Telecommunications Policy xxx (xxxx) xxx

Contents lists available at ScienceDirect

Telecommunications Policy

journal homepage: www.elsevier.com/locate/telpol

Exploring the heterogeneous link between broadband investment and coverage expansion using unconditional quantile regressions☆

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ARTICLE INFO

Keywords:
Broadband
4G
5G
FTTH
Coverage
Investment
Digital divide

ABSTRACT

One of the primary challenges of the telecommunications industry is to address the broadband connectivity divide. Policy makers, regulators, and network operators are in need to understand the amount of capital required to address this gap and generate solid evidence upon which policy options and regulatory remedies should be discussed. To date, most studies aimed at estimating the investment associated with broadband deployment have consisted in ad-hoc approaches based on cost modelling from average estimations, which lack rigor in terms of considering differences in technologies, topography, and population density. In this paper we propose a general approach, based on the use of Unconditional Quantile Regressions (UQR), that addresses the heterogeneities that arise from considering differentiated coverage targets and investment required across the different deployment phases. Our tool was found to successfully account for the increasing investment to fulfil coverage targets. Moreover, it can be applicable to a wide range of countries, as robustness checks conducted provided evidence of being suitable, to some extent, for countries with more geographic challenges (e.g., mountains, forests, etc.). On this basis, the estimated UQR coefficients were also used to simulate 4G, 5G and FTTH expansion for scenarios of accelerated deployments in Latin America, by trading off cost and target network quality requirements. We simulated some coverage goals above the current trends for 2030, targeting on average 98% of the population covered by 4G, 80% of the population covered by 5G, and two-thirds of households passed by FTTH. For the overall Latin America region, the extra capital needed above current investment trends accounts for $ 17,101 million over the period 2023–2029. Considering this challenge, potential regulatory remedies are considered.

☆ A portion of the research presented in this article was originally developed for a study commissioned by the Inter-American Development Bank (IDB) and the Centro de Estudios de Telecomunicaciones de América Latina (cet.la). The authors would like to thank the following industry specialists who contributed with useful comments and suggestions: Antonio García-Zaballos, Enrique Iglesias (IDB); Maryleana Méndez, Luis Mauricio Torres (cet.la); Ana Valero, Sergio Comín, Fernando Latterza (Telefónica); Horacio Romanelli, Fabio Mando, Enrique Fernández (Millicom); Andrea Espinoza, Eduardo Torres Orduña, Antonio Solano Hernández (América Móvil); Cristina García de Miguel, Jorge Rodriguez, Esther Riobó (Hispasat). This paper also benefited from the interesting comments provided by the audience when a preliminary version was presented in the ITS 32nd European Conference 2023 in Madrid (Spain). Finally, we also thank the journal editor-in-chief and two anonymous referees for useful comments and suggestions.

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https://doi.org/10.1016/j.telpol.2023.102623
Received 26 March 2023; Received in revised form 1 August 2023; Accepted 2 August 2023

1. Introduction

Closing the digital divide is one of the main challenges in most public policy agendas worldwide, especially in the developing world and most importantly after the pandemic. While addressing the divide has a demand dimension (focusing on affordability, and digital skills), the supply gap (fulfilling complete coverage) remains also critical. As such, the issue remains as to how to deploy broadband networks to achieve coverage for all the population. This is especially difficult since network deployments are usually profitable in urban areas, but less so in suburban and especially rural ones. Thus, estimating the investment effort required to close these coverage gaps is complex because the link between investment and coverage is not as straightforward and cannot be estimated based on average costs (in other words, the per household or population coverage for the remaining 5% could be much higher than what the average cost might forecast).

Naturally, higher telecommunications investment should contribute to increase network coverage. However, the link between investment and coverage is not necessarily contemporaneous (e.g.: it may occur with a certain time-lag), and clearly it cannot be considered uniform, as we should expect it to be stronger at the beginning of the deployment phases, focused on urban areas, compared with later phases targeting less populated territories.

In this context, the purpose of this paper is to shed some light on the link between telecommunications capital investment and network coverage, and to identify these heterogeneous effects related to different stages of deployment. Ultimately, the objective is to provide a useful tool for policy makers, regulators, and telecommunications operators alike -especially in the developing world-attempting to estimate the investment required to fulfil universal connectivity plans, and therefore support the evaluation of policy and regulatory options (for example, regarding network sharing or Universal Service Funds) to fulfil this target.

To estimate the impact of the investment required to achieve coverage throughout the geography of a given country, we follow an approach based on the estimation of Unconditional Quantile Regressions (UQR; Firpo, 2007; Firpo et al., 2009). On this basis, the coefficients estimated through UQR are applied to a sample of Latin American countries in need to accelerate network deployment. In doing so, we estimate the investment effort needed to close the coverage gap and we compare it against the natural growth extrapolation of current investment trends, to find out the magnitude of the “extra” effort required to achieve those targets.

The remaining of the paper is structured as follows. Section 2 provides a literature review of previous research regarding the estimation of broadband deployment costs. Section 3 develops the empirical specification and presents the variables to be used. Section 4 presents the regression results, first through estimations to the mean, and afterwards through the UQR approach. Section 5 provides some robustness checks to the conducted estimates. Section 6 develops a simulation for the Latin America region. Finally, Section 7 ends with some conclusions and policy discussions.

2. Research literature review

Most studies conducted to assess the investment required to deploy telecommunications technologies have focused on cost modelling based on average values rather than exploring how the heterogeneous link between investment and coverage tends to evolve. In addition, the cost studies that analyse some geographic heterogeneities (e.g., mountain ranges) are usually ad-hoc approaches based on specific countries, meaning that they are therefore difficult to extrapolate to other contexts.

The usual estimations of deployment investment consist in calculating costs by area and adding them up, an approach labelled “bottom-up”. This is the main difference with our empirical strategy, which consists in analysing the link between coverage and aggregated investment, which is more general and possible to extrapolate to other contexts, although less detailed as it does not disaggregate costs by area. Our strategy can be considered, therefore, a “top-down” approach. In fact, to the best of our knowledge, no empirical papers in the related literature have followed our empirical strategy.

The relevant “bottom-up” research on estimating telecommunications deployment investment has been conducted either by consulting companies or by academic specialists. In the first category of authors, Cartesian (2019) carried out a study to estimate the cost of deploying fiber to the home (FTTH) in the United States with the purpose of supporting the discussion of public policies related to fulfilling ultra-fast broadband coverage options. The estimation of the costs of using fiber optics for fixed network distribution considers population density as a determining economic factor, since investment tends to increase with a lower density. Cartesian (2019) begin their analysis by segmenting the uncovered territory according to population density and creating four groups. Once this is done, they calculate the deployment cost for each group based on operator experiences and benchmarks. Based on these observations a model is built that calculates the cost per household for deployment in each geography. This model estimated that the cost per household passed (that is, not connected) by FTTH in urban areas is approximately $ 700 – $ 1,500,[1] while, in rural areas, it ranges between $ 3,000 and $ 6,000, depending on population density. From these unit values, and based on households not covered by density segment, total deployment costs were calculated, projecting that the investment needed to close the FTTH coverage gap in the United States is $ 70.1 billion. Beyond the increase in cost per household passed as density decreases and topography becomes more complex, the study concludes that FTTH deployment in low-density rural areas is not economically feasible. In contrast, this area should be served by wireless technology. While useful in terms of providing an overall estimate of capital based on metrics by density areas, the approach used by Cartesian is difficult to be applied to other countries as it requires highly disaggregated census information

[1] Studies conducted for other countries usually estimate lower costs per household. This can be related to more expensive costs being faced in the United States in comparison to other economies. For example, the FTTH Council Europe (2012) estimated a cost for densely populated European areas to be close to 400 euros per household.

to categorize zones and number of households by zones and analysis of unit deployment costs.

As for 5G deployments, a report submitted to the European Commission by a consortium made up of Tech4i2, Real Wireless, Trinity College, Interdigital (2016), considers that the cost of 5G deployment per subscriber will follow an extrapolation of the investment costs for each previous generation of wireless technology. Thus, the authors project the cost per user for 5G in a linear manner based on 2G, 3G, and 4G costs derived from Selian (2001). The cost per subscriber estimated in this highly qualitative study includes, according to analysts, radio and backhaul equipment costs, excluding maintenance, sales, marketing, billing, and administrative costs. Based on this estimate per subscriber, the study estimates a cost of approximately 140 euros per 5G subscription, projecting a total investment of 58 billion euros to cover all member states with 5G.

More recently, a rigorous study developed by Oughton and Frias (2018) estimated the costs for 5G rollout in Great Britain. The analysis is based on building technology architectures based on traffic models, mobile broadband adoption, and population density. Each postcode in the country is categorized according to antenna density, extrapolating 4G site deployment and future 5G needs. The study defines scenarios based on alternative models of infrastructure sharing and quality of service by region. The urban-suburban scenario defined by the authors stipulates that deployment is carried out in all the areas corresponding to first and second level metropolitan centers. This strategy is similar to most of the 5G deployment plans formulated by operators in advanced economies, where the uniform speed to be offered is symmetrical 50 Mbps. After this first scenario, further possibilities are considered to expand the simulation to rural areas. Each scenario requires different levels of investment, but they can be disaggregated in terms of investment by geography. Derived from their findings, investment per population in cities with over 1 million inhabitants accounts to $ 45.71 per person, increasing in suburban areas to $ 197.16, and in rural areas to $ 3,981.22. Based on these estimates, the national rollout of 5G in Great Britain will require $ 53.34 billion (not including spectrum costs).

In turn, Katz and Cabello (2019) rely on the capital investment per population from the study by Oughton and Frias (2017) as a starting point and estimate the costs of deploying 5G networks in a sample of six Latin American countries: Argentina, Brazil, Chile, Colombia, Mexico and Peru.[2] They are calculated according to the same four deployment scenarios of the British study, foreseeing spectrum auctions at the end of 2020 and deployment beginning in 2021 and then towards the end of 2022, beginning with the use of millimetric bands with small cells. Under these assumptions, the authors assume that the deployment of infrastructure would be completed by 2027. According to this analysis, the investment required for the deployment of 5G in the countries under consideration presents important differences once the different deployment scenarios are calculated (for example, a full national scenario versus deployment limited to metropolitan areas). Accordingly, the investment for deploying 5G in urban and suburban areas reaches $ 50.77 billion.

Another analysis of the investment required to deploy 5G was carried out for China by the Chinese Academy of Information and Communication Technologies (CAICT, 2020), the research body linked to the Ministry of Industry and Information Technology. The premise of this study is an aggressive deployment of 5G nationwide, requiring a total investment of $ 232.2 billion by 2025. The investment estimate, in this case, was based on a projection of the number of 5G base stations to be installed and the average cost of deployment.

In parallel with estimates of investment in specific technologies such as those presented above for exclusive cases of FTTH or 5G, research studies have also been developed where the analysis focuses on diverse complementary technologies. In other words, the estimation is preceded by a technical-economic analysis, determining which are the most appropriate technologies to serve a region based on specific characteristics of density and topography.

