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# Spectrum flexibility and mobile telecommunications development☆

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ABSTRACT

We study the effects on the mobile telecommunications market from three specific spectrum policies: the presence of a secondary market, a technological neutrality approach, and the possibility of sharing agreements among operators. We find that when these policies are jointly adopted, investment is 35.9% larger than when that is not the case. After two years, network coverage and service penetration can be increased by 9.8% and 0.9%, respectively, and prices can be reduced by 5.8%. When considering an extended period, dynamic effects result in enhanced outcomes. The findings support policies that promote flexible approaches towards spectrum management for mobile development.

## 1. Introduction

Mobile operators require access to radio spectrum frequency to deliver quality and affordable services to consumers. As a result, a transparent, long-term radio-frequency plan which includes a strategy for managing and making spectrum available to operators is critical to encourage substantial investment and innovation in mobile services. The amount of spectrum allocated, the harmonization of this resource, the design of the auctions (and the determination of base prices), plus a flexible approach for license holders -for instance, in terms of technological neutrality or allowing for secondary spectrum trading- can potentially impact on market outcomes, and as a result, on adoption levels and consumer surplus. However, sometimes governments mandate particular band or technological decisions (limiting flexibility) or prioritize high prices to access spectrum, which may condition medium- and long-term market outcomes.

While the literature has focused primarily on spectrum pricing and allocation procedures, the effects of a flexible approach for the day-by-day usage period of this resource -once allocated-, remains largely unstudied. In this paper, we contribute to the literature by studying the effects on market outcome from three specific attributes linked to flexible spectrum management: the existence of secondary market trading, a technology neutrality approach, and the possibility of conducting network sharing agreements among operators. These three policies have been hypothesized to positively contribute to mobile sector development (GSMA, 2019). For our empirical analysis, we identify as market outcomes four variables: capital investment, network coverage, service pricing, and adoption. That said, those variables are, as expected, related among themselves through some causal linkages that should be carefully addressed.

The remainder of the paper is structured as follows: Section 2 provides a brief literature review. Section 3 develops a model to clarify the causal links taking place -from the investment decision from the operator to the final service adoption by consumers. Section 4 provides a descriptive analysis of the preliminary evidence arising from the selected dataset. Section 5 develops a series of econometric estimations based on the proposed models, and some policy simulations are conducted. Finally, section 6 concludes with policy recommendations.

## 2. Research literature review

The research literature tends to support the importance of spectrum management in developing wireless communications. There is consensus that it is vital to have a transparent, long-term plan that includes a strategy for making sufficient spectrum available under appropriate conditions to encourage substantial investment and innovation in mobile services. In light of this premise, spectrum management and pricing and the imposition (or absence) of associated obligations can significantly impact capital investment and innovation.

In terms of empirical evidence, Bahia and Castells (2021) studied the

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impact of spectrum pricing on several market outcomes, including coverage levels and data speeds, by considering a sample of both developed and developing countries. Their sample was based on the spectrum costs of 229 operators in 64 countries (covering 30 developing and 34 developed countries). The evidence generated by their econometric models indicated, as expected, that high spectrum costs restrict the financial ability for network investment. The researchers found strong evidence that higher spectrum prices negatively impact mobile coverage in developed and developing countries. They also found evidence that high spectrum prices negatively impact network quality, including download/upload speeds and latencies. In research examining the impact of other market conditions on capital spending, Kim et al. (2011) examined the effect of MVNOs (Mobile Virtual Network Operators) entry on the investment behavior of facilities-based carriers. The authors used firm-level data for 58 operators in 21 OECD countries between 2000 and 2008. The results suggested that the mandated provision of spectrum for MVNO was related to a lower investment intensity of network operators.

Beyond investment, other researchers focused on linking spectrum policy and other sector outcome variables, such as service adoption. Zaber and Sirbu (2012) developed an econometric analysis over a multi-country panel dataset and were able to show that spectrum management policies had a significant influence on the evolution of 3G penetration across countries. Countries that mandated a specific frequency band for 3G saw faster diffusion but experienced a slower growth rate in the long run. In addition, the research found that 3G diffusion was not significantly affected by choice of allocation mode: auctions vs. alternative license award processes. The above-cited article from Bahia and Castells (2021) also studied the impact of spectrum prices on several variables affecting consumer welfare, such as network quality and prices. Their results showed significant evidence to suggest a causal link between high spectrum prices and certain other spectrum management decisions (related to the timing of band release and quantity licensed) and consumer outcomes. In particular, higher spectrum prices may have driven higher voice and data prices in developing countries, although the authors state that evidence for most advanced economies was inconclusive.

In the same vein, Kuroda and Forero (2017) studied the impact of spectrum policies for a sample of 47 OECD countries between 2000 and 2008. They found that the consumer surplus tends to be reduced when spectrum allocation is through auctions to raise public revenues (instead of other mechanisms such as Beauty Contests). Similarly, Hazlett and Muñoz (2009) performed an empirical analysis by relying on a sample of 28 countries for the period 1999–2003. They found evidence that the amount of spectrum and the degree of market competitiveness are key drivers for market outcomes such as consumer surplus and license revenues, stating that auction rules that focus on revenue extraction may conflict with the goal of maximizing social welfare. In turn, Cambini and Garelli (2017) studied the impact of spectrum availability and fees on mobile sector revenues for a dataset of firms operating in 24 countries in the period 2005–2014. They include spectrum availability and license fees as determinants for mobile revenues, although they could not find a significant correlation among them.

It must be said that not all the empirical research on the economic impact of spectrum management reaches consistent conclusions. To mention a specific example, Park et al. (2011), examining a sample of 21 OECD countries, could not find evidence of the impact of spectrum fees on investment levels and consumer prices. Similarly, Bauer (2003) found no relationship between spectrum fees and voice prices for a sample of 18 OECD countries. However, the studies carried out by both Park et al. (2011) and Bauer (2003) had a methodological disadvantage, as they relied on cross-section samples rather than data panels, a particularity that may be affecting their results.

As shown above, research so far has focused mainly on spectrum pricing and allocation procedures. The effects of a flexible approach -beyond the allocation period-, remain largely unstudied. It seems necessary to study the effects on market outcomes from three specific attributes linked to a flexible spectrum management approach: the presence of a secondary market for spectrum trading, a technology neutrality approach, and the possibility of conducting network sharing agreements among operators. These three attributes have been recently put into practice by some countries.

Spectrum secondary markets consist of a mechanism by which license holders can transfer spectrum-usage rights voluntarily to other operators. This approach may result in more efficient use of the limited spectrum, ensuring that this resource does not lie fallow but instead is used to deliver valuable services. It also adds flexibility in business planning for mobile operators.

Technology neutrality is a policy approach that allows the use of any technology in any frequency band. According to this principle, governments allocate and license spectrum for particular services (such as mobile connectivity) but do not specify the underlying technology to be used (3G, 4G, or 5G). Technology neutrality encourages innovation and promotes competition, allowing markets to determine which technologies succeed. Neutrality is essential as the rapid pace of innovation advances makes it necessary to have flexible mechanisms allowing migration to newer technologies. Theoretically, a "technology-neutral" use of spectrum bands should have a positive and significant impact on network deployment, be more adapted to technological advances, and contribute to maximizing the financial returns of investment.

