The Effects of Screen Quotas on the Movie Exhibition Market in Brazil

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Abstract

Screen quotas in Brazil have been in effect, in their present form, since 2001. Legislation requires movie theaters to screen Brazilian movies for a minimum of days on a yearly basis. Even though two decades have passed since its inception, quantitative analyses of the policy's effects have been scarce. Furthermore, the policy is set to expire by the end of this year and renewal will demand legislative approval. To investigate policy effects, we first run a set of reduced-form regressions, using exogenous variation in the movie theater quotas per viewing room. Next, we build and estimate a simple dynamic discrete choice model of exhibitors choice. Reduced-form regressions point to small but negative effects of screen quotas on overall and foreign films box-office and ticket sales. No discernible impact is observed on Brazilian movie revenue or public. Structural parameter estimates also imply that quotas enter firm's value functions negatively, but suggest policy plays only a minor role in exhibitor choice.
Keywords: *applied microeconomics*, *audiovisual*, *cinema*, *policy analysis*, *industrial organization*

1 Introduction

Screen quotas have been adopted by several countries as a policy tool to protect domestic film industries from foreign competition, namely from Hollywood.[1] In Brazil, the policy goes back to the 1930s, but its present form originates in 2001. That year, a bill not only introduced a vast array of measures aimed at regulating, protecting and subsidizing the domestic film and audiovisual industries but also created a regulatory body for the industry, the National Agency of Cinema (Ancine), who was put in charge of regulating and enforcing screen quotas nation-wide.

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[1] See, for example, the Cinematograph Films Act, in the UK, or Messerlin & Parc (2014) for a discussion regarding the South Korean and French screen quotas. Argentina, Spain, Mexico and South Korea, all have screen quotas in effect.

The details surrounding the policy have changed throughout the years, but a basic feature has remained that quotas set a minimum amount of days of Brazilian feature films a movie theater has to screen each year. Interestingly for our purposes, the number of days a multiplex has to fulfill is a *non-linear* function of the number of its viewing rooms, meaning screen quotas *per viewing room* vary with the size of the movie theater[2].

We argue this non-linear effect was not a desired (or endogenous) byproduct of regulation, as regulatory assessment reports issued by Ancine specifically point to the non-linearity feature as a policy distortion. Also, we take advantage of the fact that screen quotas were not in effect in 2019, due to the non-issuance of an executive order by the sitting president the year before. We then exploit these sources of variation to identify the causal effects of exhibition quotas on annual multiplex revenue and ticket sales, using administrative data from 2017 to 2019 encompassing the whole industry.

The reduced-form identification strategy combines exogenous variation in quotas with compliance data, also available from the Brazilian regulatory body. Two strategies are used: first, we run a set of regressions segmented by level of regulatory compliance, since narrowly compliant agents are likely to have been the most affected by regulation; second, we run regressions where the explanatory variable, days of quota per movie theater screen, is weighted using non-linear functions according the exhibitor's level of compliance, following the same rationale. All regressions are paired with controls including movie theater and year fixed-effects.

Weighted regressions point to small but negative effects of screen quotas on overall ticket sales and box-office, driven by a small adverse impact in foreign movie revenue and public. Effects on Brazilian feature films are non-significant. Point estimates elasticities imply that a 10 day increase in screen quotas per viewing room would decrease yearly revenues by 2% for compliant movie theaters. Segmented regressions display null results across the board, but problems such as small samples and the inability to calculate chain-level fixed-effects for entities with different compliance levels across years, lead us to put more confidence in weighted regressions results.

We then build and estimate a dynamic discrete choice model using micro session-level data from movie theaters for the year of 2018 — the last year for which screen quotas were in full effect. Due to computational efficiency constraints, we restrict estimation to large multiplexes with 12 screens each. Structural parameter estimates suggest that chosen variables play a minor role in exhibitor choice, when compared to the private shock term. Nevertheless, screen quotas do display a negative, if small, effect on the firm's value function, in line with reduced-form regressions. Further research could improve the model by adding more explanatory variables to better account for exhibitor behavior.

This paper first and foremost contributes to the literature regarding the effects of screen quotas. For a policy that is in effect in several countries (Argentina, Spain, Mexico, South

[2]This was set to change in 2020, but due to pandemic-related issues, movie theaters were mostly closed throughout the year.

Korea, Brazil) and that has been enacted and abandoned in many others (such as the United Kingdom, Italy, France), there are few quantitative studies that try to address its causal effects. In Brazil, Courtney (2015) has investigated the effects of screen quotas using a panel containing the major multiplex chains from 2009 to 2014, and found overall negative effects on ticket sales. The sample, however, encompassed only a subset of the whole market, and no administrative data was used. In addition, inspection data was not taken into account. Zubelli (2017) compares and discusses Brazilian and South Korean screen quotas frameworks, but does not address policy effects' identification or measurement issues.

Having been in effect for 20 years, this is the first time formal analysis addresses the identification of the policy's causal effects using administrative data from the Brazilian audiovisual agency. This work is timely since the obligation is set to expire by the end of 2021 and congress, as of the writing of this paper, is about to start discussions regarding a new bill.

Second, the paper adds to the applied microeconomics and related industrial organization literature, following the seminal paper of Rust (1987). Due to the computational burden of Rust's proposed nested fixed point algorithm, our paper implements the forward simulation algorithm initially proposed by Hotz et al. (1994), but later refined by Bajari et al. (2007). In particular, this work addresses important issues regarding first-stage Conditional Choice Probability (CCP) estimators with large state spaces. We compare alternative approaches using kernel density estimators and flexible Logit models to obtain CCPs and show that results are somewhat sensitive to different first-stage CCP estimators.

The structure of the paper is as follows: Section 2 briefly outlines the audiovisual regulatory regime and screen quotas in Brazil. It also makes the case for screen quotas' non-linearity as a source of plausible exogenous variation. Section 3 details the data sources and describes overall structure of data used. Section 4 displays reduced-form regressions and results. Section 5 introduces the dynamic discrete choice model for the movie theater and estimation methods. Section 6 presents estimates for the model. Finally, section 7 concludes.

2 Regulatory Framework

2.1 Brief Overview

The current audiovisual policy regime goes back to the 1990s, after an executive order abolished most of the previous institutions and tax-funded sources of financing. A new legal framework was gradually established throughout the decade (for a more in-depth chronology see Zubelli, 2017, chap. 2). The landmark of this new, contemporary, policy framework was the 2001 federal act that created the National Agency of Cinema (Ancine) along with new tax-funded subsidies and regulations, namely screen quotas in their present-day form.

Audiovisual policy in Brazil encompasses a wide range of legal devices, policy tools and government institutions, at the federal, state and county levels. At the federal level, the Brazilian regulatory agency lists 33 laws aimed at the sector since 1991, and 154 regulations enacted by the agency itself since its inception.[3] Policy is not restricted to command and control regulations. There are several types of subsidies targeted at domestic audiovisual products, such as a dedicated federal endowment and tax breaks at different government levels. Funding comprises movies, games and even movie theater infrastructure and equipment. It also covers exhibition, cable TV and other market segments (for a comprehensive survey of policy instruments see Zubelli, 2017, chap. 2). Government bodies in charge of coordinating and enforcing policies include a federal council, a federal office with two subsidiary bodies, two county-level funding agencies in Rio de Janeiro and São Paulo, besides the aforementioned national regulatory agency[4].

