Regulation and Service Provision in Dynamic Oligopoly: Evidence from Mobile Telecommunications

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May 9, 2022

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Abstract

I study coverage requirements, a common regulation in the mobile telecommunications industry that intends to accelerate the roll-out of new mobile telecommunications technologies to disadvantaged areas. I argue that the regulation may engender entry deterrence effects that limit its efficacy and lead to technology introduction patterns that are not cost-efficient. To quantify the impact of coverage requirements on market structure and the speed and cost of technology roll-out, I develop and estimate a dynamic game of entry and technology upgrade under regulation. I estimate the model using panel data on mobile technology availability at the municipality level in Brazil. In counterfactual simulations, I find that coverage requirements accelerate the introduction of 3G technology by 0.7 years, on average, and reduce firms' profits by 20.04% relative to a scenario with no regulation. I find the entry deterrence effects to be small. Moreover, an alternative subsidization policy leads to a similar acceleration in the roll-out of 3G and substantially higher aggregate profits, likely increasing aggregate welfare relative to coverage requirements.

*University College London, Department of Economics, joao.granja@ucl.ac.uk I thank Aviv Nevo, Katja Seim, and Mike Abito for their guidance and support throughout this project. I also thank Gorkem Bostanci, Nick Buchholz, Juan Camilo Castillo, Federica De Stefano, Kathleen Hui, Tomas Larroucau, John Lazarev, Philipp Schmidt-Dengler, Gabrielle Vasey, Sergio Villalvazo, Andrei Zeleneev, and seminar participants at various institutions for suggestions that have substantially improved this paper.

1 Introduction

Firms' failure to appropriate the consumer surplus generated by their entry and introduction of new products may lead to underprovision of goods and services. This possibility is particularly salient in industries featuring large fixed costs and in disadvantaged areas, where the prospects of recouping these costs are dim. Concerns regarding service underprovision have led to regulatory oversight and intervention in many industries, such as postal service, healthcare, airlines, and telecommunications.[1] These concerns have historically been particularly salient in the telecommunications industry (Wu (2010)). The substantial investment costs required for network expansion raise fears that firms will not provide service and bring new mobile telecommunications technologies to low-income, rural, or isolated localities, despite the considerable benefits associated with these services.[2] These concerns have led to the regulation of the roll-out of new mobile telecommunications technologies in countries ranging from Nigeria to the United States. This paper studies the effects of existing regulation on the introduction of new mobile telecommunications technologies, and evaluates the desirability of existing regulation relative to alternative forms of intervention.

Mobile telecommunications markets are typically characterized by a small number of firms. To provide mobile telecommunications services, these firms must acquire from the government licenses to use the radio spectrum. These licenses tyically cover large geographic areas containing many local markets. In the absence of regulation, firms would choose to provide service and introduce new technologies in those markets where variable profits exceed fixed costs, potentially leaving some areas without service or access to new technologies. To avoid this outcome, regulators impose what are called coverage requirements. For the purposes of this paper, a coverage requirement tasks a single firm with providing service of a specific technology in a given area by a date set by the regulator, while imposing no constraints on its competitors'

[1]This is true even in the United States. The USPS is subject to a Universal Service Obligation. The HRSA runs the Medicare Rural Hospital Flexibility Program. The DOT runs the Essential Air Service and Small Community Air Service Development Program. The Universal Service Administrative Company spends almost ten billion dollars annually in subsidies for high-speed broadband access.

[2]Telecommunications services have been shown to have positive effects on economic growth (Roller and Waverman (2001), Czernich, Falck, Kretschmer, and Woessmann (2011)); labor productivity (Bertschek and Niebel (2016), Akerman, Gaarder, and Mogstad (2015)); market efficiency (Jensen (2007)), and risk-sharing (Jack and Suri (2014)). Aker and Mbiti (2010) discuss many other potential benefits of mobile telecommunications in developing countries. Hjort and Tian (2021) provide a recent review of the literature on the impact of internet connectivity in developing countries.

behavior.[3]

The goal of this paper is to understand the welfare effects of coverage requirements and alternative regulatory interventions. At first glance, the trade-off faced by regulators when deciding whether or not to impose such a requirement is clear. On the one hand, the requirement presumably accelerates the introduction of the new technology in the regulated area, thus increasing the discounted stream of consumer surplus. On the other hand, coverage requirements impose a cost on the regulated firm, for it is required to enter a market or upgrade its technology when it might not have done so in the absence of regulation. The oligopolistic structure of the mobile telecommunications industry overturns this apparent simplicity. A coverage requirement is a credible commitment to provide service on the part of the firm subject to the regulation. This commitment may deter entry by the other firms and lead to further changes in equilibrium behavior that diminish or even reverse the acceleration of technology introduction alluded to above.

To quantify the effects of coverage requirements and alternative policies, I develop and estimate an empirical dynamic game of entry and technology upgrade under regulation. Firms' incentives to enter a market and upgrade their technologies are determined by the incremental variable profit derived from those choices and the associated sunk costs. Therefore, an appropriate empirical model must accurately capture the key features determining those profits and costs. An important characteristic of rapidly evolving industries such as mobile telecommunications is that demand for a new technology tends to increase over time whereas the associated adoption costs tend to decrease. Also important are local market features that shape demand and costs, as well as the local market structure. To account for these key factors, I model firms' flow profits as a time-varying function of market structure and local demographic characteristics. Similarly, the costs of introducing a new technology are allowed to vary over time and to depend on local market characteristics.

The other crucial determinant of firms' incentives to introduce the new technology is, of course, the regulation. In the model, as in the data, in each market exactly one firm is required to provide 3G service by a date set exogenously by the regulator. I model the regulation's enforcement by assuming that the regulated firm must pay a fine in every period following the regulation deadline in which it fails to comply with the regulation. Given its asymmetric nature, there are two dimensions to the regula-

[3]This is the implementation of coverage requirements in my empirical setting. Another common form of coverage requirements is that firms are obliged to provide service to at least some fraction of the territory covered by their license by a date set by the regulator. This fraction varies across countries and in some cases is close to 1.

tion's effect on firms' incentives. First, the single regulated firm has an added incentive to introduce the new technology, to avoid triggering punishments for non-compliance. Second, the firms that are not subject to the regulation know that the regulated firm will be in the market in the future, and with the new technology. Therefore, they know that the market will be more competitive in the future, and that knowledge negatively affects their incentives to enter and introduce the new technology. The latter mechanism may give rise to a further response by the regulated firm: knowing that the unregulated firms will not enter the market and knowing that adoption costs decrease over time, the regulated firm may have an incentive to wait for costs to fall before introducing the new technology.[4] As this discussion makes clear, capturing these mechanisms requires an equilibrium model of entry and technology adoption.

The question of how much later (or earlier) the introduction of 3G technology would have ocurred in the absence of regulation is a question about time, and thus requires a dynamic model. The nature of the regulation, which sets a deadline for the introduction of the new technology, also makes the problem dynamic (and non-stationary). These aspects justify the dynamic nature of the model.

The time-varying nature of variable profits and technology adoption costs and the regulation deadline make the environment non-stationary, a departure from most of the literature on empirical dynamic games. I also depart from the existing empirical literature on technology adoption, which applies full-solution estimation routines based on backward induction solution algorithms. I instead assume that structural parameters stabilize before the end of the sample and focus on what I call quasi-stationary Markov Perfect Equilibria (QMPE). Essentially, QMPE have a non-stationary phase followed by a stationary phase. This structure allows me to adapt existing estimation techniques used in stationary dynamic games to a non-stationary setting.

I estimate the model using new panel data on mobile technology availability at the municipality level in Brazil from June 2013 to June 2021. I analyze firms' entry and technology upgrade behavior in a set of relatively small municipalities. In each of these municipalities, exactly one of the four major carriers in the country was required to provide 3G service by a date set by the regulator. I call that firm the regulated firm. The identity of the regulated firm varied across municipalities; all of the four major carriers in the country are regulated in some markets but not others. Comparing the behavior of regulated and unregulated firms shows that regulated firms are more likely to enter a market and upgrade their technologies. It also establishes that

[4] Appendix A provides a theoretical example, based on Fudenberg and Tirole (1985), in which the regulation leads to delay in the introduction of the new technology.

unregulated firms are less likely to enter a market or upgrade their technology when the regulated firm is yet to satisfy its coverage requirement. This pattern is consistent with the entry deterrence effect outlined above.

The model estimates show that the profits and costs associated with 3G are fairly stable over my sample period. The profits associated with 4G rise sharply, and the costs of 4G installation decrease substantially over time. The latter inference is driven by a sharp increase in 4G introductions in the final part of the sample. The cost of non-compliance with the regulation is not directly observed, but it is identified from differences in behavior between regulated and unregulated firms. I estimate it to be sizable: it amounts to 28.35% of the median entry cost.

Counterfactual exercises show that in the absence of coverage requirements, the arrival of 3G technology to relatively small and underdeveloped markets in Brazil would have happened 0.67 years later, on average – and more than 2 years later in some cases. The regulation reduces firms' aggregate expected profits by 321 million 2010 BRL, or 20.04% of the profits they obtain in the absence of regulation. I find the entry deterrence effects to be small; the overall effect of the regulation is almost equal to its direct effect on the regulated firm.

I also use the model to evaluate alternative policy interventions. I find that a policy that subsidizes the first firm to introduce 3G technology leads to a similar acceleration of its roll-out. Moreover, firms benefit substantially from the subsidy: their aggregate profits increase by 126 million BRL, or 9.83% of their earnings under coverage requirements, after accounting for the financing of the subsidy. These gains stem primarily from a more cost-efficient pattern of technology adoption. The subsidy typically leads an incumbent to introduce the new technology, whereas coverage requirements are imposed on potential entrants in many cases. Incumbents only incur technology installation costs, whereas potential entrants also incur entry costs, which I estimate to be sizeable. This difference drives the cost-efficiency gains. The cost efficiencies associated with the subsidy come at the expense of reduced competition in the market. However, I estimate that one more firm in the market has to generate a gain in consumer surplus that exceeds 40% of consumers' average expenditures for coverage requirements to be preferred to the subsidy. These results suggest that subsidization is a more efficient policy than the current form of regulation.

This paper relates to the literature studying how regulation affects market structure and market outcomes in dynamic environments. Ryan (2012) shows that stricter environmental regulation increases entry costs, thus decreasing both the number of firms in the market and consumer surplus. Gowrisankaran, Lucarelli, Schmidt-Dengler, and Town (2011) study the effect of the Medicare Rural Hospital Flexibility Program on health care provision in rural America, and show that the program expanded coverage but had a net adverse effect on consumer welfare due to provisions that limited the size and scope of regulated hospitals. Dunne, Klimek, Roberts, and Xu (2013) study the effects of entry subsidies under the Health Professional Shortage Areas program on local market structure. Most related to this paper, Fan and Xiao (2015) estimate a model of telephone service provider entry into local markets in the US and use the model to evaluate the effectiveness of different subsidies in monopolization in that industry. I extend this literature by modeling not only entry but also the set of products firms offer and by studying the equilibrium effects of asymmetric regulation on market outcomes.

This paper also relates to the empirical literature on technology adoption. Schmidt-Dengler (2006) studies US hospitals' decisions to adopt magnetic resonance imaging (MRI). Igami (2017) studies how cannibalization, preemption, and incumbents' cost advantages shape firms' adoption of a new generation of hard disk drives. My paper adds to this literature by studying how regulation affects technology adoption. My work also differs from these paper methodologically. Models of technology adoption must allow for time-varying demand and adoption costs. The aforementioned papers accommodate this source of non-stationarity and apply full solution estimation methods, based on backward induction algorithms. Backward induction can be applied in these settings due to a finite horizon assumption (Igami (2017)) or full adoption in finite time (Schmidt-Dengler (2006)). I instead model technology adoption as happening in an infinite horizon and assume that the game has a non-stationary part followed by a stationary part. The aforementioned notion of quasi-stationary Markov Perfect Equilibria allows me to adapt existing iterative estimation methods to this non-stationary setting.

My work also relates to the literature on regulation in telecommunications markets. Most recently, Björkegren (2019) has studied the adoption of mobile phones in Rwanda, and in that context evaluated the welfare effect of rural coverage requirements imposed on the dominant mobile network operator. His model is one of consumer choice, not firm rollout. I add to this work by modeling how firms respond to the coverage requirements, and moreover by doing so in an oligopoly context. My work also relates to an earlier, mostly theoretical, literature on universal service obligations, such as Armstrong (2001), Choné, Flochel, and Perrot (2002), and Valletti, Hoernig, and Barros (2002), that was motivated by liberalization in the telecommunications industry (and also in the postal services industry) in the 1990s. This paper is the first to empirically quantify the effect of such regulation on service provision and the introduction of new technologies. The focus on the role of regulation also distinguishes this paper from recent related research that analyzes infrastructure investment by mobile network operators, namely Marcoux (2022) and Lin, Tang, and Xiao (2021).

Methodologically, this paper is related to a long literature on applied dynamic games, going back to Ericson and Pakes (1995). The model I will present below will be a dynamic game with discrete controls. A number of estimators have been proposed for stationary dynamic games with discrete controls, e.g., Aguirregabiria and Mira (2007), Pakes, Ostrovsky, and Berry (2007), and Pesendorfer and Schmidt-Dengler (2008). I will depart from that literature in that my model will feature a non-stationary phase followed by a stationary phase. I show that with a cross-section of markets and the notion of Quasi-Stationary Markov Perfect Equilibria, these estimators can be applied to non-stationary settings.

The rest of the paper is organized as follows. Section 2 introduces the institutional setting, the data, and presents some preliminary evidence on the effects of coverage requirements on firm behavior. Section 3 introduces a model of entry and technology upgrade with regulated and unregulated firms. Section 4 discusses the identification and estimation of the model, and also discusses the parameter estimates. Section 6 presents the counterfactual analysis. Finally, section 7 provides concluding remarks.

2 Institutional Setting and Data

Operators of mobile telecommunications networks transmit data through the radio frequency spectrum, which is a public resource and is subject to government management in most countries. Starting in the 1990s, many countries have adopted auctions as the means to allocate spectrum to firms, including mobile telecommunications service providers. In these auctions, firms acquire licenses to use the radio frequency spectrum. These licenses typically come with a number of conditions, chief among them the coverage requirements that are the focus of this paper.

The Brazilian mobile telecommunications market is characterized by 7 mobile network operators (MNO), i.e., carriers that operate their own network infrastructure. There is also a handful of very small mobile virtual network operators (MVNO), which are carriers that do not own their own infrastructure, and instead rent space in the network of one of the MNOs. Of the 7 MNOs, four provide service in the entire country and have held licenses covering the entire Brazilian territory since the introduction of mobile telecommunications in the country. The other three MNOs provide more localized service. There has been no entry or exit in this market in the past twenty years.[5]

The Brazilian government conducted its first spectrum auction in 2007 and has since then imposed coverage requirements on the winners of these auctions. For the purpose of this paper, a coverage requirement is an imposition that a firm provide service in a municipality by a deadline set by the regulator and with a minimum technological requirement (e.g., the firm may be required to provide 4G service, or either 3G service or 4G service). In Brazil, the relevant market for the implementation of the regulation is a municipality, and the requirement is considered to be satisfied if service of the required technology is available in 80% of the municipality's territory. The details of the coverage requirements are a function of municipality population. In municipalities with more than 100,000 inhabitants, 4 MNOs were required to provide 3G service by April 2013; in municipalities with population between 30,000 and 100,000, 3 MNOs were required to provide 3G service by the end of 2017; and in municipalities with population below 30,000, 1 MNO was required to provide 3G service.[6] For the latter group of municipalities, there were four different deadlines: April 2014, April 2016, June 2017, and December 2019.

I focus on the group of municipalities with less than 30,000 inhabitants. The coverage requirements targeting these municipalities are the most likely to influence the availability of service, for in larger municipalities it is probable that firms would have sufficient incentives to enter the market by themselves.[7] I will speak of the single firm in each of these markets that is subject to a coverage requirement as the *regulated firm*; I will refer to the other firms as the *unregulated firms*. All the MNOs are regulated in some markets, but not all. Though these coverage requirements target the introduction of 3G technology, the regulated firm is considered to comply with the regulation if it deploys 4G technology instead.

The motivation for coverage requirements rests on two premisses. First, mobile telecommunications services generate substantial welfare gains.[8] In the words of the Brazilian telecom regulator:[9]

[5]In the last couple of years, a process of consolidation has started. Nextel, one of the two small MNOs was sold to Claro, one of the large ones. Oi, one of the big carriers, is in the process of being sold to a consortium formed by the other three large MNOs.

[6]There are also coverage requirements related to 4G technology. Those apply exclusively to municipalities with more than 30,000 inhabitants. Therefore, the group of municipalities I focus on is unaffected by these requirements.

[7]It is likely that the coverage requirements targeting larger municipalities affect the number of firms in the market, but not the availability of service, which is the focus in this paper.

[8]See, e.g., the references in footnote 2

[9]See, `https://www.anatel.gov.br/setorregulado/telefonia-movel` (last accessed in October 22, 2020).

> [Mobile telecommunications technologies] *create employment opportunities, improve the education system, increase firm productivity, allow access to public digital services, among other benefits.*

Second, for the intervention to be justified, it must be that firms do not internalize the entirety of the surplus generated by their entry and introduction of new technologies. This seems likely, given how multifaceted these benefits are and firms' limited ability to price discriminate.[10]

Coverage requirements are enforced by the regulator in a number of ways. First, carriers are required to deposit financial guarantees with the regulator; these guarantees can be executed if the carrier fails to satisfy its coverage requirements. Perhaps more importantly, if a carrier fails to comply with the regulation, its license can be revoked. In this case, the carrier would also be charged the value paid for its license in proportion to the time used.

The selection of which carrier was to be regulated in each municipality was subject to a number of rules. First, the country was divided into 131 "service areas". These varied substantially in size, from a single municipality to an entire code area, which include on average 83 municipalities. Within each of these service areas, the four large carriers would take turns selecting small numbers of municipalities where they would be subject to a requirement. Both the total number of municipalities to be selected and the number of municipalities chosen per turn were determined by the acquired license. Figure 15 in Appendix B shows the result of this process.

The main dataset used in this study comes from ANATEL, the Brazilian telecommunications regulator. The data records the technologies (2G, 3G, and 4G) offered by each mobile network operator in each of the 5,770 Brazilian municipalities at a monthly frequency.[11] Figure 16 in Appendix B illustrates the structure of the data.

The second important piece of data coming from ANATEL is the identity of the regulated firm in each municipality. There are two sources for that information, and the analysis below restricts attention those municipalities where the two sources agree with one another. ANATEL also provides data on the numbers of subscribers to mobile telecommunications services. These data are available for each carrier-technology combination at a monthly frequency, first at the code-area level from February 2005 to

[10] Some recent empirical results in related markets lend support to this hypothesis: using data on the French mobile telecommunications market, Elliott, Houngbonon, Ivaldi, and Scott (2021) estimate that the marginal social value of spectrum is five times firms' willingness to pay for it; studying residential broadband, Nevo, Turner, and Williams (2016) estimate a large gap between social and private incentives to invest in infrastructure.

[11] The data does not include MVNOs.

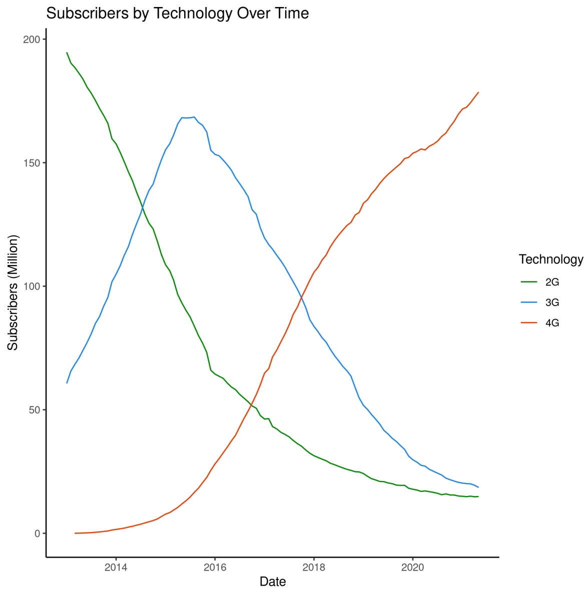

Figure 1: Subscribers by technology over time

The figure shows the total number of subscribers in the country, by technology. These quantities are calculated from ANATEL's data on subscription to mobile telecommunications services.

December 2018 and then at the municipality level from January 2019 to May 2021.[12] Figure 1 shows the total number of subscribers in the country by technology for the period from January 2013 to May 2021. The figure shows that 2G has been in decline over the period, initially being overtaken by 3G. Moreover, 3G reaches a peak in the number of subscribers towards the end of 2015, around the time when the growth of 4G accelerates. To the extent that these patterns are driven by consumer preferences, they shape firms' incentives to introduce new technologies. The empirical model introduced below will account for this pattern in demand by allowing demand-side parameters to vary over time.

