on this variable. This facilitates the interpretation of interest, as we can only focus on analyzing the coefficient of Construct 1 that is primarily originated by VOD.

Table A13
Principal components – log(VOD) and year fixed effects

Variable	Construct 1	Construct 2	Construct 3	Construct 4	Construct 5	Construct 6	Construct 7	Construct 8	Construct 9
Log(VOD)	0.687	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Year 2012	−0.293	0.196	0.277	0.160	0.126	−0.045	−0.756	−0.090	0.118
Year 2013	−0.291	0.492	−0.237	−0.167	−0.004	0.001	0.372	−0.522	−0.134
Year 2014	−0.271	−0.727	0.349	−0.012	−0.140	−0.025	0.247	−0.206	−0.030
Year 2015	−0.256	0.081	−0.118	0.088	0.324	−0.167	0.307	0.705	0.189
Year 2016	−0.023	−0.125	−0.586	0.246	−0.643	0.114	−0.186	0.140	0.008
Year 2017	0.133	0.180	0.314	−0.713	−0.357	0.111	−0.033	0.242	0.143
Year 2018	0.120	−0.049	0.003	−0.021	0.238	0.184	−0.102	0.162	−0.858
Year 2019	0.193	−0.282	−0.382	−0.223	0.509	0.285	−0.120	−0.224	0.373
Year 2020	0.249	0.233	0.380	0.560	−0.052	0.373	0.272	−0.060	0.191
Year 2021	0.295	0.000	0.000	0.082	0.000	−0.831	0.000	−0.147	0.000

Source: Prepared by the authors

When running the econometric models using these nine constructs containing both VOD and year related information, the associated coefficient of interest (that of Construct 1, built mainly from VOD) is positive and highly significant (Table A14).

Table A14
Fixed Effects estimation of broadband adoption – using construct built from log(VOD) and year fixed effects

Dep. Variable:	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)
log(Price)	−0.116**	−0.148*	−0.238	−0.310*
	[0.053]	[0.076]	[0.155]	[0.161]
log(Income)	0.318*	0.204	−0.652	−0.664
	[0.162]	[0.161]	[0.788]	[0.618]
Construct 1	0.145***	0.170***	0.650***	0.706***
	[0.015]	[0.024]	[0.060]	[0.067]
Construct 2	−0.024***	−0.027***	−0.044	−0.075**
	[0.007]	[0.007]	[0.033]	[0.030]
Construct 3	−0.010	−0.007	−0.040*	−0.059***
	[0.006]	[0.006]	[0.022]	[0.017]
Construct 4	0.008*	0.010**	0.045**	0.037**
	[0.005]	[0.005]	[0.020]	[0.018]
Construct 5	0.007	0.013*	0.080***	0.078***
	[0.007]	[0.008]	[0.023]	[0.021]
Construct 6	0.008**	0.007*	−0.062***	−0.053***
	[0.004]	[0.004]	[0.019]	[0.019]
Construct 7	0.030***	0.029***	0.136***	0.149***
	[0.009]	[0.008]	[0.030]	[0.030]
Construct 8	0.045***	0.044***	0.028	0.077**
	[0.008]	[0.008]	[0.036]	[0.034]
Construct 9	−0.002	−0.001	−0.018	−0.020
	[0.004]	[0.003]	[0.013]	[0.012]
Human Capital		−0.081		0.363
		[0.115]		[0.243]
Female population		0.129*		0.783***
		[0.069]		[0.229]

(*continued on next page*)

Table A14 (*continued*)

Dep. Variable:	log(BB)	log(BB)	log(BB > 10Mbps)	log(BB > 10Mbps)
Population 15-64		0.083***		0.409***
		[0.029]		[0.080]
Country Fixed Effects	YES	YES	YES	YES
Observations	1408	1211	1019	939
R-squared	0.303	0.351	0.437	0.532

Note: *p<10%, **p<5%, ***p<1%. Robust standard errors in brackets.
Source: Prepared by the authors

By performing these analyses, we were able to conclude that our baseline estimations that ignored the temporal variables were effectively upward biased, but after solving the collinearity issues, the estimates were proven to be robust to the inclusion of the temporal effects.

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