2.2 Screen Quotas in Brazil

Article 55 of *Medida Provisória* 2228-1 of 2001 created screen quotas in their present form. In short, the article states that, for a period of 20 years thereafter, commercial movie theaters are required by law to screen a number of days of Brazilian feature films each year. The number is to be set, on a yearly basis, by executive order.

Even though the policy, as it stands, dates from this act, screen quotas have a much older history in Brazil. Quotas were first introduced by executive order in 1932, as a result of political pressure from different groups, among them the recently founded Cinematographic Association of Brazilian Producers (Santos, 2019, chap. 2.1). Initially, quotas required the screening of educational short films at the beginning of movie sessions. A 1939 executive order introduced screen quotas for feature films, but quotas were small: from 1 movie a year at first to 3 in 1945 (Santos, 2019, chap. 2.1).

The creation of the National Institute of Cinema (INC), in 1966, shifted screen quota baseline requirements from a fixed number of movies to be featured each year to a number of screening days, on a quarterly basis. Later, new rules sought to adjust quotas to the amount of movie theater opening days per week. Further changes demanded screenings on weekends, different quotas according to the movie turnover rate and allowed for swaps of screen quotas between movie theaters within the same company, if certain conditions were met (Santos, 2019, chap. 2.5).

The National Institute of Cinema (INC) was abolished in 1975. Its successors, Embrafilme and Concine, mostly kept the same regulatory standards. A noteworthy exception was a regulation curtailing the movie theaters' discretion to take a Brazilian movie out of screens, known as *Lei da Dobra*. The new regulation required exhibitors to keep displaying

[3]See https://antigo.ancine.gov.br/pt-br/legislacao/leis-e-medidas-provisorias and https://antigo.ancine.gov.br/pt-br/legislacao/instrucoes-normativas-consolidadas.

[4]Loosely translated, the Superior Council of Cinema, National Office for Audiovisual, the Technical Center for Audiovisual, the Brazilian Cinematheque, RioFilme and Spcine, respectively.

Brazilian movies that had reached a pre-determined threshold of moviegoers (Santos, 2019, chap. 2.6).

Screen quotas were suspended for a couple of years from 1990 to 1992, and then reinstated for another 10 years. During the 1990s, they mostly took up their present-day form: minimum amount of Brazilian movie screening days as a function of the number of viewing rooms a movie theater has.

In 2001, the *Medida Provisória* 2228-1 of 2001 was put into law renewing screen quotas for more 20 years. These are the subject of our analysis. Although no amendment affecting the policy has been made to the law in the last 20 years, screen quotas have been gradually changed by the yearly executive orders needed for it to be in effect. Figure 1 shows the evolution of screen quotas per viewing room throughout the years.

This paper probes the effects of screen quotas using data from three years: 2017, 2018 and 2019. For 2017 and 2018, regulations were mostly the same, sharing their main features: a minimum of Brazilian movie days to be screened as a non-linear function of viewing rooms; a minimum of different titles to be featured in a given year; a penalty increase in day-quotas should an exhibitor display the same movie in more than a certain number of viewing rooms, again as a non-linear function of the number of viewing rooms[5]; and the possibility of swapping obligations between movie theaters belonging to the same chain, in order to fulfill regulatory requirements.

A small but nevertheless important difference between quota fulfillment in 2017 and 2018 concerns daily fractional screening of movies. In 2017, on a given day, an exhibitor could either fulfill 0, $1/2$ or 1 day of screen quotas, should she screen respectively less than half, half of more, or all sessions with Brazilian movies in a viewing room. In 2018, fractional fulfillment was unrestricted: if a viewing room had 5 daily sessions, every Brazilian movie featured would fulfill $1/5$ of a day for quota requirements.[6]

Our analysis ignores minimum title requirements, since compliance with day-based quotas goes hand in hand with compliance of title requirements[7]. Figure 2 displays screen quota compliance and noncompliance divided into screening days and title requirements violations. In the pooled sample for 2017 and 2018, only 7 multiplexes were non-compliant due to minimum title regulations alone. According to the inspection unit, to this day, not a single fine has been levied only because of title requirements noncompliance[8].

Non-linear screen quotas are thus the main source of variation used to tease out causal policy effects in reduced form regressions. Additional sources of variation come from the penalty increases mentioned before. Heterogeneity also arises from opening days: if a movie theater operates for half a year, only half of its nominal obligation is due. This

[5]Further details on how to tally penalty increases are stipulated in *Instrução Normativa n.º 116*

[6]As a matter of fact, fractional fulfillment had a quirk: if 1 out 3 sessions featured a Brazilian movie, only $1/4$ of a day would be tallied. We shall ignore this exception throughout the paper.

[7]Inspection reports are public and available at https://antigo.ancine.gov.br/pt-br/fiscalizacao/cinema-fiscalizacao

[8]This author has directly inquired the person in charge of these inspections.

FIGURE 1: Screen quotas per viewing room by movie theater size. Source: Zubelli et al. (2017)

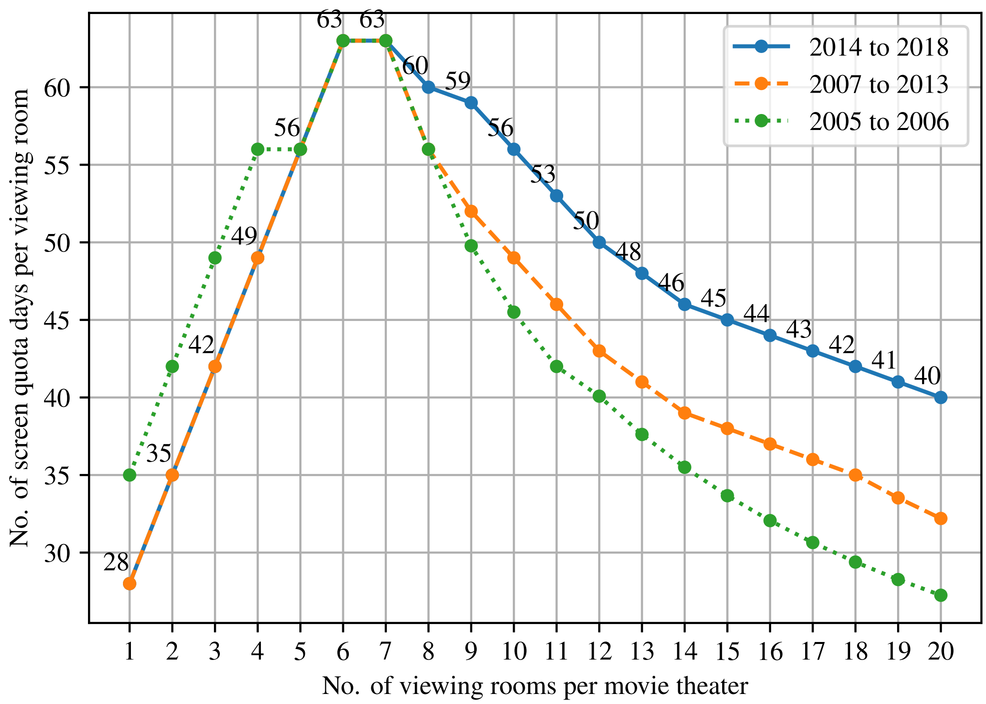
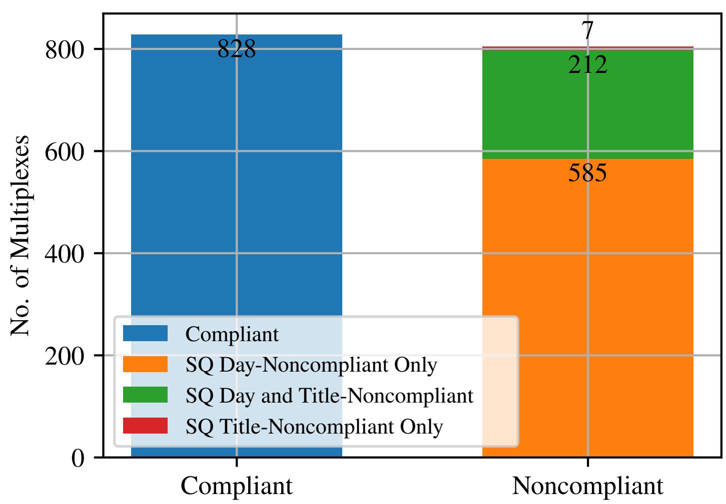