I complement the ANATEL data with a number of datasets from IBGE, the Brazilian Census Bureau. First, I utilize municipality demographics and characteristics, such as population, GDP per capita, and area. Summary statistics on these variables are shown in table 1. Second, I use the 2017-2018 Family Budget Survey, which provides information on households' income, size and their expenditure on mobile telecommunications services.[13] Third, I use the 2010 Population Census to obtain the distribution of individual-level demographics at the municipality level.

For the majority of the analysis that follows, I drop all code-areas where any of the

[12] A code area in Brazil is much coarser than a municipality. There are 67 code areas in Brazil, and 5,770 municipalities.

[13] This survey is the *Pesquisa de Orçamentos Familiares* (POF).

Table 1: Summary Statistics – Municipality Characteristics

Variable	N	Mean	Std. Dev.	p10	p90
GDP Per Capita	$3,449$	$16,221.34$	$20,357.61$	$5,440.13$	$30,668.74$
Population	$3,449$	$10,907.84$	$7,564.48$	$2,917.02$	$22,655.82$
Area	$3,449$	$1,235.85$	$3,963.64$	110.60	$2,370.71$

The data in this table comes from IBGE, the Brazilian Census Bureau. All values are averaged over time at the level of the municipality. GDP per capita is deflated to 2013 BRL. Area is in squared kilometers.

Table 2: Summary Statistics – Mobile Expenses and HH Characteristics

Variable	N	Mean	Std. Dev.	p10	p90
Mobile Spending	$80,921$	26.64	36.51	7.44	48.39
HH Income PC	$80,921$	$2,159.54$	$3,962.78$	557.54	$4,050.98$
No. Residents	$80,921$	2.20	1.04	1	4
Urban	$80,921$	0.81	0.39	0	1

The data in this table come from the 2017-2018 Family Budget Survey. The unit of observation is an individual. Mobile spending is the total amount the individual spent on mobile telecommunications, in BRL (values are deflated to 2013). It is the sum of expenditures on voice and data plans, pre-paid expenditure, and SIM cards. "HH Income PC" is the monthly per capita income in the individual's household. "No. Residents" is the number of residents in the individual's household. "Urban" is a dummy that is equal to 1 if the individual lives in an urban area.

three smaller carriers had a market share of at least 5% at any point in time. I then focus on the four major carriers. Moreover, as mentioned above, I focus on municipalities with less than 30,000 inhabitants (in 2006) and for which the two available sources of information on coverage requirements agree with one another. The resulting sample contains 3,449 municipalities. For the estimation of the structural model introduced below, all of these 3,449 municipalities will be used. However, for the majority of the counterfactual exercises I will focus on the subset of municipalities where the coverage requirement has a December 2019 deadline. The reason is that the technology availability data starts in early 2013 and these requirements were imposed in July 2012; requirements in other municipalities were imposed a few years earlier. Therefore, it is only reasonable to think of counterfactual scenarios for the December 2019 group of markets. Finally, because entering a market or upgrading a technology is a non-trivial investment that likely involves some time to build, I use data on a semester frequency rather than monthly. The unit of observation is thus a municipality-carrier-semester.

Figures 2 and 3 summarise the technology deployment data. Figure 2 shows, on the left panel, the average number of firms in a market and, on the right panel, the average number of products, where a product is a carrier-technology combination and averages are taken across municipalities. Municipalities are split into two groups: those with a coverage requirement with a December 2019 deadline and all the other ones (i.e., either an earlier deadline – the vast majority of cases – or the regulated firm is not one of the four large carriers). The figure shows an increase in the numbers of firms and products, at a slightly faster pace in the December 2019 markets. There is also a clear difference in levels for the two groups.

Figure 3 shows technology availability over time. The figure in the top left shows the fraction of markets where at least 3G is available. The one on the top right show the fraction of markets where 4G is available. The figure on the bottom left shows the fraction of markets where the regulated firm has complied with the regulation. Finally, the figure on the bottom right shows the fraction of markets where some unregulated firm provides 3G technology or better. The availability of 3G technology or better in the Dec. 2019 (the most vulnerable) group grows from just over 25% of markets to 100% over the sample period. The availability of 4G grows from zero to about 96%. The bottom panel shows that regulated firms are more likely to provide advanced technologies since the beginning of the sample and also introduce these technologies at a faster pace than unregulated firms.

Figure 3 suggests an important role for coverage requirements in explaining the diffusion of new mobile telecommunications technologies. The difference in behavior between regulated and unregulated firms is potentially composed of two different

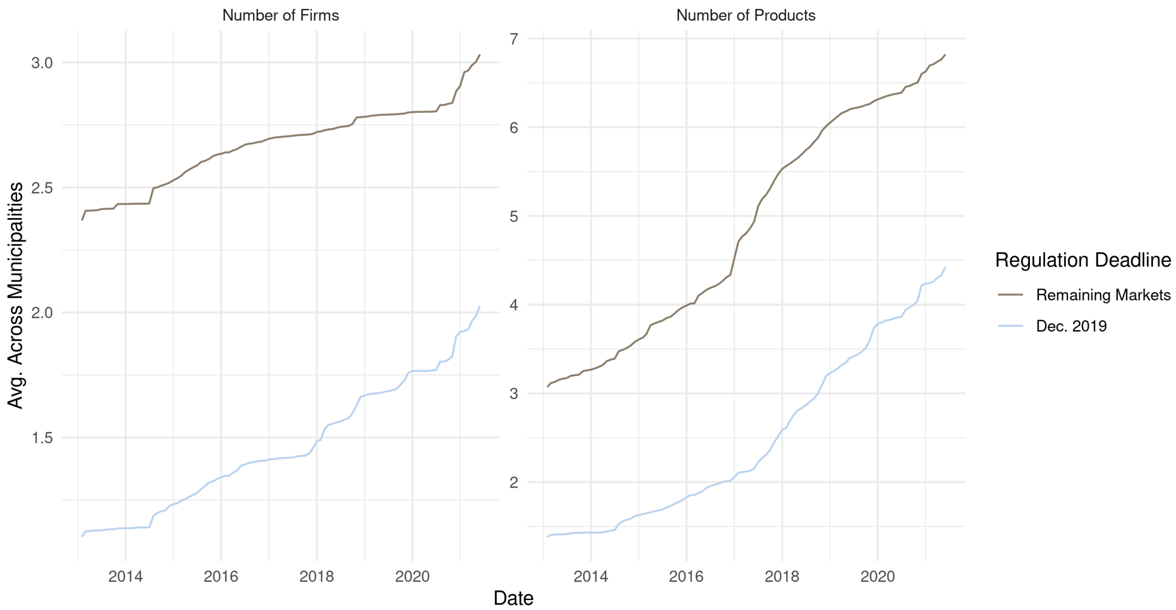

Figure 2: Numbers of firms and products over time

This figure shows the average numbers of firms and products (firm-technology pairs) over time, where the average is taken across municipalities. Municipalities are separated into two groups: those with a coverage requirement with a December 2019 deadline and all the other ones.

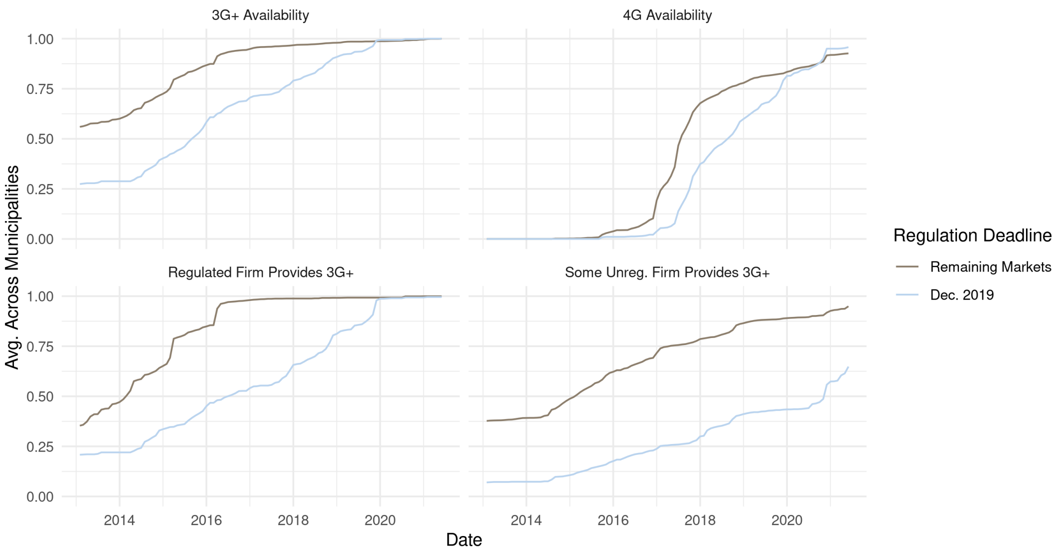

Figure 3: Service availability over time.

This figure shows technology availability over time. The figure in the top-left shows the fraction of municipalities where 3G service is available. The one on the top-right shows the same for 4G. The figure in the bottom-left shows the fraction of municipalities where the regulated firm has introduced 3G technology or better. The one in the bottom-right shows the fraction of municipalities where some unregulated firm has introduced 3G technology or better. Municipalities are separated into two groups: those with a coverage requirement with a December 2019 deadline and all the other ones.

effects of coverage requirements: a positive effect on regulated firms and a negative effect on unregulated firms. Unregulated firms may be less likely to enter new markets or upgrade their technologies because they know that the regulated firm will introduce 3G by the requirement deadline. This knowledge of tougher competition in the future may reduce the incentives for the unregulated firm to enter the market or upgrade its technology.

The data allow further investigation of these potential effects. In table 3 I report linear probability models of firms' technology upgrade decisions. The dependent variable is a dummy that is equal to one if and only if firms choose to upgrade their technology (or enter the market if they are not already active). The key explanatory variables are the dummies "Regulated", "Regulated Competitor - Out", and "Regulated Competitor - 2G". The first of these variables is equal to 1 when the firm is regulated, and 0 otherwise. The second variable is equal to 1 when the firm faces a regulated competitor that is out of the market. The third variable is equal to 1 when the firm faces a regulated competitor that has 2G technology. The omitted category is when either the regulated firm has satisfied its coverage requirement or the regulated firm is not one of the four large carriers.[14] The models also control for the logarithms of GDP per capita, population, and area, and also include the number of competitors with each technology.[15] Moreover, to account for unobserved municipality-level heterogeneity, these models also include group fixed effects, where the groups are defined by a heuristic pre-estimation step.[16]

The columns in Table 3 use different subsamples. The first column uses those observations where the firm provides no service in the relevant municipality, i.e., the firm is out of the market. The second column uses those observations where the firm's best

[14]Because I restrict the sample to regions where the small firms have always had negligible market shares, I interpret both of these cases as no firm being influenced by regulation.

[15]It may also be expected that a firm's network infrastructure in neighboring municipalities is important for the their choices. I test for that in Appendix B. There I do find that having service in a neighboring municipality increases the probability of entry and technology upgrade. However, the inclusion of those variables changes the other estimated coefficients only slightly, if at all. This suggests that the choice of the regulated firm is uncorrelated with their local network infrastructure. Indeed, in Appendix B, I show that service in neighboring municipalities does not increase the probability that a firm is regulated in a given market. Firms' presence in neighboring municipalities will not be included as a state variable in the structural model, as doing so would increase the computational burden by several orders of magnitude. The descriptive results discussed here, however, suggest that this omission will not bias the inference regarding the effect of the regulation.

[16]Specifically, I first run a regression of the number of products (carrier-technology pairs) on municipality and semester fixed effects. I then project the municipality fixed effects onto (averages over time) of their GDP per capita, population, and area. Municipalities are grouped according to quintiles of the residuals of the latter regression. Appendix B shows the results obtained estimating the model in Table 3 without the group fixed effects. The coefficients on the number of competitors are affected the most by the group fixed effects. The other coefficients change only slightly.

Table 3: Entry/Upgrade Models

	Dependent variable:		
		Upgrade	
	Out	2G	3G
	(1)	(2)	(3)
Log GDP PC	0.013***	0.014***	0.021***
	(0.001)	(0.003)	(0.002)
Log Pop.	0.026***	0.049***	0.0004
	(0.001)	(0.003)	(0.003)
Log Area	−0.006***	−0.014***	0.001
	(0.001)	(0.001)	(0.001)
Regulated	0.102***	0.150***	−0.034***
	(0.003)	(0.004)	(0.003)
Regulated Competitor - Out	−0.017***	−0.006	−0.035***
	(0.002)	(0.006)	(0.009)
Regulated Competitor - 2G	−0.006***	−0.051***	−0.091***
	(0.002)	(0.005)	(0.007)
No. Competitors 2G	−0.012***	−0.007***	−0.011***
	(0.001)	(0.003)	(0.002)
No. Competitors 3G	−0.021***	−0.013***	−0.002
	(0.001)	(0.003)	(0.003)
No. Competitors 4G	−0.008***	−0.027***	0.002
	(0.001)	(0.003)	(0.003)
Group FE	Yes	Yes	Yes
$\bar{Y}$	0.026	0.079	0.083
Observations	92,088	47,074	49,245

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows estimates of linear probability models in which the dependent variable is a dummy that is equal to 1 if and only if a technology upgrade is observed. The explanatory variables are, in this order: the log of GDP per capita, log of population, log of municipality area, a dummy that is equal to 1 if and only if that firm is regulated, a dummy that is equal to 1 if and only that firm faces a regulated competitor that is out of the market, a dummy that is equal to 1 if and only that firm faces a regulated competitor that has 2G technology, and the numbers of competitors with 2G, 3G and 4G technology. Each column corresponds to the subsample of the data where firms' best technology is as indicated in the column heading.

technology is 2G, and the third column those where the firm's best technology is 3G. There are two key results in Table 3. First, regulated firms that have not satisfied their coverage requirements are more likely to enter the market and upgrade their technologies than firms that are not subject to regulation. Second, unregulated firms are less likely to enter and upgrade their technologies when the regulated competitor is either out of the market or has 2G technology. These results show that the regulation indeed accelerates the introduction of the new technology by regulated firms, but also that it delays the introduction of new technologies by unregulated firms. This is consistent with the entry and technology upgrade deterrence effects outlined above. Given these two contrasting results, it is a priori unclear whether the regulation accelerates the introduction of new technologies.

The rest of the paper is concerned with developing tools that allows us to quantify the net effect of regulation on the time to introduction of new mobile telecommunications technologies, as well as the entry deterrence effects alluded to above and the costs that the regulation imposes on firms. This requires a model of how firms make their entry and upgrade decisions. That is the topic of the next section.

3 Model

In this section, I introduce an empirical model of mobile service providers' decisions to enter a market and upgrade their technologies. The model operates at the level of a municipality. Firms' flow profits depend on their own technologies, their competitors' technologies, and the local distribution of consumers' demographic characteristics. Inactive firms make entry decisions, and both entrants and incumbents choose what technologies to offer in the market; firms incur sunk costs of entry and technology upgrade. In each market a single firm is required to provide 3G technology by an exogenously specified deadline. If it fails to do so, it pays a fine every period, until it does introduce 3G technology to the market.

There are four carriers in each market. The four carriers compete by choosing which technology to operate, if any. The available technologies are 2G, 3G, and 4G. I assume that firms offer every technology less advanced than their best technology.[17] Time is discrete and the horizon is infinite. Within a period, the timing of the game is as follows. In the beginning of each period t incumbent firms earn their flow profits.

[17]This assumption is broadly consistent with the data. Mobile service providers typically keep old technologies in place as a fallback option. This assumption also reduces the dimension of the state space considerably, making the model computationally tractable.

Each firm then privately observes action-specific cost shocks, and firms simultaneously decide which of the available actions to take. Potential entrants can enter with any technology and incumbents can choose to upgrade to any technology that is more advanced than their current technology. After choosing an action, firms pay the associated costs. Technologies change deterministically according to firms' decisions.

Let s_{fmt} denote firm f's technology in market m and period t: $s_{fmt} \in \mathcal{S} := \{0, 2, 3, 4\}$, where $s_{fmt} = 0$ denotes that firm f is out of the market and the other values correspond to each of the available technologies, namely 2G, 3G, and 4G. The market's *technological state* $s_{mt} \in \mathcal{S}^4$ is a vector recording each firm's technology. Firms' flow profits are given by a time-varying function of the market's technological state s and the distribution H_x^m of demographics x in market m: $\pi_t(s, H_x^m)$. The specification of π_t is deferred to subsection 3.3.

Entry and technology upgrade are costly. The modeling of these costs reflects the fact that entry requires the installation of passive infrastructure, i.e., cell phone towers. Moreover, service provision also requires the installation of technology-specific active infrastructure, the radios or transmitters. To reflect the fact that the costs of introducing new technologies fall over time, technology upgrade costs are time-varying.[18] Firms know the dynamics of flow profits and the costs of entry and technology upgrade.

Formally, costs are modeled as

$$c_t\left(a, s_f, z_m, \varepsilon\right) = \begin{cases} -\varepsilon(a) & \text{if } a = s_f \\ \sum_{\{g' : g' > s_f\}}^{a} z_m' \theta_{g',t} + \mathbf{1}\left(s_f = 0\right) z_m' \theta_e - \varepsilon(a) & \text{if } a > s_f \end{cases} \tag{1}$$

In equation 1, $a \in \{s_{fmt}, \ldots, 4\}$ is the action chosen by the firm, s_f is firm f's state (its best technology), and z_m is a vector of observed market characteristics. The term $\varepsilon(a)$ is an action-specific cost shock, ε is a vector collecting all the $\varepsilon(a)$, and the θ's are parameters to be estimated. If $a = s_{fmt}$, the firm pays no costs (other than receiving the cost shock). A potential entrant that decides to enter pays an entry cost $z_m' \theta_e$. Moreover, associated with every technology g there are installation costs $z_m' \theta_{g,t}$. The term $z_m' \theta_e$ captures the cost of installing passive infrastructure. The term $z_m' \theta_{g,t}$ captures the cost of installing technology-specific active infrastructure. The summation in equation (1) reflects the previous assumption that firms offer all technologies less advanced than their best technology. If, for example, a firm's current best technology is 2G, and that firm upgrades to 4G, equation (1) says that the firm will pay the costs

[18] The cost of installing 2G is not allowed to vary over time, reflecting the fact that 2G is an old technology at the beginning of my sample period.

of installing both 3G and 4G.[19] The cost shocks are assumed to be independent across firms, periods, and actions, and they follow a Type 1 Extreme Value distribution with scale parameter λ.

In each market m, exactly one firm is required to provide 3G service by a date T_m exogenously specified by the regulator. I will call that firm the *regulated* or *committed* firm and the other firms the *unregulated* or *uncommitted* firms. A regulated firm that does not provide 3G technology or better by $T_m + 1$ pays a fine φ and does so every period until it complies with the regulation.

Firms choose their actions to maximize their discounted expected profits, taking their competitors' behavior as given. I focus on Markov Perfect Equilibria (MPE), as is common in empirical applications of dynamic games. I allow regulated and unregulated firms to behave differently, but beyond that I impose symmetry.

There are two sources of non-stationarity in this environment. First, flow profits and entry and technology upgrade costs vary over time. Second, coverage requirements imply that firm behavior depends on the date. Suppose that the regulated firm has not satisfied its commitment and $t < T_m$; as time goes by, the regulated firm gets closer to being fined and therefore should become more likely to comply with the regulation. Unregulated firms respond to this change in behavior. Thus, conditional choice probabilities vary over time. Therefore, stationary Markov Perfect Equilibrium is not an appropriate solution concept. Instead, I focus on what I call Quasi-Stationary Markov Perfect Equilibria. These equilibria respect the two sources of non-stationarity just identified, but beyond that impose that behavior is independent of the date. This brings me to a more detailed discussion of the game and its solution concept.

3.1 Symmetric Markov Perfect Equilibria

A Markov Perfect Equilibrium is a strategy profile $(\sigma_1, \ldots, \sigma_4)$, such that σ_i is a function that maps a firm's state variables into a feasible action and maximizes firm i's expected discounted profits given the behavior of its competitors. In a symmetric Markov Perfect Equilibrium, strategies do not depend on firms' identities. Instead, I define value and policy functions for regulated and unregulated firms. To simplify the notation, I subsume all the market-specific variables that do not vary over time in a superscript. The state of an unregulated firm f is $(s_f, s_r, s_-, t, \varepsilon)$, where s_f is that firm's technology, s_r is the technology of the regulated firm, and s_- is a vector with

[19] Note that this implies that an entering firm will always offer 2G. Because the cost of installing 2G is only paid by an entering firm, θ_e and θ_{2G} will not be separately identified. Therefore, in estimation I drop θ_{2G}. The estimate of θ_e thus includes both entry costs and 2G installation costs.

the technologies of the other two firms. The state of a regulated firm f is $(s_f, s_-, t, \varepsilon)$ where now s_- denotes the technologies of the three remaining firms. Let Ω_0, Ω_1 denote the state space for unregulated and regulated firms, respectively, with typical element $\omega_r, r \in \{0,1\}$. A strategy is a function $\sigma_r : \Omega_r \to \{0,2,3,4\}$ satisfying the restriction that $\sigma_r(\omega_r) \in A(s_1(\omega_r)) := \{s_1(\omega_r), \ldots, 4\}$, where $s_1(\omega_r)$ is the first coordinate of ω_r, i.e., the firm's current technology.[20]

Let $\sigma^m = (\sigma_0^m, \sigma_1^m)$ be a symmetric strategy profile. Define the implied ex-ante value function

$$V_{r,\sigma^m}^m(s,t) := \mathbb{E}_\varepsilon \Big\{ \sum_{\tau=t}^{\infty} \delta^{\tau-t} \Big[\pi_\tau^m(s_{f\tau}, s_{-f,\tau}) - c_\tau^m(a_{f\tau}, s_{f\tau}) + \\ + \varepsilon_{f\tau}(a_\tau) - \varphi r \mathbf{1}(T_m < \tau, s_{f\tau} < 3) \Big] \Big| r, s, t; \sigma \Big\}$$

where m indicates the market, $r \in \{0,1\}$ is equal to 1 if the firm is regulated and zero otherwise, $\mathbb{E}_\varepsilon$ indicates that the expectation is taken over the sequence of ε's for all firms, and firms' states evolve according to (σ_0^m, σ_1^m).

