

Saringkarnpoonperm, Suttiwit; Khemakongkanonth, Chate; Srinuan, Pratompong

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The Impact of Spectrum Prices in the Telecommunication Sector on Network Investments

Suttiwit Saringkarnpoonperm¹, Chate Khemakongkanonth¹, Pratompong Srinuan¹

¹Policy Assessment Bureau, Office of The National Broadcasting and Telecommunications Commission (Head Office), Bangkok, Thailand

This paper represents the views of the authors and does not necessarily reflect the views or opinions of the NBTC

Keyword: Auction, Investment, Spectrum prices

Abstract:

This paper aims to examine the impact of spectrum prices on mobile operators' industry investment using country-level data from 13 countries spanning 2013 to 2022. We employ four models to explore the quantitative evidence, with a preference for the one-step system GMM model through hypothesis testing. The results indicate that significant factors influencing investment include prior CAPEX, urban population, ARPU, GDP, and HHI, while spectrum prices and fees do not show significance. To address limitations, we suggest expanding sample sizes and incorporating additional instruments and dependent variables to establish evidence-based insights into the relationship between spectrum prices and CAPEX.

1. Introduction

Most countries allocate spectrum licenses via auctions because it is more efficient than a beauty contest (Cramton, 2013). However, governments sometimes have an incentive to set the price as high as possible for revenue maximization. Although spectrum prices seem to have reached a stable state and experienced a gradual decline over time, the matter remains significant. Particularly, crucial bands such as the 2100 MHz for 3G, allocated around a decade ago, are likely nearing the expiry date of spectrum allocation (Fig. 1). This implies that the preceding bands, alongside newly designated spectrum bands, will be auctioned in the upcoming years.

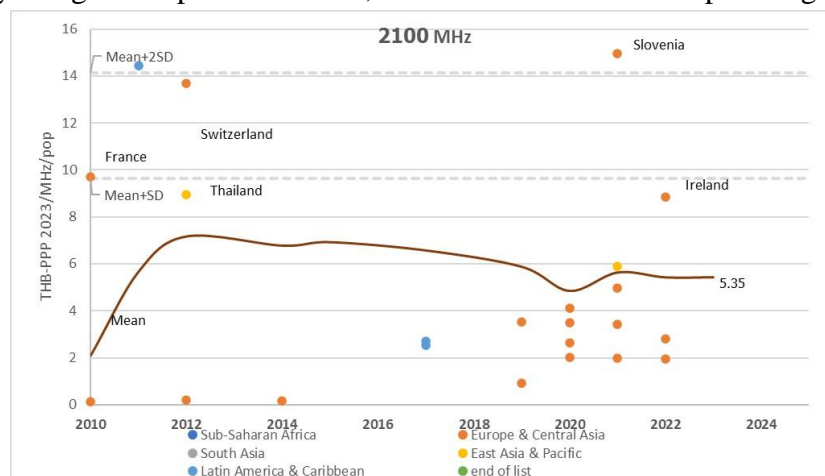


Fig 1: The winning price of 2100 MHz during 2010 - 2023

Furthermore, the quantity and cost of spectrum acquired can significantly impact future operations, as investment and sales strategies are likely to adapt post-allocation. For instance, if the reserve price exceeds a telecommunication operator's valuation, they might need to raise prices

post-allocation, considering market competition, to ensure adequate returns and fund their investment. Similarly, many telecommunications operators are publicly listed on stock exchanges, which impose constraints on their access to capital. As a result, they are obligated to fulfill shareholder demands for acceptable returns. If they fail to achieve these returns, potentially due to exorbitant spectrum costs, it could lead to an increase in their cost of capital in the long term, thus impacting their investment decisions.

Meanwhile, the current economic literature has two directions regarding the relation between spectrum prices and investment. Some economists support the notion that spectrum prices should be considered sunk costs, which theoretically should have no effect on decision-making going forward. For instance, Park, Lee, and Choi (2011) found no evidence to support the idea that high license fees from spectrum auctions affect consumer prices and telecommunication investment. This is also similar to the results of Cambini and Garelli (2017), Cave and Valetti (2000), Morris (2005), and Jung and Katz (2022), who stated that spectrum prices have no impact on consumer prices and investment.