In the first example of this approach, Feijoo Gonzalez and Gómez Barroso (2013) undertook an analysis considering the options of FTTH, VDSL, DOCSIS and LTE to serve 100% of homes and companies in Spain. The authors classified each of the Spanish municipalities according to their population density, determining that fixed broadband is more suited for urban municipalities, while rural ones, defined according to a threshold of 100 inhabitants per square kilometre, would be served with LTE, with a download speed of 30 Mbps. The authors estimated that to reach 100% coverage of inhabitants and companies in Spain, 12.6 billion euros would be required.

With an exclusive focus on the Spanish rural context, Ovando et al. (2015) calculated the investment required for coverage according to alternative scenarios of competition for infrastructure and sharing of LTE networks. The analysis addressed each of the rural municipalities, estimating whether it is possible to serve it through competing infrastructure operators offering LTE service for 30 Mbps speed, and if this is not feasible, considering an infrastructure sharing model. The study estimated a total investment between 755 million and 917 million euros.

Another comparative investment study of different technologies is that of Katz (2022), where the author estimates the deployment cost required to cover urban and rural communities in the United States. Using a community of 19,000 users as a starting point, the analysis compares the cost of acquiring service from a private operator with the investment required if the community decides to deploy a private network using LTE or Wi-Fi technology. The study calculates the investment required for each option and stipulates the demographic and topographic conditions that determine the suitability of one or another technology.

In conclusion, the studies reviewed to estimate the investment required for the deployment of broadband networks cover a very wide range of methodologies and levels of analytical depth. However, most cases are based on ad-hoc analysis for specific countries or contexts, not necessarily being capable of addressing a wide range of geographies. This study intends to address this gap. In addition, all the reviewed studies were conducted before the beginning of 5G network deployment. In contrast, our methodology relies on statistical series from 2012 onwards to build econometric models that allow estimating investment and coverage based on real data.

[2] The authors adjusted CAPEX requirements considering income differentials in each country with respect to the UK.

That said, the research literature review provides useful insights regarding the different costs and suitability of technologies by geography: for instance, urban areas targets may require advanced fixed and wireless technologies, while in rural areas the high capital requirements make 4G as the more accurate alternative.

3. Empirical specification

In this section we present the empirical specification and the dataset to be used in the study. We start describing the regression model to be estimated to measure coverage for 4G, 5G and FTTH technologies. We selected coverage as dependent variable as our focus is on the supply-side (network deployment) rather than on the demand (usually measured through adoption). The population covered by these broadband technologies is expected to be driven by four variables: capital investment of telecommunication operators (*CAPEX pc)*,[3] plus a vector X of additional controls (population density, population, and GDP per capita). In addition, coverage is expected to depend on topographic conditions, as the presence of forests or hilly terrain. As these latest indicators are time-invariant, they will be captured by the country fixed effects. As a result, the equation is represented as:

$$\log\left(COVERAGE_{it}\right) = \alpha_i + \beta \log\left(CAPEX\ pc_{it-n}\right) + \delta X_{it} + \varepsilon_{it}$$

Where i and t denote respectively country and year, and α_i captures the country-level unobservable characteristics. Naturally, we expect $\beta > 0$. However, since investment may take some time to be translated into coverage gains because of construction times, permit delays, equipment imports required, and the like, we will have to determine which is the n period lag that better suits the model ($n = 0$, 1, or 2).

Table 1 presents the descriptive statistics and sources for the variables to be included in the regression models. The period considered is 2012–2021, while data was compiled for 108 countries (complete list in Appendix 1). Coverage variables are defined as the percentage of population (for 4G and 5G) and percentage of households passed (for the case of FTTH). The source for both wireless technologies is GSMA Intelligence, while the FTTH variable was compiled by Telecom Advisory Services (TAS) from data provided by IDATE, OECD and regulatory agencies. CAPEX variables are measured in per capita terms. For mobile CAPEX, the data was extracted from GSMA Intelligence, while the fixed CAPEX dataset was built using overall telecom CAPEX reported by the International Telecommunications Union (ITU), and the share of fixed investment over the total levels, as reported by OMDIA. The three control variables were extracted from the World Bank database.

As reported, average 4G coverage for the period considered is 61.9%, while 5G naturally was at the time in its infancy (4.5%). On the other hand, 26.2% is the average for households passed by fiber networks. Average fixed CAPEX per capita is $ 37.5. For mobile CAPEX, averages $ 37.2 per capita.

4. Results

4.1. Estimation at the mean

Before turning into quantile regressions, we will conduct estimates at the mean with the objective of identifying the accurate lag between investment and coverage. As explained above, a delay exists between the moment that an investment is approved, and coverage gains are achieved. We need to estimate this gap to factor it in the timing linking capital spending and coverage increases. As the coverage variables are transformed into logs, all observations with zero values are dropped from the estimation. This means that only observations with positive coverage values are considered in the regressions. Table 2 presents the fixed effects model results for the case of FTTH coverage.

In column [I] we test the contemporaneous link between fixed investment and FTTH coverage. The coefficient associated with fixed investment is positive and significant (at a 5% level). When we incorporate the first lag of investment (column [II]), the coefficient is similar in magnitude and significance, and the model fit remains almost unchanged (measured through the R-squared). Finally, if we consider the second lag (column [III]), the coefficient is no longer significant and the model fit decreases. Based on this evidence, the temporal link between investment and coverage for the case of FTTH should be either contemporaneous or with one-lag, but we can discard the possibility of the second lag.

Next, we turn to 4G coverage (Table 3). We replicate the analysis for the contemporaneous value, the first and the second lag for mobile investment. In this case, the coefficients are positive and significant in all cases, while the model fit increases with the longer lag.

Based on these results, the selected lag should be of two time periods. However, it does not seem reasonable for the deployment of mobile infrastructure to require longer than fixed networks, so by combining the evidence for both FTTH and 4G, we consider it reasonable to pursue the analysis by relying in a one-period lag for both technologies.

Finally, we perform an estimate for 5G (Table 4). Naturally, the number of observations drops abruptly as only few countries have started to deploy this technology standard by 2021. In addition, this model is estimated with the more efficient random effects procedure rather than with fixed effects, as suggested by the results of the conducted Hausman test (Table A.1 in Appendix 2). In this case,

[3] Even if this specification means a flow indicator (CAPEX) explaining a stock variable (Coverage), the introduction of country-level fixed effects is expected to capture differences in starting levels.

Table 1
Descriptive statistics.

Variable	Mean	Standard deviation	Obs.	Source
4G Coverage (% population)	0.619	0.377	1,090	GSMA Intelligence
5G Coverage (% population)	0.045	0.147	1,090	GSMA Intelligence
FTTH Coverage (% households)	0.262	0.321	1,090	IDATE, OECD, TAS
FX CAPEX per capita ($)	37.505	49.114	1,090	ITU, TAS, OMDIA
MB CAPEX per capita ($)	37.170	31.879	1,090	GSMA Intelligence
Density (population/km2)	243.742	778.713	1,090	World Bank
Population (million)	60.600	186.000	1,090	World Bank
GDP per capita ($)	19,686.680	22,673.760	1,090	World Bank

Source: authors' analysis

Table 2
Fixed Effects model: Drivers of FTTH coverage.

Dep. Var. = Log (FTTH COV)	[I]	[II]	[III]
Log (FX CAPEX pc)	0.371**		
	[0.157]		
Log (FX CAPEX pc) $_{t-1}$		0.345**	
		[0.151]	
Log (FX CAPEX pc) $_{t-2}$			0.252
			[0.156]
Log (Density)	−0.594	−0.545	−0.548
	[2.400]	[2.315]	[2.223]
Log (Population)	8.256***	8.086***	8.349***
	[2.824]	[2.720]	[2.663]
Log (GDP pc)	−0.108	−0.068	0.063
	[0.397]	[0.385]	[0.386]
R-squared (within)	0.631	0.630	0.625
Observations	723	723	723

Note: ***p<1%, **p<5%. All estimates include country fixed effects and a temporal trend. Robust standard errors in brackets.
Source: authors' analysis

Table 3
Fixed Effects model: Drivers of 4G coverage.

Dep. Var. = Log (4G COV)	[I]	[II]	[III]
Log (MB CAPEX pc)	0.347***		
	[0.092]		
Log (MB CAPEX pc) $_{t-1}$		0.464***	
		[0.086]	
Log (MB CAPEX pc) $_{t-2}$			0.544***
			[0.098]
Log (Density)	1.128	0.453	0.721
	[2.254]	[0.378]	[2.288]
Log (Population)	6.425**	6.488***	5.310**
	[2.519]	[2.366]	[2.575]
Log (GDP pc)	0.415	0.406	0.394
	[0.406]	[0.378]	[0.349]
R-squared (within)	0.294	0.317	0.342
Observations	940	940	940

Note: ***p<1%, **p<5%. All estimates include country fixed effects. Robust standard errors in brackets.
Source: authors' analysis

the coefficient associated to the first lag of mobile investment is similar as that for the case of 4G.

In sum, based on regressions at the mean to identify the accurate lag between investment and coverage, one year time lag was selected for all technologies. Having completed this first analysis, we move to estimate the UQR coefficients that link capital spending with technology coverage.

4.2. UQR estimates

As denoted in Section 3, the impact of telecom investment on coverage is captured by β, that in a standard regression model is assumed to represent the average observation. However, to be able to test the hypothesis that the link between investment and coverage varies across the actual coverage distribution, we must follow a different approach. Quantile regressions are used to obtain an estimate of the coefficient of interest in different points of the distribution. In that regard, the standard practice has been to use the Conditional Quantile Regression (CQR) approach developed by Koenker and Bassett (1978). However, if we use CQR we will obtain estimates of the effect of the measure of investment on the conditional distribution of coverage, that is likely to differ markedly from the actual distribution. In other words, CQR provides the estimated impact of a covariate on a quantile of the coverage conditional on specific values of the other covariates. As a result, CQR generates estimates that may not be generalizable or interpretable in the population context, limiting thus their utility from a policy perspective. Hence, to consider the kind of heterogeneities of interest in this study, the effect of investment on different parts of the coverage distribution is estimated by means of UQR. Following this approach, we can obtain more interpretable results as UQR marginalizes the effect over the distributions of the other covariates. As we are especially concerned with the effect of increasing investment on the unconditional coverage distribution, the UQR is far more suitable to test our hypothesis.

Among the methods proposed so far to implement the UQR approach, we choose that proposed by Firpo et al. (2009),[4] that consists of running a regression of a transformation —a (recentred) influence function— of the outcome variable on the explanatory variables.

