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Telecommunications and adoption of Pix in Brazil

Undergraduate Thesis

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I hereby declare that this work is my own and that I did not resort to any form of external assistance in its preparation, except as authorized by the academic advisor.

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Abstract

"Telecommunications internet and adoption of Pix in Brazil" In this study we observe if Pix forced telecommunications companies to expand their 4G coverage and improve service quality in municipalities lacking access to a bank branch. Using a Differences-in-Differences aproach we consider municipalities without any bank branch as a control group for the municipalities with one branch only and compare before and after Pix introduction. Our analysis focuses on the number of telecom operators and 4G service quality, providing insights into the indirect effects of Pix on market dynamics and infrastructure development in underserved areas. Our main regression shows highly significant coeficients for the effects pix had on the number of operators after its introduction, while regressions focusing on the quality of 4G shows no difference in it´s quality.

Keywords

Pix; Telecommunication; Dif-in-Dif; Financial inclusion; Brazil.

CONTENTS

1 Introduction

The Pix system was introduced by the Brazilian Central Bank on 19th February 2020, but only available to the population in November of the same year, as an efficient, competitive, safe and inclusive bank transfer method. It is widely regarded as one of the most efficient banking transfers systems in the world. After the official launch on November 2020, data availability began immediately, as the system was fully operational and widely adopted from the start. The consequences go from an acceleration in transaction speed, it reduced costs from transfers to zero, it gave access to financial transfers for almost anyone with a phone and internet connection, and is safe for users (BRASIL, 2020). Though it's widely acknowledged that Pix is advantageous Almeida2021, few are aware of its implications in different sectors, especially its impact on the telecommunications system.

Brazil has 4 big telecommunication enterprises that represent more than 95% of the Brazilian market (TELECOMUNICAçõES, 2020). Claro, Vivo, Tim, and Oi represent a modern day oligopoly that determine the internet broadband market. The advances made in one company are quickly absorbed by the others given their competition, proximity and facility to incorporate the technology in the sector. Although the covered area from all four and their qualities are similar, the objective is to observe if they changed with the incentive of gaining clients with the use of Pix. Specifically, the increased demand for digital financial accessibility facilitated by Pix prompted the companies to expand their 4G coverage and enhance service quality in these financially neglected areas.

The Brazilian market presents several key advantages for this study. Firstly, Brazil benefits from Pix, also its vast territorial expanse, diversity and cultures offer a rich context for exploring how competition in the telecom sector evolves and how market players seize the opportunities presented to them. Furthermore, ANATEL plays a crucial role in regulating the service quality, stimulating competition and encouraging innovation (SARKISYAN, 2020).

Using five different databases, our approach is a Dif-in-Dif regression using municipalities without access to a bank branch as a control group and with access as treatment; this study aimed in interpreting the Pix as an incentive for the telecommunications companies to expand their coverage and mantain a competitive outlook with this catalyst for new profits.

In this study we utilized data from five distinct databases to conduct a Difference-in-Difference analysis, it examined the impact of Pix's introduction in Brazil on the telecommunications sector. Municipalities with and without access to bank branches were compared before and after Pix's implementation, to see if the telecom operators responded to the introduction of Pix as an incentive for expanding their coverage area and 4G quality.

Motivation

The introduction of Pix in the Brazilian economy during the pandemic had diverse consequences to its players. This paper aims to contribute to the research around the implementation of Pix and its effects on major telecommunications companies. The results will collaborate with an investigation on whether Brazilian telecommunications companies were motivated to respond to the implementation of Pix and how this shaped the sector. The analysis focuses both on its extensive margin and its intensive margin; it is relevant to understand how Pix affected the coverage of 4G as well as its service quality respectfully. Additionally, it is important to consider that these improvements have enhanced the lives of residents in marginalized municipalities.

There are more than 2000 municipalities in Brazil that didn´t have any bank branches at the time of the study. This exclusion from typical banking system shows how a large part of Brazil suffers from inefficiencies and delays in important social developments. It is also important to note that Pix ends most of this problems, with instant and free transactions, most small businesses benefited greatly from its usage.

Understanding the impacts of Pix is crucial not only for telecommunications companies but also for public policies and the economic development of neglected regions. Brazil has one of the highest number of smartphones per person, with 249 million devices (FGV Portal, 2024), showing the relevance of this impact. This study presents insights into how financial infrastructure can promote digital inclusion and improve the quality of life in communities previously excluded from the traditional banking system.

2 Data

The data gathered comes from public Brazilian organs such as ANATEL (Agência Nacional de Telecomunicações), its Central Bank, SUS (Sistema Único de Saúde) and IBGE (Instituto Brasileiro de Geografia e Estatística). All sources are official, ensuring the credibility and accuracy of the information used. This data have been used extensively in other studies, ANATEL in (SILVA et al., 2021), ESTBAN in BCBStudy, Pix in (FERREIRA; SILVA, 2022), SUS in (CARVALHO; SOUZA, 2023) and IBGE in (MARTINS; NASCIMENTO, 2020).

ANATEL has an extensive database on the quality of broadband internet across all of Brazil's municipalities. ANATEL has been required to keep track of the service's quality monthly after it was published in the 'Official Gazette of the Union' in 2015. The data collects the quality of voice calls, 2G, 3G and 4G monthly from August 2012 to June 2022. It is relevant to note that the absence of data in some municipalities means no telecommunication coverage. (Anatel - Agência Nacional de Telecomunicações, 2024)

Another database used is from ESTBAN. Brazilian regulations require BCB to collect monthly hundreds of information about bank branches in all of Brazil's municipalities. This information can be accessed at their website, the municipalities can easily be identified utilizing their unique ID. (Banco Central do Brasil, 2024b)

All of Pix data is stored at DICT, which is a large database containing all information about Pix transactions. The BCB publishes monthly data divided by the number of transactions received and made per municipality, and whether they involve an individual or corporate entity. Notably, data availability began in November 2020, marking the point at which Pix became fully implemented and started generating measurable impacts even in smaller municipalities. (Banco Central do Brasil, 2024a)

The fourth database comes from SUS, Brazil's public health system. During the pandemic, they developed this website to be the official communication vehicle about the COVID-19 pandemic developments. The data was updated daily by the Ministry of Health through official information provided by the State Health Departments of the 27 Brazilian Federative Units. The data gathered shows new cases and deaths for each municipality from February 2020 until 2024. It is available at the "Coronavírus Brasil" website. (Ministério da Saúde, 2024)

The fifth database merges IBGE's estimates of the population per municipality and the actual census. The population estimates provided by IBGE were relevant for my analysis of municipal populations in Brazil from 2017 to 2021. These annual estimates, based on statistical methodologies, offer a consistent approximation of population size, filling the gap between the decennial census operations. (IBGE - Instituto Brasileiro de Geografia e Estatística, 2024).

The census is the most comprehensive demographic survey conducted every ten years, it provides detailed and accurate information about the population and its characteristics. In 2022, with the new census results available, I prioritized it over the annual estimates to ensure precision and alignment with the most recent demographic reality. The estimates are available at IBGE (2022).

The coverage across Brazil´s 5570 municipalities in the five datasets was near perfect, as they originate from official government sources. Below, I present a table summarizing the results.

Table 1 – Municipal coverage across datasets.

	Total Municipalities	Used	Not Used
ANATEL Dataset	5570	5569	1
ESTBAN Dataset	3430	3428	2142
COVID Dataset	5570	5569	1
Pix Dataset	5569	5569	1
Population Dataset	5570	5569	1

The table summarizes the utilization of the merged data. The ESTBAN dataset shows data only from municipalities that have access to a bank branch, calling attention to the 2142 other municipalities that don´t have. It is noticeable that our merged dataset ex ESTBAN, has only one municipality not explored in common, emphasizing the quality of the dataset used.