Symmetry implies restrictions on $\sigma_0, \sigma_1, V_0, V_1$. For example, for a regulated firm, it is irrelevant whether $s_- = (3,2,1)$ or $s_- = (1,2,3)$. Therefore $V_1(s_f, 3, 2, 1, t) = V_1(s_f, 1, 2, 3, t)$ and similarly for the policy function σ_1. Similar restrictions apply to unregulated firms. Furthermore, symmetry implies that V_0 and V_1 are equal for some states. For example, if $s_f = s_{f'} \geq 3$ then $V_0(s_f, s_{f'}, s_-, t) = V_1(s_f, s_{f'}, s_-, t)$. Symmetry implies further restrictions on value and policy functions. Appendix C provides further detail on these restrictions.

Finally, note that the recursive characterization of Markov Perfect Equilibria (e.g., Doraszelski and Escobar (2010)) implies that $\{\sigma_0^m, \sigma_1^m\}$ is a symmetric MPE if and only if

$$\sigma_r^m(s,t,\varepsilon) = \underset{a \in A(s_f)}{\operatorname{argmax}} \left\{ \pi_t^m(s_{ft}, s_{-f,t}) - c_t^m(a, s_f) + \delta \mathbb{E}_{\varepsilon_{-f}} \left[V_{r,\sigma^m}^m \left(a, s'_{-f}, t+1\right) | r, s, t \right] + \varepsilon(a) \right\} \tag{2}$$

where, for firms $h \neq f$, $s'_h = \sigma_{r_h}^m(s, t, \varepsilon_h)$ and the expectation is with respect to the shocks ε_h of firms $h \neq f$.

[20] In the absence of the distinction between regulated and unregulated firms and under the symmetry restriction, the state variables could be defined to be a firm's own technology and the numbers of competitors with each technology. Here, however, we must keep track of the technology of the regulated firm separately, as the incentives it is exposed to differ from those of unregulated firms. The symmetry restriction is then imposed via restrictions on policy and value functions.

3.2 Quasi-Stationary Markov Perfect Equilibria

As discussed above, there are two sources of non-stationarity in this environment. First, flow profits and investment costs vary over time. Second, coverage requirements imply that firms' policy functions respond to the proximity of the requirement expiration date T_m. In this subsection, I introduce assumptions that accommodate these two sources of non-stationarity while imposing a degree of stationarity.

I will assume that entry and technology upgrade costs and flow profits vary over time (in a way known to firms) but stabilize at a date known to the firms and the econometrician.[21] I then make two assumptions regarding equilibrium behavior. First, after parameters have stabilized and the regulated firm has complied with the regulation, behavior ceases to depend on the date. Second, the same holds if parameters have stabilized and the regulation deadline has passed. In the latter case, though firms still have to account for the presence of regulation, it affects the environment in a way that does not change as time passes.

Formally, I focus on *Quasi-stationary Symmetric Markov Perfect Equilibria*, defined below. Let T_θ denote the earliest time period such that flow profits and costs do not vary after T_θ.

Definition 1. A Symmetric Markov Perfect Equilibrium (σ_0, σ_1) is said to be *quasi-stationary* if there exist functions $\tilde{\sigma}_r(s, \varepsilon), r \in \{0, 1\}$, such that, if either

(i) $t \geq \max\{T_m + 1, T_\theta\}$, or

(ii) $t \geq T_\theta$ and $s_r \geq 3$,

then $\sigma_r(s, t, \varepsilon) = \tilde{\sigma}_r(s, \varepsilon)$.

I assume throughout that the data is generated by a Quasi-Stationary Symmetric Markov Perfect Equilibrium. Note that this imposes restrictions on value functions over time. For example, if $t \geq T_\theta$ and $s_f = s_{f'} \geq 3$, then $V_1(s_f, s_{f'}, s_-, t+1) = V_0(s_f, s_{f'}, s_-, t)$. Essentially, the model has a non-stationary phase followed by a stationary phase. Models of technology adoption must somehow contend with the fact that the demand for and costs of adopting a new technology vary over time. One way of dealing with the time-varying nature of demand and costs that appears in the literature is to assume a finite horizon and solve the game played by firms via backward induction; see, e.g., Igami (2017). That method raises the issue of assigning continuation values to different industry states in the final time period. In Igami (2017), that

[21]Specifically, costs and flow profits vary yearly until 2018, after which they stabilize.

is done by assuming that the state of the industry does not change after the terminal period, and computing the implied discounted stream of profits. Quasi-stationarity instead assumes that firms will keep playing the entry and technology upgrade game forever, so that firms' continuation values are given by the equilibrium value function in the relevant states.

3.3 Modeling Flow Profits

It is not uncommon in applications of dynamic games for flow profits to be derived from an estimated demand system paired with an assumption on firms' pricing behavior. Following that route would require data on available mobile telecommunications bundles, their prices, and consumers' choices from the available bundles. Unfortunately, such data is not available in my setting. I thus follow a different approach that requires data on the quantities of subscribers to different technologies and consumers' expenditures on mobile telecommunications. Suppose that consumer i in market m with demographic characteristics x_i chooses what carrier to subscribe to, what technology to use, and how much to spend on mobile telecommunications services, e_i. Let $\mu_{fgt}(s, H)$ be the resulting market share of firm-technology pair (f, g) in period t when the industry state is s and the distribution of demographics is H; a model for μ_{fgt} will be specified below. Let M be the size of the market and, as before, let s_f be firm f's state.[22] Finally, denote by $\mathbb{E}_t[e_i|g]$ the expectation of consumers' expenditures e_i, conditional on a consumer choosing technology g in period t.[23] Assuming zero marginal costs, firms' profits are given by[24]

$$\begin{aligned}\pi_t(s_f, s_{-f}, H) &= M \sum_{g\in s_f} \mu_{fgt}(s, H)\mathbb{E}_t[e_i|g] \\ &= M \sum_{g\in s_f} \mu_{fgt}(s, H) \int \mathbb{E}[e_i|g, x_i] dH_t(x_i|g)\end{aligned} \tag{3}$$

[22]I set the market size to be twice the population of the municipality. The number of mobile telecommunications subscriptions in Brazil is larger than the population.

[23]Here I condition only on the chosen technology, and not on the firm identity, because firms are assumed throughout to be symmetric.

[24]The expression on the right hand side of 3 is an approximation. Firms' profits are equal to $\sum_{g\in s_f} \sum_{i\in fg} e_i$, where the summations are over the technologies offered by firm f and over individuals i subscribing to firm-technology pair (f, g). This approximation holds in the sense that the difference between firms' profits and the right hand side of equation 3 is $O_p(\sqrt{M})$, whereas the included term is $O(M)$. This implies that the approximation error becomes negligible relative to the included term for large M. This approximation is analogous to the (implicit) approximation to profit functions used routinely in supply and demand models in empirical industrial organization.

The summation over $g \in s_f$ is over all technologies offered by firm f: $\{g : 2 \leq g \leq s_f\}$. Note that in equation (3), the conditional distribution $H_t(x_i|g)$ is indexed by t. That is because consumers' preferences over technologies are allowed to vary over time (as indicated by the t subscripts in μ_{fgt}), so that the distribution of demographics conditional on technology choice also varies over time. In contrast, the conditional expectation of expenditures $\mathbb{E}[e_i|g, x_i]$ is assumed to be time-invariant.

The main data limitation I face is that I never observe consumer expenditures together with their technology (and carrier) choices. I will therefore make the following assumption:

Assumption 1. $\mathbb{E}[e_i|g, x_i] = \mathbb{E}[e_i|x_i]$.

This assumption says that conditional on individual characteristics x_i, consumer expenditure is mean independent of the technology chosen by that consumer. This is, admittedly, a strong assumption. It would hold, e.g., in a world in which consumers pay per usage (a popular model in Brazil), and technology doesn't affect usage. This assumption would fail if better technologies induce consumers to utilize more data. Assumption 1 would thus be untenable if we were dealing with a population that uses high-bandwith applications. Because we are dealing with small municipalities in Brazil, the assumption is more palatable. Importantly, note that Assumption 1 does not imply that consumers that subscribe to different technologies will spend (on average) the same amount, for individuals with different demographic characteristics are still allowed to sort into different technologies.

Assumption 1 and equation 3 imply that

$$\pi_t(s, H) = M \sum_{g \in s_f} \mu_{fgt}(s, H) \int \mathbb{E}[e_i|x_i] dH_t(x_i|g) \tag{4}$$

I model $\mu_{fgt}(s, H)$ as arising from a nested logit model. Specifically, consumer i's utility of subscribing to firm-technology pair $j = (f, g)$ in market m and year τ is given by[25]

$$u_{ijm\tau} = \underbrace{\gamma_{r(m),p(\tau)} + \mu_{g(j),p(\tau)} + \beta_{g(j),p(\tau)} y_{m\tau} + \theta_{g(j),p(\tau)} d_{m\tau}}_{v_{g(j)m\tau}} + \xi_{jm\tau} + \zeta_{im\tau}(\rho) + (1-\rho)\varepsilon_{ijm\tau} \tag{5}$$

where $r(m)$ is the state of municiality m, $p(\tau) \in \{E, L\}$ groups periods into an early

[25]I specify equation 5 at the year level because the demographic variables in it are observed with that frequency. A period in the model, which corresponds to six months, is mapped to its corresponding year and the choice model introduced in the text is used to compute market shares.

(2015 and earlier) and late (2016 onwards) phase, and $g(j)$ is the technology of the firm-technology pair j. Moreover, $y_{m\tau}$ is GDP per capita, and $d_{m\tau}$ is population density.[26] The term $\xi_{jm\tau}$ is an unobserved product characteristic, $\zeta_{im\tau}(\rho)$ is a disturbance common to all goods other than the outside good, and $\varepsilon_{ijm\tau}$ is a Type 1 Extreme Value shock. The parameter ρ is the nesting parameter, and $\zeta_{im\tau}(\rho)$ has the unique distribution such that $[\zeta_{im\tau}(\rho)+(1-\rho)\varepsilon_{ijm\tau}]$ also has an extreme value distribution (see Cardell (1997)).

In equation (5), $\gamma_{r(m),p(\tau)}$ is a state-phase fixed effect meant to capture variation in the share of the outside good anad $\mu_{g(j),p(\tau)}$ is a technology-phase fixed effect, which captures changes in the popularity of each technology over time. The effect of income and population density on consumer preferences is allowed to vary by technology and phase. For example, one might expect the effect of income on preferences for 4G relative to alternative technologies to decrease over time, as the technology becomes more diffused, handsets become more affordable and more consumers desire to join networks that require 4G technology.

The distributional assumptions above imply that market shares are given by

$$\mu_{jm\tau}(s, v_{m\tau}, \xi_{m\tau}) = \frac{e^{(v_{g(j)m\tau}+\xi_{jm\tau})/(1-\rho)}}{D} \times \frac{D^{1-\rho}}{1+D^{1-\rho}} \tag{6}$$

where $v_{m,\tau}$ is a vector collecting the $v_{gm\tau}$, $\xi_{m\tau}$ is a vector similarly defined, and $D := \sum_{j\in s} e^{(v_{g(j)m\tau}+\xi_{jm\tau})/(1-\rho)}$, where the summation is over the products offered in the market, which are encoded in the industry state s. The predicted quantity of subscribers is $M\mu_{jm\tau}(s)$.

Equation 4 also includes $\mathbb{E}[e_i|x_i]$. I assume that individual i's expenditure, e_i, is given by

$$\log(e_i) = \alpha_{r(i)u} + \alpha_1 \log(y_i) + \alpha_2 n_i + \eta_i \tag{7}$$

In equation (7), $r(i)$ indicates i's state of residence; u indicates whether the municipality is classified as urban or rural by the Census; y_i is income; n_i is the number of residents in i's household; and η_i is an error term that is uncorrelated with the included regressors. We now have all the ingredients needed to compute firms' profits in equation 4, except for the distribution $H_t(x_i|g)$. I obtain that distribution using the technology choice model outlined above and Census data on municipality-level demographics; for details, see section 4.

[26] Using y_i in equation 5 would add one more integration in the estimation routine and add to the computational cost. In the analysis that follows, when calculating $H_t(x|g)$, I will treat the coefficient on $y_{m\tau}$ as the effect of an individual's income on her utility.

The final aspect of the model is an assumption regarding the distribution of $\xi_{jm\tau}$. I introduce this assumption to deal with the fact that I observe the quantities of subscribers at different levels of geographic granularity over time; see section 4 for details.

Assumption 2. Let $c(m)$ denote the code-area that municipality m belongs to. There exists a distribution F such that the unobserved product characteristic $\xi_{jm\tau}$ satisfies

$$\xi_{jm\tau} = \xi_{jc(m)\tau} + \eta_{jm\tau}$$

where $\eta_{jm\tau} \overset{iid}{\sim} F$ and $\mathbb{E}_F[\eta_{jmt}] = 0$.

Assumption 2 says that $\xi_{jm\tau}$ can be decomposed into a random variable that varies only across code-areas, on which I place no restrictions, and another random variable that varies across municipalities within a code-area, that I assume is iid with some unrestricted distribution F.

Under Assumption 2, an argument relying on a large number of municipalities within a code-area c implies that

$$\mu_{jc\tau} = \sum_{m \in c} \omega_m \int \mu_{jm\tau}(s_{m\tau}, v_{m\tau}, \xi_{c(m),\tau} + \eta_{m\tau}; \theta) dF(\eta_{m\tau}) \tag{8}$$

holds approximately.[27] In equation (8), ω_m is the fraction of the population in area-code c in municipality m. For its justification, see Appendix D. I will use equation (8) in estimation; see section 4.

4 Identification and Estimation

I start this section by discussing the estimation of the flow profit function in subsection 4.1. In subsection 4.2 I discuss the estimation of the dynamic parameters of the model, i.e., the entry and upgrade costs and the fine for non-compliance with the regulation.

4.1 Estimation of the Flow Profit Function

The flow profit function is given by equation (4). Computing profits requires three objects: $\mu_{fgt}(s, H)$, $\mathbb{E}[e_i|x_i]$, and $H_t(x_i|g)$. The first task is to estimate the parameters underlying the market share terms, $\mu_{fgt}(s, H)$. Here I have to deal with the fact that the data on mobile subscriptions come at different levels of geographic granularity

[27] See Appendix D for details.

over time. First, equation (6) implies the usual analytical nested logit inversion (see Berry (1994)):

$$\log(s_{jmt}) - \log(s_{0mt}) = v_{g(j)mt} + \rho \log(s_{j|\mathcal{J}_{mt}}) + \xi_{jmt} \tag{9}$$

where $s_{j|\mathcal{J}_{mt}}$ is the share of good j in the total number of subscriptions in the market. This equation yields ξ_{jmt} as a function of data and parameters, $\xi_{jmt}(\theta)$. The term $v_{g(j)mt}$ contains municipality characteristics that are assumed to be uncorrelated with ξ_{jmt}. Nevertheless, $\log(s_{j|\mathcal{J}_{mt}})$ is a function of ξ_{jmt}. I interact $\xi_{jmt}(\theta)$ with instruments Z^1_{jmt} to form moment conditions $\mathbb{E}[\xi_{jmt}(\theta)Z^1_{jmt}] = 0$.

The intuition for the identification of the nesting parameter ρ is similar to that in Berry and Waldfogel (1999). The nesting parameter determines the extent of business stealing when a new product enters the market. If we can exogenously vary the number of products in the market, we learn the value of λ by observing the effect on the aggregate share of the goods in the market. Following this intuition, I exploit coverage requirements themselves as a source of exogenous variation in the number of products in the market. Specifically, though the dynamic game focuses on relatively small municipalities where a single firm is subject to a 3G requirement, larger municipalities are also subject to regulation. In these larger municipalities, more firms are subject to a coverage requirement. The number of regulated firms is a function only of population measured in 2006 and 2012, which are credibly uncorrelated with ξ_{jmt}. Therefore, I use the number of firms subject to 3G and 4G coverage requirements as instruments for $\log(s_{j|\mathcal{J}_{mt}})$.

The moments discussed above are informative about the nesting parameter and preference parameters in the later period of the data, but not about preference parameters in the earlier period of the data. To construct additional moments to identify those parameters, I leverage assumption 2 and equation (8). Equation (8), repeated here for convenience, states that market shares at the area-code level are approximately given by

$$\mu_{jct} = \sum_{m \in c} \omega_m \int \mu_{jmt}(s_{mt}, v_{mt}, \xi_{c(m),t} + \eta_{mt}; \theta) dF(\eta_{mt}) \tag{10}$$

Equating observed market shares at the area-code level with their predicted counterparts, given by the right hand side of equation 11, allows one to solve for ξ_{jct} as a function of data and parameters. These structural error terms, $\xi_{jct}(\theta)$, could then be interacted with instruments to form moment conditions of the form $\mathbb{E}[\xi_{jct}(\theta)Z^2_{jct}] = 0$. The one hindrance to that approach is the integration with respect to $F(\eta_{jmt})$. Here, again, assumption 2 offers a solution. Given any vector of structural parameters, θ, equation (9) gives us $\xi_{jmt}(\theta)$. We can then make use of assumption 2 to recover $\hat{\eta}_{jmt}(\theta)$, which gives us an empirical distribution of η_{jmt} given θ, $F(\eta;\theta)$. In this way, the integration in equation (11) can be performed for any guess of θ by sampling from the implied $F(\eta;\theta)$, and moment conditions can be formed as described above.

To summarise the preceding discussion, the steps involved in evaluating the GMM objective function for a given value of θ are as follows. First, use equation (9) to obtain $\xi_{jmt}(\theta)$. Second, use assumption 2 to obtain $\eta_{jmt}(\theta)$. Third, solve for $\xi_{jct}(\theta)$ from

$$s_{jct} = \sum_{m\in c} \omega_m \frac{1}{N_s} \sum_{i=1}^{N_s} \mu_{jmt}(s_{mt}, v_{mt}, \xi_{c(m),t} + \eta_i; \theta) \tag{11}$$

where s_{jct} is the observed market share of firm-technology pair j in area-code c and period t, η_i is a vector of $|\mathcal{J}_{mt}|$ independent draws from $F(\eta;\theta)$ and N_s is the number of simulation draws. Fourth, interact ξ_{jmt} with Z^1_{jmt} and ξ_{jct} with Z^2_{jct} and average, to get sample analogs of the moment conditions discussed above; call these sample analogs $\bar{g}^1(\theta)$ and $\bar{g}^2(\theta)$, respectively. For a chosen weight matrix W, the GMM objective is then given by

$$J(\theta) := \begin{pmatrix} \bar{g}^1(\theta)' & \bar{g}^2(\theta)' \end{pmatrix} W \begin{pmatrix} \bar{g}^1(\theta) \\ \bar{g}^2(\theta) \end{pmatrix} \tag{12}$$

The GMM estimator is, as usual, $\hat{\theta} := \operatorname{argmin}_\theta J(\theta)$. I have discussed the instruments Z^1_{jct} above. The instruments Z^2_{jct} used in estimation are the population-weighted averages of the demographics included in v_{gmt}. I use the identity matrix as the weighting matrix.

The term $\mathbb{E}[e_i|x_i]$ in equation (4) is calculated from equation (7), which is estimated by ordinaty least squares using the Household Budget Survey. From (7) it follows that $\mathbb{E}[e_{im}|x_i] = \exp(\alpha_{r(m)u} + \alpha_2 n_i) y_i^{\alpha} \mathbb{E}[\exp(\eta_{im})|x_i]$. I assume that $\exp(\eta_{im})$ is mean independent of x_i and estimate $\mathbb{E}[\exp(\eta_{im})]$ using the residuals from equation (7).