Consider that we are estimating a regression of an outcome variable Y on a series of covariates denoted by X. Let F_Y represent the marginal (unconditional) distribution of the outcome variable, while ν reflects the point in the distribution. The influence function $IF(Y; \nu, F_Y)$ of a distributional statistic $\nu(F_Y)$ will then represent the influence of an individual observation on that distributional statistic. Adding back the statistic $\nu(F_Y)$ to the influence function yields what Firpo et al. (2009) call as "recentred influence function" (*RIF*), that can be represented as:

$$RIF(Y; q_\tau, F_Y) = q_\tau + IF(Y;\ \nu, F_Y)$$

Being q_τ the τ-quantile. In the case of the mean of the distribution (μ), *RIF* is simply the outcome variable, so the regression of $RIF(Y;\mu)$ will just yield the same result as an Ordinary Least Squares (OLS) estimate of Y on X. On the other hand, for the case of quantiles, the dependent variable to be estimated is:

$$RIF(Y; q_\tau, F_Y) = q_\tau + (\tau - 1\{Y \le q_\tau\}) / f_Y(q_\tau)$$

As a result, the dependent variable in the regression is the *RIF*, and a simple OLS regression of this new dependent variable can be run on the covariates.

By running this transformed measure as dependent variable, we will be able to identify specific coefficients of interest for the different points of the distribution. While in a standard regression $Y = h(X, \varepsilon)$ the associated coefficient of interest takes the form of $\frac{\partial h(X, \varepsilon_\tau(X))}{\partial x} = \beta$, in the case of UQR estimates, the unconditional quantile partial effect associated to the τ-quantile will be:

$$UQPE(\tau) = E\left[\omega_\tau(X)\frac{\partial h(X, \varepsilon_\tau(X))}{\partial x}\right]$$

where $\omega_\tau(X)$ a weighting function defined as the ratio between the conditional and unconditional densities. The full demonstration is provided in Firpo et al. (2009).

In sum, the estimation conducted through UQR will provide us with coefficients β_τ for the respective τ-quantiles. In the context of our study, a downward sloping trend in the β over the quantiles should be read as a higher increase in coverage for the less covered observations generated by the increase in investment.

Table 5 provides the results for the UQR estimate of drivers of FTTH coverage. We selected the following percentiles of the distribution of the dependent variable: P5, P10, P20, P30, P30, P40, P50, P60, P70, P80, P90, and P95. All estimates incorporate country level fixed effects and bootstrapped standard errors (200 reps).

From the analysis of Table 5, there seems to be a downward sloping trend for the coefficients that link investment and coverage. Just to cite some examples, at the 5th percentile, an increase of 1% in investment yields an increase of FTTH coverage of 2.015% the following year. However, that elasticity takes a value of 0.494% in the 40th percentile, and of 0.144% in the 70th percentile. From the median onwards, some non-significant coefficients appear, and even a negative elasticity is registered at the 95th percentile. Although at a first glance this negative coefficient seems to be counter-intuitive, there exist some reasons for this to happen. For instance, a potential process of pole network decommissions in rural areas to increase in the long-term coverage for a larger population, transitioning to mobile access, can generate a short-term reduction of coverage. An alternative explanation can be associated to the fact that in less populated areas coverage advances may have been financed with universal service funds rather than by the telecom operators. If these investments are not properly captured by the CAPEX variable, then coverage increases can be associated with lower or reduced investments, resulting in a negative coefficient.

By allocating the corresponding coverage level for each estimated decile and considering the positive and significant coefficients from Table 5, we can plot the different elasticity levels for each degree of coverage (Fig. 1). Moreover, we can approximate by a potential function the coefficient at each potential coverage level.

In synthesis, the impact of investment on coverage decreases with coverage because the capital required to grow a comparable amount of households is larger with diminishing density, a result coincident with Cartesian results presented in the review of the literature. The advantage of this methodology is that it can be applied broadly to most countries.

Next, in Table 6 we calculate same estimates for the case of 4G technology. Again, a clear pattern of downward slope is appreciated

[4] Other alternatives include the methods by Rothe (2010) and Frölich and Melly (2013).

Table 4
Random Effects model: Drivers of 5G coverage.

Dep. Var. = Log (5G COV)	
Log (MB CAPEX pc) $_{t-1}$	0.436***
	[0.169]
Log (Density)	0.033
	[0.052]
Log (Population)	0.002
	[0.060]
Log (GDP pc)	0.419***
	[0.150]
R-squared (within)	0.660
Observations	131

Note: ***p<1%. All estimates include country random effects and a temporal trend. Robust standard errors in brackets.
Source: authors' analysis

for the elasticities once we move across to higher percentiles, starting from P10 in this case.

Mirroring the previous exercise of plotting the elasticity for each coverage level, in Fig. 2 we present the corresponding chart for the case of 4G.

In this case, the function that better fits the evolution of the elasticity is a logarithmic one. Interestingly, the fall in the investment impact is less abrupt in the case of 4G than in FTTH, something that is explained by the fact that wireless technologies are less costly to deploy, and because of this, the territorial scope is usually larger. For example, moving from 60% to 80% coverage makes the respective coefficient to decrease in more than half of its value, something that does not happen for a similar variation in the case of FTTH, because the coverage resulting from the investment was already at its minimum level.

Although hardly noticeable in Fig. 2, the coefficient that links mobile investment with 4G coverage effectively drops abruptly at the end of the distribution. To illustrate this point, in Fig. 3 we use the estimated coefficients to approximate the required increase in investment to increase 4G coverage in 1%. The results are clear to suggest that, on average, 4G deployment becomes more expensive as we advance in the deployment plans, but a dramatic expansion in costs takes place at the 95th percentile, equivalent to a coverage level of 99% in our sample. This explains why it is not reasonable to expect 100% coverage in 4G, having to rely instead on an alternative technological mix (e.g., satellite or Wi-Fi) to cover the final segments of the population.

Finally, it does not seem accurate to perform UQR regressions in the case of 5G because of a lack of observations, considering the limited number of countries that started to deploy this technology by 2021. In addition, there is clear lack of mature countries for this technology to cover a wide range of deployment phases as required to identify the heterogeneities found for the cases of FTTH and 4G. The only result we dispose of for 5G is the coefficient estimated at the mean in Table 4, 0.436. The mean for 5G for the 131 observations of Table 4 is 37.6% of people covered. If we compare with 4G, by the time 37.6% persons were covered, the simulated coefficient takes a value of 0.795 (according to the logarithmic function presented in Fig. 2). This means that, at a similar stage of development, the investment in 4G is 1.8 times more profitable in terms of coverage, than 5G. This is reasonable as 5G is a technology that demands much more densification of base stations, which is consistent with the findings of (Tech4i2, Real Wireles, Trinity College, & Interdigital, 2016) and Selian (2001) presented in the review of the literature, in the sense that new technologies are more expensive to deploy than the previous generations.

If we assume that the ratio that explains the differences in investment between 4G and 5G can be extrapolated to other points of the distribution, we can simulate, based on the trajectory of 4G across the distribution, how the coefficient for 5G may take place for each potential coverage level. This will look like in Fig. 4.

5. Robustness checks

While the estimates conducted by UQR appear to be reasonable, in this section we will test some additional checks to find if they are robust enough. This chapter is broken down into two sections. First, we check if results vary significantly after the introduction of additional controls to account for cross-country disparities. Second, we analyse whether our results are applicable to a wide range of countries, even those with more problematic geographic contexts.

5.1. Additional controls

While the baseline UQR estimates account for disparities in population, density, and income levels, plus the inclusion of fixed effects that absorbs time-invariant topographic factors, it could still be argued that additional controls may be needed, especially to account for regulation disparities and further sources of costs.[5]

Empirically, a well-developed regulatory framework has been found in prior research to be relevant to stimulate

[5] We are grateful for an anonymous referee for raising up this point.

Table 5
UQR Fixed Effects model: Drivers of FTTH coverage.

Dep. Var. = Log (FTTH COV)	FTTH coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (FX CAPEXpc)$_{t-1}$	2.015**	0.905*	0.781**	0.555**	0.494***	0.157	0.100	0.144*	0.078	−0.086	−0.212**
	[1.004]	[0.523]	[0.393]	[0.235]	[0.189]	[0.153]	[0.108]	[0.085]	[0.096]	[0.095]	[0.085]
Log (Density)	31.673	30.190*	7.187	−9.368	−9.214**	−13.212***	−8.317***	−7.059***	−7.509***	−7.494***	−2.261
	[27.108]	[17.090]	[8.892]	[7.931]	[4.631]	[2.309]	[2.425]	[1.855]	[1.787]	[2.598]	[2.402]
Log (Population)	29.550	6.583	6.588	15.508**	11.140***	10.794***	7.456***	5.239**	5.044***	4.664	−1.418
	[25.152]	[18.125]	[9.500]	[7.292]	[4.261]	[2.486]	[2.589]	[2.124]	[1.959]	[3.084]	[2.965]
Log (GDP pc)	4.046	−0.230	−0.756	−0.609	−1042**	−1.024**	−0.393	0.322	0.071	0.129	0.564**
	[3.804]	[1.472]	[1.050]	[0.769]	[0.519]	[0.419]	[0.341]	[0.330]	[0.246]	[0.295]	[0.230]
R-squared (within)	0.147	0.208	0.231	0.299	0.323	0.344	0.318	0.326	0.246	0.181	0.165
Observations	723	723	723	723	723	723	723	723	723	723	723

Note: ***p<1%, **p<5%, *p<10%. All estimates include country fixed effects and a temporal trend. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

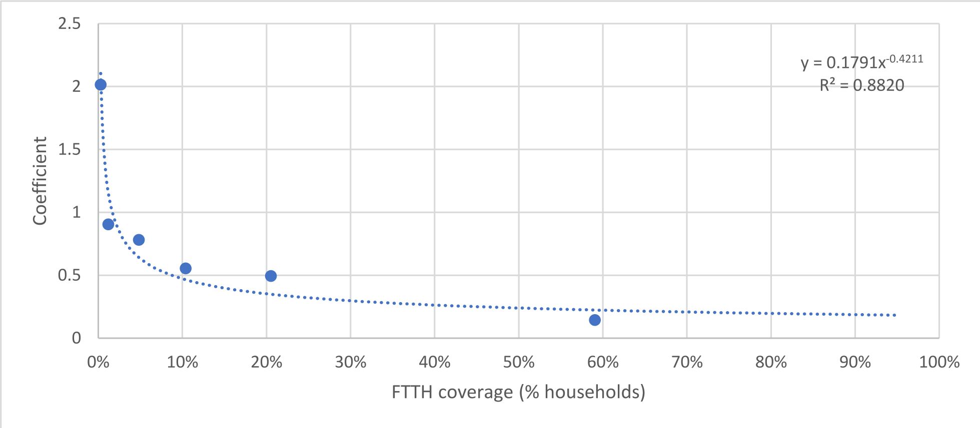

Fig. 1. Coefficient for the impact of fixed investment on FTTH coverage.
Source: authors' analysis

telecommunications investment (Katz & Jung, 2021). However, there are other sound regulations that may generate additional efficiencies and a better optimization of resources and thus, facilitate coverage expansion by reducing investment levels. To account for regulatory differences, we compiled the ICT Regulatory Tracker composite index provided by the ITU, a metric that records the existence of certain institutional and regulatory characteristics considered to be good practices for the sector development. This composite index helps to track progress and identify gaps in regulatory frameworks, being based on 50 indicators.[6]

As for further costs sources, we will account for cross-country disparities in labour costs, through the monthly average wages for the IT sector reported by the International Labour Organization (ILO). Considering that the ILO data is incomplete for some countries, we interpolated for missing information by assuming that IT wages evolved at a similar rate as the average salaries in each economy, and for cases where average salaries were not available, we made yearly adjustments based on the inflation.