The growth in data traffic means mobile operators must gain access to an increasing amount of spectrum to meet demand. When clearing new frequency bands for mobile use is not possible, spectrum sharing can offer a way to help by enabling mobile access to additional bands in areas, and at times, when other services or providers are not using them. In addition, the possibility of performing voluntary sharing agreements allows maximizing the opportunities for operators to make investment profitable, creating incentives for network deployment. Network-sharing agreements can optimize the use of infrastructure, generally reducing costs, thus being beneficial for both service providers and consumers. For that reason, policymakers increasingly see spectrum sharing as a means of opening additional frequency bands for 4G and 5G services. However, sharing is only possible if regulations do not prohibit it and it results from voluntary agreements and not mandates.

This research focuses on the impact of these three policies on market outcomes. As four potential outcome variables (closely linked to each other) are identified, it is first important to understand the chain of causality linking policies to market outcomes, as explored in the next section.

## 3. Model specification

Several contextual factors (competition, regulation, and institutional conditions) impact mobile capital investment (CAPEX). In addition, capital spending is also conditioned by spectrum policies. In turn, investment drives network coverage levels, which are expected to impact

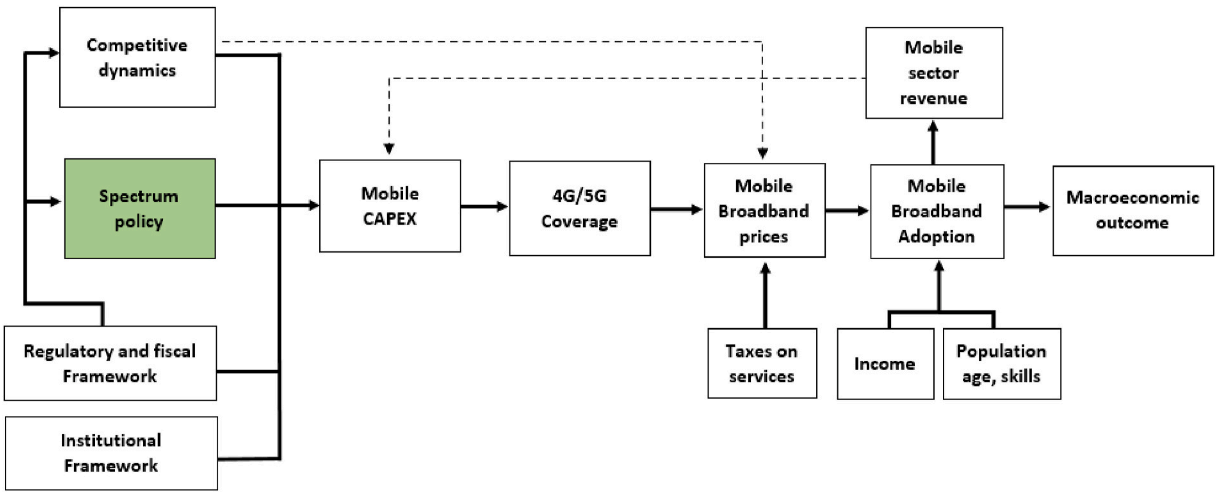


**Fig. 1.** Causality flows in the Mobile sector.
Source: elaborated by the authors

prices. Finally, adoption levels (demand) are a function of the prices, as well as other contextual factors. This causal chain is presented in Fig. 1.

Based on this causal chain, the linkages taking place in the mobile sector can be explained through four equations: (i) the investment equation, (ii) the coverage equation, (iii) the price equation, and the (iv) demand equation. Each link and the corresponding equation will be explained in turn.

### 3.1. The investment equation

The first equation explains the drivers of mobile telecommunications investment. Mobile *CAPEX* is expected to depend on its prior-year value,[1] on sector revenues (*REVENUE,* to proxy financial capabilities for investment and market size), on *SPECTRUM POLICY* indicators, on *COMPETITION* dynamics, plus a vector *X* combining other control variables. This equation is defined as follows:

$$log(CAPEX_t) = \alpha + \beta \log(CAPEX_{t-1}) + \gamma \log(REVENUE_{t-1}) + \delta(SPECTRUM\ POLICY_t) + \zeta(COMPETITION_t) + \mu(X_t) + \varepsilon$$

From an econometric perspective, there are three issues regarding endogeneity that need to be addressed in this investment equation.

In the first place, introducing the lagged dependent variable as a regressor is expected to correlate with the fixed effects in the error term. This situation creates a "dynamic panel bias" (Nickell, 1981), as the reported correlation violates the necessary assumptions for consistency in Ordinary Least Squared (OLS) estimators. As a result, it cannot be estimated through the usual fixed effects approach.

In the second place, a reverse causality link may exist between revenue and investment. On the one hand, revenues provide the funding for investment, but on the other hand, investment is fulfilled to increase future revenues. Even if this identification concern is not significant for us (as investments are expected to translate into greater revenues only in the future), we will follow a cautious approach and rely on the lagged revenue regressor rather than on the contemporaneous variable. We assume that, at the beginning of each year, the mobile operator designs an investment plan for the whole year, considering the latest revenue figures from the year-end.

Finally, sector-specific policies (such as those regarding spectrum) may be endogenous to investment, possible due to regulatory reforms taking place contemporaneously with idiosyncratic shocks to investment[2] or because of policy reforms being promoted due to, perhaps, low investment levels (reverse causality). All spectrum policy variables entering the investment equation will be treated as endogenous to overcome these concerns.

### 3.2. The coverage equation

We will measure coverage for the 4G technology, as 5G network deployment is still in its infancy. This variable $(4G\ COVERAGE)$ is defined as the percentage of the population covered. The population covered by 4G networks is driven by four variables: capital investment of mobile operators (*CAPEX*), past coverage improvements,[3] the percentage of the population living in urban areas (variable *URBAN*), and topographic conditions, such as the presence of forests or hilly terrain. As these latest indicators are time-invariant, they will be captured by the country fixed effects. It is important to stress that coverage levels are also expected to depend on the specific frequencies allocated in each country. However, the lack of information on specific bands allocated by country prevented us from incorporating this additional regressor. In any case, we can expect the past coverage levels to absorb most of these effects.[4] Therefore, the second equation is modeled as follows:

[1] Some studies have used theoretical models from which *CAPEX* is determined as a function of the sector physical capital stock (Jung, 2020; Jung and Melguizo, 2020). However, the lack of data for telecom physical capital for a worldwide sample prevented us from following that approach. As a second-best possibility, we consider that controlling by past *CAPEX* is an appropriate measure to reflect country-differences in investment. In addition, given the conventional breakdown of *CAPEX* in terms of non-discretionary spending and modernization investment, it is reasonable to consider the prior year *CAPEX* as a valid variable. The empirical specification used is roughly similar as that followed by Kim et al. (2011) and Jung (2019).

[2] See for instance Alesina et al. (2005).

[3] Even if those advances were specific to prior technologies. For instance, 4G deployments are surely facilitated by the presence of passive infrastructure previously deployed for 3G or 2G (towers, base stations, posts, ducts).