The last ingredient needed to use equation (4) is the conditional distribution $H_t(x_i|g)$. By Bayes' rule,

$$h_t(x_i|g) = \frac{\mu_t(g|x_i)h(x_i)}{\int \mu_t(g|x_i')h(x_i')dx_i'} \tag{13}$$

The term $\mu_t(g|x_i)$ is derived from the technology choice model; the unconditional distribution of x_i comes from the Census data. I obtain $h_t(x_i|g)$ by drawing a uniform random sample from the municipality-level Census data, computing $\mu_t(g|x_i)$ for each draw x_i, and calculating $\mu_t(g|x_i)/\sum_j \mu_t(g|x_j)$.

4.2 Identification and Estimation of Dynamic Parameters

The flow payoffs of the dynamic game introduced in the previous section are linear in the structural parameters. For this class of models (dynamic games with linear flow payoffs), it is possible to show that structural parameters are identified if conditional choice probabilities are identified.[28]

The conditional value functions inherit the linearity from the flow payoffs: there exist functions $f_{rt,P^m}(a,s)$ and $g_{rt,P^m}(a,s,z)$ such that

$$\frac{v^m_{r,t}(a,s)}{\sigma} = f_{rt,P^m}(a,s) + g_{rt,P^m}(a,s,z)'\sigma^{-1}\Psi$$

where Ψ is a vector collecting all structural parameters (see Appendix E for details). This fact can be used to establish identification.

Since the idiosyncratic errors follow a Type 1 Extreme Value distribution, the conditional choice probabilities have the logit form:

$$P^m(a|s,r,t) = \frac{\exp(v^m_{r,t}(a,s)/\sigma)}{\sum_{a'\in A(s_f)} \exp(v^m_{r,t}(a',s)/\sigma)}$$

We can apply the usual logit inversion to this equation to obtain:

$$\ln(P^m(a|s,r,t)) - \ln(P^m(s_f|s,r,t)) = \frac{v^m_{r,t}(a,s)}{\sigma} - \frac{v^m_{r,t}(s_f,s)}{\sigma}$$

Using the linear representation of the conditional value functions we can then write

$$\ln(P^m(a|s,r,t)) - \ln(P^m(s_f|s,r,t)) - f_{rt,P^m}(a,s) + f_{rt,P^m}(s_f,s) = \Big[g_{rt,P^m}(a,s,z) - g_{rt,P^m}(s_f,s,z)\Big]'\frac{\Psi}{\sigma} \tag{14}$$

Equation (14) leads to an OLS-like formula for Ψ/σ. Moreover, as shown in appendix E, the first coordinate of Ψ is 1, so that σ is also identified.

The intuition for identification is that the structural parameters are identified by exogenous variation in (π_m, z_m, s, r, t) and the fact that we observe how firms respond to this variation (i.e., we observe conditional choice probabilities). One can, for example, entertain the thought experiment of varying one of the exogenous covariates and observing how firm behavior changes. For example, varying a municipality's area while holding constant variables that affect firms' flow profits identifies how area affects investment costs, as we observe investment responses. Note that we can do so for firms

[28] This is a known result, see, e.g., Aguirregabiria and Nevo (2013). I review the argument here for completeness.

that have 3G technology, so we identify the effect of area on the cost of 4G. Knowing that we can move to firms that have 2G, so we identify the effect of area on the cost of 3G, and then we move to potential entrants. The fine parameter φ is identified by the difference in behavior between regulated and unregulated firms. Time variation provides additional variation to identify φ. Intuitively, for small φ the behavior of regulated firms will change only slightly as the regulation deadline approaches; large φ, on the other hand, should lead to larger changes in behavior as time passes.

Note that the argument above refers to municipalilty-specific CCPs P^m, and indeed in estimation and counterfactuals I will allow for municipality-specific CCPs. Accommodating observed market-level heterogeneity to the fullest degree possible is at the service of the economic and policy questions that motivate this paper. However, this may seem at odds with the common assumption of an unique equilibrium being played in the data. Alternative approaches that that accommodate this assumption would be to discretize the space of observables and postulate that, in that discretized space, a unique equilibrium is played in the data – as in Fan and Xiao (2015). Alternatively, one may group markets with similar observables and posit that the data comes from a unique equilibrium for each group, as in Dunne et al. (2013). Either of these approaches is at the expense of observed heterogeneity. The approach of the present paper has the benefit of fully exploiting observed heterogeneity, but CCPs P^m still have to be recoverable from the data. For this to be the case, it is sufficient that there be a unique (quasi-stationary, symmetric) MPE for each market and that the map from market-level observables to MPE be continuous. Under these conditions, one can use nearby markets (in the space of observables) to estimate a market's CCPs. Computational experimentation supports uniqueness. Figure 17 in Appendix E provides evidence in favor of continuity. Finally, observe that the CCPs also vary with t due to non-stationarity. In both cases, it is important to observe a large cross-section of markets, as is the case in the present paper.

4.3 Estimation

I apply the Nested Pseudo Likelihood (NPL) algorithm of Aguirregabiria and Mira (2007) to estimate the dynamic parameters. In light of the results of Pesendorfer and Schmidt-Dengler (2010), my choice of estimator requires some justification. A popular alternative is to use a two-step estimator, e.g. Bajari, Benkard, and Levin (2007), Pakes et al. (2007) or Pesendorfer and Schmidt-Dengler (2008). These estimators all proceed by flexibly estimating policy functions in a first stage and then using those policy functions to construct a second-stage objective function that is then minimized to yield structural estimates. Because of the high degree of flexibility I require of CCPs, I opt to use an estimator that makes fuller use of the already imposed structural assumptions.

The maximum likelihood estimator is a natural option, but its computational cost is prohibitive in the case of dynamic games. I thus adopt Aguirregabiria and Mira (2007). An alternative that was recently proposed is Dearing and Blevins (2019).[29] The estimator proposed by Dearing and Blevins (2019) enjoys good theoretical properties. In particular, it is guaranteed to converge, thus overcoming the main issue of NPL raised by Pesendorfer and Schmidt-Dengler (2010). However, the algorithm in Dearing and Blevins (2019) requires solving large systems of linear equations, which renders its application to the empirical setting in this paper substantially more costly than Aguirregabiria and Mira (2007).

A Nested Pseudo Likelihood (NPL) fixed point is a pair $(\tilde{\theta}, \{\tilde{P}^m\}_m)$ that satisfies

(i) $\tilde{\theta} = \text{argmax}_\theta \sum_{m,t,f} \ln \Psi(a_{fmt}|s_{mt}, r_{fm}, t, m; \theta, \tilde{P}^m)$

(ii) $\tilde{P}^m = \Psi(\tilde{P}^m; \tilde{\theta})$ for all m

where $\Psi(a_{fmt}|s_{mt}, r_{fm}, t, m; \theta, \tilde{P}^m)$ is the probability that action a is optimal at state (s_{mt}, r_{fm}, t) in market m, when the firm believes that its competitors' and its own behavior will follow the conditional choice probabilities $\tilde{P}^m$ from $t+1$ onwards, and $\Psi(\tilde{P}^m; \tilde{\theta})$ is an array collecting all such probabilities. The NPL *estimator* is the NPL fixed point with the maximum value of the pseudo-likelihood. The set of NPL fixed points is known to be non-empty. However, it need not be a singleton. This implies that the researcher must explore the parameter space to ensure that the pseudo-likelihood is being maximized in the set of NPL fixed points.

In practice, one finds NPL fixed points via an iterative algorithm. Starting with a guess for CCPs, $\{\tilde{P}^m\}_m$, the implied pseudo likelihood is maximized (see condition (i) above). One then uses the resulting guess for θ to update firms' CCPs (see condition (ii) above). These two steps are repeated until the CCPs and the structural parameters converge.

5 Estimation Results

Table 4 presents the estimates of the parameters in the market-share model. Table 5 presents the estimates of the expenditure equation. The results show that the effect of income on a technology's utility is stronger the more advanced the technology is,

[29] See also Aguirregabiria and Marcoux (2021) for a related recent contribution.

both in the early and late periods. This suggests that individuals with higher earnings make more frequent use of high-bandwidth applications of mobile telecommunications. Population density also increases the demand for mobile telecommunications services, and to a similar degree for all technologies. This is consistent with individuals in more densely populated areas having more social connections and therefore having higher demand mobile telecommunications. Estimates of the expenditure model show that income increases expenditures on mobile telecommunications, as one would expect. Mobile expenses also increase in the number of residents in the household; this is consistent with individuals in larger households having more reasons to communicate and therefore being more active users of mobile telecommunications services.

Table 4: Parameter Estimates – Market Shares

Variable	Phase	Technology	Estimate	2.5 Quantile	97.5 Quantile
GDP	early	2G	0.121	-0.186	0.598
GDP	early	3G	0.322	-0.072	0.827
GDP	early	4G	0.869	0.457	1.466
GDP	late	2G	-0.425	-0.665	0.121
GDP	late	3G	-0.304	-0.600	0.230
GDP	late	4G	0.184	-0.086	0.806
Intercept	early	3G	-2.032	-3.192	-0.704
Intercept	early	4G	-9.226	-11.727	-7.100
Intercept	late	3G	-0.334	-1.447	1.108
Intercept	late	4G	-4.150	-5.618	-2.159
Pop Density	early	2G	0.268	0.060	0.490
Pop Density	early	3G	0.297	0.159	0.541
Pop Density	early	4G	0.302	0.104	0.539
Pop Density	late	2G	0.442	0.026	0.557
Pop Density	late	3G	0.420	0.105	0.502
Pop Density	late	4G	0.434	0.031	0.463
Nesting Parameter			0.262	0.126	0.392

This table displays GMM estimates of the market share model. A combination of the Variable, Phase, and Technology columns defines a parameter in the model. GDP and Pop Density represent the logarithm of GDP per capita and the logarithm of population density. The Estimate column indicates the point estimate and the final two columns together define a 95% confidence interval for the respective parameter. The confidence interval is calculated by bootstrap, which is performed at the area-code level. The estimated models also include state-phase fixed effects.

Moving on to the dynamic parameters, I estimate the median entry cost (which accounts for the cost of setting up 2G service) to be equal to 5.33 million BRL, the fifth and ninety-fifth percentile being 4.99 million and 5.53 million BRL. This variation is

Table 5: Expenditure Equation

	Dependent variable:
	Log of Expenditures
Log Income	0.360***
	(0.004)
Number of Residents	0.029***
	(0.002)
State * Rural/Urban FE	Yes
Observations	72,775
R^2	0.201
Adjusted R^2	0.200
Note:	*p<0.1; **p<0.05; ***p<0.01

This table displays OLS estimates of equation 7.

due to differences in municipality area. The cost of non-compliance with the regulation, φ, is estimated to be 1.51 million BRL, or 28.35% of the median entry cost. Firms, therefore, perceive the cost of non-compliance to be substantial.

Figure 4 plots the estimated dynamics of the cost of introducing 3G technology. The figure plots, for the years 2014-2018, the average cost together with the tenth and the ninetieth percentiles of the distribution – where, as before, the variation is driven by differences in municipality area. The figure shows that the average cost of introducing 3G declined from just below 4 million BRL in 2014 to about 2.5 million BRL in 2018. Figure 5 displays the analogous figure for 4G technology. The figure shows a much more marked decrease in the cost of introducing 4G. This is consistent with the notion that 4G was a relatively new technology in 2014. Estimates of the dynamic parameters can be found in Appendix F.

6 Counterfactual Analysis

The counterfactual exercises I conduct in this section directly address the questions posed in the beginning. In subsection 6.1, I use the model to analyze the effect of coverage requirements on the time to introduction of 3G technology. I also use the model to quantify the cost that the regulation imposes on firms and to decompose the total effect of coverage requirements into a direct effect on the regulated firm and indirect equilibrium effects. In subsection 6.2, I use the model to evaluate an alternative

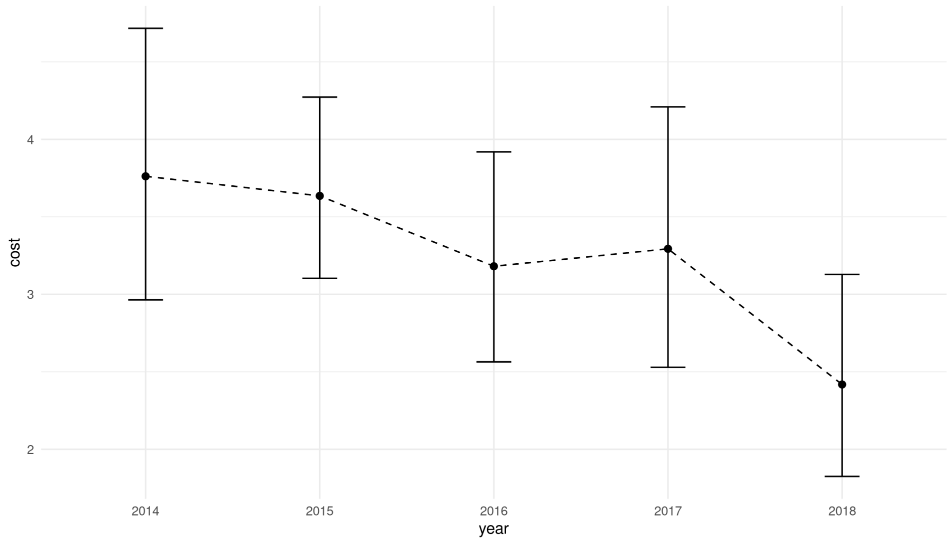

Figure 4: Cost of 3G Introduction

This figure displays the estimated dynamics of the cost of 3G introduction. For each year in the model, the dot shows the average cost across municipalities of introducing 3G technology. The whiskers indicate the tenth and ninetieth percentiles of the distribution, where the variation is driven by differences in municipality area.

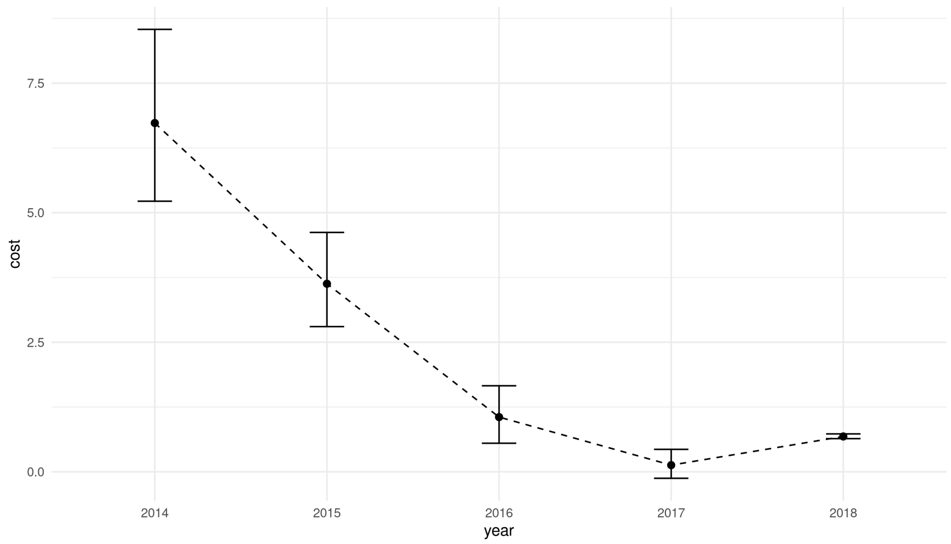

Figure 5: Cost of 4G Introduction

This figure displays the estimated dynamics of the cost of 4G introduction. For each year in the model, the dot shows the average cost across municipalities of introducing 3G technology. The whiskers indicate the tenth and ninetieth percentiles of the distribution, where the variation is driven by differences in municipality area.

regulation in which the first firm to introduce 3G technology receives a subsidy.

In estimation, I used all of the 3,449 markets subject to a 3G requirement. For the counterfactuals, I will focus on those markets with a deadline on December 31, 2019. The reason for this is that this set of requirements was imposed in mid-2012, whereas the remaining requirements were imposed earlier. Because the technology deployment data starts in early 2013, its starting point already reflects those earlier requirements to a large extent, but not the December 2019 requirements. There are 941 markets in my sample with a December 2019 deadline. I will perform the simulations for the subset of these markets in which the regulated firm does not offer 3G technology at the start of the data. There are 743 such markets in my sample. Finally, when comparing the time to 3G introduction under alternative scenarios, I only consider those markets that start without 3G, of which there are 679.

6.1 The Effect of Coverage Requirements

To quantify the effect of coverage requirements on the time to introduction of 3G technology and firms' ex-ante expected profits, I use the estimated model to solve the game and simulate data for each municipality under two alternative regulatory regimes: under the estimated fine $\hat{\varphi}$ and setting $\varphi = 0$, i.e., with no regulation. I simulate 250 paths of play for each municipality under each of these two regulatory regimes.

The first question we can ask the model is whether coverage requirements are really necessary. More precisely, would 3G technology be introduced within a reasonable amount of time in the absence of regulation? To answer this question, I compute the share of simulations in which some firm introduced 3G technology by December 2019. Figure 6 shows the distribution of those probabilities across municipalities. The figure shows that just over 60% of the municipalities in the sample would have had access to 3G technology by December 2019 with at least 75% probability. For another 33.72% of the municipalities, the probability of having 3G access is between 50% and 75%. This suggests that for most municipalities, market forces would most likely than not be sufficient to guarantee provision of 3G service. Figure 6 also shows that for just over 6% of municipalities, the probability of having 3G service by December 2019 is less than 50%. In these municipalities, market forces are most likely insufficient to guarantee service provision. Out of these 41 municipalities, 21 do not have service in the beginning of the data.

The results above may suggest that the regulation has a limited effect. However, it may affect not only the ultimate availability of 3G but also the speed of its introduction. To investigate effects on the time to 3G availability, I use the model to simulate

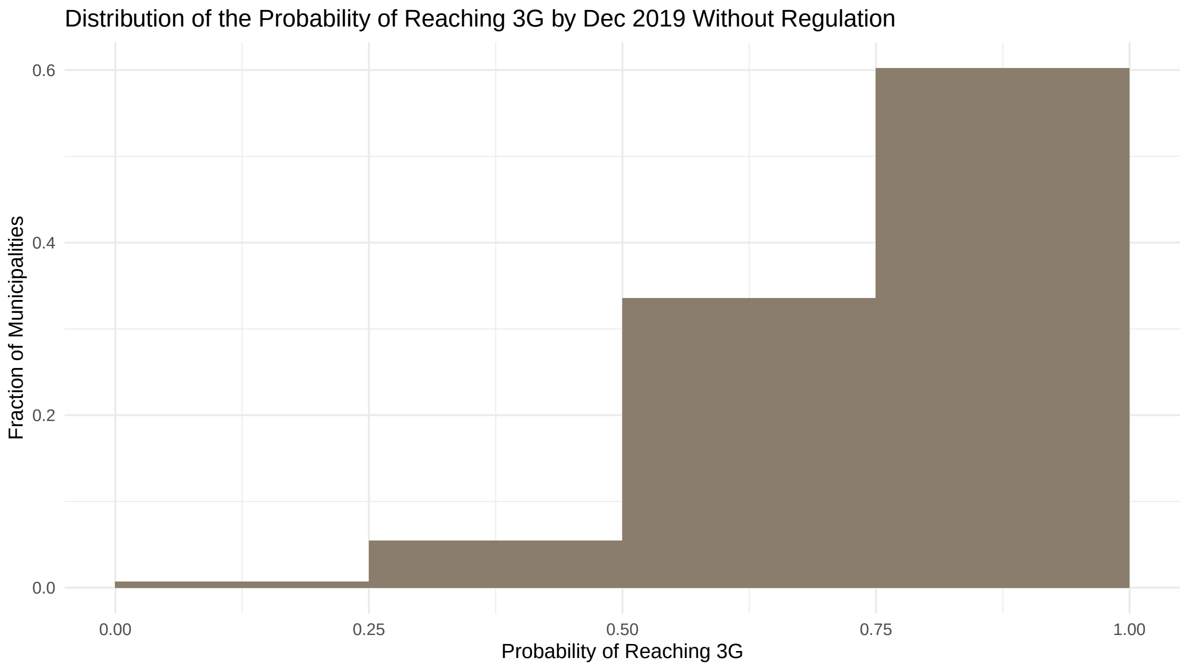

Figure 6: Distribution of the Probability of Reaching 3G by December 2019 Without Regulation.

data with and without regulation until 2023. For each municipality and regulatory regime, I calculate the time to 3G introduction, in years.[30] Figure 7 shows the resulting distributions. The label "Status quo" refers to results obtain setting the fine to $\hat{\varphi}$. The label "No regulation" corresponds to setting the fine to zero. Coverage requirements reduce the average time to 3G introduction by 0.67 years, on average. The regulation also considerably reduces the dispersion in the time to introduction of 3G, mostly by eliminating a long right tail present in the absence of regulation. Figure 8 shows the same information in a different way. For each municipality, I compute the accelleration in the introduction of 3G due to the regulation. Figure 8 plots the resulting distribution across municipalities. The effects are concentrated between 0 and 1 year, though there is a long right tail, consisting of the most vulnerable markets.