3 Methods

To enhance comprehension of the data we have a Descriptive Statistics table containing the mean, standard deviation and number of observations from municipalities with zero and one bank branches, followed by a Two-Tailed T-test statistic and difference (including statistical significance) between those municipalities. Those means were all in accordance with our previous expectations of the data. Based on this descriptive analysis, we classify municipalities with one bank branch as treatment and those without any bank branch as control. This classification serves as the foundation for a Differences-in-Differences approach, enabling the comparison of changes in telecommunication outcomes between these two groups before and after Pix's introduction. The central assumption guiding this analysis is that, in the absence of Pix, treated and control municipalities would have followed parallel trends in the number of telecom operators and 4G quality. While exact equivalence between treated and control cities is not necessary, having similar baseline characteristics bolsters the credibility of the parallel trends assumption and strengthens our empirical strategy.

The treatment and control group were chosen because they share similar structural characteristics, infrastructure, economic activity, limited access to public services and lower population density while differing in the access to the Brazilian banking system. However, having one branch indicates slightly better financial inclusion and economic activity. This difference creates a useful comparison point for studying Pix's effects. By comparing these similar groups, we can better isolate the impact of Pix, minimizing other factors that could influence the results and showing how even basic financial infrastructure can affect market dynamics.

This approach aligns with findings by Juliano (2013), who documented how the number of bank branches in Brazil increased significantly in the past but later declined due to the growth of correspondent banking services. This change shows how financial inclusion in Brazil has developed over time and emphasizes that even a single bank branch can play a key role in shaping local economic activity and improving access to financial services, making it a strong point of comparison for this study.

In the next section, we further explore the differences between the two groups through regression analysis. However, balancing of covariates between two groups are not required for some statistical methods, for instance we are going to apply the Differences-in-Differences methodology. This method requires a weaker assumption that is called parallel trends. This approach allows us to estimate the impact of the presence of a bank branch on the analyzed variables.

$$NumberOfOperators_{m,t} = \beta \cdot Pix \times Access_{m,t} + \alpha \cdot Access_{m,t} + \Gamma' X_{m,t} + \gamma_m + \theta_t + \varepsilon_{m,t}$$

The dependent variable Ym,t is the number of operators, located at municipality m, during month-year t; Beta captures the effect of the dummy Pix when the municipality has at least one bank branch; the alfa captures the effect of having access to a bank branch; Gamma is a control vector for relevant variables such as covid-related variables, population and a dummy for monopolies; gamma captures the fixed effects of municipalities; theta represents the fixed effects of time; varepsilon is the error.

In a subsequent analysis we separate the Pix variable into a set of dummy variables accounting for each month-year in our dataset. Thus, we are able to observe the dynamic effect of Pix comparing municipalities with one x zero commercial bank branches. It is also interesting to turn Pix into a continuous variable by the number of Pix transactions per municipality, this way its effect will be focused and directly linked to the actual effects of Pix.

$$NumberOfOperators_{m,t} = \beta_0 + \sum_{t \neq 202011} \beta_t \cdot Dates_t \cdot DummyAccess_m + \beta_2 \cdot Population_{m,t} + \beta_3 \cdot MonopolyOperator_{m,t} + \beta_4 \cdot LogNewCovidCases_{m,t} + \Gamma' X_{m,t} + \gamma_m + \theta_t + \varepsilon_{m,t}$$

The dependent variable Number of Operators is the number of telecommunication operators on the municipality m during month year t, regarding we used information from Vivo, Claro, Oi and Tim. Beta 0 represents the expected number of operators in a municipality with no bank branch access. The next section is a sum of the interaction between dates and a Dummy representing access to one bank branch, These coefficients capture the effects of having no bank branch on the number of operators before and after the introduction of Pix, the Beta 2 captures the effects the size of the population, Beta 3 captures the effects on municipalities with only one operator prior to Pix, Beta 4 reflects the effects of the COVID-19 pandemic. Gamma is a control vector for relevant variables such as Covid-related variables, population and a dummy for monopolies; gamma captures the fixed effects of municipalities; theta represents the fixed effects of time; varepsilon is the error.

For this regression to be possible data from five different databases were merged together by the municipality id and date from 2018-01 until 2022-06, basing our identification strategy on (FONSECA; MATRAY, 2022). The data is rich in possible control variables and facilitate various analyses, such as if the bank branch was public or private or if pix was made from citizens or legal entities.

The merged dataset had to be adjusted for the regressions, all variables, except the broadband internet data, had to be logarithmically adjusted for visualization means with log(1+x). We also grouped the municipalities by the number of agencies as of a specific date, and used the averages of these municipalities for the calculations of the broadband quality.

For further understanding of the behavior presented by our variables, we have plotted different graphs, as the ones below to better understand existing trends.

In Figure 1 we can see an existing negative trend driving 4G quality, the pandemic doesn´t

Figure 1 – Average 4G Quality by Telecom Companies in Municipalities with 0 and 1 Branch

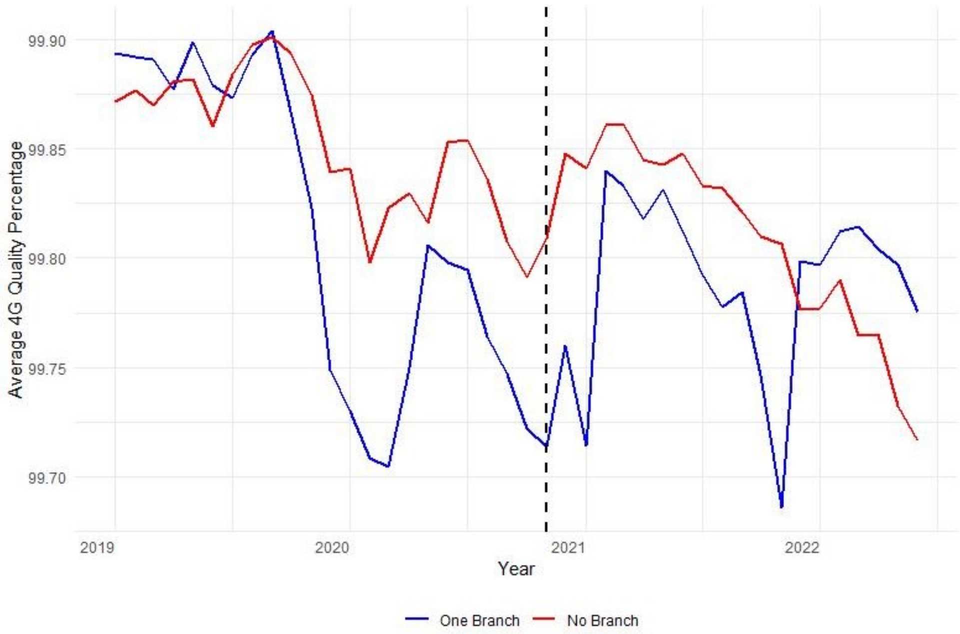
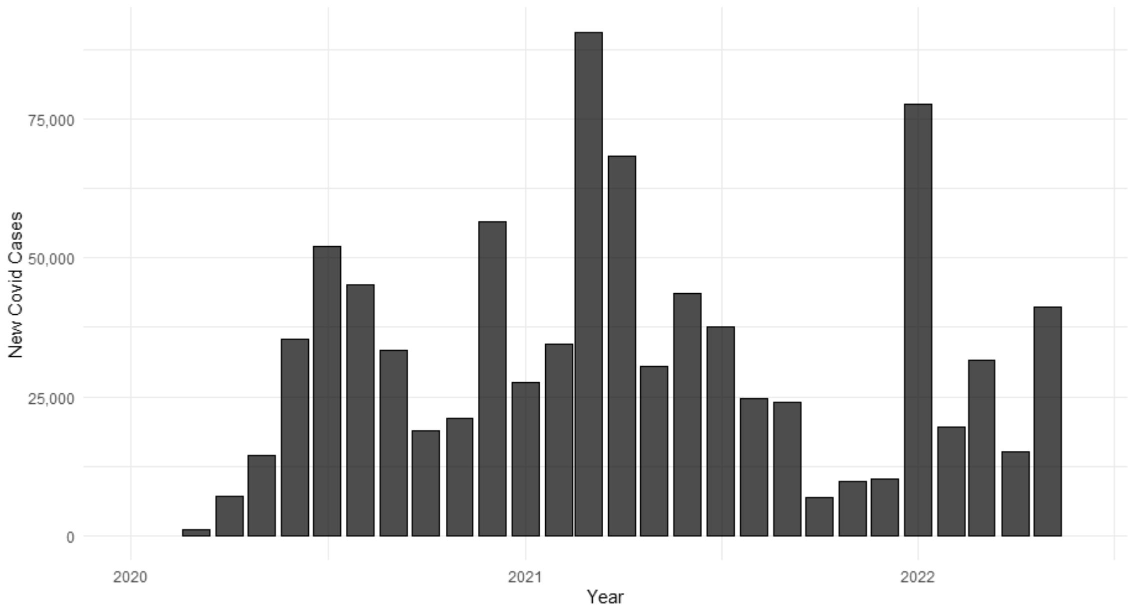