Next, we replicated the UQR estimates incorporating as additional controls the Regulatory Tracker and the IT wages. Results are presented for the FTTH models (Table 7) being the investment coefficients mostly unchanged with respect to those reported in Table 5, suggesting that any omission in regulatory or additional cost measures should not be biasing the main results. We checked for each of the reported points in the distribution to determine if the coefficient associated with investment in Table 5 was statistically different to the one provided in Table 7, with results not rejecting in neither case the null hypothesis of equality in both estimates.[7] This provides robustness to the results presented in Table 5.

For the case of the 4G regressions (Table 8) the inclusion of further controls generates some minor differences in the first few quantiles, although the estimates behave mostly as those in Table 6. We also checked if each of the reported coefficient associated with investment in Table 6 was statistically different to those provided in Table 8, with results not rejecting in neither case the null hypothesis of equality in both estimates.[8] Again, this provides support for our main estimations.

5.2. Suitability check for geographically complex countries

Beyond the introduction of additional controls, an additional critique of our model could be related to the fact that while it reflects the evolution of the coefficient linking investment and coverage for an "average" country, it may not be useful for countries exhibiting topographic features with important differences from the average one.

To check if this is the case, we compiled two variables to account for geographic complexity. First, we built a variable for average elevation by country.[9] Second, we extracted from the World Bank the share of each country's land area covered by forests. While it is difficult to find a metric that covers all dimensions of geographic complexity, we remain confident that the selected indicators provide an accurate and complementary value.

We start the analysis with the average elevation variable, a measure that takes higher values in countries with more mountains, hence, a higher value should be associated with larger topographical complexity. The mean of the average elevation variable in our sample is 535.37 meters. However, the distribution of this variable suggests that the main problem may be arising from observations situated at the right-tail of the distribution, that is, those that present much higher average elevation than the mean (Fig. 5).

To check if our main results would change significantly for geographically complex countries, we split the sample and re-estimated our UQR models only for those observations situated at the final quartile of the distribution of average elevation, that is, countries with

6 See full details in https://app.gen5.digital/tracker/metrics.
7 Available upon request.
8 Available upon request.
9 The compilation was done from diverse sources, mainly Wikipedia and ChatGPT.

Table 6
UQR Fixed Effects model: Drivers of 4G coverage.

Dep. Var. = Log (4G COV)	4G coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (MB CAPEXpc)$_{t\text{-}1}$	1.277**	1.778***	0.969***	0.656***	0.198***	0.108***	0.066***	0.069***	0.077***	0.056***	0.013**
	[0.635]	[0.584]	[0.252]	[0.154]	[0.058]	[0.034]	[0.024]	[0.019]	[0.022]	[0.017]	[0.007]
Log (Density)	2.169	9.150	0.907	0.636	0.565	0.137	0.108	0.053	−0.588	0.040	0.056
	[7.351]	[10.825]	[4.485]	[2.635]	[1.132]	[0.708]	[0.584]	[0.602]	[0.516]	[0.298]	[0.227]
Log (Population)	13.352	19.704	17.657***	10.179***	3.919***	1.840**	1.218**	1.151**	1.304**	0.465	0.095
	[8.965]	[12.047]	[5.625]	[3.355]	[1.354]	[0.788]	[0.613]	[0.557]	[0.617]	[0.307]	[0.212]
Log (GDP pc)	1.774	1.158	0.341	0.085	0.133	0.003	0.101*	0.107**	0.088**	0.062*	−0.009
	[1.208]	[0.872]	[0.523]	[0.338]	[0.162]	[0.085]	[0.052]	[0.046]	[0.037]	[0.034]	[0.014]
R-squared (within)	0.127	0.203	0.239	0.207	0.164	0.115	0.102	0.092	0.067	0.045	0.017
Observations	940	940	940	940	940	940	940	940	940	940	940

Note: ***p<1%, **p<5%, *p<10%. All estimates include country fixed effects. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

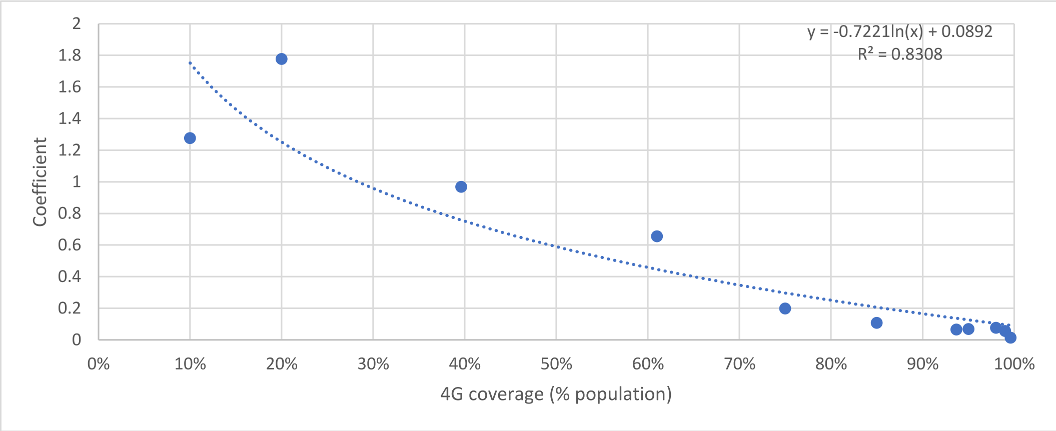

Fig. 2. Coefficient for the impact of mobile investment on 4G coverage.
Source: authors' analysis

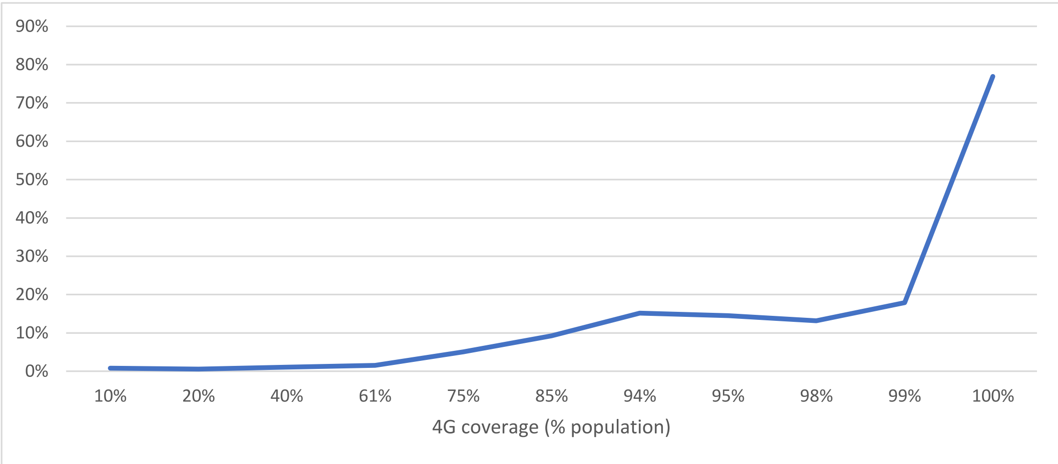

Fig. 3. Mobile CAPEX increase needed (%) to increase 4G coverage in 1%.
Source: authors' analysis

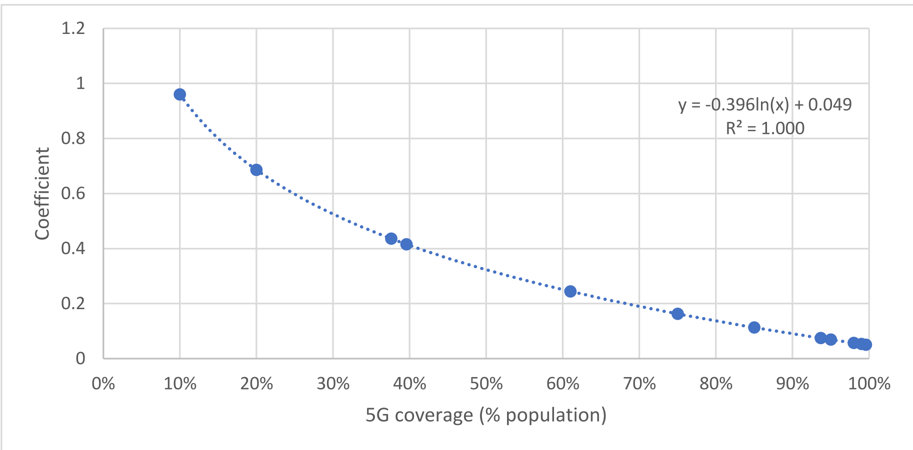

Fig. 4. Coefficient for the impact of mobile investment on 5G coverage.
Source: authors' analysis

Table 7
UQR Fixed Effects model: Drivers of FTTH coverage (Model with additional controls).

Dep. Var. = Log (FTTH COV)	FTTH coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (FX CAPEXpc)$_{t-1}$	2.064*	0.933*	0.789**	0.552**	0.527***	0.148	0.093	0.135*	0.067	−0.079	−0.207**
	[1.110]	[0.550]	[0.402]	[0.252]	[0.192]	[0.145]	[0.114]	[0.081]	[0.088]	[0.097]	[0.083]
Log (Density)	27.554	29.917**	7.515	−10.454	−8.941*	−13.436***	−8.388***	−6.772***	−7.509***	−7.140***	−2.008
	[23.805]	[14.624]	[9.366]	[8.264]	[4.706]	[2.501]	[2.357]	[1.759]	[1.869]	[2.120]	[2.078]
Log (Population)	40.092	8.256	6.317	17.794**	10.155**	10.868***	7.406***	4.348**	4.690**	4.047*	−1.849
	[25.883]	[17.487]	[9.770]	[7.851]	[4.279]	[2.449]	[2.682]	[1.882]	[2.092]	[2.420]	[2.441]
Log (GDP pc)	7.565*	1.077	−0.241	−0.023	−1.199*	−1.130**	−0.452	0.051	−0.141	−0.220	0.397*
	[3.916]	[1.786]	[1.152]	[0.822]	[0.614]	[0.435]	[0.363]	[0.297]	[0.297]	[0.305]	[2.411]
Regulatory Tracker	0.042	0.083	0.058	−0.012	0.008	−0.013	−0.007	−0.003	−0.009	−0.011	−0.001
	[0.086]	[0.059]	[0.039]	[0.023]	[0.016]	[0.011]	[0.008]	[0.008]	[0.007]	[0.007]	[0.004]
IT wages	−0.002***	−0.001**	−0.000	−0.000*	0.000	0.000	0.000	0.000*	0.000*	0.000***	0.000*
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R-squared (within)	0.164	0.224	0.241	0.305	0.334	0.348	0.321	0.336	0.266	0.197	0.163
Observations	722	722	722	722	722	722	722	722	722	722	722

Note: ***p<1%, **p<5%, *p<10%. All estimates include country fixed effects and a temporal trend. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

Table 8
UQR Fixed Effects model: Drivers of 4G coverage (Model with additional controls).