In contrast, some have found that their investment strategies are affected by high spectrum fees. One example is the 'hold-up problem,' where operators decide to reduce or delay network investments due to financial constraints (GSMA, 2017). Marsden et al. (2017), Bahia and Castells (2022), GSMA (2019), and Datta (2012) also found results indicating that spectrum prices cause a negative effect on consumer welfare and industry investment. Overall, the findings regarding spectrum fees and investment remain ambiguous.

Our contribution to the literature involves attempting to measure the impact of spectrum fees on subsequent investment, particularly in capital expenditure (CAPEX), utilizing country-level panel data from 13 both developing and developed countries during 2013-2022. We also consider other factors that may impact capital expenditure, such as market concentration, revenues per subscriber, gross domestic product (GDP), urban population, and available spectrum. We adopt independent variables from various literature and economic concepts, including HHI, ARPU, GDP, urban population, spectrum fees, and the number of spectrums. Moreover, our panel model resembles the investment equation proposed by Jung and Katz (2022), who analyzed the effects of previous CAPEX, prior revenues, spectrum policy, and competition on industry CAPEX through a panel data model.

We developed four models: a pooled OLS model, a fixed effects panel data model, a random effects panel data model, and a one-step system GMM model. Through hypothesis testing, we favored the one-step system GMM model over the others. Our analysis revealed significant correlations between prior CAPEX, HHI, GDP, ARPU, and urban population with CAPEX. However, we couldn't establish quantitative evidence regarding the impact of spectrum fees and spectrum availability on CAPEX. Adjustments to the model, inclusion of more variables and instruments, and exploring new implications of CAPEX in future studies might be necessary to uncover this quantitative evidence.

The paper covers the following sections. Section 2 presents the literature review on the impact of high spectrum prices on industry investment. Section 3 represents the variables that may

impact CAPEX in our model. Section 4 describes the panel data that we use to estimate, and section 5 provides the empirical analysis of our work. Lastly, section 6 presents the conclusion, limitations, and suggestions for further study.

2. Literature review

The economics literature review yields two results. On one hand, some economists found that spectrum fees are sunk costs for telecommunication operators and do not impact future investment.

Cave and Valetti (2000) argued that spectrum fees from auctions, when accounting for future revenues, investments, and competition since spectrum allocation, suggest a forward-looking approach where operators consider spectrum prices as sunk costs, thus not impacting consumer prices or the expansion of telecommunication infrastructure.

Similarly, Morris (2005) argued that there is a lack of empirical evidence supporting the idea that spectrum auctions are distortionary. He presented that revenue raised through spectrum auctions could potentially mitigate other distortionary revenue instruments. The crucial factor determining whether spectrum auctions are efficient or distortionary (i.e., resulting in higher prices for spectrum-dependent services and inducing substitution away from such services, thus reducing overall welfare) depends on whether firms are likely to pass along additional costs to users.

Some papers have used quantitative analysis to investigate this circumstance. Park et al. (2011) employed a simple regression analysis to study firm-level data in mobile markets of 21 OECD countries, where there was a mixture of beauty contests and auctions. Their analysis included three variables: revenue per minute, indicating the price per minute used; the lag in years until 3G services were launched after the auction, assessing whether the company's progress was impeded by the auction process; and the change in the Herfindahl-Hirschman Index (HHI) before and after the spectrum auction.

Likewise, Cambini and Garelli (2017) found that spectrum fees and spectrum availability are not significantly correlated with mobile revenues. Their analysis involved a dataset of operators in 24 countries during 2005 to 2014. To conduct their analysis, they employed fixed effects estimation after applying a log-log transformation to relevant determinants. Furthermore, they addressed the potential endogeneity of license fees by using difference GMM with lagged levels serving as instruments.