[4] The only data available by frequency is that of digital dividend allocation for IMT (data reported by the ITU). However, this variable was found to be not significant to explain coverage levels (results available upon request). We would like to thank an anonymous referee for raising up this point.

$$\log(4G\ COVERAGE_t) = \eta + \Phi\log(CAPEX_{t-2}) + \sum_{i=1}^{i=3}\nu_i\log(COVERAGE_{t-i}) + \lambda\log(URBAN_t) + \varepsilon$$

where we expect $\Phi > 0$. Given that investment may take some time to be translated into coverage gain, we model *COVERAGE* in period *t* as a function of *CAPEX* in period *t-2*.[5] In addition, the possibility of relying on previous technologies to account for previous coverage advances contributes to avoiding the lag of the dependent variable, thus preventing the "dynamic panel bias" as described above.

### 3.3. The price equation

Once network coverage is estimated, we turn to mobile broadband price (*MBB PRICES*), a variable that will drive adoption through elasticity. End-user prices are assumed to depend on taxation applied to the services, as well as competition intensity. End-user pricing is a function of value-added taxes that increase the consumer's total cost of ownership of mobile service. Competitive intensity would, as expected, negatively impact pricing. In addition, coverage improvements resulting from past investments contribute to reducing prices as the supply curve shifts to the right. Coverage gains can also be interpreted as the result of technological improvements that, from a dynamic perspective, usually translate into lower prices. In addition, we introduce the *URBAN* variable as an additional control for possible cost-differences driven by the density of the user base.

Spectrum allocation procedures can also be expected to affect end-user prices. For instance, if the government chooses to maximize revenue through spectrum allocation, we may expect this to affect service prices. Similarly, spectrum scarcity may elevate the prices from competitive auctions, with its corresponding incidence on end-user prices. Unfortunately, the lack of public data on spectrum allocation prices prevented us from considering this potential effect.

These causal links are captured in the following equation:

$$\begin{aligned}\log(MBB\ PRICES_t) = {} & \Lambda + \pi(TAX_t) + \Psi\log(4G\ COVERAGE_t) \\ & + \Gamma(COMPETITION_t) + \tau\log(URBAN_t) + \varepsilon\end{aligned}$$

As described above, we expect $\Psi < 0$.

### 3.4. The adoption equation

Following the price equation, pricing will be a determinant of service adoption, measured as mobile broadband unique subscribers' penetration. Adoption is also expected to depend on income levels, which will be proxied through GDP per capita (in lags, to avoid reverse-causality concerns), and on the population's age structure, as elder groups are expected to be less prone to adopt the technology:

$$\begin{aligned}\log(MBB\ PENETRATION_t) = {} & \Theta + \eta\log(MBB\ PRICES_t) + \varsigma\log(GDPpc_{t-1}) \\ & + \sigma(AGE_t) + \varepsilon\end{aligned}$$

Naturally, higher prices should reduce demand (that is to say, we expect $\eta < 0$).

### 3.5. The effects of spectrum policy on outcome variables

As implied in the four equations, we explicitly assume that spectrum policy variables do not directly impact the coverage, price, and adoption equations, but only indirectly because of the backward linkages with investment. From the investment equation, it seems straightforward to calculate the impact on *CAPEX* from a spectrum policy reform:

$$\frac{\partial\log(CAPEX_t)}{\partial(SPECTRUM\ POLICY_t)} = \delta$$

Turning next to the second equation, we can assess the impact that will yield in coverage improvement by considering the *CAPEX* gains as a consequence of *SPECTRUM POLICY*:

$$\frac{\partial\log(COVERAGE_{t+2})}{\partial(SPECTRUM\ POLICY_t)} = \Phi\left[\frac{\partial\log(CAPEX_t)}{\partial(SPECTRUM\ POLICY_t)}\right] = \Phi\delta$$

Note that the increase in coverage happens in period $t+2$, as CAPEX improvements are not supposed to materialize immediately into coverage gains. In turn, coverage increases as a result of all the above are expected to bring down prices:

$$\frac{\partial\log(MBB\ PRICES_{t+2})}{\partial(SPECTRUM\ POLICY_t)} = \Psi\left[\frac{\partial\log(COVERAGE_{t+2})}{\partial(SPECTRUM\ POLICY_t)}\right] = \Psi\Phi\delta < 0$$

The prices will be reduced as long as $\Psi < 0$. Finally, reduced prices will yield an increase in demand:

$$\frac{\partial\log(MBB\ PENETRATION_{t+2})}{\partial(SPECTRUM\ POLICY_t)} = \eta\left[\frac{\partial\log(MBB\ PRICES_{t+2})}{\partial(SPECTRUM\ POLICY_t)}\right] = \eta\Psi\Phi\delta > 0$$

The variation in demand will be positive, assuming our expectations on the sign of the coefficients is effectively verified.

All in all, what started in period *t* with a particular spectrum policy turned into an increase in adoption in period $t+2$. In turn, an increase in broadband adoption is expected to translate into macroeconomic gains, as has been widely verified in the research literature.

## 4. Data and exploratory analysis

To carry out our empirical analysis, we built an unbalanced panel consisting of 145 countries for 2008–2019. Table 1 describes the variables used to estimate the equations described in the previous section.

Before the empirical estimate of the 4-equation model as described in the previous section, we will show some descriptive statistics and tests as a brief explanatory analysis regarding the link between spectrum policies and two mobile outcomes defined before: investment and adoption. Table 2 reflects the descriptive statistics and mean difference tests for mobile CAPEX (in per capita terms, for comparative purposes), depending on groups defined by the spectrum policies.

As indicated in Table 2, those countries that allow spectrum secondary trading invest on average 50.9 dollars per capita, in countries that do not allow that policy is 25 dollars per capita. The difference is statistically significant at a 1% level. Similar conclusions can be reached for the case of other spectrum policies such as sharing ($ 43.1 for countries that do allow it versus $ 29.3 for those that do not) and technological neutrality ($ 38.4 for those that consider it versus $ 33.3 for those that do not). In the last case, the difference is smaller than the other two and significant at 5%. When all three flexibility attributes in spectrum policy are present (the "Spectrum flexibility dummy" scenario), CAPEX per capita reaches $ 56.4. In contrast, when the three attributes are not present (or some may be, while others do not), the average investment per capita is $ 34.8 per capita, with the difference being statistically significant at a 1% level.

Table 3 presents a similar analysis but considers mobile broadband penetration the market outcome variable. Countries that allow secondary spectrum markets exhibit on average 54.2% mobile broadband

[5] This was the approach followed by Katz and Jung (2021a).