FIGURE 2: Screen quota compliance days vs. titles (pooled sample 2017 and 2018). Source: Inspection Data/Ancine



type of variance, however, is controlled for, since it has impacts on dependent variables such as income and number of tickets sold, but does not change the fraction of quotas in relation to operating days. Finally, we handle variation stemming from swaps by looking at chain-level overall quotas, where net transfers add to zero. Independent movie theaters, i.e. not belonging to a chain, are thus treated as "single unit" chains.

To make the case for the exogeneity of the non-linearity of quota size, we point to a regulatory assessment of the policy, published by Ancine (Zubelli et al., 2017, paragraphs 1.6 to 1.21), in a section aptly titled "on screen quota distortions". Specifically, it argues that screen quotas have penalized disproportionately medium-sized movie theaters, who show the highest rates of regulatory noncompliance. As a result, the official report proposes to abolish non-linear obligations as a way to render screen quotas neutral to movie theater size. This formal suggestion was adopted, and screen quotas were set to become linear in 2020, as explained before.

To conclude, the year 2019 had no screen quota in effect, which provides us with an additional source of variation. The year before, the sitting president — not reelected and in the final year of his term — failed to issue the executive order required to put the policy in effect. The rationale behind this is not fully clear and some endogeneity in this case is plausible, specially because there was some expectation that the president-elect would sign a new order once he was sworn in. It was also unclear how this order would handle the (unprecedented) fact that it would have to be issued after the year had started, and this could have plausibly affected exhibitor behavior for a part of the year even though no order had been in effect. To account for this problem, we run regressions excluding observations from 2019, but the results stay the same.

3 Data

This paper uses administrative micro-level data from the Brazilian national regulator (Ancine). Three are the main sources of data used: **(a)** ticket-sales session-level data from exhibitors, from 2017 to 2019; **(b)** inspection reports regarding screen quotas, available from 2009 to 2018; and **(c)** registry data comprising companies, movie theaters and movies. All data is submitted by regulated agents, and submission is mandatory[9].

For our purposes, registry data provides us with information regarding the number of seats a viewing room has; how many screens each movie theater complex possesses; to which company and chain a multiplex belongs to; whether the movie theater is commercial or not. Movie-level data provides release dates in Brazil, genre and origin — whether Brazilian or foreign. Registry data has been merged, when possible, with information from other datasets outlined below.

[9]*Medida Provisória* 2228-1, article 22, states that companies in the business of producing, distributing and displaying movies in Brazil are legally required to register with Ancine. Movie theaters are required to submit daily ticket sales reports in accordance with *Instrução Normativa n.º 123*

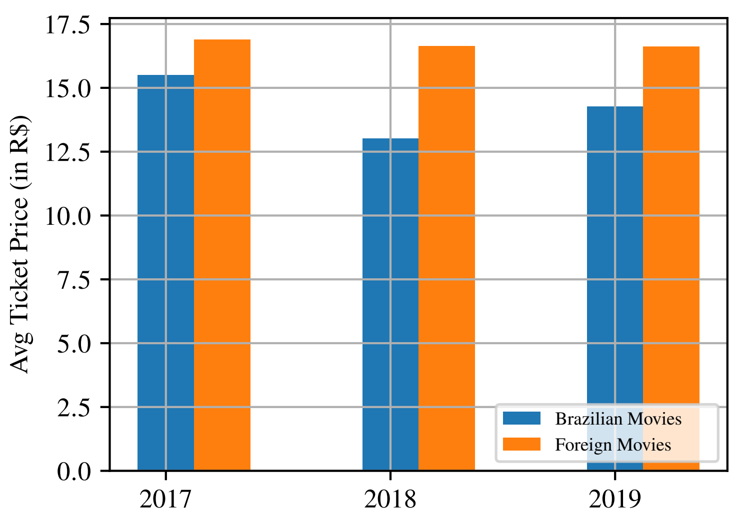
Session-level box-office data encompasses 2017, 2018 and 2019 — information is not available for previous years. It includes data on total revenues, number of tickets sold, date, time, duration, and the movie featured at each session (for more details, see the technical information manual, 2018).

The whole dataset consists of 12,820,617 individual sessions, spanning 2,178 unique titles (823 of which are Brazilian), 70 movie theater chains[10], with 928 movie theaters and 3,797 screens. Table 1 presents summary statistics. Note that seat occupation is normalized to 1. Brazilian movie market-share (as a fraction of sessions) can be gleaned by the mean of the "Nationality" dummy variable — and has remained mostly stable throughout the sample years. Starting hours range from 0 to 23.

Figure 3 shows another interesting feature of the Brazilian exhibition market: the difference between average ticket prices of Brazilian and foreign films. Orbach & Einav (2007) try to explain the puzzle of uniform prices of differentiated goods in the US movie market. In Brazil, the difference shown hints at the existence of a margin of differentiation. It also explains why we choose to divide dependent variables in ticket sales and box-office in the reduced form regressions.

Even though this difference could be driven by screen quotas lowering Brazilian movie ticket prices, results indicate that other forms of price differentiation are at play. A preliminary glance at the data suggests lower prices are a result of Brazilian movies being screened at earlier hours, but further research is needed to ascertain causes.

FIGURE 3: Average Ticket Price (2017 to 2019). Source: Session Data/Ancine



Inspection data compiles several important pieces of information at the movie theater level: legal screen quotas; screen quotas as a proportion of opening days; penalty increases

[10]This excludes "independent" movie theaters consisting of a single multiplex. If they are included, the number goes up to 240.

Table 1: Session Dataset Descriptive Statistics

Statistic	N	Mean	Min	Median	Max	St. Dev.
Year 2017						
Ticket Sales	4,151,236	42	0	25	850	48.195
Box-Office (in R$)	4,151,236	709.65	0	377.99	50,833.58	916.07
Seat Capacity	4,151,236	206	20	191	2,000	89.530
Starting Hours	4,151,236	17:30	0	18	23	3.091
Seat Occupation	4,151,236	0.21	0	0.13	1	0.220
Nationality	4,151,236	0.159	0	0	1	0.366
Year 2018						
Ticket Sales	4,306,632	37	0	20	1,242	46.807
Box-Office (in R$)	4,306,632	599.002	−9.11	295.220	967,036.000	959.85
Seat Capacity	4,306,632	205	30	191	2,000	89.827
Starting Hours	4,306,632	17.560	0	18	23	2.995
Seat Occupation	4,306,632	0.19	0	0.11	1	0.215
Nationality	4,306,632	0.160	0	0	1	0.367
Year 2019						
Ticket Sales	4,362,749	39	0	22	850	48.347
Box-Office (in R$)	4,362,749	645.24	0	326.57	166,163.10	878.28
Seat Capacity	4,362,749	204	29	188	2,000	92.750
Starting Hours	4,362,749	17.497	0	18	23	3.037
Seat Occupation	4,362,749	0.20	0	0.12	1	0.225
Nationality	4,362,749	0.152	0	0	1	0.359