Figure 2 – New Covid Cases



seem to affect this metric. It is visible that municipalities with one and zero branches follow the same tendencies and respond in similar intensities to shocks. It seems municipalities with no branches display slightly higher quality levels, the difference is marginal, ranging between 99.8% and 99.9%, making it practically insignificant in the context of overall service quality. On Figure 2 we show our data for New Covid Cases, clearly showing different waves of the virus that hit the country.

Figure 3 – Average Log of New COVID-19 Cases by Bank Branches

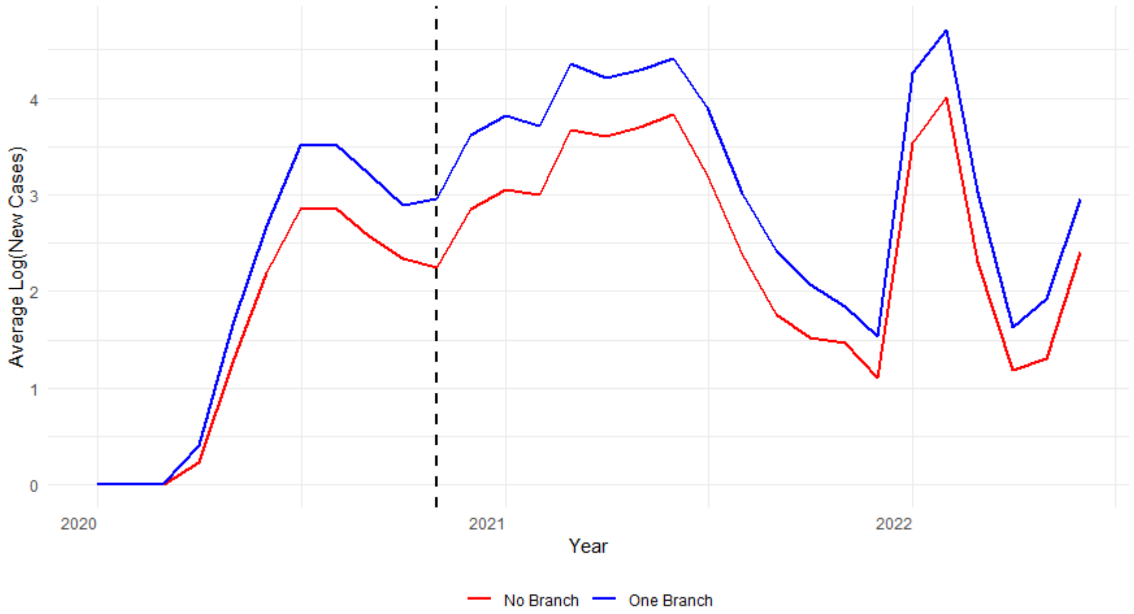


Figure 4 – Average Log Value of Individual Pix Payers by Bank Branches

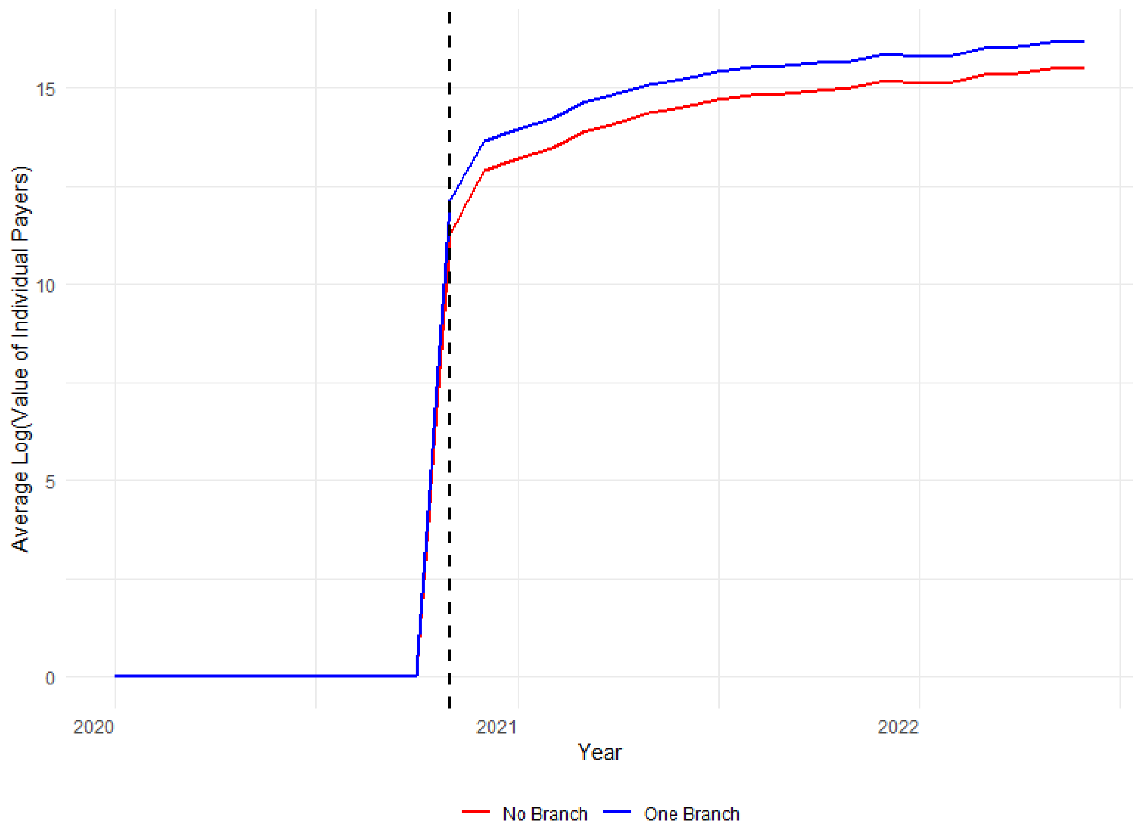


Figure 3 shows that municipalities with access to one bank branch experienced a higher number of COVID-19 cases than the ones without. It is also relevant to indicate that the tendencies seem parallel, with both groups responding similarly in magnitude to external shocks. In Figure 4 the parallel trend is even more explicit in both groups, the number of transactions have exploded since the introduction and expanded continually afterwards.