**Table 1**
Variables used in the empirical analysis.

| Group | Variable | Description | Source |
|---|---|---|---|
| Outcome variables | Mobile CAPEX | Investment in mobile telecommunication services. | GSMA |
| | 4G Coverage | Percentage of population covered by a 4G network. | GSMA |
| | MBB prices | Data-only mobile broadband price for 1.5 GB. | ITU |
| | MBB penetration | Mobile broadband unique subscribers' penetration. | GSMA |
| Spectrum variables | Spectrum secondary trading allowed | Dummy variable that takes the value of 1 if a secondary market for spectrum is allowed.[1] | ITU |
| | Spectrum sharing allowed | Dummy variable that takes the value of 1 if spectrum sharing for mobile operators is permitted.[2] | ITU |
| | Spectrum technological neutrality | Dummy variable that takes the value of 1 if technological neutrality principles apply in spectrum allocation and use. | ITU |
| | Spectrum flexibility scale | Scale taking values from 0 to 3 depending on the number of the above spectrum policies in each country (e.g., 3 if all three policies are implemented). | Built from ITU data |
| | Spectrum flexibility dummy | Dummy variable that takes the value of 1 if all three spectrum policies are applied. | Built from ITU data |
| | Spectrum for LTE allocated | Dummy variable that takes a value of 1 if a spectrum allocation was carried out for LTE services | ITU |
| | Spectrum of digital dividend allocated | Dummy variable that takes a value of 1 if the digital dividend (700 MHz band) was allocated for IMT | ITU |
| Control variables | Mobile Revenue | Revenue from mobile telecommunication services. | GSMA |
| | ICT Regulatory Tracker | Composite index based on 50 indicators grouped into clusters: Regulatory Authority, Mandates, and Regime and Competition Framework. | ITU |
| | Cellular coverage | Percentage of population covered by a mobile-cellular network. | ITU |
| | Taxation | Tax rate for mobile cellular tariffs (includes VAT). | ITU |
| | HHI Mobile | Herfindahl Hirschman Index of the mobile sector. | GSMA |
| | SMP (Significant Market Power) | Index taking values from 0 to 2 depending on the definition of SMP and its scope (geographical, market share, essential facilities, access to financial resources, countervailing power of consumers, economies of scale). | ITU |
| | GDP per capita | Gross Domestic Product per inhabitant in current US dollars. | IMF |
| | Urban population | Percentage of population living in urban areas. | World Bank |
| | Population age | Percentage of population over 65 years old. | World Bank |

[1] In some countries, spectrum trading has been admitted only for specific frequencies, in case of transactions required by competition authorities to permit mobile mergers. However, the lack of detail in the data provided by the ITU prevented us to identify these specific situations. We would like to thank an anonymous referee for raising up this point.
[2] In some cases, sharing may be restricted to certain frequency bands or for geographic areas of the country. Unfortunately, the data provided by the ITU does not specifies such situations.
Source: elaborated by the authors

unique subscriber's penetration, while the countries that do not allow that policy reach only 26.0%. The difference is statistically significant at a 1% level. A similar conclusion can be reached for the case of spectrum sharing (48.6% versus 36.2% penetration). However, in the case of technological neutrality, no statistical differences can be detected across groups (average penetration is 43%). When all three flexibility attributes of spectrum management are present, mobile broadband penetration is 60.7%. In contrast, when not all the three attributes are present, average penetration reaches only 38.7%, with the difference being statistically significant at a 1% level.

A similar conclusion can arrive when comparing the kernel density functions for the same outcome variables. Fig. 2 plots the density functions for CAPEX per capita depending on two specific groups of countries based on whether or not they exhibit total flexibility. As indicated in Fig. 2, the density function for the total flexibility group shifts to the right, indicating higher CAPEX per capita. Additionally, the

**Table 2**
Descriptive stats and mean difference test for Mob. CAPEX pc (2008–2019).

| Spectrum policy | Yes/No | Mean (Mobile CAPEX per capita) | Observations | T-stat | p-value for Ho (diff = 0) |
|---|---|---|---|---|---|
| Spectrum secondary trading allowed | Yes | 50.891 [1.469] | 487 | −16.461*** | 0.00 |
| | No | 25.002 [0.704] | 1882 | | |
| Spectrum sharing allowed | Yes | 43.201 [1.389] | 662 | −5.999*** | 0.00 |
| | No | 29.307 [1.808] | 352 | | |
| Spectrum technological neutrality | Yes | 38.404 [1.315] | 809 | −2.272** | 0.012 |
| | No | 33.295 [1.573] | 351 | | |
| Spectrum flexibility dummy | Yes | 56.423 [2.708] | 181 | −7.190*** | 0.00 |
| | No | 34.812 [1.390] | 657 | | |

Notes: *p<10%, **p<5%, ***p<1%. Standard errors in brackets.
Source: elaborated by the authors

**Table 3**
Descriptive statistics and mean difference test for MBB unique subscribers' penetration (2018–2019).

| Spectrum policy | Yes/No | Mean (MBB Penetration) | Obs. | T-stat | p-value for Ho (diff = 0) |
|---|---|---|---|---|---|
| Spectrum secondary trading allowed | Yes | 0.542<br>[0.009] | 428 | −28.669*** | 0.00 |
| | No | 0.26<br>[0.005] | 1420 | | |
| Spectrum sharing allowed | Yes | 0.486<br>[0.008] | 673 | −9.577*** | 0.00 |
| | No | 0.362<br>[0.008] | 354 | | |
| Spectrum technological neutrality | Yes | 0.425<br>[0.007] | 819 | 0.116 | 0.546 |
| | No | 0.426<br>[0.011] | 354 | | |
| Spectrum flexibility dummy | Yes | 0.607<br>[0.012] | 181 | −13.991*** | 0.00 |
| | No | 0.387<br>[0.007] | 668 | | |

Notes: *p<10%, **p<5%, ***p<1%. Standard errors in brackets.
Source: elaborated by the authors

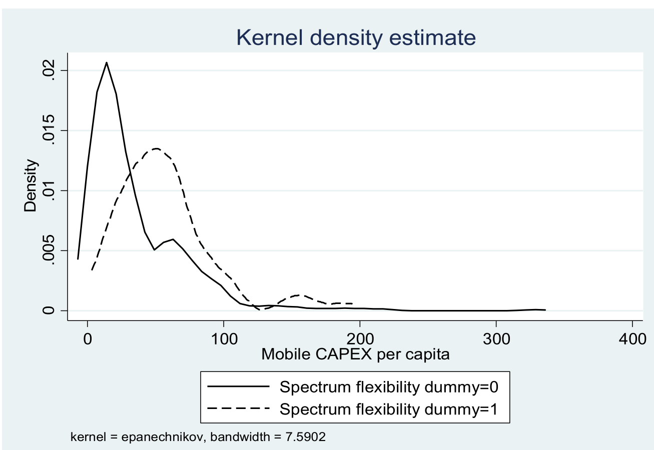


**Fig. 2.** Kernel density estimate for Mobile CAPEX per capita (By spectrum flexibility level).
Source: elaborated by the authors

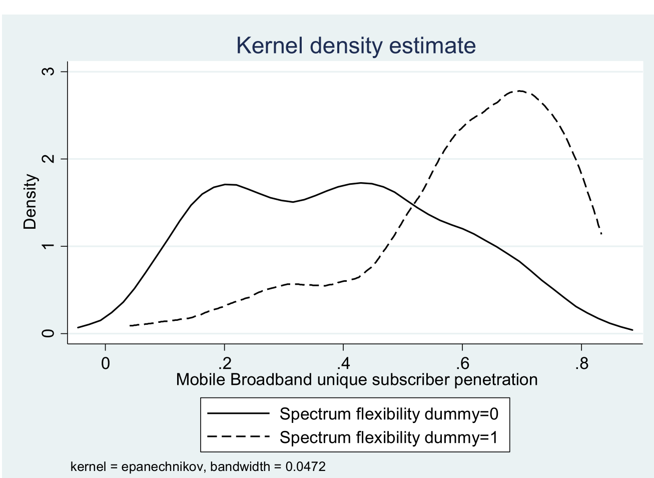


**Fig. 3.** Kernel density estimate for MBB unique subscribers' penetration (By spectrum flexibility level).
Source: elaborated by the authors

density function for those countries with less spectrum management flexibility seems highly concentrated, suggesting that the total flexibility approach is more significant than carrying out isolated specific policies.