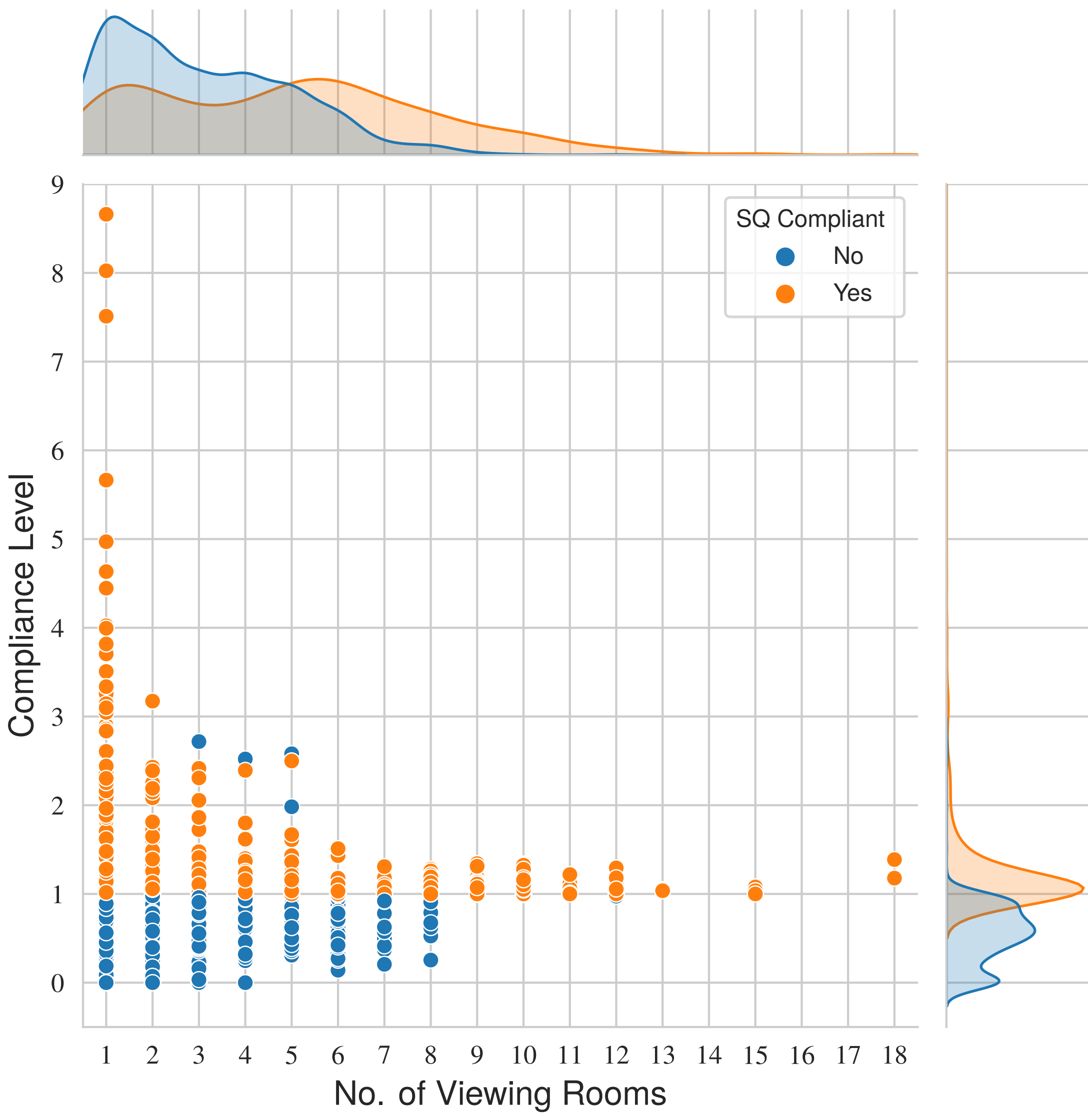
Note: *Nationality* is a dummy variable coded 1 for Brazilian films and 0 otherwise.

(see section 2); transfers between movie theaters; final net screen quotas; number of quota days fulfilled; and a flag stating whether screen quota obligations were accomplished.

Figure 4 depicts the relationship between multiplex size (as measured by number of screens) and quota compliance. Compliance levels are normalized to 1. Note that variance is higher among small-size movie theaters. It is also interesting to see that big multiplexes (> 9 screens) are fully — and narrowly — compliant with regulations.

To run reduced-form regressions, we build a panel grouping data by movie-theater chain/year level, combining information regarding screen quota obligations and fulfillment from inspection data. For the structural model, we also use registry data to calculate

FIGURE 4: Multiplex Size vs. Screen Quota Compliance (2017 and 2018). Source: Inspection Data/Ancine



session-level occupation (tickets sold divided by viewing room seat capacity).

As an auxiliary source of data, we use administrative data from distributors, from 2009 to 2019, containing movies in display each week. We also correct all prices for inflation using price index data (IPCA) from Brazilian official inflation statistics data.

4 Reduced-Form Regressions

In this section, we specify and run simple least squares regressions to identify policy effects on two dependent variables: box-office and ticket-sales. As discussed in section

3, dependent variables were chosen to identify possible effects of screen quotas on movie theater ticket prices. Quotas could, for instance, lower ticket prices for Brazilian movies.

Observations are aggregated at movie theater chain level to account for possible transfers. Otherwise systematic differences between movie complexes that originate and receive swaps could bias results — less profitable multiplexes could systematically receive obligation transfers from more profitable ones, in order to mitigate quota effects. Ultimately, screen quota would be an endogenous decision within theater chains.

The primary explanatory variable we use is yearly quota days per screen. However, even with exogenous screen quotas, regulation per se does not necessarily translate to changes in agent behavior. Some agents may deem the expected (negative) value of punishment to be worth the risks of disregarding regulation altogether. For others, regulations may not be binding on the opposite end: it could be so profitable to feature Brazilian films that they'd do it even in the absence of quotas.

To capture policy effects on agent behavior we therefore focus on the interaction between quota size and compliance. In other words, firms are more likely to have had their behaviors determined by regulation the more narrowly they fulfill their obligations: a movie theater that exactly fulfills 100% of its screen quota is more prone to have been affected by regulation than one that has either fulfilled 200% or 0% of its own.

We propose two approaches to deal with the problem. First, we segment regressions according to the level of compliance. We divide compliance into five bins: $< 40\%$; $40-80\%$; $80-120\%$; $120-160\%$; $> 160\%$. Doing so, we try to lessen small sample bias in each bin. Nevertheless, results are non-significant for the relevant explanatory variables, suggesting null policy effects. Second, we weight compliance levels to account for the fact that compliant agents are more likely to be influenced by policy. In this scenario, results suggest negative but small policy effects: box office and ticket sales are negatively affected by screen quotas, but Brazilian movies display non-significant results.

In the segmented regressions, we run the following regression in each bin:

$$\ln(y_{it}) = \beta_0 + \beta_1 q_{it} + \theta \mathbf{x}_{it} + \varepsilon_{it} \tag{1}$$

Where y_{it} are 3 dependent variables for chain i and year t: total box-office revenues; box-office revenues for foreign films; box-office revenues for Brazilian films. On the right hand side, q_{it} represents quotas per viewing room (after penalties and reductions due to closings) and $\mathbf{x}_{it}$ is a vector of controls consisting of opening days[11], in addition to year and movie theater chain fixed-effects.