4 Results

In this study, we performed a Differences-in-Differences regression analysis as outlined in the Methods section. Three main regressions were conducted to evaluate the impact of the introduction of Pix. The first regression examines the introduction of Pix on the number of telecom operators per municipality, comparing municipalities with one and zero bank branches. This regression follows a classic Dfferences-in-Differences approach.

The second regression further explores the extensive margin of Pix's introduction by incorporating interactions between dates and bank branch access. This allows for a more detailed understanding of how Pix influences the number of telecom operators in marginalized municipalities. The third regression focuses on the intensive margin by analyzing the effect of Pix on the quality of 4G services, using the average 4G quality instead of the number of operators. This regression is structurally similar to the first but shifts its focus to a quality metric.

4.1 Descriptive Statistics

In the table presented, metrics are compared between municipalities with zero and one bank branch. For most variables, there are notable differences in averages and distributions between the two groups.

Table 2 – Descriptive Statistics

Variable	With One Branch			Without Branch			Two-tailed T-test	
	Mean	S.D.	Obs.	Mean	S.D.	Obs.	Difference	T-statistic
Average Operators	99.7980	0.9850	88 618	99.8140	0.6680	143 476	−0.0160***	−4.7370
Number of Operators	1.6460	0.9780	101 345	1.1000	0.8910	197 589	0.5470***	153.5530
Dummy Access	1.0000	0.0000	101 345	0.0000	0.0000	197 589	NA	NA
Pix Log Value for Individual Payers	15.1690	1.1990	35 369	14.4680	1.2640	71 304	0.7010***	86.7050
Pix Log Value for Corporate Payers	14.0830	1.6610	35 369	12.9190	2.1510	71 304	1.1650***	89.4600
Population	26 893.4610	139 476.9630	101 327	20 165.1970	124 794.9000	197 583	6728.2640***	13.3990
Operator Monopoly	0.3290	0.4700	101 345	0.4270	0.4950	197 589	−0.0980***	−52.2470
Log of New Covid Cases	1.4570	1.9350	99 217	1.2080	1.6920	192 764	0.2490***	35.8460

The variable "Average Operators" shows a slightly higher mean for municipalities without agencies 99,814 compared to those with agencies 99,798, though the difference is minimal - 0,016 it is statistically significant (t = -4,737 and P-Value <0,0001). Similarly, the variable "Number of Operators" is considerably higher in municipalities with one bank branch 1,646 than in those without 1,1, with a substantial difference of 0,547 (t = 153,553, P-Value <0,0001), suggesting that agencies are located in areas with better telecommunication infrastructure. The "Dummy Access" variable, representing access to a banking branch, shows no variability across observations, with a mean of 1 for those with agencies and 0 for those without, as expected.

The variable “Pix Log Value for Individual Payers” shows a higher mean in municipalities with agencies 15,169 compared to those without 14,468. The difference of 0,701 is statistically significant (t = 86,705, P-Value <0,0001), indicating a concentration of financial activity in municipalities with agencies and highlighting how Pix affected municipalities excluded from traditional banking (MOURA; CASTRO, 2021). A similar trend is observed for “Pix Log Value for Corporate Payers”, where municipalities with one branch have a mean of 14,083 compared to 12,919 in those without, with a difference of 1,165 (t = 89,460, P-Value <0,0001).

Population, as expected, is significantly higher in municipalities with bank branch 26,893 compared to those without 20,165, highlighting the correlation between branch presence and population density (t = 13,399, P-Value <0,0001). Conversely, the variable “Operator Monopoly” shows slightly higher values in municipalities without access to bank branch 0,427 compared to those with access 0,329, with a significant difference of -0,098 (t = -52,247, P-Value <0,0001), implying reduced competition in underserved areas.

Lastly, “Log of New Covid Cases” shows a higher mean in municipalities with one branch 1,457 compared to those without 1,208. The difference of 0,249 is also statistically significant (t = 35,846, P-Value <0,0001), which may reflect the influence of population density on case numbers.

In summary, the table highlights clear and significant differences between municipalities with and without a bank branch across multiple dimensions. These differences are essential for understanding our dataset, as well as their implications for telecommunication and financial systems.

4.2 Regressions

4.2.1 Differences-in-Differences

In this analysis, we divided our Pix variable into Individual Payers and Corporate Payers to gain deeper insights into the implications of Pix implementation. The dependent variable in our study is the number of telecom operators per municipality. To ensure robustness, we control for key factors such as access to bank branches (Dummy Access), population size (Population), operator monopoly (Operator Monopoly), the log of new COVID-19 cases (Log of New Covid Cases), as well as fixed effects for municipality (gamma) and date (theta). Additionally, we analyze the interaction between ”Pix Log Value for Individual Payers” and ”Dummy Access” to further explore the dynamics between Pix adoption and financial access.

$$Y_{m,t} = \beta \cdot Pix \times Access_{m,t} + \alpha \cdot Access_{m,t} + \Gamma' X_{m,t} + \gamma_m + \theta_t + \varepsilon_{m,t}$$