Jung and Katz (2022) investigated the impact of spectrum policies on various indicators, including capital expenditure (CAPEX). Their empirical study defined CAPEX as influenced by factors such as its previous value, previous revenue, spectrum policy, competition level, and some other control variables. They employed a two-step generalized method of moments (GMM) estimation technique. While they did not directly incorporate spectrum price into the investment equation, certain controls such as spectrum allocated for LTE and spectrum allocated for digital dividend were not significant in all model specifications.

On the other hand, some literature found evidence supporting a negative impact of high spectrum prices on investment and consumer prices. Marsden et al. (2017) used country-level data

from 2008 to 2016 and found an inverse correlation between spectrum expenses and investment. They identified a proxy for network investment called a “wireless score”, derived from 3G/4G coverage, average speed, and 4G subscriber share, all of which should have a positive relationship with investment. Furthermore, they employed a two-stage regression approach to estimate a demand equation, estimating the impact on consumer surplus from price changes induced by spectrum fees.

Bahia and Castells (2022) also found similar results. They examined spectrum policies across 64 countries from 2010 to 2017, focusing on the 4G era and addressing empirical limitations including omitted variable and simultaneous causality bias. They discovered that decreased spectrum availability or increased spectrum costs led to lower network coverage and service quality.

GSMA (2019) used an econometric model with data on spectrum costs of 229 operators in 64 countries from 2010 to 2017, employing an instrumental variable model to estimate the impact of spectrum costs on consumer outcomes. The results showed that spectrum prices can have adverse effects on consumers in terms of reduced coverage and decreased data speeds.

Lastly, Datta (2012) employed a game-theory approach to theoretically validate that firms that finance their payment for high spectrum fees via borrowing from banks are motivated to decrease infrastructure investment per unit of service, consequently reducing service quality. While this incentivizes reducing spectrum fees, the author raised concerns about the government securing lower funds, which might inadvertently affect regulation. Therefore, he proposed that the government should earmark some portion of fees for support towards the expansion of the telecom industry.

3. CAPEX and the other variables

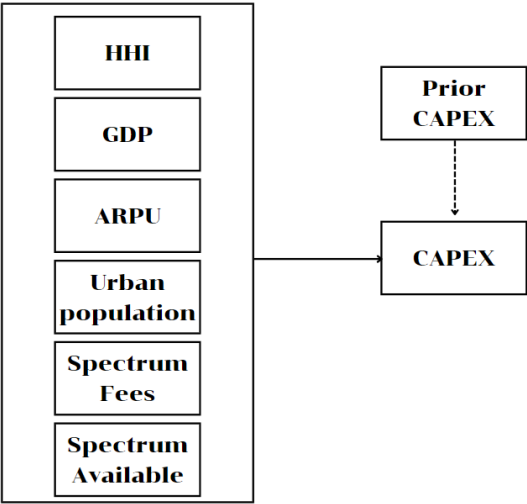


Fig 2: The factors that might impact CAPEX in the telecommunication sector

We expected that several factors would impact the decision of investment in the telecommunications sector (Fig 2). Generally, market structure and market concentration might influence firms' investment decisions. The Structure-Conduct-Performance (SCP) framework suggests that market structure and concentration can influence how firms behave and perform, including their investment decisions. This theory emphasizes that the conduct and performance of firms, such as their investment strategies, are shaped by the dynamics and interactions within the market, particularly among competing firms. Despite the existence of ambiguous evidence, we included the HHI variable representing market concentration in our model to assess its potential impact on investment within the telecommunications sector.

There is ample economic literature supporting the positive relationship between output and investment at the macro-level scale. Shapiro (1986) used a dynamic model and found that output and labor are correlated with investment, while the price of capital and discount rate are not. Ali et al. (2015) also constructed a single-equation model to examine the relationship between economy output and investment. The results showed that investment has a statistically significant positive relationship with output. Thus, we included GDP in our model and expect a positive correlation between CAPEX and GDP.