To further understand the determinants of the effects of the regulation, I investigate how the time to 3G introduction in the absence of regulation and the acceleration afforded by coverage requirements relate to observable market characteristics. Specifically, I project the time to introduction of 3G with no regulation and the acceleration induced by coverage requirements onto observable market characteristics and vari-

[30]In those instances in which 3G is not introduced by the end of the simulated data, I set the time to 3G introduction equal to the length of the simulated sample. This implies that the numbers I present on the effect of the regulation are, in some cases, a lower bound.

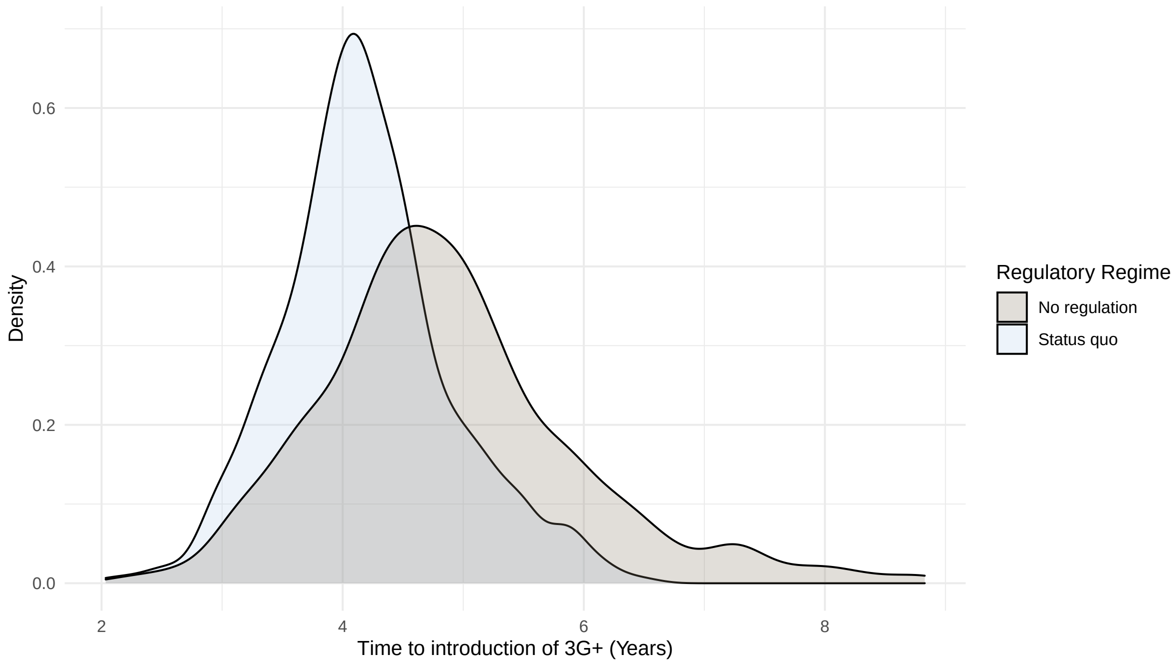

Figure 7: Distribution of the time to introduction of 3G technology or better under alternative regulatory regimes.

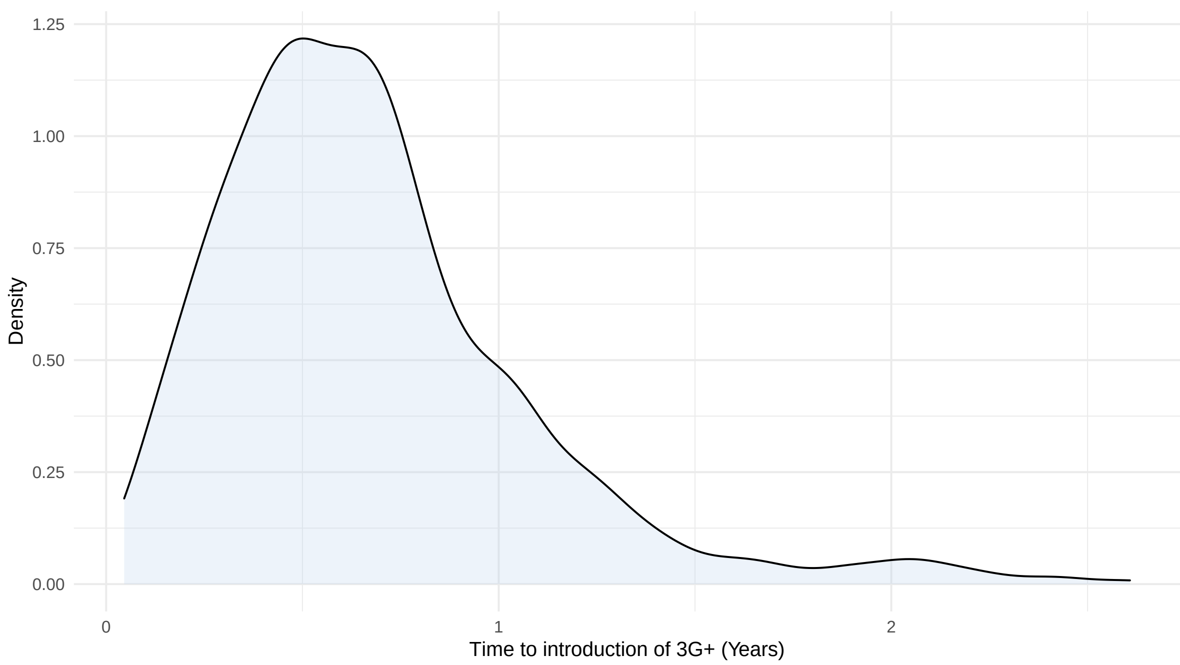

Figure 8: How much faster is the introduction of 3G+ under regulation?

ables that capture the initial market structure. Table 6 reports the results.

Table 6: Explaining Time to Adoption and the Effect of Regulation

	Dependent variable:	
	Time to 3G	Reg. Effect
	(1)	(2)
Log Area	0.604***	0.208***
	(0.019)	(0.007)
Log Population	−0.651***	−0.254***
	(0.053)	(0.020)
Log GDP Per Capita	0.049	−0.008
	(0.041)	(0.015)
Number of Firms in t = 0	−1.594***	−0.357***
	(0.058)	(0.025)
Regulated Firm Active in t = 0		0.090***
		(0.017)
Constant	7.941***	1.923***
	(0.675)	(0.249)
Observations	679	655
R^2	0.728	0.629
Adjusted R^2	0.727	0.626
Note:	*p<0.1; **p<0.05; ***p<0.01	

The dependent variable in column 1 of table 6 is the time to 3G introduction without regulation, measured in years. The explanatory variables are a municipality's GDP per capita, population, and area, all in logarithms, as well as the number of firms in the beginning of the data.[31] The results show that the time to 3G introduction without regulation is decreasing in a municipality's population, and it is increasing in its area. The effect of GDP per capita not statistically significant.[32] Moreover, the time to 3G introduction is decreasing in the number of firms in the market in $t = 0$. These results

[31] I take averages over time of these municipality characteristics. The sample is restricted to those markets that do not have 3G service in the beginning of the data.

[32] In results not reported here I perform the same exercise but focusing on the introduction of 4G. In that case, GDP per capita does have a negative and statistically significat effect on the time to introduction of that technology.

are intuitive: firms are more likely to enter and upgrade their technologies in more populous markets with a smaller area to be covered; since incumbents have a lower cost of introducing 3G than potential entrants, a larger initial number of firms leads to faster 3G introduction.

The second column in table 6 models the acceleration in the introduction of 3G induced by coverage requirements, measured in years, as a function of the same variables included in column 1, and a dummy for whether the regulated firm was active in the market in the beginning of the data.[33] The coefficients on the market characteristics and the number of firms show the same pattern as column 1, i.e., markets where, in the absence of regulation, 3G would be introduced faster also experience a smaller acceleration, as one might expect. Lastly, the estimates imply that regulating an incumbent leads to a slightly larger acceleration than regulating a potential entrant.

Next, I use the model to calculate the cost that the regulation imposes on firms.[34] Solving the dynamic game under the estimated fine and under no regulation, I obtain, for each municipality, firms' ex-ante expected profits under those two regimes. The cost of the regulation is the aggregate difference in firms' ex-ante expected profits in the no-regulation and the status-quo regimes:

$$\text{Regulation Cost} = \sum_m \sum_f \left(V^m_{\varphi=0}(s_{f0}, s_{-f0}, t=0) - V^m_{\varphi=\hat{\varphi}}(r_f, s_{f0}, s_{-f0}, t=0) \right)$$

where $V^m_\varphi(\omega)$ is the firm's ex-ante expected profit in municipality m and state ω when the fine is set to φ.[35] I calculate that the cost of the regulation amounts to 321 million 2010 BRL, or 183 million 2010 USD.[36] This amounts to 20.04% of firms' aggregate ex-ante expected profits without regulation.

Table 7 helps us understand the sources and incidence of these costs. The first column of the table indicates whether or not the firm is regulated and the second column indicates its initial state in the data. The next three columns show, respectively, the total cost, the average cost and the fraction of the total cost borne by the respective group of firms. Costs are shown in million of BRL. Average costs are positive for all groups of firms. The reason why the regulation imposes costs on unregulated firms is that it makes competition in the market tougher. This effect is more pronounced for

[33]To aid in the interpretability of the coefficient on the dummy, this regression further restrict attention to those municipalities that had at least one active firm in the beginning of the data.

[34]Note that in the real world part of this cost is borne by the government, via reduced revenue in spectrum auctions.

[35]Note that in the first term, $V^m_{\varphi=0}(s_{f0}, s_{-f0}, t=0)$, I do not include the regulation indicator r_f as an argument because there is no regulation in that case; r_f does appear as an argument in the second term.

[36]This conversion uses the average exchange rate in 2010 of 0.5685 USD per BRL.

firms that are active in the market in the beginning of the data because they necessarily face that tougher competition, whereas potential entrants are only hurt in case they enter the market. The costs imposed on regulated firms are larger, especially when the regulated firm is not active in the beginning of the data. Regulated firms are forced to take actions they might not have taken in the absence of regulation. If they are not active in the beginning of the data, they have to pay not only technology installation costs, but also entry costs. This drives the large magnitude of the costs borne by these firms. The last column shows that the large majority of the aggregate costs are imposed on regulated firms, in particular those that have to enter the market to comply with the regulation.

Table 7: Incidence of Regulation Cost

Regulated	Initial State	Total Cost	Average Cost	Fraction of Total Cost
0	Out	6.03	0.003	0.02
0	2G	11.78	0.03	0.04
0	3G	2.02	0.03	0.01
1	Out	267.33	0.75	0.83
1	2G	34.65	0.09	0.11

This table shows the total, average, and fraction of total costs borne by firms as a function of their regulated status and their initial technology in the data. Total and average costs are in millions of BRL.

I close this subsection on the effects of coverage requirements by decomposing these effects into direct effects on the regulated firm and indirect equilibrium effects. To do so, I proceed in three steps. First, I solve the game and simulate data in the absence of regulation. I then set the fine to its estimated value $\hat{\varphi}$ and solve for the regulated firm's optimal policy, holding the policy functions of the unregulated firms fixed at their equilibrium policies without regulation. Next, I solve for the Markov Perfect Equilibrium under regulation. The difference between the time to adoption under the equilibrium policies with regulation and the time to adoption when only the regulated firm responds to the regulation gives the desired equilibrium effects.

Figure 9 shows the distribution, across municipalities, of the equilibrium effects. Most of the values are positive: the equilibrium adjustment leads to a longer time to introduction of 3G, relative to the case when only the regulated firm adjusts its behavior to the policy. This reflects the reduced incentives to enter and upgrade faced by unregulated firms, resulting from the increased future competition generated by the regulation. Quantitatively, however, the equilibrium effects are small. The total effects of the policy are therefore almost entirely explained by the direct effects on

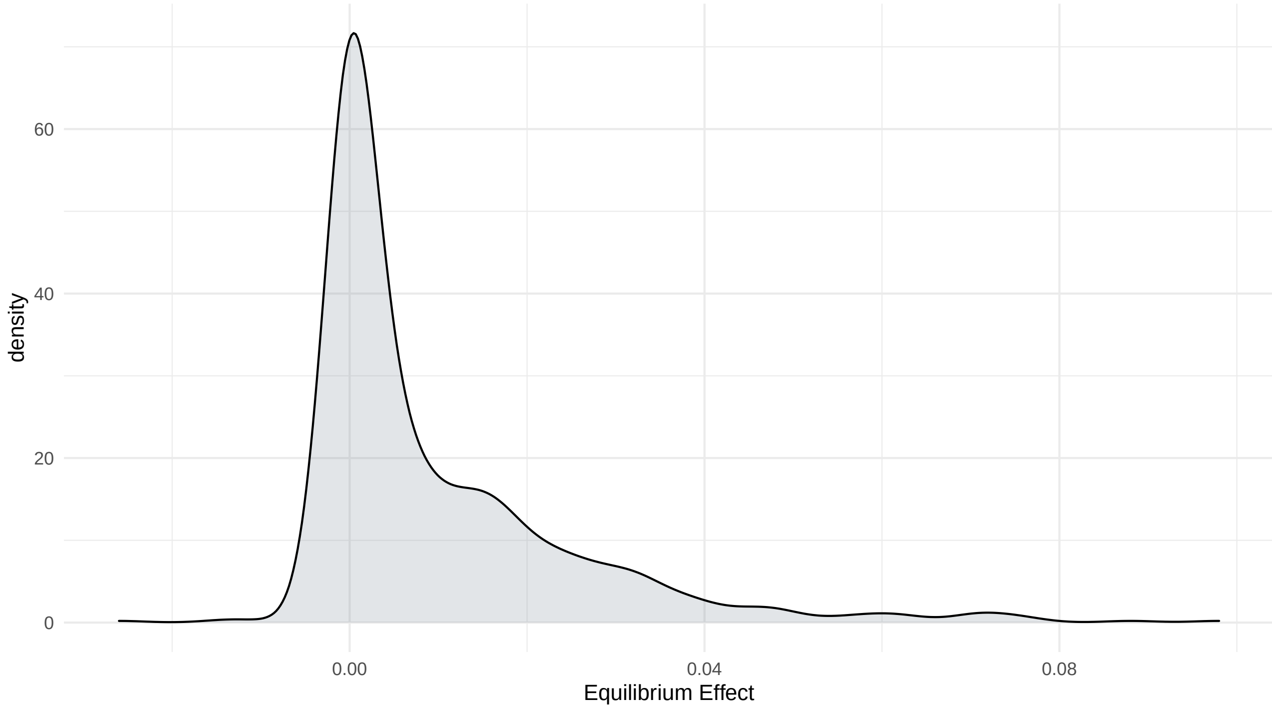

Figure 9: Equilibrium Effects

the regulated firm. Appendix G provides further detail on the equilibrium effects by looking at changes in policy functions in the two regimes.

6.2 Alternative Regulatory Interventions

The final question posed in the beginning of this paper was whether we can design regulation that is more effective than coverage requirements. As before, I am mostly concerned with two dimensions of a policy's effect: to what extent it accelerates the introduction of new technologies and the cost of adoption of these new technologies. I will also highlight the effect of different policies on market structure.

6.2.1 Subsidizing the Introduction of 3G

The large estimated cost of non-compliance and the counterfactual results above show that coverage requirements provide strong incentives for the regulated firm to introduce 3G. These strong incentives ensure service provision. However, they come at the cost of forcing a firm to enter a market or upgrade its technology when it might not have done so in the absence of regulation. The analysis above established that these costs are substantial, especially when the regulated firm is not active in the market.

A policy that treats firms symmetrically, instead of targeting a single firm, may save on these costs. The intuition is simple. By providing the same incentive to all firms, the firm that will eventually choose to introduce the new technology will tend to be the most cost-efficient one.

Motivated by this reasoning, in this section I evalute a regulation that subsidizes the first firm to introduce 3G technology or better. I denote the subsidy by β. If more than one firm introduces the new technology, those firms split the subsidy equally. Therefore, I add the following term to firms' flow profits for each state of the game and each possible action a_f:

$$\beta \times \underbrace{\mathbf{1}\left\{\left(\max_{f'} s_{f'}\right) < 3 \leq a_f\right\}}_{\text{Subsidy is paid}} \times \underbrace{\sum_{n=0}^{3} \mathbb{P}\left(\left(\sum_{f' \neq f} \mathbf{1}\{a_{f'} \geq 3\}\right) = n\right) \times \frac{1}{1+n}}_{\text{Expected fraction of the subsidy}}$$

where the probabilities in this expression are derived from the ensuing equilibrium behavior.

I experiment with two subsidy designs. I start with a budget given by

$$\text{Budget} = \sum_{m} \sum_{f} \left(V^m_{\varphi=0}(s_{f0}, s_{-f0}, t=0) - V^m_{\varphi=\hat{\varphi}}(r_f, s_{f0}, s_{-f0}, t=0) \right) \tag{15}$$

This amount is simply the aggregate cost of the regulation. Note that firms would be willing to pay this amount to move from the status quo world to a world with a subsidy. In that sense, the subsidies considered below are self-financed.[37]

I start by simply splitting the budget in equation (15) equally across municipalities. Figure 10 shows the resulting acceleration in the introduction of 3G technology obtained under coverage requirements (labeled "status quo" in the figure) and the subsidy. The average effect is very similar; the subsidy accelerates the introduction of 3G by 0.62 years on average, relative to 0.68 years under coverage requirements. The subsidy generates larger accelerations for 53.31% of the municipalities. As figure 10 shows, relative to coverage requirements, the subsidy eliminates some small effects, but also loses some large ones. The large effects lost by the subsidy come precisely from those municipalities that would experience relatively late introduction of 3G in the absence of regulation. Consider, for example, those municipalities where cover-

[37] The practical application of this idea rests on the observation that the alternative policies discussed here would make spectrum licenses more valuable than under coverage requirements. Therefore, spectrum auction revenues would increase and these increased revenues could be used to finance the subsidies proposed here.

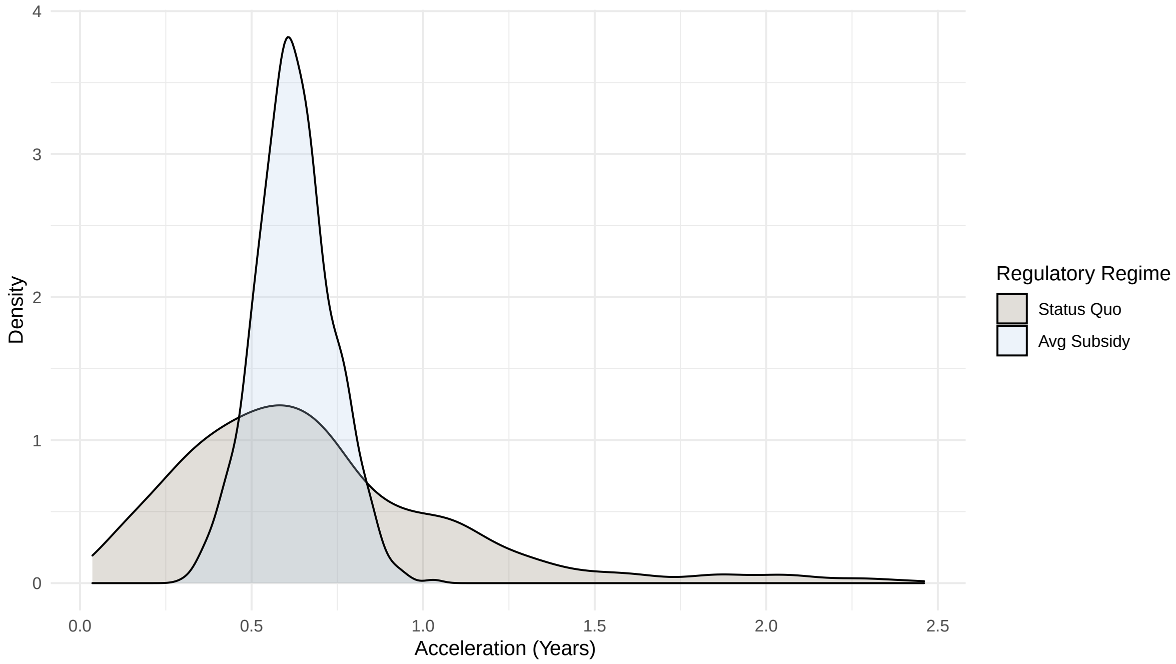

Figure 10: Acceleration of 3G Introduction Under Coverage Requirements and Subsidy

age requirements generate an acceleration in the introduction of 3G of one year or more. The average time to introduction of 3G without regulation in these municipalities is more than two years larger than in the remaining municipalities. This is a set of municipalities where the introduction of 3G is relatively unprofitable, and the homogeneous subsidy provides less incentives for 3G introduction in these municipalities than coverage requirements do. For this set of municipalities, the subsidy leads to 3G introduction 0.7 years later than coverage requirements, on average.