Table 3 – Individual Payers Dif-in-Dif

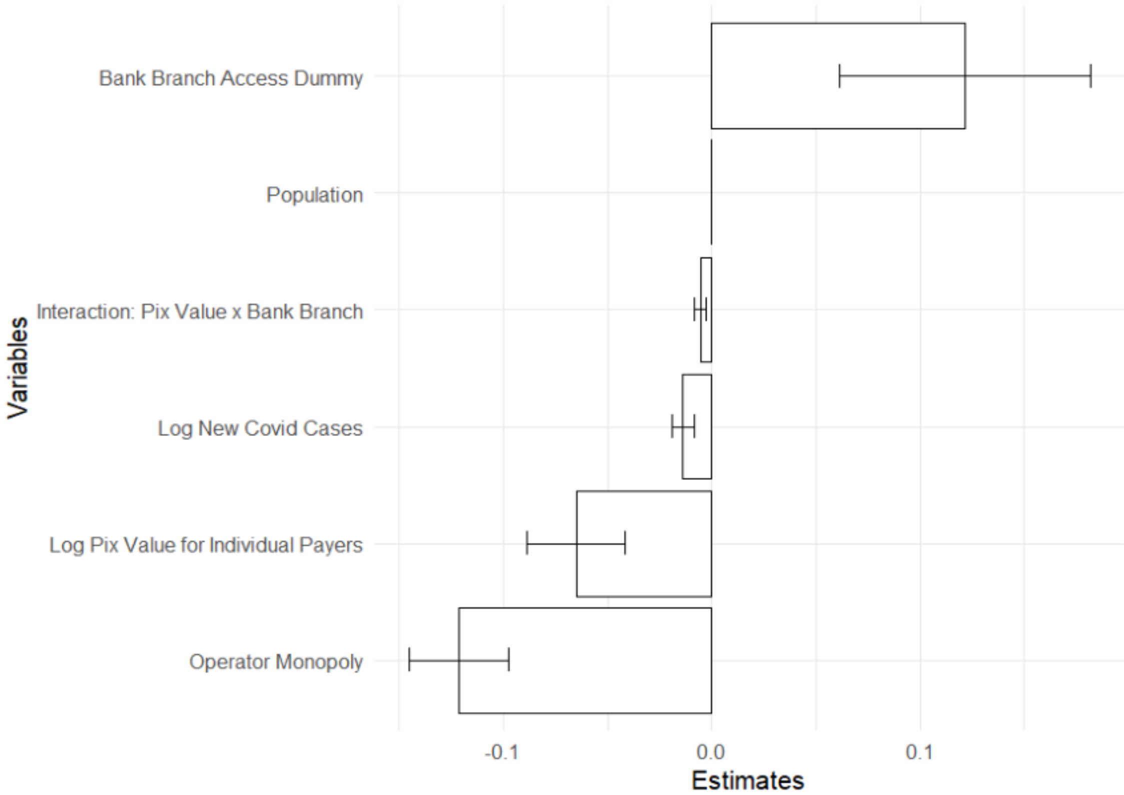
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Dependent Var.:	Number of Operators						
Constant	0.8882***						
	(0.0166)						
Pix Log Value for Individual Payers	0.0466***	0.0441***	0.1774***	-0.0628***	-0.0628***	-0.0693***	-0.0650***
	(0.0009)	(0.0008)	(0.0190)	(0.0123)	(0.0123)	(0.0121)	(0.0120)
Dummy Access	0.5996***	0.0566	0.6046***	0.1203***	0.1203***	0.1244***	0.1212***
	(0.0327)	(0.0313)	(0.0326)	(0.0308)	(0.0308)	(0.0307)	(0.0307)
Pix Log Value for Individual Payers × Dummy Access	-0.0084***	-0.0104***	-0.0147***	-0.0051***	-0.0051***	-0.0057***	-0.0055***
	(0.0017)	(0.0014)	(0.0019)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Population					-1.23e-10	-1.48e-10	-6.48e-11
					(5.64e-10)	(5.65e-10)	(5.4e-10)
Operator Monopoly						-0.1223***	-0.1211***
						(0.0120)	(0.0121)
Log of New Covid Cases							-0.0137***
							(0.0026)
Fixed-Effects:							
COD_IBGE	No	Yes	No	Yes	Yes	Yes	Yes
Dates	No	No	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered by: COD_IBGE	Clustered by: COD_IBGE						
Observations	278,984	278,984	278,984	278,984	278,984	278,984	277,170
R^2	0.18658	0.79167	0.22756	0.82712	0.82712	0.82895	0.82927
Within R^2	–	0.30767	0.10107	0.00902	0.00902	0.01956	0.02024

An increase of 1% in the Pix volume from individual payers is associated with a reduction of 0.065 in the number of telecom operators. This effect is more pronounced in municipalities with one bank branch, where the reduction intensifies to -0.0705, as indicated by the interaction term Pix Log Value for Individual Payers x Dummy Access. These findings suggest that while Pix promotes financial inclusion, its impact on telecom markets varies depending on access to financial infrastructure. It can be understood as a different aproach telecommunications companies had on expanding coverage in areas that would greatly benefit from it with the Pix implementation.

Similarly, the positive and significant coefficient for Dummy Access indicates that municipalities with bank branches have, on average, 0.1212 more operators than those without. This can be explains some of the differences of our two groups, even though they are very similar, access to a bank branch can have some relevant changes in infrastructure and development.

The control variables align with previous expectations. Higher monopoly concentration among telecom operators is associated with a reduction of 0.1211 in the number of operators, emphasizing the restrictive effect of market dominance on operator diversity. Additionally, a 1% increase in the Log of New Covid Cases correlates with a reduction of 0.0137 operators, reflecting the pandemic's penalizing impact on market expansion. Population remains statistically insignificant, showing minimal influence on the number of operators. Notably, except for Population, all coefficients are significant at the 0.1% level (***), reinforcing the robustness of these findings.

Figure 5 – Coefficient Plot of Individual Pix Payers Dif-in-Dif



We also examined a Coefficient Plot graph to further examine the impacts of each variable on our model. It is shown that the Dummy Access has the biggest Standard Deviation, and is the only positive variable. The Population control didn´t show any relevant results, The Pix and Monopoly variables had very significant coefficients, with some variation. The Pix x Dummy Access interaction and the COVID-19 control coefficients show very little standard deviation, showing the robustness of the findings.

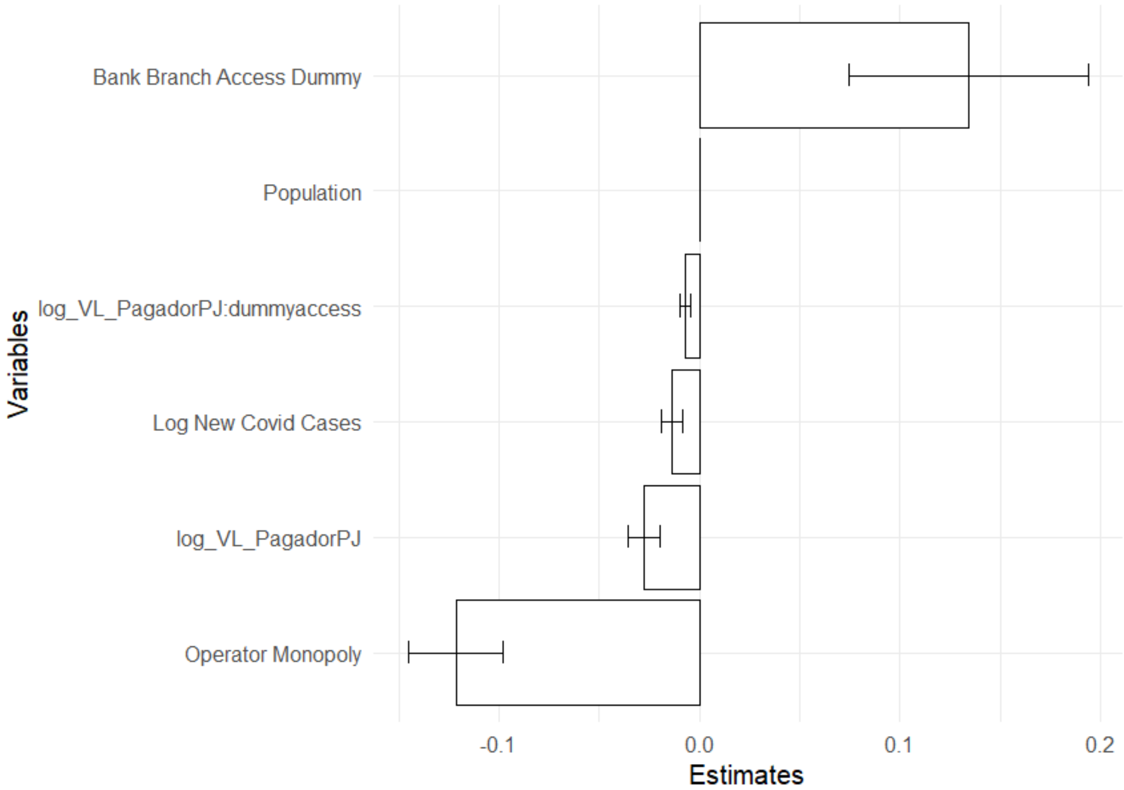
To ensure the robustness of the data we also examined the effects of Corporate Payers, as shown bellow. This variation of our regression deepens our study regarding whether individual payers and corporations. Individual Pix payments are likely to represent broader efforts toward financial inclusion, especially in financially excluded regions, while corporate transactions are more closely linked to business-related financial activities and may have distinct impacts on market dynamics. By separating both, we gain a clearer understanding of how Pix influences both individual and corporate behavior.