Most telecommunication companies are listed on the stock exchange market to raise funds for investing in infrastructure. When they increase their revenues significantly, stakeholders might accept more rollout infrastructure plans. For example, Razzak et al. (2024) studied 53 industrial companies listed on The Amman Stock Exchange from 2018 to 2022 and found evidence that profitability strongly relates to investment. Similarly, Suwanrat and Sincharoonsak (2022) used financial data from 49 companies listed on The Stock Exchange of Thailand between 2016 and 2020. They analyzed using multiple linear regression and found statistically significant relationships at the 0.05 level between revenues and CAPEX. Therefore, we expect telecommunication revenues to be statistically significant for industry investment. However, we did not have revenues for all companies in the country, so we used ARPU at the country level as a proxy for telecommunication revenues.

Cambini and Garelli (2017) adopted the function proposed by Hazlett and Munoz (2009) to construct the mobile investment function. Mobile investments are mainly influenced by the cost of spectrum, the availability of spectrum, and the population density in urban areas. We will follow this function to observe the relationship between these factors and CAPEX, expecting them to be statistically significant.

Meanwhile, the prior CAPEX value would also affect current CAPEX. This finding is supported by Jung and Katz (2022), who found a relationship between lagged mobile CAPEX and current mobile CAPEX in the two-step GMM estimation. This may impact our estimation because the lagged dependent variable as a predictor in a regression model is likely to correlate with the fixed effects included in the residual term of the model. This is called the Nickell bias, which means we cannot use the fixed effects model and must use dynamic panel data to solve the problem. Therefore, we may use dynamic panel data or static panel data depending on whether the Nickell bias is present.

4. Panel data

The panel data is selected from both developing and developed countries among 13 countries, including Belgium, the Czech Republic, France, Germany, Lithuania, Malta, the Netherlands, Norway, Slovenia, Sweden, Switzerland, Turkey, and Thailand. Each country is observed for a consecutive 10 years (2013 – 2022).

Table 1 shows the dependent and independent variables in our data, as well as their descriptions and sources. Meanwhile, Table 2 represents the details of descriptive statistics of the variables. Note that all data are at the country level and recorded in Euro currency at the end of the year. The panel data is highly balanced, with the exception of one missing data point out of a total of 130 observations. Specifically, there is a lack of data for spectrum fees and spectrum availability for Slovenia in 2013.

Table 1: Variables, descriptions, and sources used in our panel data

Variables	Description	Sources
CAPEX	The total amount of money spent on mobile capital investments during the specified period.	GSMA
HHI	A commonly accepted measure of market concentration, typically depicted on a scale ranging from 0, indicating evenly distributed competition, to 10,000, indicating no competition.	
ARPU	The weighted average of total Average Revenue Per User (ARPU) for Mobile Network Operators (MNOs) operating within the market.	
Urban population	Urban population denotes people living in urban areas as defined by national statistical offices.	World Bank
GDP	GDP at purchaser's prices equals the combined gross value added by all domestic producers, inclusive of any product taxes and exclusive of any subsidies not accounted for in product values.	
Spectrum fees	The prices for spectrum allocated to telecommunication operators through auctions divided by its duration.	Cullen international spectrum
Spectrum available	The amount of megahertz (MHz) acquired by operators through auctions.	

Table 2: descriptive statistics of our variables

Variable	Obs.	Mean	Std. Dev	Min	Max
CAPEX (Euro Mil.)	130	1,169.50	1,501.94	20.14	5,512.21
HHI	130	3380.24	558.89	2,138	4,541
ARPU (Euro/User)	130	15.52	8.03	0.51	38.69
Urban population (%)	130	77.29	13.85	46.19	98.15
GDP (Euro Mil.)	130	755,928.7	943,808.2	7,675.88	3,814,659
Spectrum fees (Euro Mil.)	129	324.49	447.51	0.32	2207.88
Spectrum available (MHz)	129	853.91	877.20	90	4205