The municipalities where coverage requirements generate small accelerations (less than 6 months) are relatively competitive. The average number of firms in $t = 0$ in those municipalities is 1.24, relative to 0.96 in the remaining municipalities. The introduction of 3G in these municipalities in the absence of regulation is relatively fast: 3.89 years, on average, compared to 5.44 years in the other municipalities. In these markets, the effect of the subsidy is very close to the mean effect, so that these markets are moved from the left tail of the "Status Quo" distribution in figure 10 to the middle of the subsidy distribution. In summary, relative to coverage requirements, a flat subsidy increases the acceleration of 3G introduction in some localities where there seems to be little need for regulation, and has smaller effects in some municipalities where regulation seems to be particularly important.

This point is shown clearly in figure 11. The figure shows a scatterplot of the time

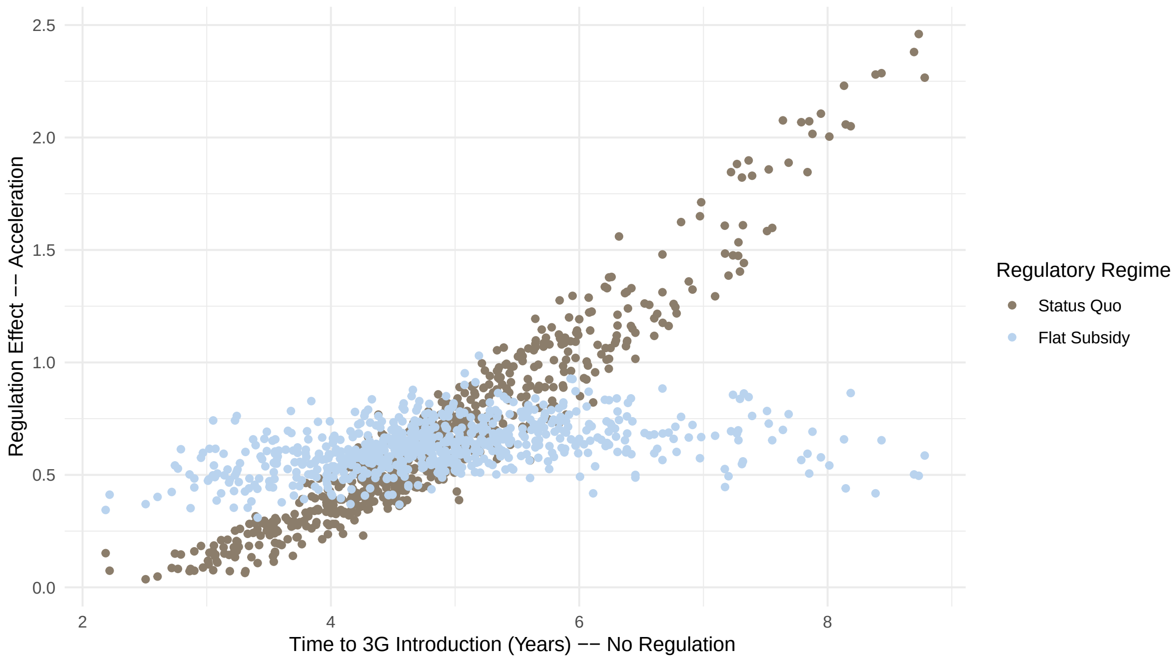

Figure 11: Targeting Properties of Coverage Requirements and a Flat Subsidy

to introduction of 3G technology in the absence of regulation against the effects of coverage requirements and the flat subsidy. Each dot in the figure is one municipality. For the case of coverage requirements, we see a positive correlation: the regulation has stronger effects in those markets where, in the absence of intervention, it would take longest for 3G to be introduced. The flat subsidy does not display the same correlation. In fact, for the most vulnerable municipalities the correlation seems to be slightly negative.

In light of these results, I consider a subsidization policy that allocates a larger share of the budget towards the most vulnerable municipalities. Specifically, let τ_m be the time for 3G introduction in municipality m in the absence of regulation and let f be a positive and increasing real function. Allocate to municipality m the fraction $f(\tau_m)/\sum_{m'} f(\tau_{m'})$ of the budget specified in equation (15). The more convex f is, the stronger the targeting towards the most vulnerable municipalities. For the results below, I set $f(\tau) = \tau^{3/2}$.[38] Figure 12 shows the results. This subsidy leads to an acceleration in the roll-out of 3G of 0.65 years relative to 0.68 for coverage requirements and 0.62 for the flat subsidy. As shown in the figure, the municipality-specific sub-

[38]This subsidy design relies on τ_m, and one may thus be concerned that its informational requirements are substantial. However, note that the results in table 6 show that a substantial portion of the variation in τ_m is explained by observables. Therefore, it might be possible to design a subsidy with similar properties that relies only on data that is available to regulators.

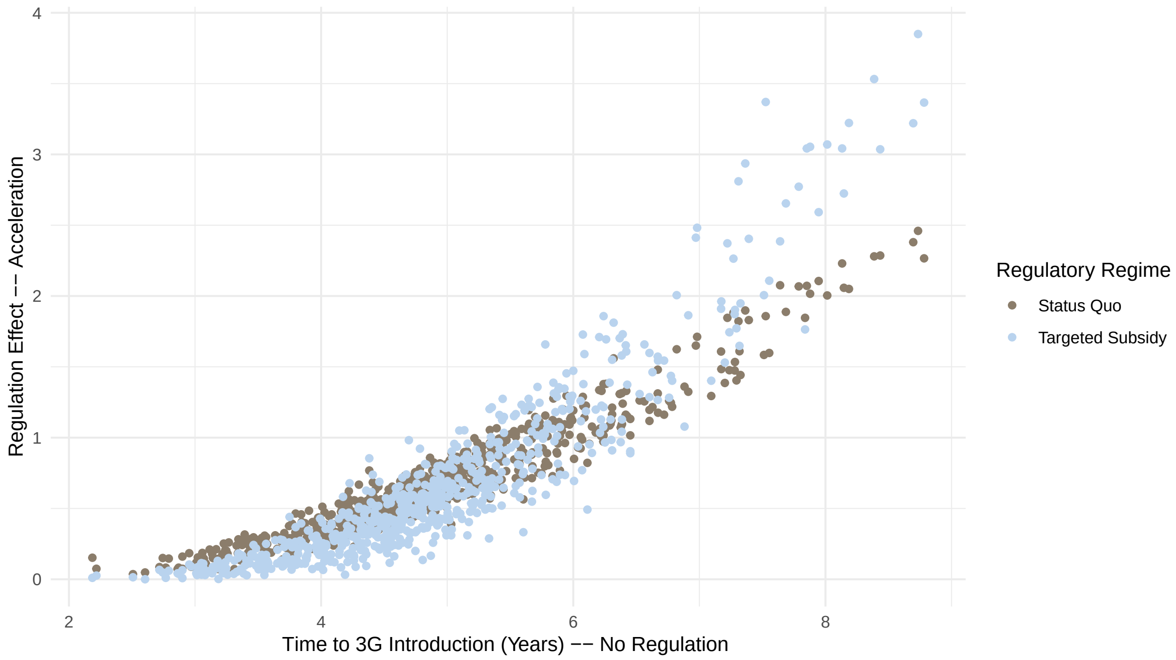

Figure 12: Targeting Properties of Coverage Requirements and a Municipality-Specific Subsidy

sidy restores the desired positive correlation between the effect of the regulation and the time to 3G introduction in the absence of regulation. In fact, this subsidy leads to larger accelerations in the roll-out of 3G in the most vulnerable municipalities than do coverage requirements. This comes at the expense of slightly smaller effects in those municipalities that even in the absence of regulation obtain access to 3G technology relatively quickly. The optimal way to navigate this trade-off (e.g., the optimal choice of exponent in $f(\tau)$) depends on the relative changes in consumer surplus in those two groups of municipalities, which cannot be quantified with the limited data available for this study.

Finally, firms substantially benefit from the municipality-specific subsidy relative to coverage requirements.[39] Firms' ex-ante aggregate expected profits grow by 126 million BRL, after accounting for their financing of the subsidy (as per equation (15)); this amounts to 9.83% of firms' aggregate profits without regulation. These gains essentially come from reallocating the introduction of the new technology from inactive and regulated firms, who have to pay entry costs to enter the market, to incumbents, who only pay technology installation costs.

This reallocation leads to a more cost-efficient technology roll-out, but at the ex-

[39] Similar results hold for the flat subsidy.

pense of reduced competition in the market. The subsidy leads to entry of 0.93 firms, on average, by the end of 2022. In contrast, coverage requirements lead to entry of 1.17 firms. Moreover, this difference is entirely driven by those markets where the regulated firm is a potential entrant, which are the source of the cost savings discussed above. The average number of entrants in these markets, under coverage requirements, is 1.60, whereas it is equal to 1.00 under the subsidy. In the remaining markets, those where the regulated firm is an incumbent, coverage requirements result in entry of 0.83 firms, on average; the subsidy results in entry of 0.87 firms.

The simulations can be used to perform a heuristic calculation that is informative of where we stand in this cost-competition trade-off. For each simulation s, I compute the discounted average number of firms present in each market: $\bar{n}_s = \sum_{t=0}^{T} \delta^t \sum_f \mathbf{1}(s_{ft} > 0)$. I then average this quantity across simulations for each regulatory regime to obtain a discounted average number of firms for each regulatory regime and municipality. This quantity, multiplied by a municipality's population (averaged over time), gives a count of consumers exposed to an additional firm. I find that 243,303 consumers are exposed to an additional firm under coverage requirements, relative to the targeted subsidy.[40] For this added competition to overturn the cost efficiency results discussed above, the average gain in consumer surplus has to be at least 8.21 BRL.[41] This is equal to 44.99% of the mean predicted expenditure for these markets, where the predictions come from the expenditure model in equation 7. This suggests that the targeted subsidy is more efficient than coverage requirements.

7 Conclusion

Concerns regarding lack of service provision are present in many industries and so is regulatory intervention. This paper studies the effect of coverage requirements, a common form of regulation in the mobile telecommunications industry, on the speed of roll-out of new technologies, market structure, and firms' profits. To do so, I use new municipality-level mobile technology availability data from Brazil to estimate a dynamic game of entry and technology upgrade under regulation.

I show that the regulation accelerated the arrival of third generation mobile telecommunications technology to relatively small and underdeveloped markets in Brazil by 0.7 years on average – and by more than 2 years in some cases. This, however, comes

[40]The aggregate population (averaged over time) of the municipalities considered in these counterfactuals is 3.2 million.

[41]Note that this is a conservative estimate, as it assumes that the gain in consumer surplus from additional entrants is constant.

at a high cost: the regulation reduces firms' ex-ante expected profits by 20.04%. I also show that a policy that subsidizes the first firm to introduce 3G technology, by an amount that the firms themselves would be willing to finance, achieves a similar acceleration of the introduction of 3G, better targets the most vulnerable markets, and leads to a more cost-efficient pattern of roll-out. These cost-efficiency gains are accompanied by reduced competition in certain markets, but the losses in consumer surplus needed to overturn the efficiency gains are implausibly large. These findings have immediate implications for the design of regulation in mobile telecommunications markets, and potentially to other markets where universal service is also a concern.

Some interesting and related questions are not addressed in this paper. First, though my results are informative for the design of regulation, data limitations preclude me from conducting a complete welfare analysis. It would be interesting to combine data such as the one used in this paper with detailed price and quantity data to compare the gains in consumer surplus from having earlier access to new technologies and the regulatory costs imposed on firms. Second, my analysis abstracted away from geographic interdependencies in firms' costs. It would be interesting, though challenging, to extend the model in this paper to allow for such interdependencies. These, however, are left for future research.

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Appendix

Appendix A Regulation and Delay in the Fudenberg-Tirole Model

A.1 The Model

There are two firms. Firm 1 is an incumbent and firm 2 a potential entrant. Time is continuous and the discount rate is r. Firm 1 initially operates as a monopolist with constant marginal cost $\bar{c}$. At any point in time $t \geq 0$, firms can adopt a technology with constant marginal cost $\underline{c}$. Adopting this technology at time t costs $C(t)$, where $C(t) > 0$, $C'(t) < 0$ and $C''(t) > 0$, for all $t \geq 0$.

Let $p^m(c)$ and $\pi^m(c)$ be, respectively, the monopoly price and profit when marginal cost is c. I focus on the case in which the innovation is *non-drastic*, i.e., $p^m(\underline{c}) \geq \bar{c}$. If both firms are in the market, they compete à la Bertrand. Let $\pi^d(c, c')$ be a firm's profit when its cost is c and its competitor's cost is c'. Under the assumption of a non-drastic innovation and Bertrand competition, π^d satisfies

$$\pi^d(\underline{c}, \bar{c}) = (\bar{c} - \underline{c})D(\bar{c}), \quad \pi^d(\bar{c}, \underline{c}) = 0 \quad \text{and} \quad \pi^d(c, c) = 0 \quad \forall c$$

Firms' strategies specify their decisions to adopt or not the new technology as a function of t and their competitor's technology[42]. Note that due to the Bertrand assumption, a firm will never adopt the new technology after its competitor has adopted, as they would incur the positive adoption cost but their flow profits would stay at zero.

If the incumbent is first to adopt at date t_1, its overall profit is

$$L_1(t_1) = \int_0^{t_1} \pi^m(\bar{c})e^{-rt}dt + \int_{t_1}^{\infty} \pi^m(\underline{c})e^{-rt}dt - C(t_1)e^{-rt_1} \tag{16}$$

If the incumbent is preempted at date t_2, its present discounted profit is

$$F_1(t_2) = \int_0^{t_2} \pi^m(\bar{c})e^{-rt}dt \tag{17}$$

[42] The discussion here is somewhat informal. Fudenberg and Tirole 1985 provide a careful description of appropriate strategies for this game. Their analysis is far from trivial.

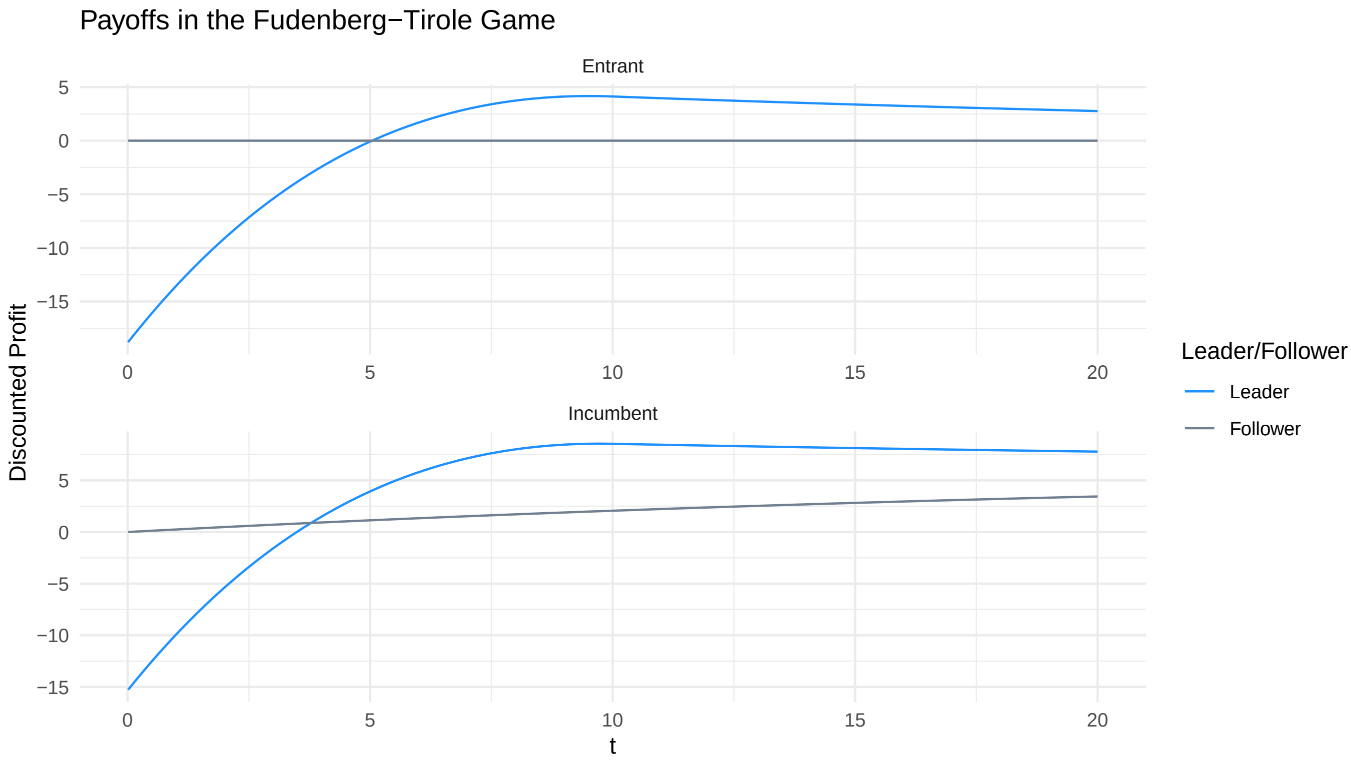

Figure 13: Payoffs in the Fudenberg-Tirole Model.

If the entrant is first to adopt at date t_2, its overall profit is

$$L_2(t_2) = \int_{t_2}^{\infty} \pi^d(\underline{c}, \bar{c})e^{-rt}dt - C(t_2)e^{-rt_2} \tag{18}$$

Finally, it the entrant is preempted at time t_1, its profit is given by $F_2(t_1) = 0$.

Figure 13 plots the functions[43] L_1, F_1, L_2, F_2. That figure is sufficient to determine the equilibrium outcome of the game[44]. Let t_2^* be defined by $F_2(t_2) = L_2(t_2)$. In Figure 13, $t_2^* \approx 5$. Firm 2 will not adopt before t_2^*, as it would prefer to be preempted by firm 1. Knowing this, firm 1 will wait to adopt, as $L_1(t_1)$ is increasing over $t_1 < t_2^*$. Now suppose firm 2 is first to adopt at some $t_2 > t_2^*$. Since $L_1(t_2 > F_1(t_2))$, firm 1 prefers to adopt at $t_2 - \varepsilon$. In equilibrium, firm 1 adopts at $t_1 = t_2^*$, and firm 2 never adopts.

[43]The specification is as follows. $D(p) = 2 - p$, $\bar{c} = 1$, $\underline{c} = 3/4$, $C(t) = \mathbf{1}\{t <= 10\}\left(\frac{t^2}{4} - 5 * t + 25\right) + 0.1$.

[44]But not the equilibrium itself, i.e., the strategy profile.

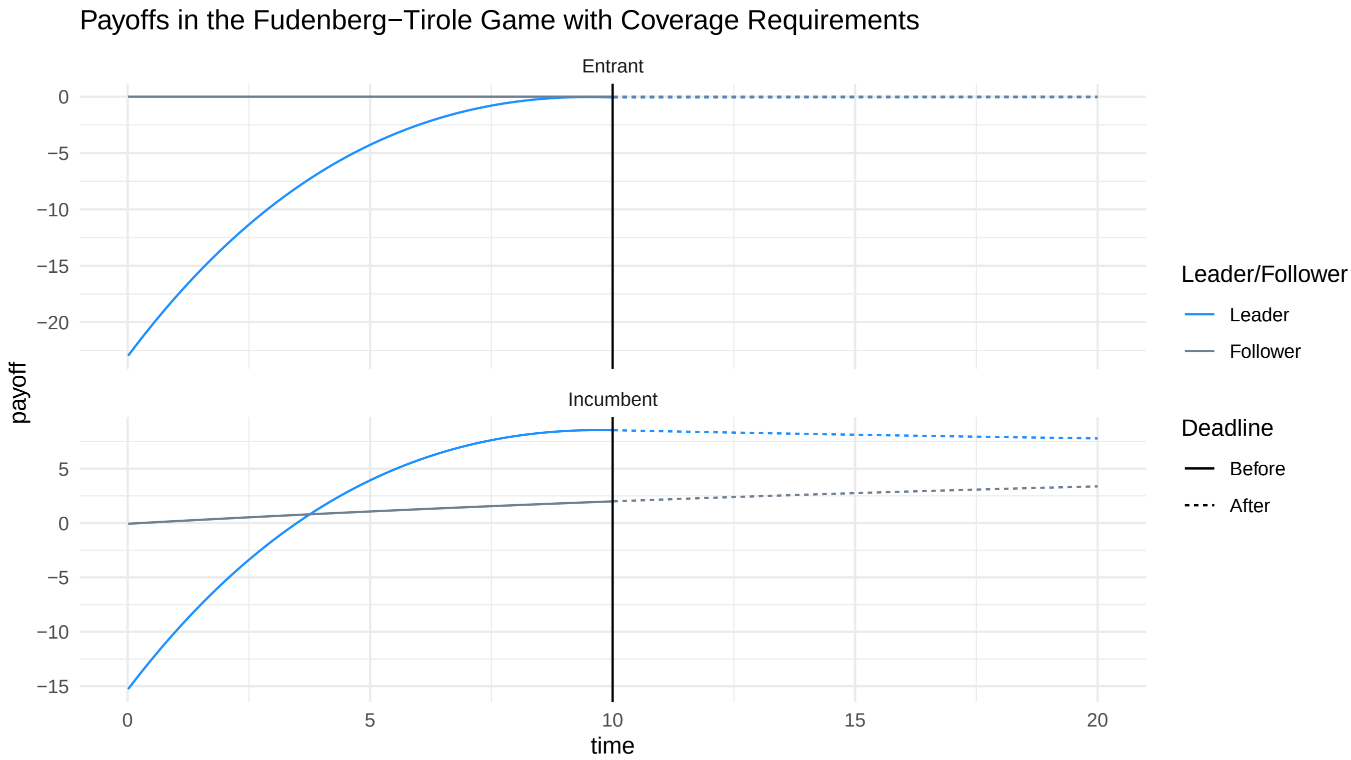

Figure 14: Payoffs in the Fudenberg-Tirole Model with Regulation.