Table 4 – Corporate Payers Dif-in-Dif

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Dependent Var.:	Number of Operators						
Constant	0.8853***						
	(0.0164)						
Pix Log Value for Corporate Payers	0.0528***	0.0484***	0.1063***	-0.0264***	-0.0264***	-0.0294***	-0.0275***
	(0.0010)	(0.0009)	(0.0076)	(0.0041)	(0.0041)	(0.0041)	(0.0040)
Dummy Access	0.5992***	0.0601	0.5999***	0.1332***	0.1332***	0.1383***	0.1343***
	(0.0327)	(0.0317)	(0.0326)	(0.0306)	(0.0306)	(0.0306)	(0.0305)
Pix Log Value for Corporate Payers × Dummy Access	-0.0110***	-0.0124***	-0.0148***	-0.0067***	-0.0067***	-0.0074***	-0.0071***
	(0.0018)	(0.0015)	(0.0019)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Population					-9.6e-11	-1.18e-10	-3.58e-11
					(5.63e-10)	(5.64e-10)	(5.39e-10)
Operator Monopoly						-0.1226***	-0.1214***
						(0.0120)	(0.0121)
Log of New Covid Cases							-0.0137***
							(0.0026)
Fixed-Effects:							
COD_IBGE	No	Yes	No	Yes	Yes	Yes	Yes
Dates	No	No	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered by: COD_IBGE	Clustered by: COD_IBGE						
Observations	278,984	278,984	278,984	278,984	278,984	278,984	277,170
R^2	0.19231	0.79019	0.23146	0.82715	0.82715	0.82900	0.82931
Within R^2	–	0.30273	0.10561	0.00923	0.00923	0.01982	0.02047

An increase of 1% in the Pix volume from corporate payers is associated with a reduction of 0.0275 in the number of telecom operators, with this effect becoming more pronounced, 0.0346, when considering municipalities with one bank branch compared to those without, as shown by the interaction term Pix Log Value for Corporate Payers x Dummy Access. These results highlight how Pix influences corporate transactions differently across municipalities. Additionally, the number of operators is 0.1343 higher in municipalities with one bank branch, underscoring the significant role of financial infrastructure in fostering market competition. The second table confirms broadly consistent outcomes with individual payers, though corporate transactions display slightly more pronounced variations in intensity. The negative and significant coefficient for Pix Log Value for Corporate Payers (*** at 0.1%) mirrors its restrictive impact on operator numbers, while the interaction term suggests that Pix's influence on corporate payers amplifies disparities across municipalities. The results also reveal that higher monopoly concentration reduces the number of operators by 0.1214, while a 1% increase in the log of new Covid-19 cases leads to a 0.0137 reduction, reflecting pandemic-driven challenges. Meanwhile, Population remains statistically insignificant, showing minimal influence.

Figure 6 – Coefficient Plot of Corporate Pix Payers Dif-in-Dif



This coefficient plot is very similar as the one above, given the similarity of the regressions. It is visible the difference in the Pix variable using the corporate payers, it is clearly smaller, showing how the individual payers in financially marginalized municipalities were more relevant than the effect on the number of operators than the coporate ones. This supports our thesis that Pix played a more significant role in benefiting individuals in excluded municipalities rather than corporations.

4.2.2 Full Differences-in-Differences

The Differences-in-Differences Full regression serves as the main model in this study, highlighting the significant impact of Pix on the number of operators. Two regressions are presented in this section: one without control variables (Model 1) and one with controls (Model 2).

Model 1:

$$NumberOfOperators_{m,t} = \beta_0 + \sum_{t \neq 202011} \beta_t \cdot Dates_t \cdot DummyAccess_m + \Gamma' X_{m,t} + \gamma_m + \theta_t + \varepsilon_{m,t}$$

Model 2:

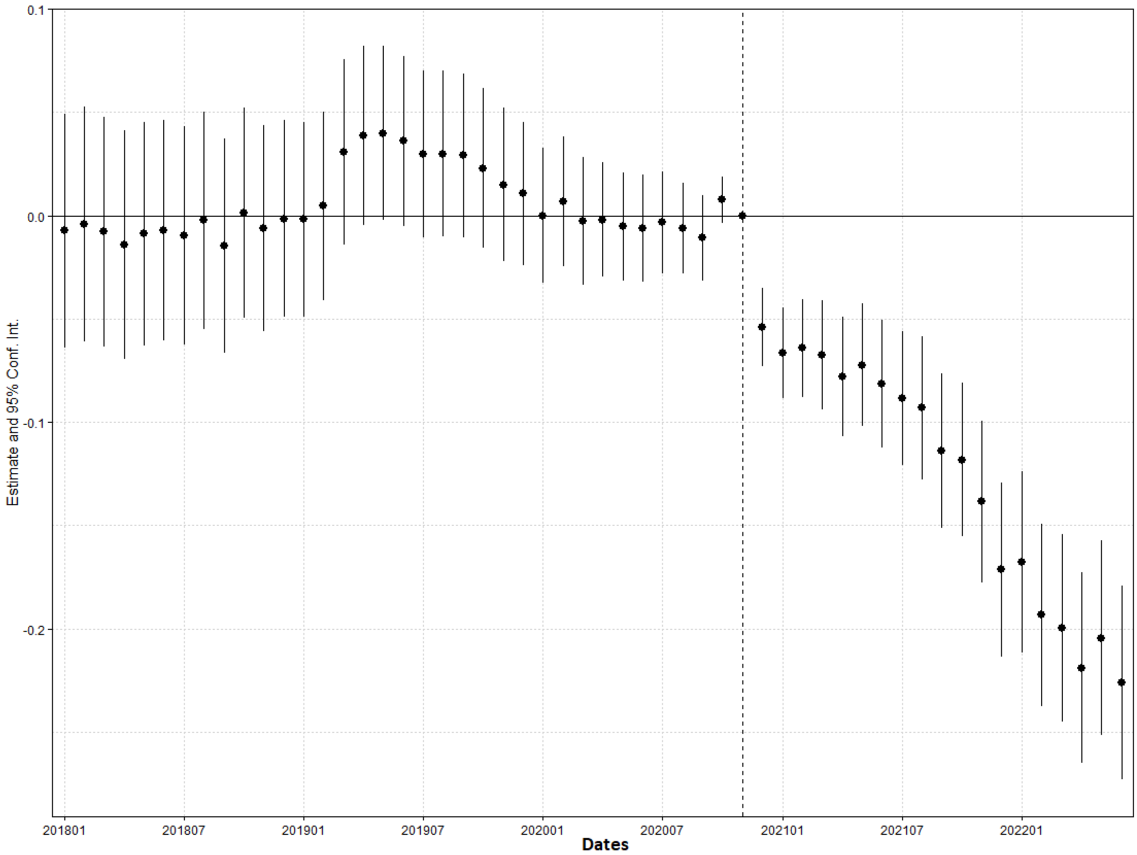
$$NumberOfOperators_{m,t} = \beta_0 + \sum_{t \neq 202011} \beta_t \cdot Dates_t \cdot DummyAccess_m + \beta_2 \cdot Population_{m,t} + \beta_3 \cdot MonopolyOperator_{m,t} + \beta_4 \cdot LogNewCovidCases_{m,t} + \Gamma' X_{m,t} + \gamma_m + \theta_t + \varepsilon_{m,t}$$

In these models, we explore the interaction between Dates and Dummy Access, capturing how the presence of a bank branch influences the number of operators over time, particularly in response to the introduction of Pix. To ensure consistency with previous models, we included the same control variables: municipality fixed effects (γ_m), month-year fixed effects (θ_t), and an error term (ε_{it}) to capture unexplained variation.