A similar analysis was performed for the case of mobile broadband unique subscribers' penetration (Fig. 3). In this case, again, the density function corresponding to the total spectrum flexibility group is positioned to the right. However, in this case, disparity levels within both observation groups are much larger than in Fig. 2. The explanation can be related to the adoption variable depending on many other factors such as affordability, age, and the like.

In sum, this preliminary evidence suggests a positive link between spectrum flexibility approaches and mobile service development. However, it remains to be seen if these are simple correlations or if these relations represent a causality direction as depicted in Fig. 1, robust to the addition of control variables and measures to control endogeneity. This will be explored in the next section.

## 5. Econometric results

As presented in the investment equation, *CAPEX* is expected to depend on its own lagged value, sector revenues, spectrum policies, and competition. To avoid the endogeneity concerns related to the "dynamic panel bias", we need to rely on an estimation strategy that considers the existence of cross-country individual unobservable elements but does not incur the problems generated by the conventional fixed-effects approach. For that purpose, the estimator proposed by Arellano and Bond (1991) based on the Generalized Method of Moments (GMM), and later improved by Arellano and Bover (1995) into the System-GMM methodology is designed explicitly for panels exhibiting short time-periods, larger cross-section dimensions, a left-hand-side variable that is dynamic (that is to say, it depends on its past realizations), fixed individual effects, and heteroskedasticity and autocorrelation within individuals but not across them (Roodman, 2009). This methodology relies on using lagged variables as instruments.[6] To avoid the fact that the two-step procedure tends to offer biased standard errors, we will compute the finite-sample correction as in Windmeijer (2005) to achieve robust estimates.

Another concern was that of potential endogeneity between

[6] As pointed out by Arellano and Bover (1995), the original Arellano and Bond (1991) estimator presented a weakness, as lagged levels are usually poor instruments for first differenced variables. For that reason, their proposed modification includes lagged levels as well as lagged differences.

**Table 4**
Two-step GMM estimation results for the investment equation.

| Dependent variable: Log (Mobile CAPEX) | [I] | [II] | [III] | [IV] | [V] |
|---|---|---|---|---|---|
| Log (Mobile CAPEX) t-1 | 0.771*** | 0.782*** | 0.647*** | 0.682*** | 0.683*** |
| | [0.055] | [0.095] | [0.077] | [0.092] | [0.076] |
| Log (Mobile Revenue) t-1 | 0.193*** | 0.198** | 0.320*** | 0.281*** | 0.282*** |
| | [0.055] | [0.082] | [0.073] | [0.091] | [0.076] |
| Log (HHI Mobile) | 1.675* | 0.851 | 1.091 | 1.395 | 2.757 |
| | [0.997] | [2.930] | [1.691] | [1.547] | [2.687] |
| Log (HHI Mobile) - sq | −0.102* | −0.050 | −0.070 | −0.084 | −0.168 |
| | [0.060] | [0.176] | [0.101] | [0.092] | [0.163] |
| Spectrum secondary trading allowed | 0.147* | | | | |
| | [0.078] | | | | |
| Spectrum sharing allowed | | 0.087** | | | |
| | | [0.044] | | | |
| Spectrum technological neutrality | | | 0.319** | | |
| | | | [0.127] | | |
| Spectrum flexibility scale | | | | 0.126*** | |
| | | | | [0.091] | |
| Spectrum flexibility dummy | | | | | 0.349*** |
| | | | | | [0.130] |
| Regional fixed effects | YES | YES | YES | YES | YES |
| Time-trend | YES | YES | YES | YES | YES |
| Arellano-Bond test for AR (1) in first differences | −5.38*** | −4.16*** | −3.76*** | −4.16*** | −4.09*** |
| Arellano-Bond test for AR (2) in first differences | −0.26 | 1.26 | 1.44 | 1.28 | 0.78 |
| Hansen test of overid. Restrictions | 127.54 | 114.96 | 102.92 | 91.69 | 96.07 |
| Observations | 1341 | 744 | 735 | 618 | 618 |

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

spectrum policy variables and investment. To control for this concern, we will treat these variables as endogenous, relying on external instruments. These instruments must verify a double condition: help explain the regulatory variable but not directly link to the dependent variable. In our case, we will rely on a specific indicator linked to the energy-market regulation. This instrument helps explain a country's approach towards regulation and can thus help explain spectrum policies. However, it is not related to mobile CAPEX, as it belongs to a different economic sector. We will rely on the RISE[7] index, developed by the World Bank and the Energy Sector Management Assistance Program (ESMAP). The index comprises 30 indicators for 138 countries for the period 2010–2019, offering a snapshot of a country's policies and regulations in the energy sector. Estimation results for the investment equation are reported in Table 4.

The lagged CAPEX value and Revenue exhibit the expected sign and significance levels in all estimates. On the other hand, the selected instruments were verified to be suitable according to the Hansen-J test: the null hypothesis of exogeneity was rejected in neither case.

Results provide arguments to support flexible spectrum approaches. Due to the high correlation between the three spectrum policy variables creating multicollinearity problems, we introduce these variables one by one. Column [I] suggest, albeit at a 10% significance level, that countries allowing secondary markets for spectrum invest 14.7% more than countries that do not allow this possibility. According to column [II], countries that allow spectrum sharing invest 8.7% more than countries that do not. In addition, column [III] indicates that countries that follow a technological neutrality approach for spectrum invest 31.9% more than countries that do not follow this principle.

However, this is only a preliminary conclusion, as these regressions may be affected by the omitted variable bias. As we introduce spectrum variables one by one, some of them may be capturing a part of the effect from the omitted ones. Thus, we need to consider all three variables within the same regression framework but avoid the collinearity problems. We then group them into a spectrum flexibility scale, taking values from zero to three depending on the number of these policies carried out by each country. Results are reported in column [IV] of Table 4, indicating that mobile investment increases on average 12.6% for each policy a country adopts. For example, if a country with zero flexibility adopts all three policies, then CAPEX should increase by 37.8%, a lower figure than that resulting from adding the individual coefficients from estimates of columns [I] to [III]. This result suggests that at least one of the previous estimates was contaminated by the omitted variable bias. Finally, in column [V], we introduce the spectrum flexibility dummy, which exhibits a positive and significant coefficient, suggesting that adopting all three policies is associated with an increase of investment of 34.9%, in comparison to countries that have not followed that approach.

While the previous results highlight the relevance of flexible spectrum approaches, we performed additional checks to avoid any further risk of omitted variable bias. The initial risk is that the spectrum policy variables may be capturing country differences in terms of spectrum allocation. In order to control for this potential bias, we will reproduce the estimates performed in columns [IV] and [V] of Table 4 but introducing as additional controls dummies for spectrum allocation for LTE services and digital dividend allocated for IMT.[8] The results, reported in Table 5, remain almost unchanged when introducing these further controls, either separately or jointly (in interaction).

Beyond the quantity of spectrum allocated, further checks were carried out by controlling for income differences (through GDP per

[7] Acronym for Regulatory Indicators for Sustainable Energy.