A.2 Incorporating Regulation

Now suppose that the incumbent is regulated: is must adopt by some exogenously set deadline τ, lest it pay an exorbitant fine. The L_i and F_i functions are now defined (for $t_i \leq \tau$) as follows:

$$\begin{aligned}
L_1(t_1) &= \int_0^{t_1} \pi^m(\bar{c})e^{-rt}dt + \int_{t_1}^{\infty} \pi^m(\underline{c})e^{-rt}dt - C(t_1)e^{-rt_1} \\
F_1(t_2) &= \int_0^{t_2} \pi^m(\bar{c})e^{-rt}dt - C(\tau)e^{-r\tau} \\
L_2(t_2) &= \int_{t_2}^{\tau} \pi^d(\underline{c}, \bar{c})e^{-rt}dt - C(t_2)e^{-rt_2} \\
F_2(t_1) &= 0
\end{aligned} \tag{19}$$

Figure 14 plots these payoffs for the same parametrization underlying Figure 13, and $\tau = 10$. As can be seen from the figure, the fact that the incumbent will adopt the technology at time τ, at the latest, eliminates all incentive for the entrant to adopt the new technology. With no need to preempt the entrant, the incumbent is free to delay its own adoption to its most preferred time, which in this example is $t_1^* \approx 9.7$. Therefore, the regulation delays the adoption of the new technology from $t \approx 5$ to $t \approx 9.7$. Of course, if $\tau < 5$, the regulation speeds up the adoption of the new technology.

Appendix B Supplementary Figures and Alternative Specifications of Descriptive Models

Figure 15 illustrates the result of carriers' iterative choices of municipalities where they would be suject to a coverage requirement. The figure shows a map of the Brazilian Midwest, color-coded according to the identity of the regulated carrier. Figure 16 illustrates the data on technology availability. Each cell contains a map of the state of Pará, in the north of Brazil. The subdivision within each map are the municipalities in that state. Each row shows data for one of the four large carriers, and columns indicate the year for which the data is plotted. Municipalities are colored according to the best technology provided by the respective carrier in that municipality at the end of the year indicated in the column.

The tables below report alternative specifications of the descriptive models in table 3. In particular, table 8 reports models without group fixed effects, and table 9 reports models that include characteristics of firms' networks in neighboring states. Specifically, it includes dummies for whether or not the firm provides 2G, 3G, and 4G service in any neighboring municipality. Comparing table 8 and table 3 shows the importance of the group fixed effects. Without them in table 8, the competition coefficients are mostly small in absolute value and sometimes positive. That is in stark contrast with the results in table 3, where the competition coefficients are almost all negative and much larger in absolute value. This suggests that the group fixed effects capture important unobserved factors related to how desirable it is to provide service in a given market.

Now let me turn to table 9. The first thing to note is that service in neighboring municipalities is important. The estimated coefficients on 3G service and 4G service are sizeable and precisely estimated. Interestingly, the coefficients on 2G service in neighboring municipalities are negative. This is surprising because these coefficients are relative to not having service in the neighboring municipality. The next thing to observe is the effect of the network variables on the competition coefficients. These effects are mostly small, except perhaps for the number of competitors with 4G technology. Albeit small, the effects are always in the direction of increasing (in absolute value) the estimated competition coefficients. This may suggest that there are unob-

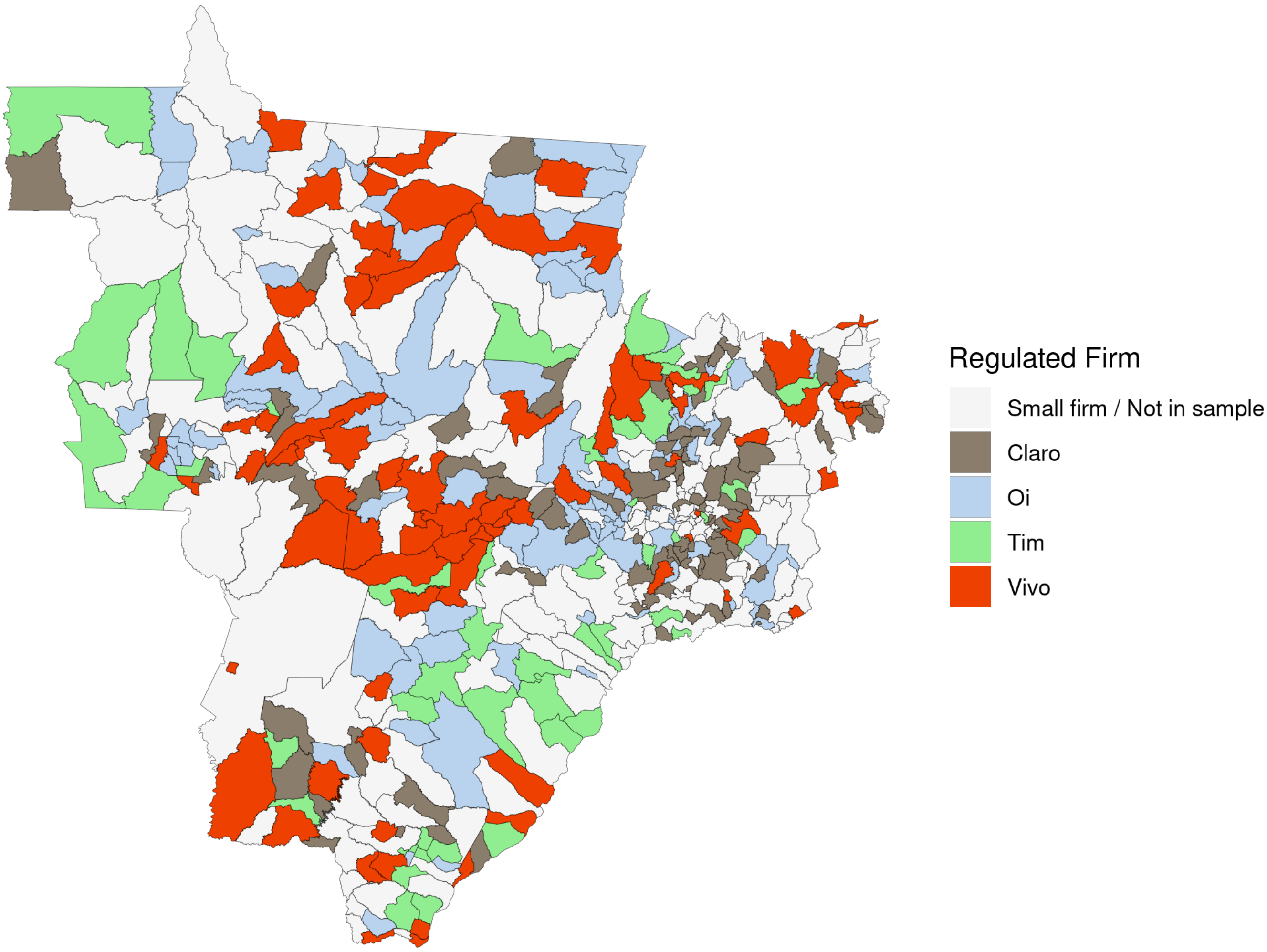

Figure 15: Regulated Carriers – Midwest

This figure shows a map of the Brazilian Midwest, color-coded according to the identity of the single regulated firm in each market. The subdivisions in the map are municipalities. The municipalities without a color are either not in the estimation sample (municipalities with more than 30,000 inhabitants in 2006) or the regulated firm is one of the small carriers. Claro, Oi, Tim, and Vivo are the four large carriers in Brazil.

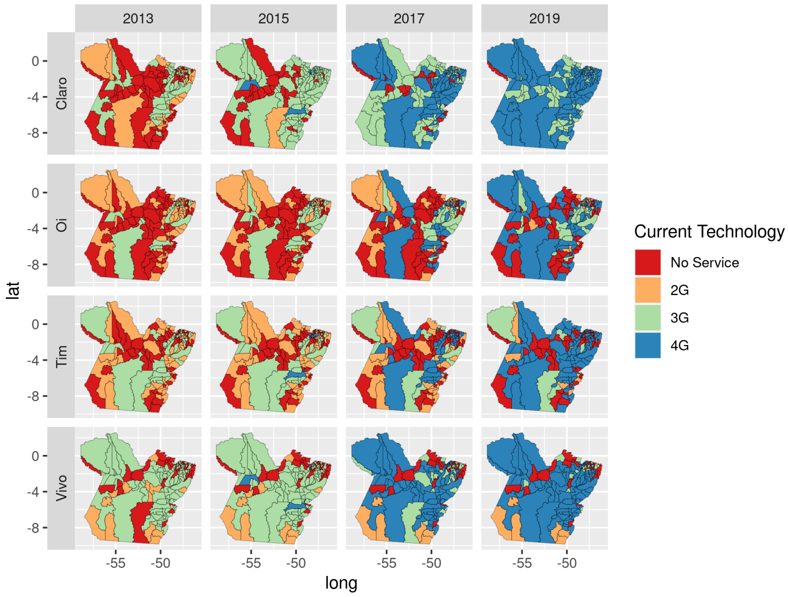

Figure 16: Technology availability in the state of Pará.

Each cell in this matrix contains a map of the state of Pará, in the north of Brazil. The subdivision within the state are municipalities. Rows correspond to the four large carriers in Brazil: Claro, Oi, Tim, and Vivo. Columns correspond to calendar years. Municipalities are color-coded according to the best technology offered in that municipality by the relevant firm in the end of the year.

Table 8: Entry/Upgrade Models – Without group fixed effects

	Dependent variable:		
		Upgrade	
	Out	2G	3G
	(1)	(2)	(3)
Log GDP PC	0.002	0.001	0.015***
	(0.001)	(0.002)	(0.002)
Log Pop.	0.011***	0.034***	-0.008^{***}
	(0.001)	(0.002)	(0.002)
Log Area	-0.002^{***}	-0.011^{***}	0.003**
	(0.0005)	(0.001)	(0.001)
Regulated	0.105***	0.155***	-0.035^{***}
	(0.003)	(0.004)	(0.003)
Regulated Competitor - Out	-0.015^{***}	0.001	-0.028^{***}
	(0.002)	(0.006)	(0.009)
Regulated Competitor - 2G	-0.007^{***}	-0.045^{***}	-0.089^{***}
	(0.002)	(0.005)	(0.007)
No. Competitors 2G	-0.001	0.005***	-0.001
	(0.001)	(0.002)	(0.002)
No. Competitors 3G	-0.011^{***}	0.006***	0.008***
	(0.001)	(0.002)	(0.002)
No. Competitors 4G	0.004***	-0.011^{***}	0.013***
	(0.001)	(0.002)	(0.002)
Group FE	Yes	Yes	Yes
$\bar{Y}$	0.026	0.079	0.083
Observations	92,088	47,074	49,245
Note:			*p<0.1; **p<0.05; ***p<0.01

servable factors that are geographically correlated[45]. Finally, and most importantly for the analysis in this paper, note that the effect of the network variables on the regulation variables is very minor, if it exists at all. This suggests that the regulation variables (in particular, whether or not a firm is regulated) are not correlated with the surrounding network infrastructure.

Table 10 tests the hypothesis of no correlation between a firm's status as the regulated firm and that firm's infrastructure in neighboring markets. The unit of analysis for the models in table 10 is a firm-market pair, and only data from the June 2016 (the first period in the data) is used. The table reports estimation results of a logit model and a linear probability model (included for the sake of interpretability) where the dependent variable is a dummy that takes the value 1 if the firm is regulated, and 0 otherwise. The explanatory variables are a constant and a set of dummies. The variable "2G Service" is equal to 1 if the firm provides 2G service in that market; "3G service" is analogously defined. "2G Service Nb." is equal to 1 if the firm provides 2G service in some neighboring market, and "3G Service Nb." is defined similarly. The results show that, conditional on the technologies offered by a firm in the market, which are included in the structural model, its infrastructure in neighboring municipalities has a small effect on the probability that the firm is regulated. The point estimates are in fact negative. These results suggest that there is no cause for concern that the difference in behavior between regulated and unregulated firms, which identifies the fine parameter φ in the structural model, is driven not by the regulation itself but by omitted differences in firms' neighboring infrastructure. Therefore, despite the importance of neighboring infrastructure shown in table 9, I omit these variables from the structural model, as doing so would likely not bias the inference regarding the effects of regulation and would increase the computational burden by several orders of magnitude.

Appendix C Restrictions on Value and Policy Functions

As before, let T_θ be the first date after which parameters do not vary anymore and let T_m be the regulation deadline in market m. The assumptions of symmetry and quasi-stationarity imply the following restrictions on value functions (and policy functions):

- $V_0(s_1, s_r, s_-, t) = V_0(s_1, s_r, P(s_-), t)$ for any permutation P.

[45] Variables that are currently omitted and could potentially be included are variables related to the terrain.

Table 9: Entry/Upgrade Models – With Neighboring Network Info

	Dependent variable:		
	Out	Upgrade 2G	3G
	(1)	(2)	(3)
Log GDP PC	0.016***	0.020***	0.032***
	(0.001)	(0.003)	(0.002)
Log Pop.	0.031***	0.059***	0.017***
	(0.001)	(0.003)	(0.003)
Log Area	−0.007***	−0.019***	−0.006***
	(0.001)	(0.001)	(0.001)
Regulated	0.104***	0.163***	−0.021***
	(0.003)	(0.004)	(0.003)
Regulated Competitor - Out	−0.014***	0.003	−0.024***
	(0.002)	(0.006)	(0.009)
Regulated Competitor - 2G	−0.001	−0.038***	−0.072***
	(0.002)	(0.005)	(0.006)
No. Competitors 2G	−0.014***	−0.013***	−0.017***
	(0.001)	(0.003)	(0.002)
No. Competitors 3G	−0.026***	−0.023***	−0.015***
	(0.001)	(0.003)	(0.003)
No. Competitors 4G	−0.022***	−0.059***	−0.043***
	(0.001)	(0.003)	(0.003)
Nb. Service 2G	−0.012***	−0.025**	−0.017*
	(0.002)	(0.012)	(0.009)
Nb. Service 3G	0.018***	0.033***	0.014**
	(0.001)	(0.003)	(0.006)
Nb. Service 4G	0.025***	0.094***	0.125***
	(0.001)	(0.003)	(0.003)
Group FE	Yes	Yes	Yes
$\bar{Y}$	0.026	0.079	0.083
Observations	92,088	47,074	49,245

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: Testing for Selection on Infrastructure in Neighboring Municipalities

	Dependent variable:
	Regulated
2G Service	0.226***
	(0.007)
3G Service	0.203***
	(0.010)
2G Service Nb.	−0.016
	(0.016)
3G Service Nb.	−0.047***
	(0.007)
Constant	0.111***
	(0.015)
Observations	13,796
R^2	0.137
Adjusted R^2	0.137
Note:	*p<0.1; **p<0.05; ***p<0.01

- $V_1(s_1, s_{-1}, t) = V_1(s_1, P(s_{-1}), t)$, for any permutation P.
- In $V_0(s_1, s_r, s_-)$, write $s_- = (s_-^1, s_-^2)$. If $s_r \geq 3$ and $\exists\, j \in \{1, 2\}$ such that $s_-^j \geq 3$, then $V_0(s_1, s_r, s_-) = V_0(s_1, s_-^j, s_r, s_-^{-j})$.
- If $s_1, s_r \geq 3$, then $V_1(s_1, P(s_r, s_-)) = V_0(s_1, s_r, s_-)$ for any permutation P.
- If $t > T_\theta > T_m$, $V_r(s_1, s_-, t) = V_r(s_1, s_-, T_\theta)$.
- If $T_\theta < T_m$, $T_\theta < t$ and $s_r \geq 3$, then $V_0(s_1, s_r, s_-, t) = V_0(s_1, s_r, s_-, T_\theta)$ and $V_1(s_r, s_-, t) = V_1(s_r, s_-, T_\theta)$.

Starting from the state space

$$\Omega := \{0, \ldots, \max\{T_m + 1, T_\theta\}\} \times \{0, 1\} \times \{0, 2, 3, 4\}^4 ,$$

we can reduce its cardinality using the restrictions above by mapping each state to an element of the equivalence class induced by these restrictions. I do so by using a variable-base number system to order the states in Ω and then mapping each state to the minimal (in this order) state in its equivalence class.

Appendix D Market Shares at the Code Area Level

This appendix justifies equation 8 for market shares at the code-area level, repeated here for convenience

$$\mu_{jc\tau} = \sum_{m \in c} \omega_m \int \mu_{j\tau}(s_{m\tau}, v_{m\tau}, \xi_{c(m),\tau} + \eta_{m\tau}; \theta) dF(\eta_{m\tau}) \tag{8}$$

Let h_i denote the alternative chosen by a consumer i. Within a given code-area c, we have, by the Law of Total Probability

$$\mu_{jc\tau} = \mathbb{P}(h_i = j) = \sum_{m \in c} \omega_m \mathbb{P}(h_i = j | m) = \sum_{m \in c} \omega_m \mu_j(s_m, v_m, \xi_{c(m)} + \eta_m; \theta) , \tag{20}$$

where I have dropped time subscripts, ω_m is the probability that the consumer comes from municipality m in code-area c, and $\mathbb{P}(h_i = j|m)$ is the probability that consumer i chooses j given that she comes from market m (and thus her demographic attributes come from a market-specific distribution). I will simplify the notation further and write simply $\mu_{jm}(\eta_m)$ instead of $\mu_j(s_m, v_m, \xi_{c(m)} + \eta_m; \theta)$.

I will show that $\text{plim}_{n\to\infty}\left(\sum_{m=1}^{n}\omega_{nm}\mu_m(\eta_m)-\sum_{m=1}^{n}\omega_{nm}\mathbb{E}[\mu_m(\eta_m)]\right)=0$. When considering $n\to\infty$, I am considering an infinite sequence of markets with known μ_m (i.e., known characteristics (s_m, v_m)) and a triangular array of weights ω_{nm}

$$\begin{array}{cccc}
\omega_{1,1} & & & \\
\omega_{2,1} & \omega_{2,2} & & \\
\omega_{3,1} & \omega_{3,2} & \omega_{3,3} & \\
\vdots & \vdots & \vdots & \ddots
\end{array}$$

such that $\omega_{nm}>0$ for all n,m, $\lim_{n\to\infty}\omega_{nm}=0$ for all m, and $\sum_{m=1}^{n}\omega_{nm}=1$ for all n. Moreover, I assume that the η_m's are independent – see assumption 2.

By Chebyshev's Inequality

$$\begin{aligned}
\mathbb{P}\left(\left|\sum_{m=1}^{n}\omega_{nm}\{\mu_m(\eta_m)-\mathbb{E}[\mu_m(\eta_m)]\}\right|>\varepsilon\right) &\le \frac{1}{\varepsilon^2}\sum_{m=1}^{n}\omega_{nm}^2\text{Var}(\mu_m(\eta_m)) \\
&\le \frac{1}{\varepsilon^2}\sum_{m=1}^{n}\omega_{nm}^2
\end{aligned}$$

where the second inequality follows because $\omega_m(\eta)\in[0,1]$ for all η.

Now it suffices to show that $\sum_{m=1}^{n}\omega_{nm}^2\to_n 0$. Assume without loss of generality that $w_{w_{n1}}=\max_{1\le m\le n}w_{nm}$. Then

$$\sum_{m=1}^{n}\omega_{nm}^2\le w_{n1}^2+v(w_{n1}) \tag{21}$$

where

$$\begin{aligned}
v(w_{n1}) := \max_{w_{n2},\dots,w_{nn}} & \sum_{m=2}^{n}w_{nm}^2 \\
\text{s.t.} \quad & 0<w_{nm}\le w_{n1} \\
& \sum_{m=2}^{n}\omega_{nm}=1-w_{n1}
\end{aligned}$$

Let k_n be the largest integer such that $k_n w_{n1}\le 1-w_{n1}$, i.e., $k_n=\left\lfloor\frac{1-\omega_{n1}}{\omega_{n1}}\right\rfloor$. Then

$$\begin{aligned}
v(\omega_{n1}) &\le k_n\omega_{n1}^2+[1-(k_n+1)\omega_{n1}]^2 \\
&\le \frac{1-\omega_{n1}}{\omega_{n1}}\omega_{n1}^2+\left(1-\frac{1-\omega_{n1}}{\omega_{n1}}\,\omega_{n1}\right) \\
&=(1-\omega_{n1})\omega_{n1}+\omega_{n1}^2
\end{aligned}$$

It follows that $\lim_{n\to\infty} v(\omega_{n1}) = 0$ and, by 21, $\lim_{n\to\infty}\sum_{m=1}^{n}\omega_{nm}^2 = 0$.