Table 5 – Full Difference-in-Difference

Dependent Var.:	Number of Operators	
	Model 1	**Model 2**
Dummy Access	0.1458*** (0.0326)	0.1435*** (0.0325)
Dummy Access x 201801	-0.0222 (0.0284)	-0.0074 (0.0288)
Dummy Access x 201802	-0.0182 (0.0286)	-0.0041 (0.0289)
Dummy Access x 201803	-0.0192 (0.0281)	-0.0078 (0.0284)
Dummy Access x 201804	-0.0252 (0.0280)	-0.0140 (0.0283)
Dummy Access x 201805	-0.0197 (0.0272)	-0.0087 (0.0276)
Dummy Access x 201806	-0.0170 (0.0269)	-0.0073 (0.0272)
Dummy Access x 201807	-0.0184 (0.0266)	-0.0098 (0.0270)
Dummy Access x 201808	-0.0111 (0.0266)	-0.0023 (0.0269)
Dummy Access x 201809	-0.0217 (0.0261)	-0.0146 (0.0264)
Dummy Access x 201810	-0.0049 (0.0258)	0.0013 (0.0260)
Dummy Access x 201811	-0.0101 (0.0252)	-0.0063 (0.0254)
Dummy Access x 201812	-0.0042 (0.0240)	-0.0015 (0.0243)
Dummy Access x 201901	-0.0030 (0.0236)	-0.0019 (0.0240)
Dummy Access x 201902	0.0035 (0.0229)	0.0047 (0.0232)
Dummy Access x 201903	0.0300 (0.0224)	0.0309 (0.0228)
Dummy Access x 201904	0.0386. (0.0218)	0.0388. (0.0222)
Dummy Access x 201905	0.0405. (0.0212)	0.0400. (0.0215)
Dummy Access x 201906	0.0368. (0.0207)	0.0360. (0.0210)
Dummy Access x 201907	0.0307 (0.0204)	0.0297 (0.0206)
Dummy Access x 201908	0.0321 (0.0201)	0.0300 (0.0204)
Dummy Access x 201909	0.0321 (0.0199)	0.0291 (0.0203)
Dummy Access x 201910	0.0260 (0.0194)	0.0229 (0.0197)
Dummy Access x 201911	0.0178 (0.0189)	0.0148 (0.0190)
Dummy Access x 201912	0.0163 (0.0176)	0.0106 (0.0178)
Dummy Access x 202001	0.0064 (0.0165)	-0.0001 (0.0167)
Dummy Access x 202002	0.0130 (0.0158)	0.0068 (0.0160)
Dummy Access x 202003	0.0054 (0.0155)	-0.0025 (0.0157)
Dummy Access x 202004	0.0037 (0.0140)	-0.0021 (0.0141)
Dummy Access x 202005	-0.0023 (0.0132)	-0.0052 (0.0134)
Dummy Access x 202006	-0.0051 (0.0132)	-0.0061 (0.0133)
Dummy Access x 202007	-0.0058 (0.0124)	-0.0033 (0.0125)
Dummy Access x 202008	-0.0068 (0.0109)	-0.0062 (0.0111)
Dummy Access x 202009	-0.0104 (0.0103)	-0.0107 (0.0106)
Dummy Access x 202010	0.0078 (0.0056)	0.0076 (0.0058)
Dummy Access x 202012	-0.0505*** (0.0097)	-0.0539*** (0.0097)
Dummy Access x 202101	-0.0637*** (0.0114)	-0.0663*** (0.0112)
Dummy Access x 202102	-0.0601*** (0.0123)	-0.0640*** (0.0121)
Dummy Access x 202103	-0.0635*** (0.0137)	-0.0677*** (0.0135)
Dummy Access x 202104	-0.0730*** (0.0150)	-0.0779*** (0.0147)
Dummy Access x 202105	-0.0668*** (0.0155)	-0.0724*** (0.0151)
Dummy Access x 202106	-0.0763*** (0.0163)	-0.0816*** (0.0158)
Dummy Access x 202107	-0.0841*** (0.0171)	-0.0883*** (0.0165)
Dummy Access x 202108	-0.0843*** (0.0182)	-0.0930*** (0.0177)
Dummy Access x 202109	-0.1091*** (0.0196)	-0.1139*** (0.0191)
Dummy Access x 202110	-0.1104*** (0.0195)	-0.1182*** (0.0190)
Dummy Access x 202111	-0.1276*** (0.0204)	-0.1384*** (0.0200)
Dummy Access x 202112	-0.1673*** (0.0220)	-0.1714*** (0.0214)
Dummy Access x 202201	-0.1673*** (0.0232)	-0.1678*** (0.0223)
Dummy Access x 202202	-0.1940*** (0.0236)	-0.1934*** (0.0226)
Dummy Access x 202203	-0.2046*** (0.0240)	-0.1997*** (0.0231)
Dummy Access x 202204	-0.2077*** (0.0246)	-0.2189*** (0.0236)
Dummy Access x 202205	-0.2053*** (0.0249)	-0.2044*** (0.0240)
Dummy Access x 202206	-0.2301*** (0.0251)	-0.2261*** (0.0240)
Population	–	-8.34e-11 (5.54e-10)
Operator Monopoly	–	-0.1165*** (0.0122)
Log of New Covid Cases	–	-0.0171*** (0.0028)
Fixed-Effects:		
COD_IBGE	Yes	Yes
Dates	Yes	Yes
S.E.: Clustered by: COD_IBGE	Clustered by: COD_IBGE	
Observations	279,064	277,242
R^2	0.82697	0.82907
Within R^2	0.00836	0.01922

Figure 7 – Pix introduction Effect on Number of Operators



As observed, the inclusion of controls does not significantly alter the degree of significance or the overall results, demonstrating the robustness of the findings. Notably, the interaction between Dates and Dummy Access sheds light on the evolution of the relationship between the presence of bank branches and the number of operators over time. The coefficients for the interaction terms indicate whether municipalities with bank branches experienced a distinct trend in the number of operators compared to those without branches. As is shown, they have no distinct impact on the number of operators prior to Pix. The increasingly negative and significant coefficients post November 2020 suggest an increase in competition, with operators potentially focusing efforts on municipalities without branches to access untapped markets; capturing how the treatment and control groups had significantly different behaviors after the introduction of Pix.

Overall, this regression supports the hypothesis that Pix played a significant role in shaping the number of operators on underserved municipalities, with results remaining consistent across models, reinforcing the robustness and validity of the conclusions. Its introduction has made municipalities without access to bank branches more competitive on the telecommunications sector, with the number of operators expanding exactly after the introduction of Pix. This change in dynamic shows how the financial developments helped to close gaps and improve access to important financial resources in areas that were previously excluded.

On the model with the control variables it is relevant to note that Population had no effect on the number of operators, the Operator Monopoly shows a negative coefficient, indicating the restricting effect on competition that municipalities with only one operator present, working as a kind of business moat (MAUBOUSSIN, 2002).

4.2.3 4G Quality instead of Number of Operators

This last section shows our efforts in finding intensive margin results. The same two regressions above were reassembled to see if the adoption of pix had any influence on the 4G quality of the municipality, instead of the number of operators. This analysis is very relevant to our study because it indicates whether the telecommunication companies expanded at the cost of the broadband quality or if they expanded maintaining quality in new municipalities.