[8] Ideally, we would have liked to control for the quantity of spectrum allocated for IMT (in MHz). Unfortunately, there is not a public database containing this information. As a second-best possibility, we introduced the dummies for allocating spectrum for LTE services and digital dividend, as we understand that countries verifying those conditions should have more MHz allocated to IMT than those that do not.

**Table 5**
Two-step GMM estimation results for the investment equation with further spectrum controls.

| Dependent variable: Log (Mobile CAPEX) | [I] | [II] | [III] | [IV] | [V] | [VI] |
|---|---|---|---|---|---|---|
| Log (Mobile CAPEX) t-1 | 0.700*** | 0.679*** | 0.739*** | 0.688*** | 0.676*** | 0.713*** |
| | [0.079] | [0.092] | [0.082] | [0.077] | [0.075] | [0.084] |
| Log (Mobile Revenue) t-1 | 0.259*** | 0.284*** | 0.219*** | 0.272*** | 0.294*** | 0.238*** |
| | [0.073] | [0.092] | [0.081] | [0.074] | [0.075] | [0.086] |
| Log (HHI Mobile) | 0.958 | 1.429 | 0.655 | 1.042 | 1.527 | 0.893 |
| | [1.445] | [1.828] | [1.641] | [1.731] | [1.618] | [1.768] |
| Log (HHI Mobile) - sq | −0.058 | −0.087 | −0.041 | −0.063 | −0.092 | −0.055 |
| | [0.086] | [0.109] | [0.098] | [0.103] | [0.097] | [0.106] |
| Spectrum flexibility scale | 0.128*** | 0.124*** | 0.117** | | | |
| | [0.044] | [0.046] | [0.046] | | | |
| Spectrum flexibility dummy | | | | 0.368*** | 0.357*** | 0.359*** |
| | | | | [0.119] | [0.123] | [0.118] |
| Spectrum for LTE allocated | −0.125 | | | −0.070 | | |
| | [0.086] | | | [0.080] | | |
| Spectrum of digital dividend allocated | | 0.001 | | | −0.036 | |
| | | [0.079] | | | [0.082] | |
| Spectrum for LTE allocated & Spectrum of digital dividend allocated | | | 0.113 | | | 0.089 |
| | | | [0.110] | | | [0.116] |
| Regional fixed effects | YES | YES | YES | YES | YES | YES |
| Time-trend | YES | YES | YES | YES | YES | YES |
| Arellano-Bond test for AR (1) in first differences | −3.97*** | −4.17*** | −4.25*** | −3.85*** | −4.08*** | −4.01*** |
| Arellano-Bond test for AR (2) in first differences | 1.37 | 1.28 | 1.48 | 1.12 | 0.79 | 1.18 |
| Hansen test of overid. Restrictions | 97.99 | 91.09 | 85.03 | 99.37 | 91.18 | 93.49 |
| Observations | 567 | 617 | 566 | 567 | 617 | 566 |

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

**Table 6**
Estimation results for the coverage equation.

| Dependent variable: Log (4G Coverage) | [I] | [II] | [III] |
|---|---|---|---|
| Log (Mobile CAPEX) t-2 | 0.261*** | 0.272* | 0.936*** |
| | [0.095] | [0.140] | [0.312] |
| Log (Cellular coverage) t-1 | 2.009*** | 1.259 | 2.140*** |
| | [0.712] | [0.982] | [0.564] |
| Log (Cellular coverage) t-2 | 1.655*** | 1.445* | 1.918*** |
| | [0.552] | [0.772] | [0.458] |
| Log (Cellular coverage) t-3 | 1.187*** | 0.332 | 1.223*** |
| | [0.284] | [0.709] | [0.260] |
| Log (Urban population) | 6.002*** | 5.510* | 4.957*** |
| | [2.277] | [2.913] | [1.613] |
| Country fixed effects | YES | YES | YES |
| Year fixed effects | YES | YES | YES |
| Under-identification test | n.a. | n.a. | 25.869*** |
| Weak identification test | n.a. | n.a. | 33.305† |
| Hansen test of overid. restrictions | n.a. | n.a. | 0.061 |
| Treatment for lagged CAPEX | Exogenous | Endogenous (regression over predicted value) | Endogenous (instrumented) |
| Observations | 785 | 366 | 772 |
| Estimation Method | OLS | OLS-CDM | IV-LIML |

*Notes: *p < 10%, **p < 5%, ***p < 1%. Robust standard errors in brackets. (†) Stock-Yogo weak ID test critical values: 10% maximal LIML size (8.68), 15% maximal LIML size (5.33), 20% maximal LIML size (4.42) and 25% maximal LIML size (3.92).*
Source: elaborated by the authors

capita), for cost differentials (proxied by the share of urban population), and for other regulatory factors[9] beyond spectrum policy (proxied by ITU's ICT Regulatory Tracker). In all cases, the results stand.[10]

Having assessed the link between spectrum policy variables and mobile CAPEX, we turn to the coverage equation. Our aim, in this case, is to estimate the impact of CAPEX on coverage levels, particularly the induced effect from a CAPEX variation related to spectrum policy. The coverage equation has as a dependent variable the level of 4G coverage as a function of mobile *CAPEX* (in lags, given that investment takes some time to materialize into coverage gains). We decided to approximate past investment by mobile *CAPEX* in period *t-2*, as, from a statistical viewpoint, it provided to be more relevant than CAPEX in period *t-1* to explain coverage in period *t*. A one-year lag may be too tight, especially considering that we ignore at which point of the fiscal year the deployments were mostly carried out. 4G coverage is expected to depend also on past coverage levels (defined for cellular technology rather than 4G specific, so we avoid entering the lagged dependent variable as regressor) and the percentage of the urban population. The estimated regressions also include country fixed effects, which control for national-level time-invariant unobservable factors. In addition, we include year fixed effects to account for economic cycle variations.

A key issue for the identification strategy is the treatment of the lagged CAPEX. We perform three different estimations. We run a standard OLS with fixed effects, treating the lagged CAPEX as exogenous. We then treat the CAPEX regressor as endogenous, as determined in the previous equation. We run an OLS fixed effects estimate but introducing the predicted CAPEX from the investment equation as a regressor (using the estimate of column [VI] in Table 5). This procedure is similar to the so-called CDM model (Crepon et al., 1998). In third place, we will follow

[9] According to Ezzat and Aboushady (2018), restrictive policies are expected to have a relatively lower impact on mobile than in fixed segment, as they consider that wireless market is less likely to be characterized by economies of scale as in the case of the market for landline services.
[10] These results are not shown here to save space but remain available from the authors upon request.