Dep. Var. = Log (4G COV)	4G coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (MB CAPEXpc)$_{t-1}$	1.015*	1.415**	0.796***	0.438***	0.124**	0.084**	0.061***	0.064***	0.068***	0.047**	0.013*
	[0.608]	[0.563]	[0.253]	[0.155]	[0.057]	[0.033]	[0.022]	[0.021]	[0.024]	[0.019]	[0.007]
Log (Density)	0.176	4.252	−0.369	−0.734	−0.062	−0.299	0.009	−0.047	−0.671	0.016	0.091
	[7.360]	[8.413]	[4.564]	[2.850]	[1.064]	[0.692]	[0.586]	[0.613]	[0.542]	[0.308]	[0.267]
Log (Population)	12.859	20.431**	17.242***	8.416***	3.013**	1.813**	1.125*	1.066*	1.225*	0.310	−0.021
	[9.192]	[10.143]	[5.641]	[3.255]	[1.312]	[0.762]	[0.612]	[0.549]	[0.681]	[0.344]	[0.284]
Log (GDP pc)	2.754*	2.612**	1.259**	0.915***	0.332**	0.146**	0.122**	0.128**	0.115***	0.073*	−0.019
	[1.636]	[1.212]	[0.590]	[0.327]	[0.165]	[0.070]	[0.061]	[0.050]	[0.042]	[0.038]	[0.021]
Regulatory Tracker	0.065	0.076**	0.047***	0.043***	0.021***	0.009***	0.002	0.002*	0.003**	0.003**	0.001
	[0.044]	[0.036]	[0.018]	[0.013]	[0.005]	[0.003]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
IT wages	−0.000	−0.001**	−0.000**	−0.000	−0.000	−0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R-squared (within)	0.160	0.236	0.273	0.244	0.205	0.158	0.114	0.104	0.078	0.056	0.025
Observations	927	927	927	927	927	927	927	927	927	927	927

Note: ***p<1%, **p<5%, *p<10%. All estimates include country fixed effects. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

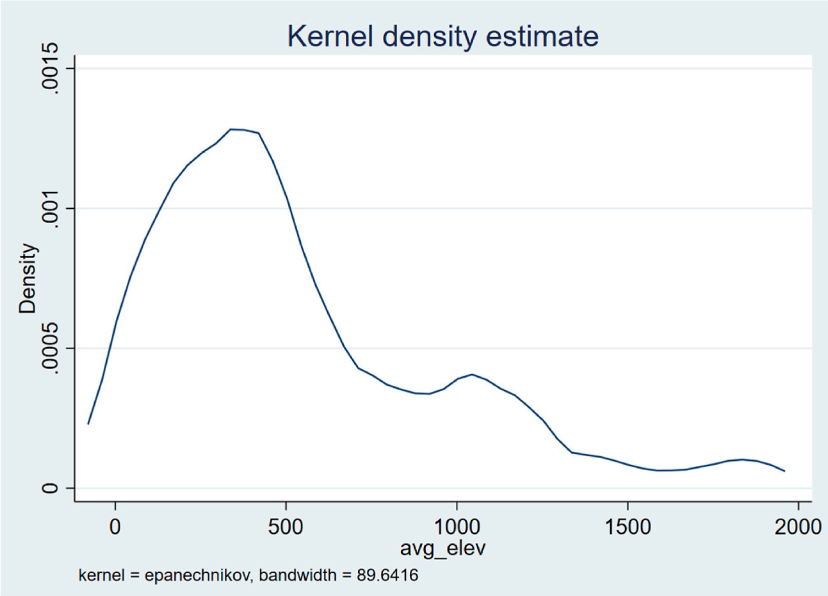

Fig. 5. Distribution of average elevation.
Source: authors' analysis

an average elevation equal or above the corresponding figure for the 75 percentile (746 meters). Results are presented next for FTTH in Table 9.

In most cases, results are like those of the main estimates, especially for the percentiles below the median. Moreover, in some of these cases the coefficients are larger than in the original regressions. This can be explained as in more geographically complex countries, the population is typically more concentrated in the more habitable areas. This would suggest that more concentrated population may be faced at the early stages of deployment, with the opposite happening after the right-end.

The significance difference test conducted to check if the parameters of Table 5 differ from those of Table 9 suggested that only in 3 of the 11 estimated points of the distribution significant differences arise.[10] First, in P30, where the coefficient of Table 9 was found to be larger than that of Table 5 (significance level 10%), for the reasons explained in the previous paragraph. Next, in P70 and P80, where as expected, the coefficients of Table 5 were found to be larger (at 10% and 5% significance levels, respectively). These results suggest that the model can be considered appropriate to simulate investment effects at an "average country with high elevation" at least up to percentile 60 of the coverage distribution. If we consider P70 as the point from which the original model is no further applicable for these complex countries, this point represents in our sample almost 60% of households passed with FTTH.

Naturally, for a smaller subsample of more extreme topographically complex countries (for example, those located in the last decile of average elevation), the applicability of our model is expected to be more limited, although the number of observations was not enough to conduct reliable UQR regressions.

Next, we present the results for the 4G coverage model estimated only for the sample of countries with average elevation above 746 meters (Table 10).

In most cases, results are like those of the main estimates, with differences across the investment parameters not being statistically significant.[11] The only significant differences arise in P40 and P50 (where the coefficients are larger for the geographically complex sample, with a significance level of 10%) and in P80 and P90 (where the baseline coefficients are larger, with a significance level of 5%).

The increased coefficients in P40 and P50 in the geographically complex subsample can be associated with the reasons explained above for the FTTH case: people tend to be more concentrated in these cases, favouring the early phases of deployment and complicating the situation at the right-tail. This suggests, again, that in these complex countries our original model can be appropriate to estimate investment effects up to a certain point, beyond it becomes unsuitable for that purpose. Assuming that the original model becomes unapplicable for points located in P80 and beyond, this corresponds in our sample for 4G coverage levels of 98%, still very high. This confirms again that wireless technologies are far more suitable than fixed ones for geographically complicated areas.

Next, we mirror the previous exercise but for the subsample of countries with larger forest area. Again, the distribution of this variable suggests a twin-peak distribution around the variable mean (0.300), with an important mass of observations located at the right (Fig. 6). We will focus on these complex observations situated in the last quartile, those with more than 44.6% of the territory

[10] Available upon request.
[11] Available upon request.

Table 9
UQR Fixed Effects model: Drivers of FTTH coverage (Countries with average elevation > 746 m).

Dep. Var. = Log (FTTH COV)	FTTH coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (FX CAPEXpc)$_{t\text{-}1}$	0.922	2.929*	1.602*	2.070**	0.653	0.581*	0.151	−0.720	−0.595**	−0.299	−0.394
	[1.914]	[1.609]	[0.898]	[0.821]	[0.582]	[0.345]	[0.359]	[0.459]	[0.279]	[0.301]	[0.321]
Log (Density)	187.586	89.914	90.155*	3.146	36.606	43.822	32.766	22.379	−20.416	−65.986	13.762
	[117.196]	[73.908]	[53.436]	[33.760]	[29.527]	[32.160]	[32.234]	[27.856]	[29.574]	[44.195]	[30.460]
Log (Population)	1.322	54.526	−57.515	4.887	−36.211	−52.456*	−45.653	−36.762	0.576	46.983	−32.430
	[102.475]	[63.567]	[53.375]	[31.813]	[27.163]	[30.751]	[32.616]	[26.579]	[29.857]	[44.692]	[27.205]
Log (GDP pc)	19.338***	4.671	−0.706	−0.265	2.283	2.548*	1.890	1.443	0.073	0.668	2.433*
	[6.112]	[4.940]	[2.455]	[2.366]	[1.913]	[1.345]	[1.213]	[1.158]	[1.361]	[1.405]	[1.461]
R-squared (within)	0.483	0.574	0.397	0.326	0.280	0.464	0.510	0.410	0.379	0.366	0.346
Observations	185	185	185	185	185	185	185	185	185	185	185

Note: ***p<1%, **p<5%, *p<10%. All estimates include country fixed effects and a temporal trend. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

Table 10
UQR Fixed Effects model: Drivers of 4G coverage (Countries with average elevation > 746 m).

Dep. Var. = Log (4G COV)	4G coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (MB CAPEXpc)$_{t-1}$	1.776*	1.600**	1.303***	1.079***	0.652***	0.401**	0.116	−0.066	−0.123	−0.078	−0.017
	[0.956]	[0.752]	[0.501]	[0.324]	[0.242]	[0.156]	[0.134]	[0.084]	[0.081]	[0.052]	[0.056]
Log (Density)	32.560	20.877	20.922	23.493*	31.533**	9.456	4.360	6.064	0.894	−4.024	1.105
	[27.052]	[22.956]	[15.670]	[12.493]	[12.816]	[7.971]	[6.278]	[5.096]	[4.786]	[3.895]	[3.545]
Log (Population)	−24.515	−6.675	−6.159	−11.488	−20.844*	−4.581	−0.649	−3.267	1.526	5.485	−0.444
	[25.464]	[22.488]	[14.935]	[12.380]	[12.441]	[7.725]	[6.361]	[5.426]	[4.969]	[4.032]	[3.974]
Log (GDP pc)	1.015	0.655	0.221	−0.178	0.161	−0.017	−0.357	−0.308	−0.036	0.043	0.132
	[0.755]	[0.767]	[0.718]	[0.584]	[0.400]	[0.283]	[0.232]	[0.191]	[0.173]	[0.107]	[0.100]
R-squared (within)	0.154	0.241	0.418	0.408	0.364	0.233	0.183	0.126	0.072	0.052	0.023
Observations	287	287	287	287	287	287	287	287	287	287	287

Note: ***p<1%, **p<5%, *p<10%. All estimates include country fixed effects. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

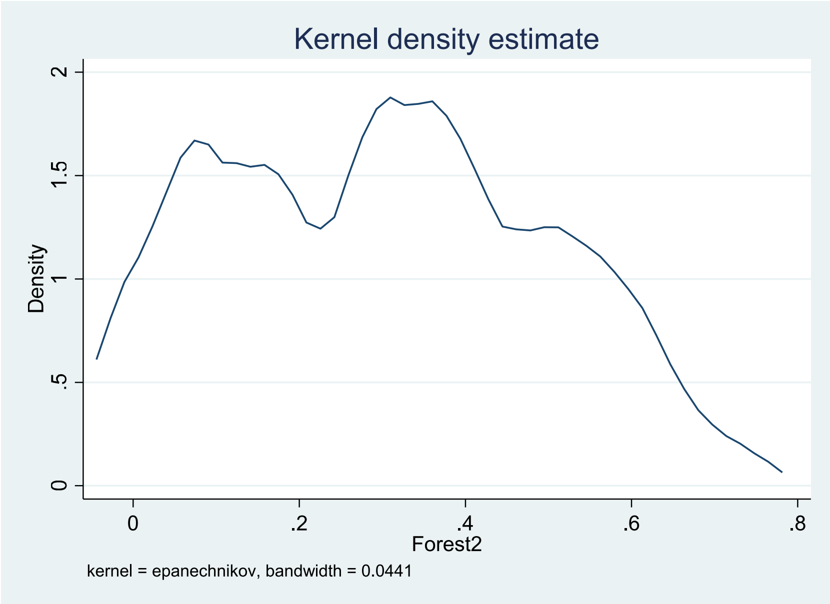

Fig. 6. Distribution of Forest land (%).
Source: authors' analysis

covered by forests.