Appendix E Conditional Value Functions are Linear in Parameters

In this section I will simplify notation by letting ω denote a generic state of the form $\omega = (t, r, s_f, s_{-f})$. Flow payoffs, net of the idiosyncratic shock, are given by

$$\pi(\omega) - \varphi r \mathbf{1}\{s_f < 3, T < t\} - c(a, s_f, z; \theta)$$

where $c(a, s_f, z; \theta)$ is the deterministic part of costs: $c(a, s_f, z; \theta) = \sum_{\{g':g'>s_f\}}^{a} z_m' \theta_{g',t} + \mathbf{1}(s_f = 0)\, z_m' \theta_e$ if $a > s_f$ and zero otherwise. This is a linear function of parameters. Abusing notation slightly, write $c(a, s_f, z; \theta) = c(a, s_f, z)\theta$.

Define

$$g(a, \omega, z) := (\pi(\omega), c(a, s_f, z), r\mathbf{1}\{s_f < 3, T < t\})$$

and

$$\Psi := (1, \theta', \varphi)'$$

Then we have

$$\pi(\omega) - \varphi r \mathbf{1}\{s_f < 2, T < t\} - c(a, s_f) = g(a, \omega, z)\Psi$$

The value function satisfies the Bellman equation

$$V(\omega, \varepsilon_f) = \max_{a\in A(s_f)} g(a, \omega, z)\Psi + \varepsilon_f(a) + \delta \sum_{\omega'} V(\omega') F_P(\omega'|\omega, a)$$

where F_P denotes the state transitions induced by the equilibrium conditional choice probabilities P and

$$V(\omega') := \int V(\omega, \varepsilon_f) dG(\varepsilon_f)$$

Denote the equilibrium policy by $\sigma^*(s, \varepsilon_f)$. Then (using σ^* as shorthand for $\sigma^*(s, \varepsilon_f)$)

$$V(\omega, \varepsilon_f) = g(\sigma^*, \omega, z)\Psi + \varepsilon_f(\sigma^*) + \delta \sum_{\omega'} V(\omega') F_P(\omega'|\omega, \sigma^*)$$

Integrating both sides of this equation yields

$$V(\omega) = \left(\int g(\sigma^*, \omega, z) dG(\varepsilon_f) \right) \Psi$$
$$+ \int \varepsilon_f(\sigma^*) dG(\varepsilon_f) + \delta \sum_{\omega'} V(\omega') \int F_P(\omega'|\omega, \sigma^*) dG(\varepsilon_f)$$

Let $\mathcal{C}(a, \omega)$ be the set of shocks $\varepsilon_f \in \mathbb{R}^{|A(s_f)|}$ such that $a = \sigma^*(\omega, \varepsilon_f)$. Then

$$\begin{aligned}
\int g(\sigma^*, \omega, z) dG(\varepsilon_f) &= \sum_{a \in A(s_f)} \int_{\mathcal{C}(a,\omega)} g(\sigma^*, \omega, z) dG(\varepsilon_f) \\
&= \sum_{a \in A(s_f)} g(a, \omega, z) \int_{\mathcal{C}(a,\omega)} dG(\varepsilon_f) \\
&= \sum_{a \in A(s_f)} g(a, \omega, z) P(a|\omega)
\end{aligned}$$

where here $P(a|\omega)$ are the equilibrium conditional choice probabilities.

Similarly,

$$\int F(\omega'|\omega, \sigma^*) dG(\varepsilon_f) = \underbrace{\sum_{a \in A(s_f)} F_P(\omega'|\omega, a) P(a|\omega)}_{F_P(\omega'|\omega)}$$

The term on the right hand side of this equation is simply the probability that the state moves from ω to ω', induced by the equilibrium conditional choice probabilities. I will denote that term by $F_P(\omega'|\omega)$.

Finally, observe that

$$\int \varepsilon_f(\sigma^*) dG(\varepsilon_f) = \sum_{a \in A(s_f)} \int_{\mathcal{C}(a,\omega)} \varepsilon_f(a) dG(\varepsilon) = \sum_{a \in A(s_f)} P(a|\omega) \mathbb{E}[\varepsilon_f(a) | a = \sigma(\omega, \varepsilon_f)]$$

It is well known that for the Type I Extreme Value distribution, $\mathbb{E}[\varepsilon_f(a)|a = \sigma(\omega, \varepsilon)] = \sigma(\gamma - \ln P(a|\omega))$, where γ is the Euler-Mascheroni constant. Therefore

$$\int \varepsilon_f(\sigma^*) dG(\varepsilon_f) = \sigma \sum_{a \in A(s_f)} P(a|\omega)(\gamma - \ln P(a|\omega))$$

Putting these pieces together, we have

$$V(\omega) = \left(\sum_a g(a,\omega,z)P(a|\omega)\right)\Psi + \sigma \sum_{a\in A(s_f)} P(a|\omega)(\gamma - \ln P(a|\omega))$$
$$+ \delta \sum_{\omega'} V(\omega')F_P(\omega'|\omega)$$

or

$$V(\omega) = \mathbb{E}_P[g(a,\omega,z)]\Psi + \sigma\gamma - \sigma\mathbb{E}_P[\ln P(a|\omega)] + \delta F_P(\omega)V$$

where $\mathbb{E}_P$ denotes an expectation with respect to a using the distribution over a defined by P, $F_P(\omega)$ is a row vector with the transition probabilities in state ω, and V a vector with the value function in each state ω.

We can now stack these equations. Let M_P denote the transition matrix induced by P, $M = [F_P(\omega'|\omega)]_{\omega,\omega'}$. Then[46]

$$V = \mathbb{E}_P[g(a,z)]\Psi + \sigma\gamma - \sigma\mathbb{E}_P[\ln P(a)] + \delta M_P V$$

From this equation we obtain

$$\begin{aligned} V &= (I - \delta M_P)^{-1}\Big\{\mathbb{E}_P[g(a,z)]\Psi + \sigma\gamma - \sigma\mathbb{E}_P[\ln P(a)]\Big\} \\ &= \sigma K(P) + (I - \delta M_P)^{-1}\mathbb{E}_P[g(a,z)]\Psi \end{aligned}$$

where $K(P) := (I - \delta M_P)^{-1}(\gamma - \mathbb{E}_P[\ln P(a)])$

The conditional value function is, by definition,

$$v(a,\omega) = g(a,\omega,z)\Psi + \delta\sum_{\omega'} V(\omega')F_P(\omega'|\omega,a) = g(a,\omega,z)\Psi + \delta F_P(\omega,a)V$$

where $F_P(\omega,a)$ is the distribution over ω' induced by taking action a in state ω when competitors follow P. Using the result above for V yields

$$\frac{v(a,\omega)}{\sigma} = \delta F_P(\omega,a)K(P) + \Big\{g(a,\omega,z) + \delta F_P(\omega,a)(I - \delta M_P)^{-1}\mathbb{E}_P[g(a,z)]\Big\}\sigma^{-1}\Psi$$

Finally, the analysis in the main text allows for municipality-specific equilibria P^m. As noted there, for the usual identification argument, based on the derivation above, to go through, it is sufficient that the map from market-level observables to the quasi-

[46] In this equation, it is to be understood that the scalar $\sigma\gamma$ is added to all coordinates. The ω-th coordinate of $\mathbb{E}_P[g(a,z)]$ is equal to $\sum_{a\in A(s_f)} g(a,\omega,z)P(a|\omega)$. Similarly for $\mathbb{E}_P[\ln P(a)]$

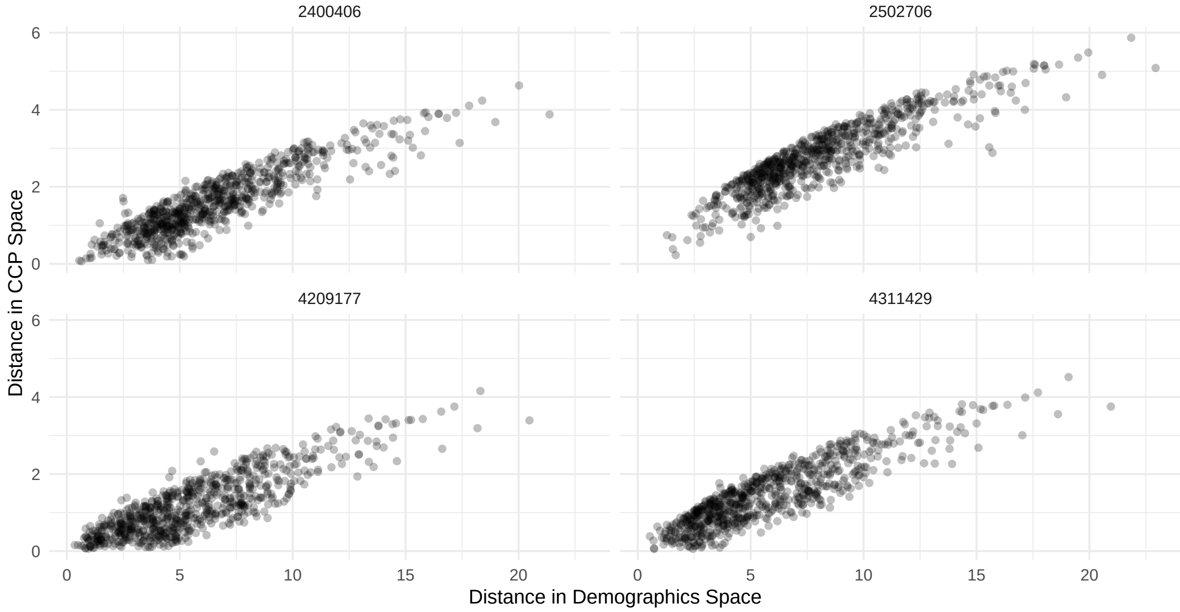

Figure 17: Equilibrium continuity

Each panel shows data for one of four randomly sampled municipalities. Each dot in a scatterplot corresponds to one of the other 742 municipalities that are part of the 3G counterfactuals. The x-axis is the Euclidean distance of the demographics of the two municipalities (a vector containing the time series of GDP per capita, population, and area). On the y-axis is the Frobenius distance of the conditional choice probability matrices of the two municipalities.

stationary symmetric Markov Perfect Equilibrium be continuous. Figure 17 provides evidence in favor of that. Each panel shows data for one of four randomly sampled municipalities. Each dot in a scatterplot corresponds to one of the other 742 municipalities that are part of the 3G counterfactuals. The x-axis is the Euclidean distance of the demographics of the two municipalities (a vector containing the time series of GDP per capita, population, and area). On the y-axis is the Frobenius distance of the conditional choice probability matrices of the two municipalities.[47] These scatterplots show that as the distance of demographics goes to zero so does the distance of CCPs, as desired.

Appendix F Estimates of Dynamic Parameters

Table 11 shows estimates of the dynamic parameters of the model, i.e. the entry and technology upgrade cost parameters and the fine for non-compliance with the regulation.

[47]Conditional choice probabilities are represented in a matrix of as many rows as (minimal, see Appendix C) states and one column per technology/action.

Table 11: Dynamic Parameter Estimates

Technology	Variable	Year	Estimate	2.5 Quantile	97.5 Quantile
Entry	Area	All	-0.138	-0.183	-0.068
Entry	Intercept	All	6.142	5.669	6.424
3G	Area	2014	0.572	0.498	0.650
3G	Area	2015	0.382	0.271	0.463
3G	Area	2016	0.442	0.337	0.525
3G	Area	2017	0.548	0.439	0.638
3G	Area	2018	0.425	0.301	0.522
3G	Intercept	2014	0.274	-0.203	0.742
3G	Intercept	2015	1.307	0.773	1.974
3G	Intercept	2016	0.484	-0.006	1.132
3G	Intercept	2017	-0.052	-0.650	0.638
3G	Intercept	2018	-0.177	-0.816	0.546
4G	Area	2014	1.082	0.993	1.222
4G	Area	2015	0.593	0.544	0.699
4G	Area	2016	0.362	0.282	0.426
4G	Area	2017	0.182	0.110	0.239
4G	Area	2018	0.030	-0.066	0.107
4G	Intercept	2014	0.130	-0.218	0.270
4G	Intercept	2015	0.012	-0.697	0.292
4G	Intercept	2016	-1.152	-1.530	-0.684
4G	Intercept	2017	-0.983	-1.329	-0.502
4G	Intercept	2018	0.499	0.033	1.092
	Fine	All	1.510	1.358	1.740

This table displays estimates of the dynamic parameters – the entry and technology upgrade cost parameters and the fine for non-compliance with the regulation. A combination of the Technology, Variable, and Year columns defines a parameter in the model. For example, the row identified by 4G, Area, and 2016 indicates to what extent the logarithm of a municipality's area increases the cost of introducing 4G technology. The Estimate column shows the point estimate and the final two columns together define a 95% confidence interval for the respective parameter. The confidence interval is calculated by bootstrap, which is performed at the municipality level.

Appendix G Equilibrium Effects of Coverage Requirements: Policy Function Adjustments

As in the main text, here I consider moving from the situation in which only the regulated firm responds to the regulation (equivalently, for unregulated firms, a situation without regulation) to a scenario with regulation. For each municipality considered in the counterfactuals and each state of the game, I compute the difference in upgrade probabilities. Then, focusing on unregulated firms first, I then those differences across states of the game conditioning on the model period, the unregulated firm's technology, and the technology of the regulated firm. Figure 18 shows the results.

We see that the move to the equilibrium with regulation leads to reductions in the upgrade probabilities of unregulated firms. This is due to the the anticipated tougher competition in the market following the entry or technology upgrade by the regulated firm. These effects are more pronounced as time passes. As the regulation deadline approaches, the upgrade by the regulated firm and the consequent reduction in flow profits become imminent, implying a stronger reduction in unregulated firms' incentives to enter or upgrade. The effect of the move to equilibrium is also stronger in those states where the regulated firm is out of the market. In those situations, compliance with the regulation will lead to a larger decrease in unregulated firms' flow profits relative to the case where the regulated firm is already active. Finally, the largest effects are observed in the behavior of "weak" incumbents – i.e., those with 2G technology. Those are the ones that experience the largest reductions in flow profits from the added competition, as inactive firms are only affected if they enter the market and incumbents with advanced technologies are in a stronger position to compete with the regulated firm.[48]

Figure 19 shows analogous results for the regulated firms, conditioning on model period, the technology of the regulated firm, and the number of competitors in the market. Upgrade probabilities of regulated firms are lower in the equilibrium with regulation than after their unilateral response to the regulation. Entry and technology upgrade have value as deterrents of upgrades by competitors. As the regulation decreases the probability of such upgrades, it reduces this deterrence incentive, leading to the results in figure 19. These effects are (mostly) increasing over time due to the similar pattern shown in 18. Finally, note that the reductions in regulated firms'

[48]The figure also includes a plot for when the unregulated firms have 4G technology as a sanity check. The changes in probability in that case are zero by construction – firms have no decision to make once they have 4G technology.

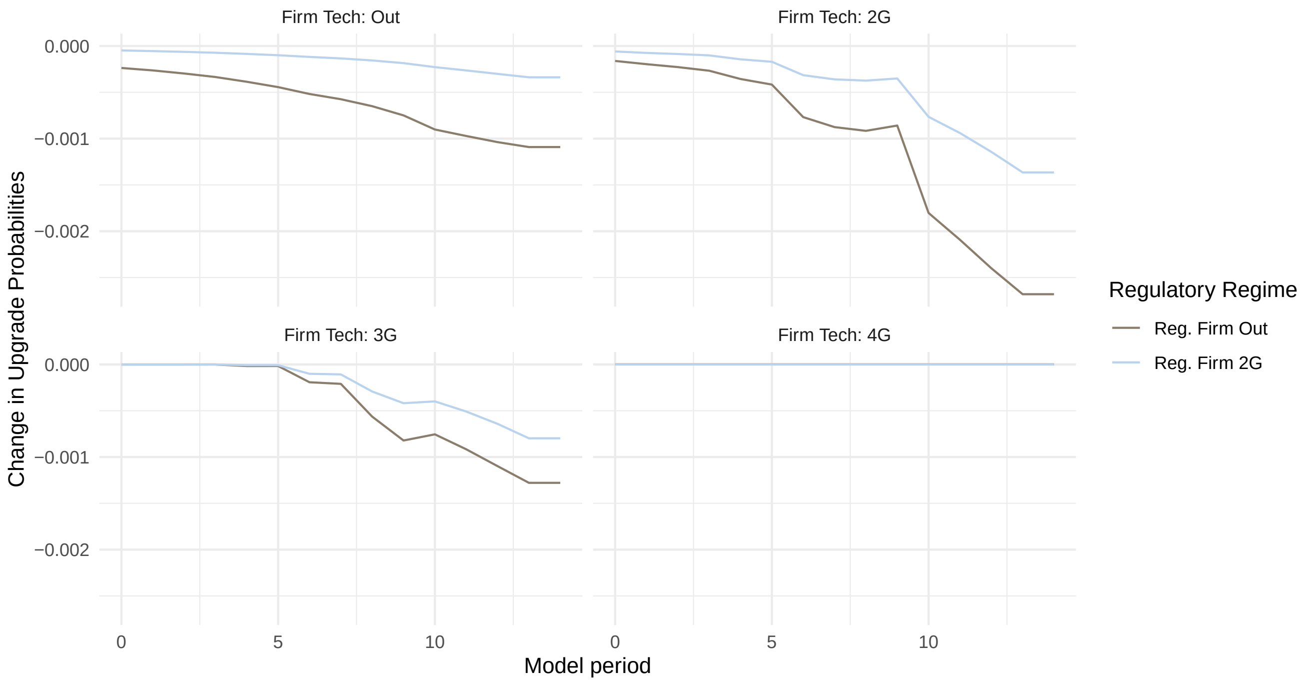

Figure 18: Equilibrium Effects: Changes in the Policy Functions of Unregulated Firms

upgrade probabilities are decreasing in competition. This is in line with the previous discussion, as deterrence incentives are less relevant the more competition there is in the market.

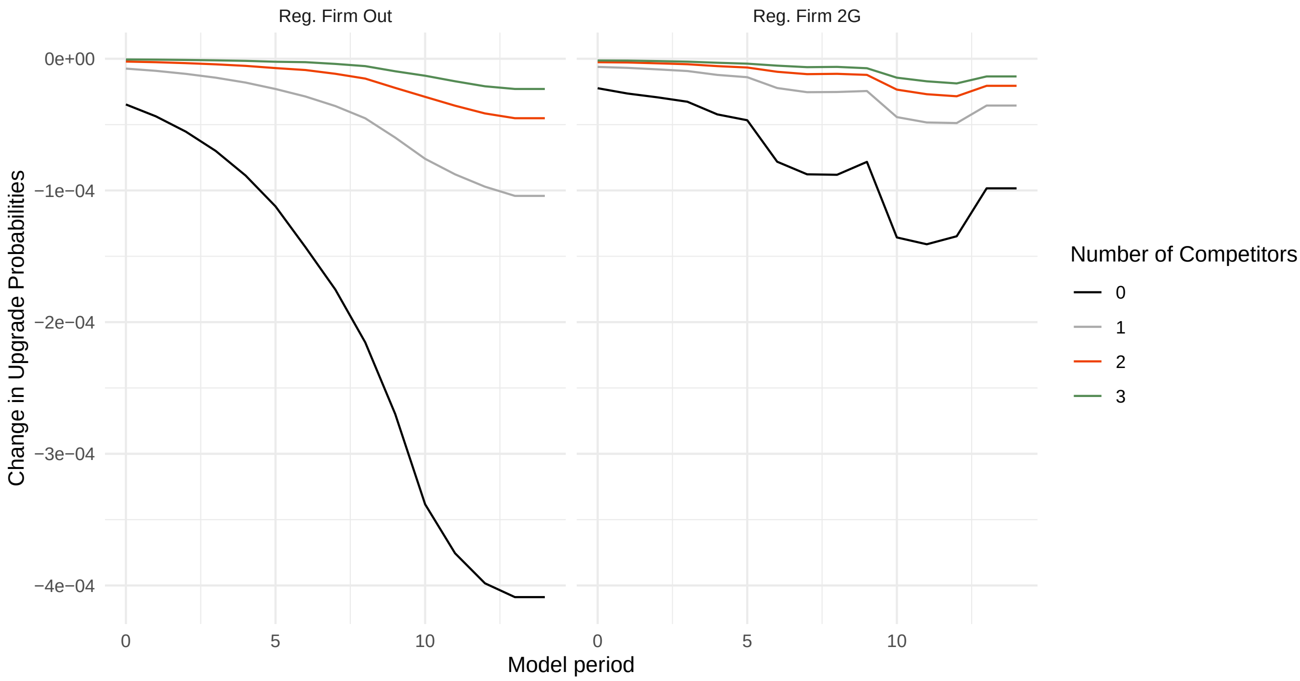

Figure 19: Equilibrium Effects: Changes in the Policy Functions of Regulated Firms