Segmented regression raises problems regarding somewhat arbitrary choices of pooling thresholds. Appendix A tinkers with alternative bin specifications, but results are uniformly non-significant. Here, thresholds are chosen such that ranges are bigger rather than smaller,

[11] It is possible that opening days constitute what Angrist & Pischke (2008) call "bad controls", in the sense that nominal screen quotas could influence measured outcomes through their effects on opening days. We address this question in Appendix A and show that nominal quotas have no effect on opening days.

comprising more observations in each bin and avoiding fixed-effects issues mentioned below.

A question also arises as to how to deal with 2019. Since no quota was in effect, observations would have to be arbitrarily placed in a 0 or 100% level of compliance — or, even worse, somewhere in between. To avoid potential problems, we leave all 2019 observations out.

Pooling samples poses an additional problem regarding entity fixed-effects. If compliance levels vary across years, repeated observations become unavailable for each bin, meaning entity fixed effects cannot be calculated.

Results are displayed in Table 2. Columns $1-3$ show results for $80-120\%$ levels of compliance for all movies, foreign movies and Brazilian movies box office, respectively. The same follows for columns $4-6$ and $7-9$, with compliance levels $40-80\%$ and $< 50\%$. Coefficients for Screen Quota per Viewing Room indicate null results across the board. Higher compliance tranches are omitted, but also display null results and very small samples. In some cases, samples are so small that regressions get fully saturated. Complete results are displayed in Appendix A.

To address the problems associated with segmented regressions, we look for an alternative approach to harness compliance effects in the full available sample.

Our second approach keeps observations from 2019 and is able to run regressions on the full panel. As discussed above, screen quotas would have to be somehow weighted by compliance. Full compliance, meaning 100% of the quota was fulfilled, should be given maximum weight, whereas lower or higher levels of compliance should be down-weighted accordingly.

To create this effect, we apply two different non-linear functions to compliance levels (normalized to 1 as 100%): a normal p.d.f. $f_x(x)$ with $X \sim \mathcal{N}(1,1)$; and $f(x) = \max\{0, 1-(1-x)^2\}$. Then, we can define regression equations:

$$\ln(y_{it}) = \beta_0 + \beta_1 q_{it} + \beta_2 f(c_{it}) + \beta_3 q_{it} * f(c_{it}) + \theta \mathbf{x}_{it} + \varepsilon_{it} \tag{2}$$

Where all variables are the same as in Equation 1, except for $f(.)$, which represents the chosen weighting function, and c_{it}, that stands for normalized compliance for agent i in year t. In this case, β_3 is the coefficient of interest.

Regressions using the squared distance weighting are displayed below in Table 3. Note that observations represent movie theater chain per year. Compliance levels are normalized to 1 and weighted according to the squared distance function. Robust standard errors are displayed in parenthesis.

Results indicate quotas have an adverse effect in box-office revenues and ticket sales. As expected, ticket sales closely follow box-office revenues, but net effects differ by a small margin. It is also interesting to note that compliance seems to have a positive effect on movie theater income. One can speculate that compliant firms are more likely to have better management, or that maybe these coefficients are somehow capturing firm size effects

TABLE 2: Segmented Regression Coefficient Results

	Dependent variable:								
	log(Box Office)								
	80-120% Compliance			40-80% Compliance			<40% Compliance		
	All	For	Bra	All	For	Bra	All	For	Bra
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SQ per VR	0.002	0.003	−0.001	0.001	0.002	−0.015	0.043	0.046	−0.380
	(0.003)	(0.003)	(0.006)	(0.007)	(0.008)	(0.013)	(0.055)	(0.056)	(0.247)
Op Days	0.0003**	0.0002**	0.0003	0.0004*	0.0004	0.0004	0.003	0.003	0.035
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.006)	(0.006)	(0.021)
Chain FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2019	No	No	No	No	No	No	No	No	No
Obs	354	352	348	120	120	120	82	82	63
R^2	0.994	0.995	0.979	0.997	0.996	0.991	0.991	0.991	0.985
Adj R^2	0.982	0.985	0.942	0.981	0.979	0.946	0.895	0.892	0.682

*p<0.1; **p<0.05; ***p<0.01

not accounted for in movie theater chain fixed-effects. Quota per Viewing Room residual coefficients are harder to interpret. Results may be driven by chain size, since bigger chains are not likely to have multiple single or double screen theaters. Fixed effects should account for this, but shifting composition of movie theater chains throughout the years, however small, could be driving observed estimates.

Finally, Table 4 presents some alternative specifications. It shows results have the same direction whether compliance is weighted by a normal p.d.f. or the alternative squared distance function. Also, leaving 2019 out reveals mostly the same effects, and preserves signs.

Point estimate elasticities imply a −0.2% (−0.7% if we leave out 2019) net marginal decrease in yearly revenues per added day of screen quotas for compliant movie theaters. At the same time, they imply a 0.1% net marginal increase in public, suggesting movie theaters respond to quota increases on different margins to recoup revenue — possibly lowering

TABLE 3: Weighted Regression Coefficient Results

	Dependent variable:					
	log(Box Office)			log(Ticket Sales)		
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Comp (squared dist)	1.804***	1.852***	0.678	1.743***	1.843***	0.568
	(0.287)	(0.299)	(0.561)	(0.273)	(0.285)	(0.535)
Quota per VR	0.043***	0.049***	−0.010	0.043***	0.050***	−0.009
	(0.008)	(0.008)	(0.016)	(0.007)	(0.008)	(0.015)
Opening Days	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Comp × Quota	−0.045***	−0.049***	0.011	−0.042***	−0.048***	0.013
	(0.009)	(0.010)	(0.018)	(0.009)	(0.009)	(0.017)
Chain Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
2019?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	626	622	601	626	622	601
R^2	0.971	0.972	0.938	0.971	0.971	0.940
Adjusted R^2	0.952	0.953	0.898	0.952	0.952	0.901

*p<0.1; **p<0.05; ***p<0.01

ticket prices. One should be cautious to over interpret net marginal effects implied by point estimates, however, as alternative specifications produce, albeit similar, results.

As both approaches suffer from somewhat arbitrary specifications regarding either pooling thresholds or weighting function choices. To assuage concerns about *ad hoc* assumptions of bin shapes and weighting design, we develop and estimate a structural model in the next two sections, to try to ground reduced-form results with more micro foundations.

TABLE 4: Regression Coefficient Results (Alternative)

	Dependent variable:					
	log(Box Office)					
	All Movies	Foreign	Brazilian	All Movies	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Comp (norm pdf)	4.112***	5.612***	0.441			
	(1.142)	(1.263)	(1.754)			
Comp (sqr dist)				2.354***	2.446***	1.267
				(0.426)	(0.446)	(0.896)
Quota per VR	0.048***	0.074***	−0.028	0.057***	0.065***	−0.002
	(0.015)	(0.016)	(0.023)	(0.010)	(0.011)	(0.023)
Opening Days	0.001***	0.001***	0.001***	0.001***	0.001***	0.001**
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Comp (n) × Quota	−0.103**	−0.170***	0.080			
	(0.040)	(0.044)	(0.062)			
Comp (sqr) × Quota				−0.064***	−0.071***	−0.002
				(0.014)	(0.015)	(0.028)
Chain Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
2019	Yes	Yes	Yes	No	No	No
Observations	626	622	601	406	404	387
R^2	0.969	0.970	0.935	0.977	0.977	0.944
Adjusted R^2	0.949	0.951	0.894	0.951	0.951	0.877

*p<0.1; **p<0.05; ***p<0.01

5 Dynamic Model

In this section, we build a partial-equilibrium dynamic discrete choice model for the firm's problem following the work of Rust (1987) and the dynamic discrete choice literature (for a general overview on the derivation and estimation of such models, see Arcidiacono & Ellickson, 2011).