Results for FTTH coverage estimates for the subsample of large forest countries are presented in Table 11. The significance difference test conducted to check if the parameters of Table 5 differ from those of Table 11 suggested that in none of the 11 estimated points of the distribution significant differences arise.[12] This suggest that the proposed model is also applicable to the average country with large forest.

Finally, in Table 12 we present the results for 4G coverage. The significance difference test conducted to check if the parameters of Table 6 differ from those of Table 12 suggested that only in 2 of the 11 estimated points of the distribution significant differences arise.[13] This takes place in P40 and P50, where the coefficients of Table 12 were found to be larger (at 5% significance level), possibly because in the forest dominated countries people tend to be more concentrated in the more habitable areas, favouring the early phases of deployment and complicating the situation at the right-tail.

All in all, the evidence suggests that the coefficients obtained from our main estimates can be considered valid, or even conservative, not only for an "average" country, but also for an "average country with large extension of forest" and for an "average country with high elevation", in this last case up to the percentiles 70 (for FTTH) and 80 (for 4G).

6. Simulation for an emerging region: Latin America

After estimating the coefficients that link investment to coverage, it is now possible to find out how much investment is required to reach certain broadband deployment targets. In this exercise, we focus on a timeline reaching 2030 for the Latin America region, a region that urgently needs to accelerate its network deployments to close the digital divide.

First, it is necessary to establish potential connectivity goals to reduce to the minimum the current coverage gaps. The criteria followed was to ensure that 98% of the population should be covered to, at least, a 4G network by 2030, while on the other hand, that percentage is expanded to 99% by adding the satellite technology for rural areas. This means that 99% of the people will be covered by a broadband solution. As for the last generation technologies, the target is that more than 80% of the population is covered by 5G, while two-thirds of households should be passed by FTTH (Table 13). Naturally, the targets vary by country, attending to the specific situation in each case in terms of current network developments.[14]

There are four countries in the Latin America sample that exhibit high average elevation (in meters) as denoted in Section 5.2: Bolivia (1,192), Chile (1,871), Ecuador (1,117), Mexico (1,111) and Peru (1,555). On the other hand, several countries in the region have important areas covered by forests, although as explained in 5.2, this does not invalidate the results of the baseline model. In all cases, the targets stablished for those countries are within the boundaries of applicability of our model according to the estimates conducted in Section 5.2, with only two exceptions. First, despite its average elevation, we treated Chile as a "normal" country, because these values are the results of the Andes mountains traversing the east of country's geography from north to south, while most of the

[12] Available upon request.
[13] Available upon request.
[14] Targets were validated through interviews conducted with telecom operators with local presence.

Table 11
UQR Fixed Effects model: Drivers of FTTH coverage (Countries with forest covering > 44.6% of their territory).

Dep. Var. = Log (FTTH COV)	FTTH coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (FX CAPEXpc)$_{t\text{-}1}$	3.020*	2.727*	1.249*	0.819*	0.928**	0.613*	0.618*	−0.077	0.091	−0.098	−0.072
	[1.677]	[1.524]	[0.690]	[0.474]	[0.432]	[0.356]	[0.355]	[0.293]	[0.279]	[0.219]	[0.173]
Log (Density)	123.114*	−43.099	−55.811	−20.061	1.322	10.791	0.306	5.554	13.855	−8.373	8.777
	[68.536]	[77.385]	[39.759]	[26.509]	[20.992]	[16.257]	[17.073]	[13.571]	[10.552]	[9.147]	[10.519]
Log (Population)	−46.313	138.921*	79.144*	35.699	9.486	−2.233	−8.856	−21.969	−30.162**	−11.126	−25.660**
	[50.914]	[74.062]	[45.266]	[28.115]	[20.364]	[16.804]	[19.256]	[14.757]	[12.090]	[10.812]	[10.398]
Log (GDP pc)	1.092	−1.526	0.284	0.426	0.555	0.745	−1.609*	−1.196	−0.259	−1.754**	0.170
	[4.053]	[3.003]	[1.862]	[1.600]	[1.313]	[1.189]	[0.050]	[0.777]	[0.930]	[0.750]	[0.969]
R-squared (within)	0.253	0.395	0.300	0.376	0.459	0.438	0.324	0.332	0.379	0.325	0.296
Observations	249	249	249	249	249	249	249	249	249	249	249

Note: **p<5%, *p<10%. All estimates include country fixed effects and a temporal trend. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

Table 12
UQR Fixed Effects model: Drivers of 4G coverage (Countries with forest covering > 44.6% of their territory).

Dep. Var. = Log (4G COV)	4G coverage percentile										
	P5	P10	P20	P30	P40	P50	P60	P70	P80	P90	P95
Log (MB CAPEXpc)$_{t-1}$	0.861	1.609**	1.317***	0.933***	0.731***	0.380***	0.232*	0.101	0.074	0.111	0.058
	[0.764]	[0.675]	[0.447]	[0.328]	[0.230]	[0.131]	[0.120]	[0.071]	[0.052]	[0.052]	[0.051]
Log (Density)	−17.868	−45.114	−36.990*	−21.091	−6.608	−5.157	0.128	2.376	−2.025	−2.026	−0.093
	[30.555]	[33.431]	[21.625]	[15.821]	[11.406]	[7.194]	[6.688]	[4.009]	[3.159]	[2.584]	[1.880]
Log (Population)	26.368	57.951*	53.201**	34.805**	13.772	8.215	1.129	−1.212	2.354	1.905	0.007
	[32.135]	[35.594]	[22.517]	[16.374]	[11.504]	[7.327]	[6.772]	[3.807]	[3.046]	[2.514]	[1.833]
Log (GDP pc)	0.906	−0.170	−1.286	−1.322*	−1.147**	−0.489	−0.429*	0.010	−0.024	−0.015	0.009
	[0.793]	[1.097]	[0.933]	[0.719]	[0.491]	[0.335]	[0.228]	[0.138]	[0.087]	[0.074]	[0.052]
R-squared (within)	0.082	0.203	0.356	0.313	0.283	0.176	0.096	0.036	0.018	0.023	0.019
Observations	285	285	285	285	285	285	285	285	285	285	285

Note: ***p<1%, **p<5%, *p<10%. All estimates include country fixed effects. Bootstrapped standard errors in brackets (200 reps).
Source: authors' analysis

Table 13
Latin America: 2030 targets to simulate.

Country	Targets simulated for 2030			
	4G Coverage	4G + Satellite Coverage	5G Coverage	FTTH Coverage
Argentina	98.0%	99.0%	85.0%	68.0%
Bolivia	95.0%	96.0%	55.0%	35.0%
Brazil	98.5%	99.0%	85.0%	68.0%
Chile	98.5%	99.0%	98.5%	85.0%
Colombia	98.0%	99.0%	75.0%	60.0%
Costa Rica	98.0%	99.0%	80.0%	60.0%
Ecuador	95.0%	96.0%	60.0%	60.0%
Honduras	95.0%	96.0%	50.0%	35.0%
Jamaica	98.0%	99.0%	50.0%	80.0%
Mexico	98.0%	99.0%	86.0%	68.0%
Paraguay	98.5%	99.0%	60.0%	45.0%
Peru	97.0%	98.0%	65.0%	45.0%
Trinidad and Tobago	98.0%	99.0%	50.0%	96.0%
Uruguay	98.5%	99.0%	98.5%	96.0%
Latin America	98%	99%	81%	65%

Source: authors' analysis

population lives in low elevated areas.[15] Second, a high value was allocated to Mexico in FTTH deployments because the country already presented across all years of our sample equal or higher coverage levels for this technology that the Latin America average.

Overall, these targets are ambitious for a region like Latin America, meaning that 4G can be effectively the technology to achieve universal coverage, while on the other hand, at least two-thirds of the population will be covered by an ultra-fast new generation network.

These targets can be disaggregated by urban and rural areas (Fig. 7). In doing so, we considered the latest figures reported by the World Bank for the share of urban population by region.[16]

The underlying assumption to disaggregate the targets across urban/rural areas is based on the fact that we expect urban areas to be covered first, and once completed, the remaining population covered will lie in the suburban and rural territories, in that order. As can be seen in Fig. 7, all urban areas (above 500.000 inhabitants) are targeted to reach almost universal coverage in all three technologies. In contrast, for suburban areas, we can expect universal 4G coverage, 81% of population covered by 5G, and 37% of FTTH coverage. For rural areas, we can expect 86% of 4G coverage, which can be expanded to 92% if we add satellite technology. Almost no coverage is simulated for rural areas for both 5G (8%) and FTTH (1%). This means that rural areas will be massively covered with 4G and Satellite, with almost no deployments of the more advanced technologies due to the lack of financial feasibility in those territories.

Fig. 8 represents the evolution of the target coverage scenario towards 2030, along with what we expect to happen according to the current trends.[17] A logistic function especially suited for technological diffusion is used to illustrate the coverage trajectory to the final points. Clearly, the biggest effort is expected to be associated to 5G and FTTH technologies. For the case of 4G, the difference between both series is hardly noticeable as their natural coverage trend is only slightly below the target. In other words, 4G already is the technology for universalization.

Once identified the target, we estimate the investment required to achieve it. The elasticities linking investment with coverage (with a year lag), already estimated in the UQR analysis, are used to calculate the required percentages increase in both fixed and mobile CAPEX to reach the targets. The coefficient linking investment with coverage is adjusted yearly for every country in the simulation, according to their respective position in the curves presented in Figs. 1, Figs. 2 and 4. To estimate the "extra" investment needed to reach the targets above current trends, we first calculate the investment needed to reach the target scenario, and to that figure we subtract the investment needed for the natural growth scenario. The difference is effectively the extra effort that the region must do to close the coverage gap by 2030. For the case of the satellite technology, the calculations are based on the cost values reported in Table A.2 of Appendix 3 applied to the new users of this technology estimated to reach the target (based on Table 13). The investment is calculated separately for each technology and added afterwards into a single value.[18]

[15] As a reference, the average elevation of Santiago is 570 meters.