**Table 7**
Estimation results for the price equation.

| Dependent variable: Log (MBB prices) | [I] | [II] | [III] | [IV] |
|---|---|---|---|---|
| Log (4G Coverage) | −0.161*** | −0.598** | −0.578*** | −0.948*** |
| | [0.040] | [0.299] | [0.160] | [0.231] |
| Taxation | 0.013* | 0.018* | 0.017** | 0.016*** |
| | [0.007] | [0.011] | [0.008] | [0.005] |
| SMP | −0.181*** | −0.200* | −0.191*** | −0.214** |
| | [0.047] | [0.106] | [0.061] | [0.091] |
| Log (Urban population) | −3.584** | 1.002 | −0.079 | 2.530 |
| | [1.413] | [3.468] | [1.424] | [2.406] |
| Country fixed effects | YES | YES | YES | YES |
| Year fixed effects | YES | YES | YES | YES |
| Underidentification test | n.a. | n.a. | 24.881*** | n.a. |
| Weak identification test | n.a. | n.a. | 12.927† | n.a. |
| Hansen test of overid. restrictions | n.a. | n.a. | 5.689 | n.a. |
| Treatment for 4G Coverage | Exogenous | Endogenous (regression over predicted value) | Endogenous (instrumented) | Endogenous (regression over predicted value) |
| Observations | 948 | 367 | 695 | 359 |
| Estimation Method | OLS | OLS-CDM | IV-LIML | Simultaneous equation with column [IV] – Table 8 |

*Notes: *p < 10%, **p < 5%, ***p < 1%. Robust standard errors in brackets. (†) Stock-Yogo weak ID test critical values: 10% maximal LIML size (5.44), 15% maximal LIML size (3.87), 20% maximal LIML size (3.30) and 25% maximal LIML size (2.98).*
Source: elaborated by the authors

**Table 8**
Estimation results for the demand equation.

| Dependent variable: Log (MBB penetration) | [I] | [II] | [III] | [IV] |
|---|---|---|---|---|
| Log (MBB prices) | −0.066** | −0.156** | −0.373*** | −0.145*** |
| | [0.029] | [0.073] | [0.117] | [0.054] |
| Log (GDP per capita) t-1 | 0.205** | 0.060 | 0.348*** | 0.071 |
| | [0.091] | [0.158] | [0.100] | [0.058] |
| Population age | −0.164*** | −0.076*** | −0.050* | −0.069*** |
| | [0.027] | [0.032] | [0.027] | [0.017] |
| Country fixed effects | YES | YES | YES | YES |
| Year fixed effects | YES | YES | YES | YES |
| Underidentification test | n.a. | n.a. | 19.936*** | n.a. |
| Weak identification test | n.a. | n.a. | 10.353† | n.a. |
| Hansen test of overid. restrictions | n.a. | n.a. | 4.47 | n.a. |
| Treatment for MBB prices | Exogenous | Endogenous (regression over predicted value) | Endogenous (instrumented) | Endogenous (simultaneous regression) |
| Observations | 1306 | 362 | 682 | 359 |
| Estimation Method | OLS | OLS-CDM | IV-LIML | Simultaneous equation with column [IV] – Table 7 |

*Notes: *p < 10%, **p < 5%, ***p < 1%. Robust standard errors in brackets. (†) Stock-Yogo weak ID test critical values: 10% maximal LIML size (6.46), 15% maximal LIML size (4.36), 20% maximal LIML size (3.69) and 25% maximal LIML size (3.32).*
Source: elaborated by the authors

**Table 9**
Evolution of mobile outcome variables after adopting spectrum flexible approach – short term effects.

| Variable affected | Period | Variation rate | Average value for Spectrum flexibility dummy = 0 | Simulated value after policy reform |
|---|---|---|---|---|
| Mobile CAPEX | T | 35.9% | $ 928.97 million | $ 1262.47 million |
| 4G Coverage | t+2 | 9.8% | 65.05% | 71.42% |
| MBB prices | t+2 | −5.8% | $ 14.61 | $ 13.76 |
| MBB penetration | t+2 | 0.9% | 38.7% | 39.05% |

Source: elaborated by the authors

Instrumental Variables using the Limited Information Maximum Likelihood approach (IV-LIML), treating the lagged CAPEX as endogenous and using as instruments a further lag for Log (Mobile CAPEX) and Log (Mobile Revenue), also in *t-3* (the rationale for using these instruments is that they are the determinants of mobile CAPEX in *t-2* according to the investment equation, and the Hansen test verifies their exogeneity). Results are reported in Table 6.

Results are in line with those expected. Past mobile investment is significant to explain current 4G coverage levels, as are the past coverage levels for previous technologies. For the case of lagged CAPEX,

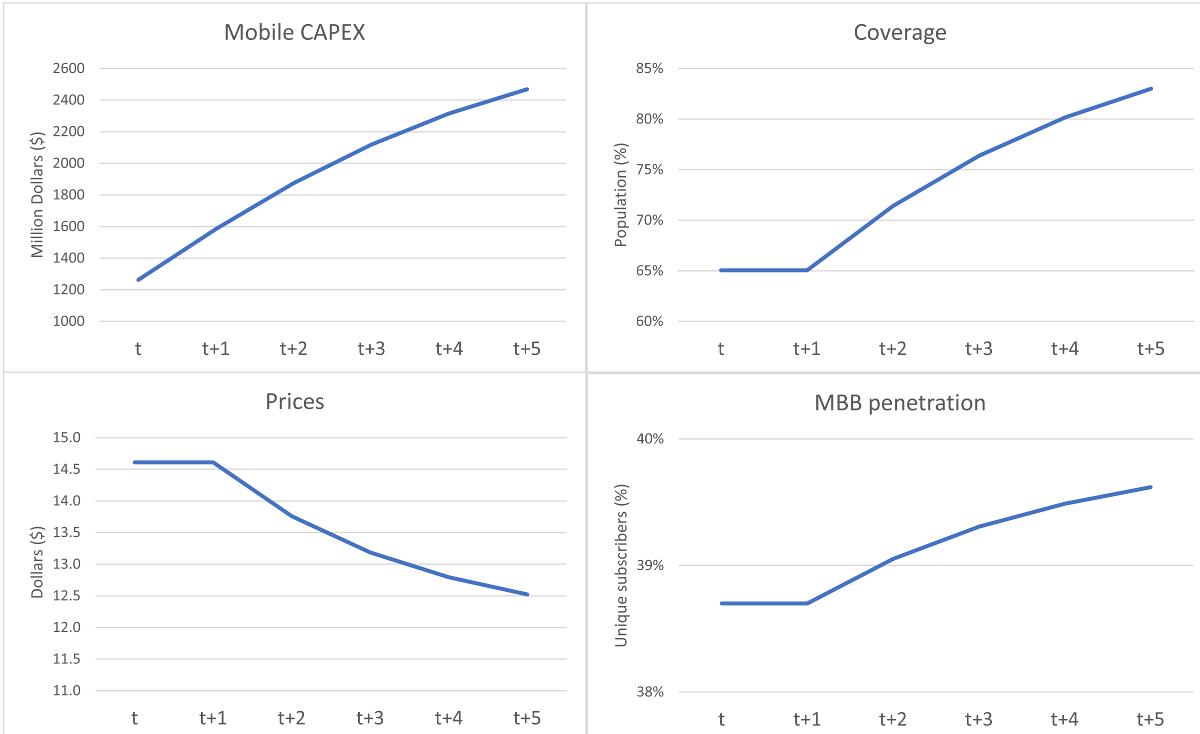


**Fig. 4.** Evolution of mobile outcome variables after adopting spectrum flexible approach – long term effects.
Source: elaborated by the authors

the OLS model (column [I]) and the estimation a-la CDM (column [II]) exhibit similar coefficients, while in the case of the IV-LIML (column [III]), this value becomes much greater. In addition, more urban countries seem to exhibit greater coverage levels, which is reasonable as investment is more profitable under such circumstances.