5. Empirical analysis

Assuming there is no correlation between the error terms and the lagged dependent variable, we can construct the equation in the log-log transformation of panel data as the following equation, where i represents the country and t represents the year of observation:

$$\ln(\text{CAPEX}_{it}) = a_0 + a_1 \ln(\text{HHI}_{it}) + a_2 \ln(\text{ARPU}_{it}) + a_3 \ln(\text{Urban population}_{it}) + a_4 \ln(\text{GDP}_{it}) + a_5 \ln(\text{Spectrum fees}_{it}) + a_6 \ln(\text{Spectrum available}_{it}) + e_{it}$$

We evaluated the relationship between CAPEX and several independent variables, including concentration in HHI, ARPU, urban population, GDP, and spectrum availability. We intend to use both fixed effects panel data model and random effects panel data model, and then choose the appropriate model using the Hausman test. Furthermore, we also developed a pooled OLS model to estimate the differences between OLS and panel data models. Note that we used the robust command in Stata to address heteroscedasticity.

Table 3: results of pooled OLS, fixed effects panel data and random effects panel data

Variable	(1)	(2)	(3)
HHI	-1.38 *** (0.26)	0.17 (0.24)	-0.68 (0.49)
ARPU	0.63 *** (0.04)	0.99 *** (0.08)	0.79 *** (0.08)
GDP	0.79 *** (0.05)	0.08 (0.07)	0.80 *** (0.10)
Urban population	-1.43 *** (0.20)	5.87 *** (1.66)	-1.38 * (0.71)
spectrum fees	0.07 *** (0.03)	-0.07 *** (0.24)	-0.004 (0.04)
spectrum available	-0.10 * (0.06)	0.12 ** (0.58)	0.07 (0.07)
F-test/Wald chi2	553.88	74.64	1044.71
Within R-square		0.57	0.37
Between R-square		0.01	0.94
Overall	0.95	0.01	0.92

Standard errors are in parentheses

*** $p < 0.1$, ** $p < 0.05$, * $p < 0.1$

Table 3 (Column 1) presents the results of the pooled OLS model. Most of the independent variables are strongly significant for CAPEX, while only spectrum availability is somewhat significant. Spectrum fees have a positive effect on CAPEX, contradicting our assumption that they may have a negative effect or be insignificant. Similarly, the urban population and available spectrum also show a negative sign, which we thought should be positive because telecommunication operators are likely to expand their infrastructure following urbanization and seek more spectrum in their portfolio, coupled with investments to address the demand for

spectrum usage. The rest of the correlations follow our assumption, with the negative sign of market concentration and positives for both ARPU and GDP.

Table 3 (Column 2) represents the results of the fixed effects panel data model. HHI and GDP are not significant factors for telecommunication investment. However, the remaining variables show strong or moderately significant correlations with the expected direction. ARPU and urban population exhibit strong significance with a positive sign, followed by spectrum availability with a moderate positive correlation. Furthermore, spectrum fees have a strong, negative, and significant impact on CAPEX.

Table 3 (Column 3) presents the results obtained from the random effects panel data model. HHI, spectrum fees, and spectrum availability are not significant in this model. However, ARPU and GDP show strong significance with a positive sign. The urban population is also significant but in a negative direction, contradicting our assumption. Overall, ARPU shows strong significance and positivity in all three models. GDP also exhibits a positive sign and strong significance, while the results of spectrum fees and the rest remain ambiguous.

Then, we tested the appropriate model using the Hausman test. The result showed that the p-value is lower than 0.05. Thus, we reject the null hypothesis that the error is not correlated with the explanatory variable and prefer the fixed effects panel data model over the random effects panel data model. However, prior CAPEX might influence current CAPEX. We therefore need to investigate the correlation between the error term in the model and prior CAPEX. We found that there is a correlation between them. As a result, we employ the dynamic panel model: a one-step system GMM model.