[16] The percentage of the population that does not live in rural areas in each country comes from the World Bank, while to identify urban areas with more than 500,000 inhabitants, a review was carried out of all the metropolitan areas by country that meet this condition. The difference between the total non-rural population and that living in areas with more than 500,000 inhabitants is considered the suburban population. Towards 2030, the variation rates of the percentage of inhabitants per area are projected according to historical trends.

[17] In the case of 4G, it is expected that in most of the countries the evolution of coverage will remain unchanged, with marginal increases towards 2030, except for those countries that are currently lagging behind, which will experience greater growth. On the other hand, in the case of FTTH and 5G, a series of criteria are taken as to what the covered population could be in 2030 according to the tendency scenario, based on the relative level of development of each country and the percentage of the population living in urban and suburban areas (see detail in Tables A.3 and A.4 in Appendix 4).

[18] Following the interviews conducted with industry specialists, we assume a 20% overlap in 4G – 5G investments. In addition, we assume that only 35% of 4G investment is destined to expand infrastructure, with the remaining 65% destined to expand capacity.

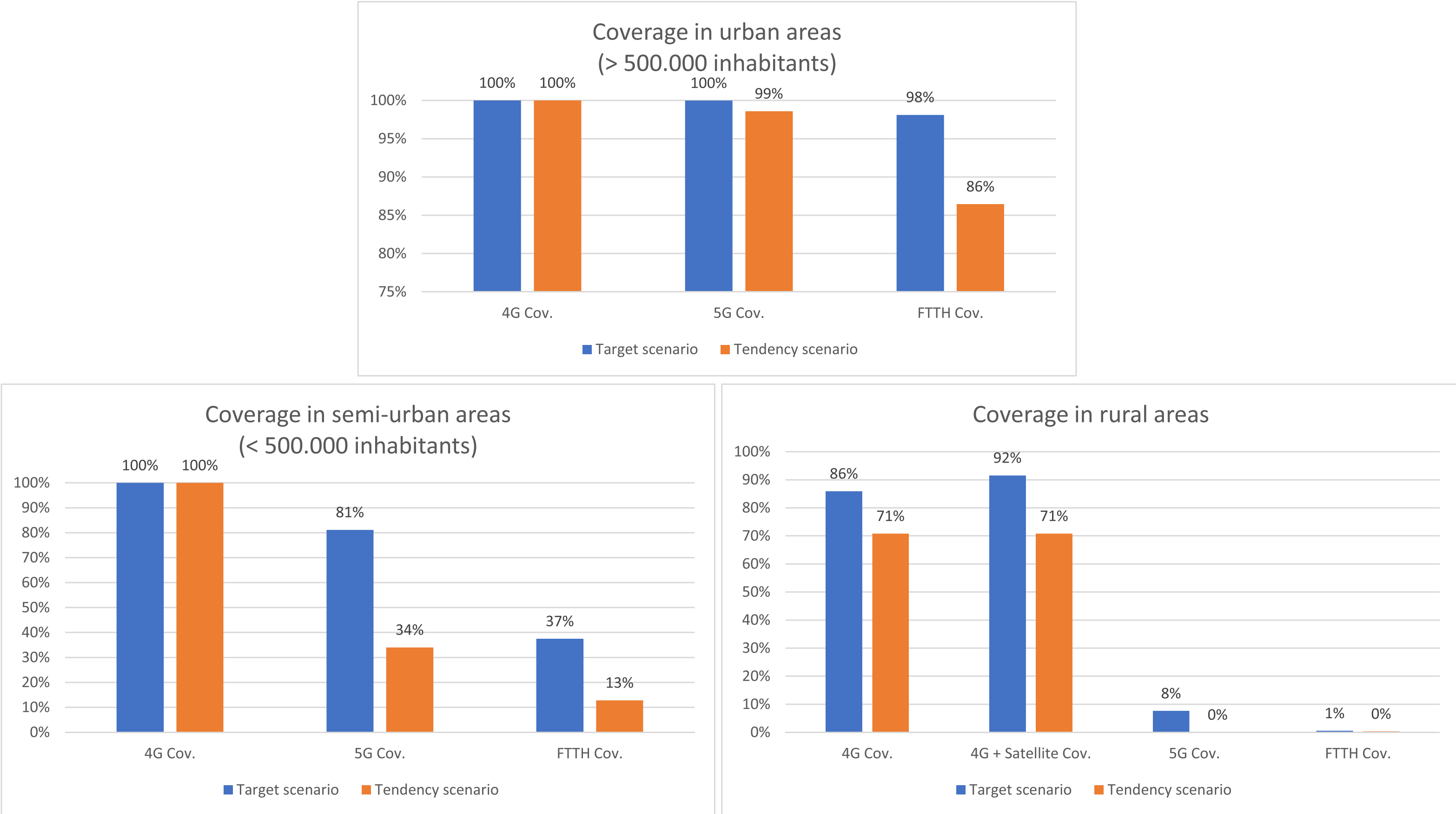

Fig. 7. Latin America: coverage targets by area.
Source: authors' analysis

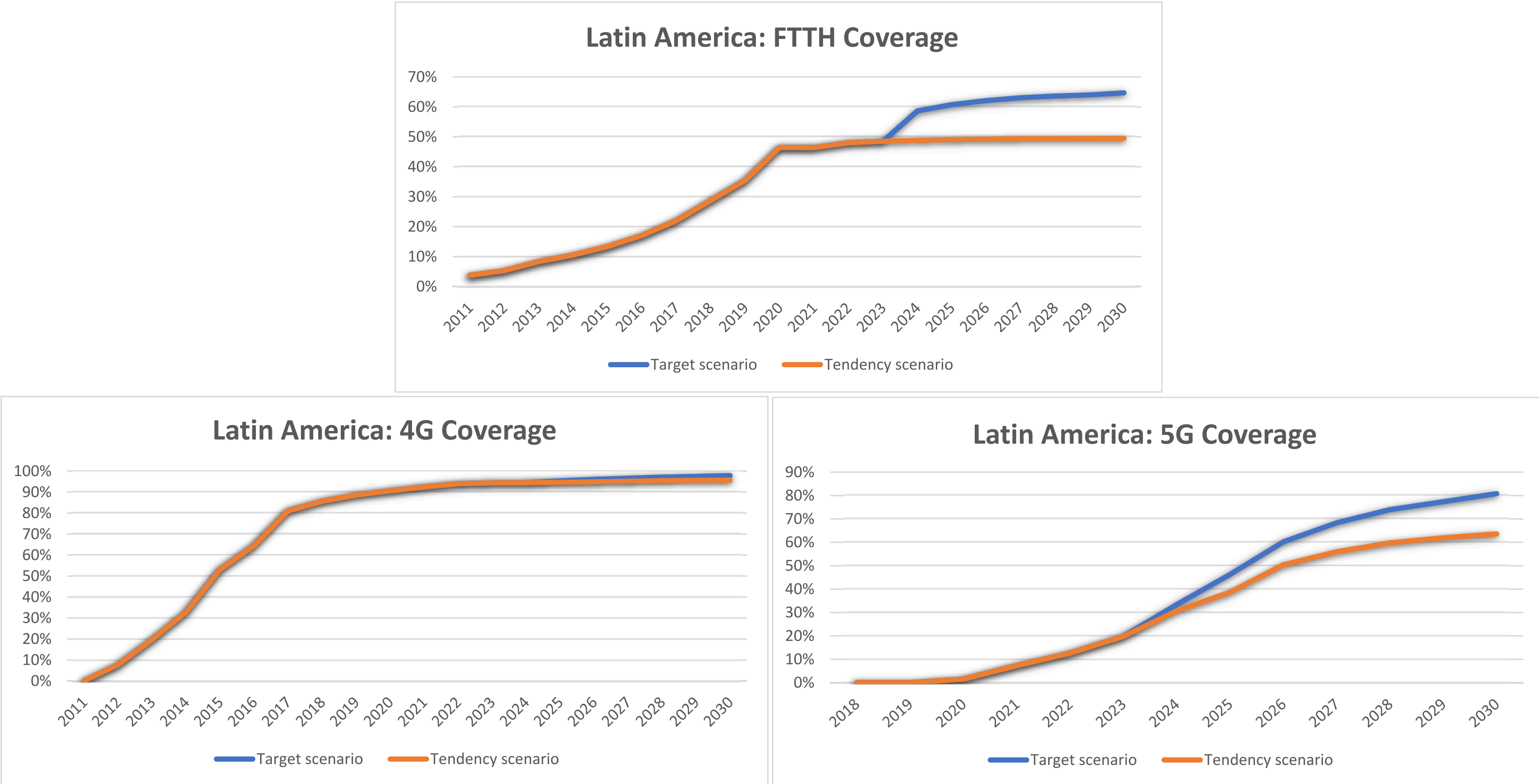

Fig. 8. Latin America: evolution of broadband coverage according to the proposed scenarios.
Source: authors' analysis

The extra investment needed above natural investment scenario for the Latin America region reaches $ 17,101 million over the period 2023–2029. That is the amount of investment needed to move from the orange curve to the blue one in Fig. 8. Naturally, the magnitude of the gap varies considerably by country, depending on the size and relative distance of the natural growth tendency to the target. The largest increase in investment effort is required in the case of Brazil ($ 4,373 million dollars), while the lowest is in Trinidad and Tobago ($ 39 million).

The additional investment can be disaggregated by technology, as represented in Fig. 9.

The main recipient of the extra investment is 5G (40%), followed by FTTH (29%). It is not surprising the prevalence of investment in the newer ultra-fast technologies, given the lack of current developments, especially for the case of 5G. On the other hand, there is still a relevant portion for 4G investment, because in some countries this technology is still far from universalization, although already in phases where investment effort is required to increase considerably according to the UQR estimates.

Finally, we conducted some checks on the estimated costs to compare them with those estimated in other research reviewed in Section 2. The average cost for each new person covered by 5G in our estimation is $ 62.17 (adjusted by PPP conversion factor), a figure that lies between the numbers estimated from Oughton and Frias (2018) of $ 45.71 (in areas above 1 million inhabitants) and $ 197.16 (in suburban areas). Considering that our approach consisted in simulating 5G coverage for urban areas, but not necessarily above 1 million people, then the estimated costs seem reasonable. In addition, the cost of each new household passed by FTTH is $ 428.8 in our estimation (adjusted by PPP conversion factor), somewhat lower than the $ 700 - $ 1500 interval estimated for US urban areas by Cartesian (2019), although very close to the figures provided by the FTTH Council Europe (2012) for Europe, that for densely populated areas are close to 400 euros per household. Moreover, since the time these previous studies were conducted, a declining trend in equipment costs has occurred.