The third equation links mobile broadband prices with the taxation of mobile services, 4G coverage and competitive pressures. We also add a further control for the urban population to proxy for cost differences. To control for competition levels, we rely on the SMP variable as defined in Table 1.[11] The estimated regressions also include country and year fixed effects. Again, the key issue is the treatment for the variable that comes from the previous equation, in this case, 4G coverage. As in the previous case, we will follow diverse approaches: considering 4G coverage as exogenous (OLS fixed effects) as well as endogenous, on the one hand using the predicted value from the previous "CDM" equation (column [II] in Table 6), and on the other hand, relying on the IV-LIML estimate instrumenting with its determinants (lagged CAPEX and previous technology coverage, and urban population). In addition, in column [IV], we replicate the estimate of column [II] but now performing it simultaneously with the demand equation. The rationale for doing so is essentially a supply and demand function, which should be estimated together (the price equation can be considered the inverse of the supply function). Table 7 provides the results.

As expected, the higher the coverage, the lower the prices, and the magnitude of the coefficient increases when we control endogeneity (in absolute value), confirming a rightward shift in the supply curve. In turn, the higher the taxation applying to mobile services, the higher the end-user prices. On the other hand, the more monitored the competition in the market is (as denoted by the SMP indicator), the lower the prices. The urban population regressor only reaches a significant level in the OLS estimate.

Finally, the adoption equation links demand (measured as mobile broadband unique subscribers' penetration) as a function of prices, income (proxied by the lag of GDP per capita), and the population's age composition. The estimated regressions include country and year fixed effects. The estimation strategies are similar to those from the previous equations.[12] As stated before, in the last column [IV], we report the result of the demand equation estimated simultaneously with the price equation (same column, Table 7). Table 8 summarizes these estimates. The results suggest that, as expected, demand is negatively linked to prices. The higher the prices, the lower the adoption level and the corresponding coefficient becomes greater (in absolute value) once measures to control for endogeneity are taken. Income, as measured by the lag of GDP per capita, tends to explain positively the adoption levels in estimates reported in columns [I] and [III], and the older the composition of the population, the lower the demand, as expected. Results are consistent across the different empirical strategies followed.

All in all, we were able to explain the causality links across the chain as described in Fig. 1, and the results are robust to the addition of control variables and endogeneity control. We were able to reach similar conclusions from very different empirical strategies.

At this point, all the effects of the causality chain can be linked as described in Fig. 1. For that purpose, we will rely on the parameters of our preferred econometric specifications, column [VI] in Table 5 and columns [II] from Tables 6–8 (the CDM approach). From those estimates, our selected parameters are the following: $\delta = 0.359$, $\Phi = 0.272$, $\Psi = -0.598$ and $\eta = -0.156$. The formulas to calculate the effects over the different outcome variables are described in Section 3. Initial effects are verified in period $t$ for CAPEX and period $t+2$ for the remaining outcome variables. Significant gains can be simulated for CAPEX (+35.9%), 4G Coverage (+9.8%), MBB prices (−5.8%) and MBB penetration (+0.9%).

[11] We decided to use the SMP variable instead of the HHI, as this latest indicator proved to be non-significant.

[12] For the IV-LIML estimate, the instruments for prices are mobile taxation, SMP criteria and the lagged 4G coverage.

Table 9 summarizes these estimations.

However, the effects on outcome variables are not limited to a single period, as CAPEX improvements will induce future CAPEX variations, which in turn will yield further variations in the rest of the outcome variables. Simulating the effects for five years and starting with the sample average values (for the group of spectrum flexibility = 0), Fig. 4 exhibits the evolution for each case.

Over five years, the dynamic effects are supposed to magnify the results, hypothetically ending with a mobile broadband prices reduction of 14.3% and mobile broadband unique subscribers' penetration increase of 2.37%. In addition, these outcomes are expected to yield macroeconomic gains for society. As found out by Katz and Jung (2021b), a 1% increase in mobile broadband unique subscribers' penetration is expected to yield an increase of 0.16% in GDP per capita. Then, the effects mentioned above can imply a gain in GDP per capita of 0.4% for this five-year simulation.

These results, again, provide empirical support for the relevance of spectrum management in general and for promoting a flexible approach in particular.

## 6. Conclusions

This study complemented prior research and generated new evidence about the impact of the spectrum policies on the performance of the mobile sector. Beyond the specific results estimated, we believe that a contribution of this paper is to trigger future research in the field.

We developed a 4-equation model with the precise linkages in the mobile sector: from policy reforms to adoption gains. We focused on assessing the effects of three specific policies related to a flexible spectrum approach: the presence of a secondary market, a technological neutrality approach, and the possibility of conducting sharing agreements among operators. Four possible variables were identified as market outcomes: investment, coverage, prices and adoption. We were able to identify a significant impact from these spectrum policies. When those three attributes are jointly adopted, mobile investment is expected to be 35.9% larger than when that is not the case, according to the parameters estimated. In addition, promoting these policies can increase coverage within two years by 9.8%, bring down mobile prices by 5.8%, and increase mobile broadband penetration by 0.9%. When we consider an extended time period, dynamic effects are expected to take over, resulting in mobile broadband prices being reduced by 14.3% and mobile broadband unique subscribers' penetration potentially increasing by 2.4%. These results were verified to be robust after adding control variables and for controlling potential endogeneities associated with these causal frameworks. Different empirical strategies were followed, all arriving at the same conclusion.

All in all, we understand that following a flexible approach towards spectrum management can contribute significantly to the development of the mobile sector, and as a result, policymakers and regulatory authorities should take steps in that direction to maximize social welfare. This empirical evidence is expected to provide policymakers with a deeper understanding of the linkages between the regulation and mobile market outcome and the characteristics that effective spectrum policies should have.

However, some caveats need to be made regarding the study results. While it is essential to highlight the effort conducted by the ITU to make publicly available a database that incorporates country-level information on spectrum policy, some of the indicators are limited in terms of their predictive ability. For example, the binary nature of the spectrum policy indicators (i.e., the existence or not of a particular policy) does not indicate their quality and the degree of implementation. Some of these policies may be gradually adopted, only for specific frequencies or for some geographic areas of the country. This limitation prevented a more granular look at how these policies affect the market outcomes. In addition, technological progress might render some of the indicator's imperfect. For example, the coverage variable is measured regarding 4G wireless technology and does not address causality with future 5G deployment (for which data is currently scarce), although we believe that the conclusions can be extended. For that reason, we recognize the limitations that constrained our analysis and expect more precise estimates to be carried out in future research when richer datasets become available.

On another note, the COVID-19 pandemic is expected to impact the analysis. On the one hand, worldwide GDP contraction could reduce telecommunication revenues,[13] therefore negatively impacting capital spending levels (investment equation). On the other hand, the lockdown period is expected to result in the expanded use of digital technologies, thus representing an unobservable shock affecting adoption levels (demand equation). These effects were out of the scope of the current research. That being said, policymakers and regulators should assess the quality of their spectrum management framework and examine whether some of the policies found to be critical in promoting improvement to sector performance are in place.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[13] Even if the ITU has not yet reported revenue information for the overall sector during 2020, for the mobile segment GSMA intelligence estimated revenue loses in several markets with respect to 2019, such as Mexico (−2.4%), Canada (−4.3%), United States (−0.9%) or Brazil (−2.2%).