Table 6 – Dif-in-Dif for Corporate Payers and 4G Quality

Dependent Var.:	**4G Quality**	
	Model 1	**Model 2**
Pix Log Value for Corporate Payers	-0.4633 (0.4264)	-0.3160 (0.3752)
Dummy Access	0.6738 (2.147)	0.4065 (2.229)
Pix Log Value for Corporate Payers x Dummy Access	0.1756 (0.2287)	0.2017 (0.2436)
Population		4.47e-8 (6.35e-8)
Operator Monopoly		0.4037 (2.257)
Log of New Covid Cases		-1.120 (0.7288)
Fixed-Effects:		
COD_IBGE	Yes	Yes
Dates	Yes	Yes
S.E.: Clustered	by: COD_IBGE	
Observations	223,315	221,606
R2	0.34635	0.34702
Within R2	8.73E-05	0.00035

Table 7 – Full Difference-in-Difference using 4G Quality

Dependent Var.:	4G Quality	
	Model 3	**Model 4**
Dummy Access	-4.372 (5.331)	-4.145 (5.358)
Dummy Access x 201801	17.47* (8.321)	16.81* (8.323)
Dummy Access x 201802	16.94* (7.943)	16.28* (7.947)
Dummy Access x 201803	14.90 (7.746)	14.22 (7.752)
Dummy Access x 201804	10.44 (7.031)	9.752 (7.036)
Dummy Access x 201805	7.053 (6.561)	6.358 (6.565)
Dummy Access x 201806	4.638 (6.173)	3.946 (6.171)
Dummy Access x 201807	-0.7347 (5.715)	-1.428 (5.715)
Dummy Access x 201808	2.294 (5.559)	1.597 (5.553)
Dummy Access x 201809	1.317 (5.641)	0.6179 (5.640)
Dummy Access x 201810	3.192 (5.336)	2.491 (5.336)
Dummy Access x 201811	5.506 (5.072)	4.794 (5.074)
Dummy Access x 201812	6.094 (5.095)	5.379 (5.101)
Dummy Access x 201901	6.536 (5.052)	5.817 (5.057)
Dummy Access x 201902	5.880 (5.031)	5.157 (5.035)
Dummy Access x 201903	6.373 (5.133)	5.648 (5.135)
Dummy Access x 201904	4.547 (5.259)	3.836 (5.251)
Dummy Access x 201905	5.845 (5.314)	5.127 (5.374)
Dummy Access x 201906	6.298 (5.566)	5.572 (5.611)
Dummy Access x 201907	7.106 (7.091)	6.378 (7.021)
Dummy Access x 201908	4.276 (5.350)	3.563 (5.406)
Dummy Access x 201909	5.170 (5.315)	4.480 (5.367)
Dummy Access x 201910	6.800 (6.302)	6.097 (6.298)
Dummy Access x 201911	4.671 (5.936)	3.957 (5.974)
Dummy Access x 201912	1.716 (7.840)	0.9933 (7.977)
Dummy Access x 202001	-0.3963 (8.482)	-1.123 (8.643)
Dummy Access x 202002	1.589 (8.984)	0.8607 (9.096)
Dummy Access x 202003	-1.285 (8.681)	-1.994 (8.850)
Dummy Access x 202004	2.371 (6.563)	1.856 (6.595)
Dummy Access x 202005	9.115 (6.058)	8.848 (6.020)
Dummy Access x 202006	4.550 (5.765)	4.417 (5.780)
Dummy Access x 202007	4.062 (5.837)	4.105 (5.854)
Dummy Access x 202008	2.659 (6.755)	2.660 (6.770)
Dummy Access x 202009	3.644 (7.248)	3.548 (7.279)
Dummy Access x 202010	2.841 (3.707)	2.884 (3.698)
Dummy Access x 202012	0.1110 (2.220)	0.2568 (2.224)
Dummy Access x 202101	-3.898 (3.043)	-3.756 (3.029)
Dummy Access x 202102	6.723 (7.052)	6.802 (7.072)
Dummy Access x 202103	6.368 (6.869)	6.420 (6.894)
Dummy Access x 202104	6.719 (7.206)	6.693 (7.229)
Dummy Access x 202105	8.349 (6.877)	8.297 (6.885)
Dummy Access x 202106	5.842 (6.173)	5.770 (6.190)
Dummy Access x 202107	5.285 (5.566)	5.431 (5.611)
Dummy Access x 202108	3.829 (5.240)	3.681 (5.262)
Dummy Access x 202109	5.364 (5.921)	5.232 (5.983)
Dummy Access x 202110	2.493 (5.241)	2.138 (5.280)
Dummy Access x 202111	-2.640 (5.839)	-3.399 (5.947)
Dummy Access x 202112	10.97 (7.323)	11.18 (7.450)
Dummy Access x 202201	10.65 (7.094)	10.79 (7.207)
Dummy Access x 202202	10.92 (7.277)	11.05 (7.395)
Dummy Access x 202203	13.62 (7.624)	14.03 (7.765)
Dummy Access x 202204	12.70 (7.633)	12.52 (7.831)
Dummy Access x 202205	15.14 (7.746)	15.37 (7.947)
Dummy Access x 202206	14.44 (7.413)	14.44 (7.544)
Population	–	4.89e-8 (6.56e-8)
Operator Monopoly	–	0.1573 (2.307)
Log of New Covid Cases	–	-1.132 (0.7532)
Fixed-Effects:		
COD_IBGE	Yes	Yes
Dates	Yes	Yes
S.E.: Clustered by: COD_IBGE	Clustered by: COD_IBGE	
Observations	223,365	221,650
R^2	0.34712	0.34781
Within R^2	0.00126	0.00155

The results of the four regressions do not show statistically significant coefficients, indicating that 4G quality did not experience a meaningful variation following the introduction of Pix. This lack of impact on quality can be interpreted as evidence that operators were able to expand their market presence without compromising 4G quality, reinforcing the idea that Pix fostered financial inclusion without negatively affecting existing infrastructure.

5 Conclusion

In this study we utilized data from five distinct databases to conduct a Difference-in-Difference analysis, examining the impact of Pix's introduction in Brazil on the telecommunications sector. Municipalities with and without access to bank branches were compared before and after Pix's implementation, to see if the telecom operators responded to the introduction of Pix as an incentive for expanding their coverage area. Our findings confirmed that Pix contributed to market expansion by increasing the number of telecom operators in financially excluded regions, thereby fulfilling its role as a catalyst for financial inclusion and competition. On the other hand, our study found no significant change in the quality of the 4G services provided, indicating that the increased competition was not compromised by service standards.

Given the lack of studies on Pix's introduction and its broader economic implications, these findings provide important insights, regarding the different implications Pix had in reshaping market dynamics. Such development further stimulates competition, while mantaining a high service standard, and contribute to inclusive socio-economic development in regions with limited private investment. The results remain significant and robust even when excluding controls for COVID-19 cases, dates, municipalities, and population. By possibilitating instant, zero-cost transactions, Pix has not only improved financial accessibility but also helped millions of Brazilians to access a efficient banking system. Policymakers can use these insights to replicate the success of Pix, fostering other financial innovations that advance inclusivity and generating cross-sector benefits. Even though we used high quality information, the data utilized for this paper faced limitations, primarily due to some sources not yet releasing their most recent updates. Our key dataset from ANATEL, which provided information from telecommunications companies, was last updated in June 2022, restricting our analysis to that period. Additionally, the 4G quality data raised some questions, with an average quality reported at over 99.5%. Given Brazil's telecommunications sector is marked by numerous customer complaints and service dissatisfaction, this high figure raised questions about possible inconsistencies. Future research could address alternative dimensions of telecommunications quality, such as client satisfaction, legal disputes, or service complaints.

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