7. Conclusions and policy discussions

In this paper we developed a top-down tool to estimate the required capital investment to accelerate connectivity. We propose a general approach based on the use of UQR that addresses the complexities that arise in the link between investment and coverage. These complexities are explained as the coverage impact for broadband investment is usually stronger at the beginning of the deployment phases, where the targets are usually urban areas, in comparison with more later deployment phases that target lower populated territories.

We checked the robustness of our results by adding additional controls and by re-estimating our main UQR results for a subsample of geographically complex countries, those situated in the last quartile of the distribution of average elevation. These checks provided robustness to our results, as they were not significantly altered by the addition of controls, and when estimating the regressions for the geographically complex subsample the baseline coefficients proved to be valid for most of the coverage distribution, although beyond percentiles 70 (for FTTH) and 80 (for 4G) of these countries the model loses suitability. This means that our model valid for a very wide range of countries, although we do not expect to represent accurate estimates for specific extreme situations.

Our approach has some limitations that are necessary to consider. Our analysis would have benefited from more precise data, such as CAPEX figures specific to each of the technologies (FTTH, 4G or 5G), rather than our current measures broadly split by wireline or wireless networks. Moreover, an analysis conducted with operator-level observations would have provided more granularity and detail, although unfortunately that was not possible.

Considering that the increase in investment required to accelerate network deployments is significant, public policies should pursue regulatory frameworks especially designed to facilitate investments and optimize network rollouts. These recommendations can be grouped into two main categories: those that stimulate investment, and those that, for a given investment levels, contribute to expand coverage.

In the first group, we can summarize the need to promote sound regulatory frameworks, based on flexible and light conditions avoiding the introduction of restrictions that may disincentivize investment. Other relevant topics to promote investment include taxation frameworks, comprising also the regulatory and other fees paid by the operators to public authorities, something that reduces the available funds to invest. In that respect, and considering the massive amounts expected to be involved in 5G investment in the following years, spectrum costs should be reduced, through allocation mechanisms such as beauty contests, linked to operators' deployment plans. Ensuring healthy competition conditions is also essential to stimulate investment and to create dynamic efficiencies. Finally, institutional quality (e.g.: protection of property rights) is also important to incentivize investment, as network deployments are largely irreversible, and the investment returns usually require several years to materialize.

In addition, for a given investment level, several regulations can facilitate coverage expansion, if they promote efficiencies and generate flexibilities for network optimization. Within this group we can highlight the need to ensure initiatives aimed to incentivize infrastructure sharing and co-investments between network operators.

All in all, the effort of closing the coverage divide involves all stakeholders of the telecommunications industry, where operators invest, and governments and regulators create the required incentives for the investments to take place. Only with cooperation among all involved parties this ambitious objective can be achieved, especially considering that the industry is facing an uncertain scenario, with decreasing income and margins.

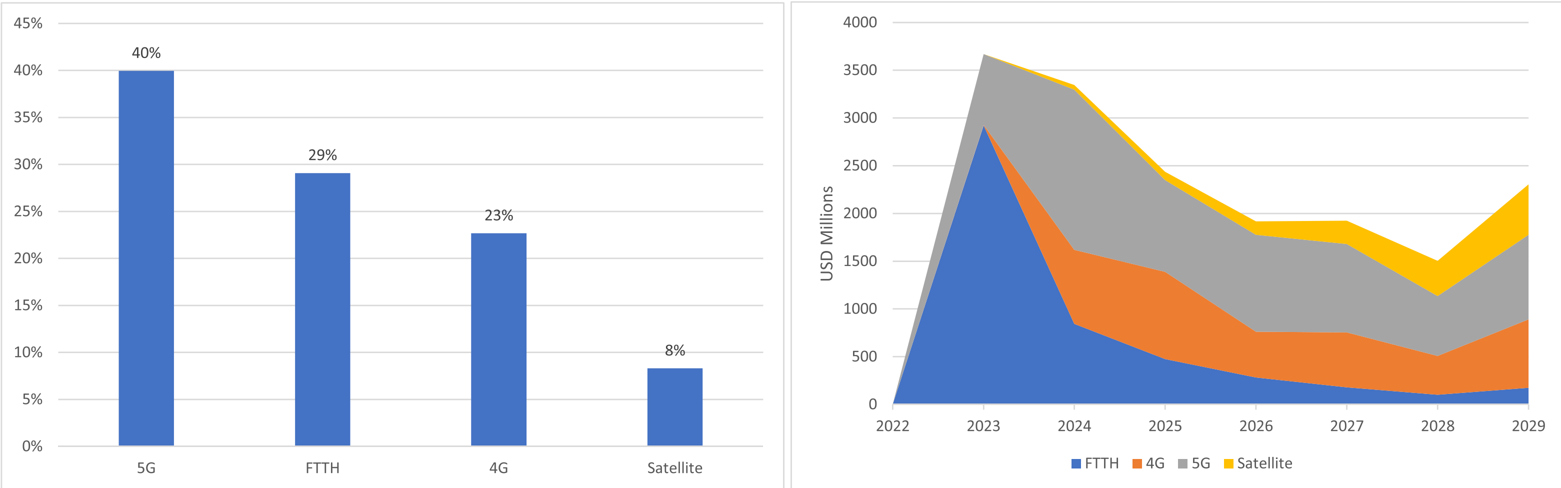

Fig. 9. Latin America: decomposition of additional investment needed by technology.
Source: authors' analysis

Appendix

1. List of Countries in the Sample

Sub-Sahara Africa: Angola, Kenya, South Africa, Benin, Madagascar, Tanzania, Botswana, Mozambique, Uganda, Burundi, Nigeria, Zambia, Cameroon, Senegal, Zimbabwe, Cote d'Ivoire.

Latin America and Caribbean: Argentina, Dominican Republic, Nicaragua, Barbados, Ecuador, Panama, Bolivia, El Salvador, Paraguay, Brazil, Guatemala, Peru, Chile, Haiti, Trinidad and Tobago, Colombia, Honduras, Uruguay, Costa Rica, Jamaica, Venezuela, Cuba, Mexico.

North America: Canada, United States.

Asia – Pacific: Australia, Japan, Philippines, Bangladesh, Korea, Singapore, China, Malaysia, Sri Lanka, India, New Zealand, Thailand, Indonesia, Pakistan, Vietnam, Islamic Republic of Iran.

Western Europe: Austria, Germany, Netherlands, Belgium, Greece, Norway, Bosnia and Herzegovina, Iceland, Portugal, Croatia, Ireland, Spain, Cyprus, Israel, Sweden, Denmark, Italy, Switzerland, Finland, Luxembourg, Turkey, France, Malta, United Kingdom.

Eastern Europe: Armenia, Hungary, Romania, Azerbaijan, Kazakhstan, Russia, Belarus, Latvia, Slovak Republic, Bulgaria, Lithuania, Slovenia, Czech Republic, Poland, Ukraine, Estonia.

Arab States: Algeria, Kuwait, Qatar, Bahrain, Lebanon, Saudi Arabia, Egypt, Morocco, Tunisia, Jordan, Oman, United Arab Emirates.

2. Criteria for selection of random-effects model in 5G coverage estimation

The 5G coverage estimate was conducted through the more efficient random-effects approach as by applying the Hausman test we couldn't reject the null hypothesis that the difference in coefficients with the fixed effects model is not systematic (Table A.1). Under these circumstances, random effects model is acceptable.

Table A.1
Hausman test to select between Fixed and Random Effects model

	Fixed Effects	Random Effects	Difference	Standard deviation
Log(MB CAPEX pc) $_{t-1}$	−0.109	0.436	−0.545	0.191
Log(Density)	−5.362	0.033	−5.395	3.832
Log(Population)	1.193	0.002	1.190	5.248
Log(GDP pc)	−0.288	0.419	−0.706	0.598
Null hypothesis		Difference in coefficients is not systematic		
Chi-squared		8.80		
P-value		0.117		

Source: authors' analysis

3. Cost modelling associated with satellite technology

Considering the relevance of satellite technology for the universalization of connectivity, the costs of cellular backhaul for satellite have also been estimated. In this case, UQR procedures are not appropriate as due to its nature, the cost of satellite coverage does not vary by geographical area. On the other hand, there is not enough public information to conduct regressions at the mean for the satellite technology.

To overcome this imitation, we relied on information provided by the Satellite industry, from where the current CAPEX costs related to the deployment of the cellular backhaul solution (satellite installation and equipment) have been taken into account, as well as the OPEX costs considering the capacity per user (based on capacity costs and their estimated projection according to the industry). Other costs faced by the satellite industry have been included, such as support and maintenance expenses. The estimates are based on a growth scenario that reaches 20 GB per month per user in 2030 (Table A.2).

Table A.2
Analysis of Cellular Satellite Backhaul Costs

Segment	2023	2024	2025	2026	2027	2028	2029	2030
GB/User	6.0	7.3	8.7	10.0	12.5	15.0	17.5	20.0
Users per-base station	1,000.0	1,000.0	1,000.0	1,000.0	1,000.0	1,000.0	1,000.0	1,000.0
Dedicated capacity per base station	27.1	33.1	39.1	45.1	56.4	67.7	79.0	90.3
Initial payment per link (CAPEX) $	6,348.5	6,348.5	6,348.5	6,348.5	6,348.5	6,348.5	6,348.5	6,348.5
Monthly payment per link (OPEX) $/month	4,766.4	5,680.0	6,428.5	7,110.4	8,590.8	10,077.4	11,502.9	12,869.1
Equivalent monthly payment per user $/user/month	4.8	5.7	6.4	7.1	8.6	10.1	11.5	12.9

Source: Hispasat projections based on the Latin America region

4. Criteria for estimating tendency scenarios in Latin America

For each country in Latin America, we projected a tendency scenario towards 2030, something that was needed to define the targets to simulate above those tendencies. Criteria for FTTH is detailed in Table A.3, while for the case of 5G the details are reported in Table A.4.

Table A.3
Criteria for defining the FTTH tendency scenario for 2030

Group	Country	2030
Outliers	Trinidad and Tobago, Uruguay, Jamaica	All urban and suburban population
Advanced	Chile, Brazil, Argentina	All urban population (>500.000 inhabitants) + up to 50% of suburban population, depending on the country
Average	Mexico, Ecuador, Colombia, Bolivia, Costa Rica	70%–90% of urban population (>500.000 inhabitants)
Lagging	Peru, Paraguay, Honduras	50% of urban population (>500.000 inhabitants)

Source: authors' analysis

Table A.4
Criteria for defining the 5G tendency scenario for 2030

Group	Country	2030
Advanced	Chile, Mexico, Brazil	All urban population (>500.000 inhabitants) + 40%–70% of suburban population, depending on the country
Average	Ecuador, Argentina, Colombia, Paraguay, Peru, Uruguay, Costa Rica, Bolivia	95%–100% of urban population (>500.000 inhabitants)
Lagging	Honduras, Jamaica, Trinidad and Tobago	70%–75% of urban population (>500.000 inhabitants)

Source: authors' analysis

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