Table 4: the results of a one-step system GMM model

Variable	(4)
Prior CAPEX	0.35 ** (0.14)
HHI	-0.92 * (0.45)
ARPU	0.37 *** (0.10)
GDP	0.54 *** (0.12)
Urban population	-1.04 *** (0.31)
spectrum fees	0.02 (0.04)
spectrum available	0.02 (0.04)
AR (1)	Z = -2.43 Pr > z = 0.015
AR (2)	Z = 0.02 Pr > z = 0.987
F-test	735.4

Standard errors are in parentheses

*** p < 0.1, ** p < 0.05, * p < 0.1

Table 4 presents the results obtained from a one-step system GMM model. We utilized the Stata command "xstrabond2" to generate unconstrained lags for constructing the instrument matrix, and robust variance-covariance matrix estimation was applied in the model implementation. The analysis reveals strong significant correlations between CAPEX and variables such as ARPU, urban population, and GDP. Despite the negative correlation with urban population, telecom operators may still need to comply with spectrum auction requirements to expand infrastructure into rural areas. Additionally, our predictions regarding prior CAPEX and market concentration (HHI) were validated, with prior CAPEX demonstrating a positive association and market concentration exhibiting a negative one. However, the model did not yield significant evidence regarding the impact of spectrum fees and spectrum availability.

6. Conclusion

We conducted a thorough analysis using a dataset spanning 13 countries from 2013 to 2022, focusing on the relationship between spectrum fees and CAPEX in the telecommunications sector. Our study also incorporated variables such as HHI, ARPU, GDP, urban population, and spectrum availability to explore their effects on CAPEX.

We employed four different models, including pool OLS, fixed effects panel data, random effects panel data, and a one-step system GMM model. Under the hypothesis tests, we preferred a one-step system GMM model to analyze our assumptions.

Our findings revealed strong positive correlations between prior CAPEX, ARPU, and GDP with CAPEX, while HHI and urban population showed negative correlations. Despite most factors aligning with our assumptions, urban population exhibited an unexpected direction, possibly due to regulatory policies favoring rural infrastructure development. Regrettably, we couldn't establish quantitative evidence linking spectrum fees and availability directly to telecommunications investment.

To enhance our model and address its limitations, several adjustments and considerations are necessary. Firstly, the small sample size of $N=13$ and $T=10$ calls for a larger sample size to construct a more reliable GMM system model. Increasing the sample size would improve the robustness of our analysis.

Secondly, incorporating additional dependent variables and instruments into our model, such as previous revenues or regulatory policies, could provide more insight into the relationship between spectrum fees, spectrum availability, and CAPEX. These variables could help capture the broader economic and regulatory context within which telecommunications companies operate.

Thirdly, focusing on firm-level panel data by examining CAPEX for each specific firm could offer a more granular understanding of investment patterns. However, this approach may present challenges in obtaining and interpreting CAPEX data accurately, as it can be influenced by factors such as cash flow or depreciation of fixed assets.

Lastly, our analysis did not thoroughly explore the potential impacts of high spectrum fees on company revenues and consumer prices. Investigating these effects could provide a more

comprehensive understanding of the implications of spectrum fees on both industry dynamics and consumer welfare.

Overall, while our model represents an initial step in examining the relationship between spectrum fees and CAPEX, further studies should address these limitations to yield more conclusive results. By considering these adjustments and limitations, future research can build upon our findings to develop a more refined understanding of this complex relationship.

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Appendix. (Diagnostics)

Performing regression analysis using all variables included in the main equation.