For each multiplex i in a given year, regulation — defined as a function $R(.)$ — sets a number of screen quota days q_i taking as arguments its s_i viewing rooms and d_i opening days: $q_i \equiv R(s_i, d_i)$. Both s_i and d_i are taken to be exogenous, such that quotas are also exogenous.

In addition, firm i programs a number of t_i sessions throughout its screens for the year. In each session, one movie m_{it} will be picked from the available options on screen that week M_t. The set M_t is defined to be the include only the movies that were actually screened on a particular week, which are retrieved from the data.

This setting allows us to model the movie theater yearly programming schedule as a succession of discrete choice problems at the session level. Screen quotas, however, introduce a dynamic feature: exhibitors must account for future impacts of their present screening decisions because of quota requirements. Screening a Brazilian film today means a multiplex will have fewer screen quota days to fulfill for the remainder of the year.

We therefore a (lean) state space with observable two variables: the time $t \in \{1, 2, ..., T\}$, representing the sequence of all sessions within a movie theater, in chronological order, and proportional fulfillment of quotas up to session t, $x_t \in [0, 1]$. Note that the law of motion of state variables is known and non-stochastic. Fulfillment of quotas follows the function:

$$x_{t+1} = f(x_t, m_t, a_t, q) = \begin{cases} x_t + \frac{\frac{1}{a_t}}{q}, \text{ if } m_t \text{ is Brazilian} \\ x_t, \text{ otherwise} \end{cases} \tag{3}$$

Subscripts i have been dropped for convenience. Variable a_t denotes the amount of sessions per viewing room in day t. It is important to keep in mind that t indexes all other movie theater and time related variables, such as viewing room id, seat capacity, day, week, time, etc.

Following the standard convention in the discrete choice literature (see Train, 2009, ch. 1), the utility from each available choice j in the choice set is assumed to be additively separable into an observable part and a part $\varepsilon_t(j)$ that is known by the firm, but unobserved to the econometrician. As is standard practice, we assume the error term follows a extreme value type I i.i.d. distribution, which yields the familiar Logit conditional choice probability form.

First, we define a simple "profit" function at each step with respect to movie m and state x_t and with $o_{mt} \equiv E(o_m|t)$:

$$\pi(m_t, x_t, \varepsilon_t(m); \theta) = o_{mt} - \theta \max(0, 1 - x_t) + \varepsilon_t(m) \tag{4}$$

$$= \tilde{\pi}(m_t, x_t; \theta) + \varepsilon_t(m) \tag{5}$$

Equation (4) breaks down the profit function into two components non-stochastic components: the expected seat occupation of movie m in time t, o_{mt}, and the remaining screen quota fraction of the movie theater, $\max(0, 1 - x_t)$, multiplied by a parameter, θ, that measures the sensibility to quota requirements.

Before we move on, a remark regarding the choice of explanatory variable o_{mt} is needed. Seat occupation is not only a good proxy for session receipts — we have seen in section 4 that ticket sales and box-office move closely together —, which is in itself a raw proxy for profits, but there is evidence that exhibitors take occupation (or any other closely related variable) to select titles. Figure 5 displays the distribution of seat occupation as movies progress weekly since their release dates. Interestingly, the plot shows that means are remarkably stable, even if medians decline throughout the weeks as the distributions get more right-skewed. This suggests exhibitors react to expected occupation declines by supplying fewer screens as movies age. The second figure shows the same phenomenon roughly occurs for both Brazilian and foreign feature films, although the former depart from a lower mean.

Returning to Equation (4), we can define a firm's dynamic problem. By Bellman's principle, the value function starting from t can be defined recursively :

$$V_t(x_t, \varepsilon_t) = \max_{m_t \in M_t} [\tilde{\pi}(m_t, x_t; \theta) + \varepsilon_t(m) + \beta E(V_{t+1}(f[x_t, m_t, a_t, q], \varepsilon_{t+1})] \tag{6}$$

Where $\beta \in (0, 1)$ is the discount factor of future states. We assume that future errors, ε_{t+1}, are independent from state t variables.[12] Now, we define a policy (or control) function that maps from the state to the movie choice, $\delta_t(x_t, \varepsilon_t) = \arg\max_m [\tilde{\pi}(m_t, x_t) + \varepsilon_t(m) + \beta E(V_{t+1}(x_{t+1}, \varepsilon_{t+1})]$. Equation (6) can then be rewritten:

$$V_t(x_t, \varepsilon_t) = \sum_{m_t} I[\delta_t(x_t, \varepsilon_t) = m_t][\tilde{\pi}(m_t, x_t; \theta) + \varepsilon_t(m) + \beta \int_\epsilon V_{t+1}(x_{t+1}, \epsilon) g(\epsilon) d\epsilon] \tag{7}$$

In Equation (7), function $g(.)$ stands for the probability density function of the vector of extreme type I errors. Note that the state vector ε_t is unbeknownst to the econometrician — even if its distribution is assumed. We define the *ex ante* value function $\bar{V}_t(x_t) \equiv \int_{\epsilon_t} V_t(x_t, \epsilon_t) g(\epsilon_t) d\epsilon_t$. Making substitutions in Equation (7) we get a more succinct form:

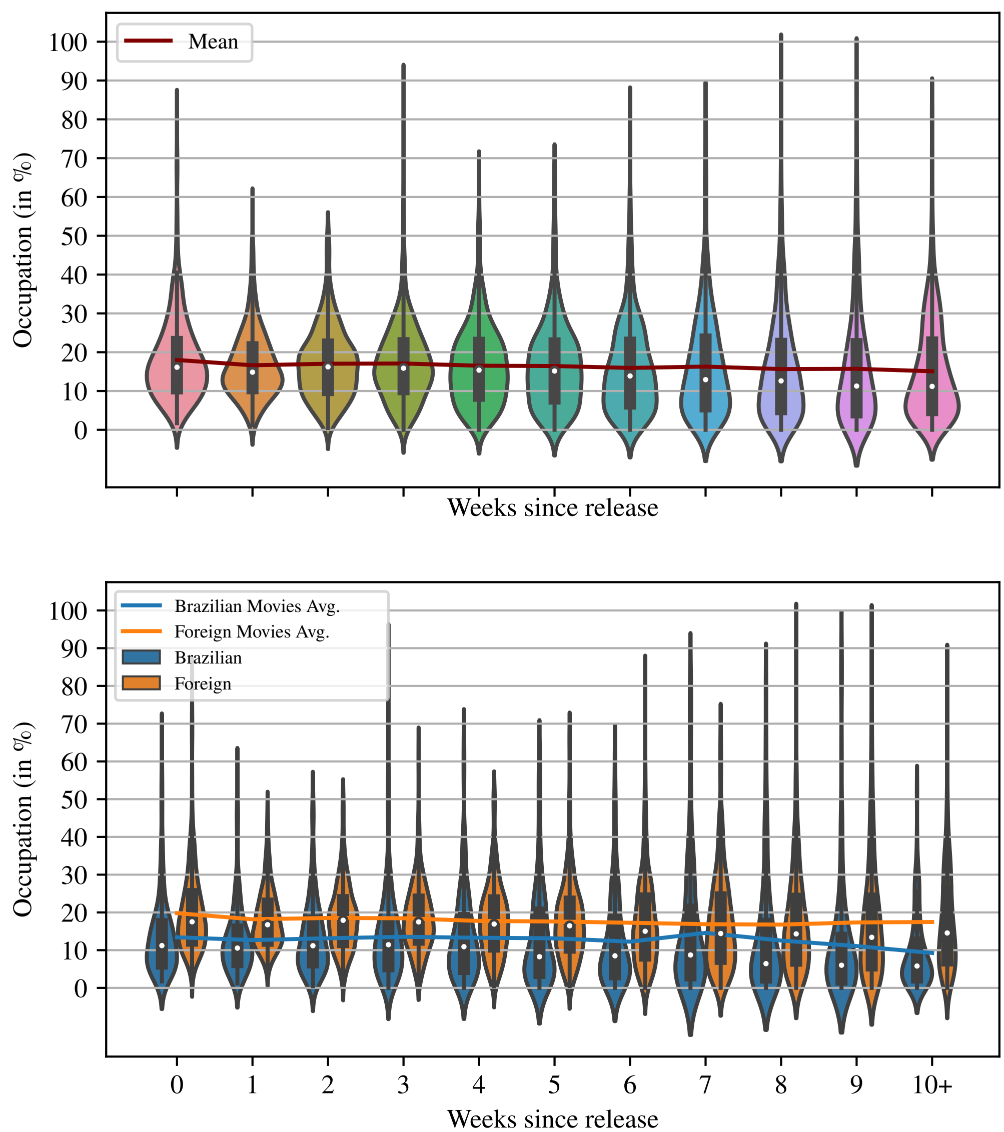
$$\bar{V}_t(x_t) = \sum_{m_t} \int_\epsilon I[\delta_t(x_t, \epsilon) = m_t][\tilde{\pi}(m_t, x_t; \theta) + \epsilon(m) + \beta \bar{V}_{t+1}(x_{t+1})] g(\epsilon) d\epsilon \tag{8}$$

It is easy to see that the conditional probability of choice m_t on state x_t, $p(m_t|m_t)$, is the result of integration over the policy function in all areas where $\delta_t(x_t, \epsilon) = m_t$:

$$p(m_t|x_t) = \int_\epsilon I[\delta_t(x_t, \epsilon) = m_t] g(\epsilon) d\epsilon \tag{9}$$

[12] Rust (1987) derives the model using a weaker conditional independence assumption that says $E(\varepsilon_{t+1}|x_t, m_t, \varepsilon_t) = E(\varepsilon_{t+1}|x_t, m_t)$.

FIGURE 5: Viewing Room Occupation Per Weeks Since Release. Source: Distributor Data/Ancine



Our distributional assumption regarding vector ϵ allows us to express this probability conditional probability in the familiar Logit form[13]:

$$p(m_t|x_t) = \frac{e^{\tilde{\pi}(m_t,x_t;\theta)+\bar{V}_{t+1}(x_{t+1})}}{\sum_{j_t \in M_t} e^{\tilde{\pi}(j_t,x_t;\theta)+\bar{V}_{t+1}(x_{t+1})}} \tag{10}$$

In other words, aside from the nested value function terms, the model reduces to simple conditional probabilities that could be estimated using traditional maximum likelihood methods, if *ex ante* value terms were knows.

In the next section, we discuss estimation strategies and implement the method developed by Bajari et al. (2007).

6 Estimation

One way to estimate parameters in the model above is to simply use maximum likelihood methods. As we have seen in Equation 10, this involves obtaining the value functions terms that show up in each conditional probability. Rust (1987) proposes a nested fixed point algorithm to calculate such value functions that can handle infinite time horizon problems through contraction mappings.

In our finite horizon problem, a full solution can be obtained directly via backwards recursion. Starting from the last period, T, the problem is static, and value functions are just the flow pay-off functions. This means computing a static version of Equation 8:

$$\bar{V}_T(x_T) = \sum_{m_T} \int_{\epsilon} I[\delta(x_T, \epsilon) = m_T][\tilde{\pi}(m_T, x_T; \theta) + \epsilon(m)]g(\epsilon)d\epsilon \tag{11}$$

Having a guess for θ, we can compute *ex ante* values for all possible states at T. This means value functions for $T-1$ can then be obtained as a simple static problem. Repeating this process until we get to $t = 0$, one can calculate all value functions for a guess of θ. Finally, this means the likelihood can be straightforwardly computed. We can then rinse and repeat, using a search algorithm on the parameter space[14] to get estimates by maximum likelihood.

This method is straightforward enough, but can get computationally very expensive when the sample and associated state space is large. In our case, the sample involves circa 4 million observations and a almost continuum of quota fulfillment, x_t, from 0 to 1. As an alternative, Keane & Wolpin (1994) propose reducing the state space and interpolating between chosen values to make the problem tractable.

We choose not to pursue full solutions through backwards recursion, because even interpolation would be computationally expensive with our available resources. Instead, we follow the Conditional Choice Probability (CCP) methods pioneered by Hotz & Miller

[13] For a complete derivation of Logit conditional probabilities from extreme value type I error vectors, see Train, 2009, ch. 3

[14] Rust (1987) uses a Newton-Kantorovitch algorithm to search over the parameter space.

(1993), later refined by Hotz et al. (1994) and Bajari et al. (2007), as a means to dramatically reduce the computational burden of point estimation.

Hotz & Miller (1993) first noted that one could recover utility differences associated with any pair of choices by inverting the conditional probability functions. Indeed they proved that, given the conditional independence assumption, the fact that errors are additively separable and that they are independent through time, utility differences can always be reduced to CCPs.

In the Logit case, inversion yields a very simple expression for choice-specific utilities. Defining $v_t(m_t, x_t, \theta) \equiv \tilde{\pi}(m_t, x_t; \theta) + \bar{V}_{t+1}(x_{t+1})$:

$$\frac{p(i_t|x_t, \theta)}{p(j_t|x_t, \theta)} = \frac{e^{v_t(i_t, x_t, \theta)}}{e^{v_t(j_t, x_t, \theta)}} \tag{12}$$

$$\ln p(i_t|x_t, \theta) - \ln p(j_t|x_t, \theta) = v_t(i_t, x_t, \theta) - v_t(j_t, x_t, \theta) \tag{13}$$

Drawing on Conditional Choice Simulation (CCS) methods first proposed by Hotz et al. (1994), Bajari et al. (2007) propose a two step estimation strategy using CCPs to simulate paths in the first stage and then retrieve *ex ante* value functions from $t = 0$. In the second stage, structural parameters are obtained by minimizing violations of Markov Perfect Equilibrium[15] conditions. A short outlook of the estimation approach is outlined below. Full details regarding the estimation algorithm developed and deployed in this paper are reported in Appendix B.

Before we delve into details, let us define more precisely our estimation strategy scope. We estimate the dynamic model for the set of 12-screen multiplexes. In 2018, there are only 6 movie theaters this large, none of which has breached quota obligations — the former and latter reasons explaining why we chose this category. Together, they comprise 102,512 movie sessions. Restricting estimation was necessary because of the computational burden associated with simulations, even if they were drastically more efficient than full solutions methods discussed above.