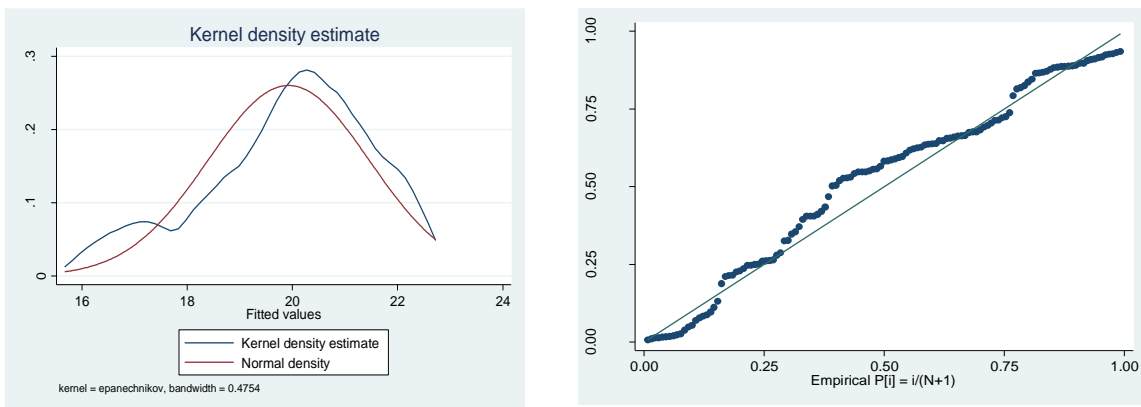


Fig A1: Kernel density plot (left) and standardized normal probability (p-P) plot (right)

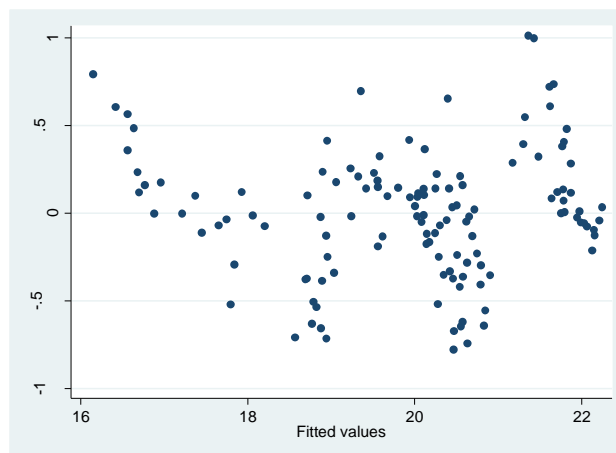


Fig A2: Plot of residuals vs. fitted values

Table 1A: White test results decomposition

Source	Chi2	Df	p
Heteroscedasticity	79.32	27	0.00
Skewness	16.43	6	0.01
Kurtosis	0.20	1	0.65
Total	95.96	34	0

We plot the residuals in Fig. 1A and find that they do not follow a normal distribution. Additionally, we examine the residual versus fitted values plot in Fig. 2A to observe heteroscedasticity. Consequently, we confirm heteroscedasticity in our model, as indicated in Table 1A, where White's test rejects the null hypothesis of homoscedasticity. Therefore, we employ the Stata command "robust" to address this issue.

We establish three models: pooled OLS, fixed effects panel data, and random effects panel data, using the robust command as explained in Section 5. Fixed effects are applied when certain individual-specific factors are assumed to influence or bias the predictor or outcome variables, necessitating their removal to assess the true impact of the predictor on the outcome. Conversely, random effects are employed when entity-level variations are perceived as random and unrelated to the predictor or independent variables in the model. To determine which model to use, we conduct the Hausman test, as shown in Table A2.

Table A2: Hausman test results

Variable	Coefficients			
	(b) fixed	(B) random	(b - B) difference	sqrt (diag (V_b-V_B)) S.E.
lnHHI	0.17	-0.68	0.85	0.2
lnARPU	0.99	0.79	0.20	0.08
lnGDP	0.08	0.80	-0.72	0.138
lnUrbanpop	5.87	-1.38	7.25	1.71
lnSpectrumfees	-0.068	-0.003	-0.065	
lnSpectrumav	0.12	0.07	0.05	0.02

Test: Ho: difference in coefficients not systematic

Chi2: 48.95

Prob > Chi2 = 0.00

The Hausman test rejects the null hypothesis, indicating that fixed effects panel data is preferred. However, we need to test whether the lagged dependent variable (CAPEX lagged) is correlated with the error term. If the correlation exists, we cannot utilize static panel data and would instead prefer dynamic panel data.

Fig A3: Correlation error term and lagged dependent variable test

```
pwcorr e L.lncapex , star (0.05) sig
```

	e L.lnca~x	
e	1.0000	
L.lncapex	0.1963*	1.0000
	0.0339	

Considering Fig. A3, there is a correlation between the error and the lagged dependent variable. Consequently, we prefer the dynamic panel data model over the static panel data model.

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