Our model also has only two parameters. Recalling Equations 4 and 8, take the value function of agent i starting from $t = 0$, and $x_0 = 0$:

$$\bar{V}_{i0}(0, \theta_1, \theta_2) = E\left[\sum_{t=0}^{T} \beta^t [\tilde{\pi}((\delta(x_t, \varepsilon_t), x_t, \theta_1, \theta_2) + \varepsilon_t(\delta(x_t, \varepsilon_t))] \mid x_0 = 0\right] \tag{14}$$

$$= E\left[\sum_{t=0}^{T} \beta^t [\theta_1 o_{\delta(x_t, \varepsilon_t), t} - \theta_2 \max(0, 1 - x_t) + \varepsilon_t(\delta(x_t, \varepsilon_t))] \mid x_0 = 0\right] \tag{15}$$

Where $\theta_1 = \frac{1}{\sigma}$ is just the inverse normalized standard deviation of the errors. Likewise, $\theta_2 = \frac{\theta}{\sigma}$. This means both parameters are adjusting to take into account the relative weight of errors and the observable variables, with θ_1 being merely the inverse of the standard

[15] In the literature, procedures allow for flexible Markov transition state functions

deviation. Recall also that $o_{mt} \equiv E(o_m|t)$ is a simple average of viewing room occupation for a given movie in a specific week determined by t.

First stage value function estimates begin with CCPs, since they are the basis for policy function estimates. Even though this is the primary step in CCS approaches, both Hotz et al. and Bajari et al. mostly gloss over procedures to obtain estimates, while emphasizing that one should be careful to avoid overly parametric assumptions to recover $v_t(m_t, x_t, \theta)$ differences.

In our case, the state space is too large to secure consistent estimates from simple bin estimators — many possible state-choice pairs are not available in the data. We thus try two approaches and compare results. The first one is to use Gaussian kernel density estimators in the x_t/day space to glean densities for each movie, calculating probabilities from relative densities at each point. The second one is to use a flexible Logit regression using movie theater fixed effects, day fixed effects and the state x_t.

Having at our disposal the CCPs for every possible movie and state, we start from $t = 0$ and follow the steps:

1. Starting at $x_0 = 0$, draw random shocks for each choice;
2. Calculate the chosen movie i, i.e., the movie such that $v_t(i_t, x_t, \theta) + \varepsilon_t(i) > v_t(j_t, x_t, \theta) + \varepsilon_t(j), \forall j_t \in M_t$;
3. Get a new state x_1 given the choice and the transition function $x_1 = f(0, \delta(0, \varepsilon_0), a_0, q)$;
4. Repeat 1-3 for the next state until the terminal state $t = T$ is reached.

Having all the choices and associated shocks, we can easily calculate an estimate for the *ex ante* discounted value function an agent i, $\hat{\hat{V}}_{0i}(0; \theta)$. We then average out the function over 20 simulated paths[16] to get consistent estimates for $\hat{\hat{V}}_{0i}(0; \theta)$ for each agent (see Bajari et al., 2007).

In the second stage, we estimate parameters θ_1 and θ_2. In order to do so, we calculate several alternative value functions following the same procedure of the first stage, but using disturbed conditional choice probabilities. Basically, we take CCP estimates and introduce random and systematic noise, and then calculate new disturbed value functions. We will call them $\hat{D}_{0i}^{(n)}(0; \theta)$, for each n disturbance tested. We will use $n = 5$, with 1 disturbance including simple random noise in CCPs and 4 other deviations involving systematic bias for and against Brazilian movies conditional probabilities. Note that because our period utilities $v_t(j_t, x_t, \theta)$ are linear in the parameters, we need not repeat the simulation every time we search over different parameters. CCPs are independent of parameters and just add with private shocks to get policy functions. This allows us to store policy profiles and shocks associated with choices to quickly obtain values and disturbances for each set of parameters. Details of such procedures are discussed in Appendix B.

[16]We restricted simulations to 20 due to time and computational constraints.

With estimates for $\hat{\hat{V}}_{0i}(0;\theta)$ and $\hat{D}^{(n)}_{0i}(0;\theta)$, we get parameter bound estimates minimizing Markov Perfect Equilibrium violations. We adopt the Bajari et al. (2007) strategy to minimize the function:

$$(\hat{\theta}_1, \hat{\theta}_2) = \arg\min_{(\theta^1,\theta^2)} \sum_{i=1}^{6} \sum_{n=1}^{5} (\max\{0, \hat{\hat{V}}_{0i}(0;\theta) - \hat{D}^{(n)}_{0i}(0)\})^2 \tag{16}$$

Parameters are thus chosen as the minimums of squared violations of equilibrium conditions. In our case, a violation meas that a disturbed value function attains a value higher that the "true" value function estimate for agent i. We sum this over all 6 multiplexes to get total squared deviations.

Table 5 presents estimates for the dynamic model using the conditional choice forward simulation algorithm. Standard errors are in parenthesis obtained from Hessian inverse matrix. Estimates for $\hat{\theta}_1$ point to a high private shock component variance, which is to be expected since our model has only two explanatory variables. Almost all of the heterogeneity across firm choices is being driven by private errors terms not captured by the model. The second coefficient, $\hat{\theta}_2$, also points out that quotas play a small role compared to private shocks. Nevertheless, results do point out that, in accordance to previous reduced-form results, screen quota enters negatively agents' value functions.

TABLE 5: Dynamic Model Parameter Estimates

	Kernel Density CCPs	*Logit CCPs*
	(1)	(2)
$\hat{\theta}_1$	0.00204853	−0.00825534
	(0.000027)	(0.000020)
$\hat{\theta}_2$	−0.10801806	−0.01818042
	(0.002122)	(0.000119)

We can also see that Kernel Density and Logit estimates produce different results. This points to a potential difficulty in the Bajari et al. (2007) forward simulation method, meaning estimates are sensitive to the chosen method for obtaining first stage conditional choice probabilities.

Some possible explanations may account for the fact that our explanatory variable o_{mt} seems to have so little impact on firm choices (and oddly a slight negative impact in the Logit CCP). First, it is possible that, due to general equilibrium effects, the variable hasn't got enough variation. As shown in figure 5, movie theaters may accurately anticipate dwindling ticket sales and adjust overall supply of movies such that the marginal screening of each movie has the same expected occupation. As a result, observed occupation in can be highly homogeneous because it is an endogenous variable at the aggregate level. Even if this shows that expected occupation is a relevant variable in the exhibitor choice, *observed* occupation average *differences* may not be able to account for heterogeneity across firms' choices. This brings us to a second point: expected occupation could be a relevant and good variable to predict movie theater behavior, but observed average aggregate occupation may be a bad way to measure it. To better explain the mechanics of how firms form expectations requires further refinements to the model that could be the subject of future research.

7 Conclusion

Screen quotas, in their present day form, have been in effect in Brazil for 20 years. By the end of this year, they are set to expire and will require incoming legislative action to be renewed. Quotas have also been used as a policy tool in several countries in Latin America, Europe and Asia. Nonetheless, quantitative analysis trying to assess causal regulation effects has been scant not only in Brazil, but in other countries. This paper tries to fill this gap, being the first to use Brazilian regulatory authority micro-level administrative data to gauge screen quota causal impacts.

First, we run least squares regressions weighted and segmented by compliance levels to measure policy effects. The idea is that narrowly compliant agents are more likely to have been affected by regulation. Movie theaters that either fulfill much more than what they are required to or that disregard regulatory obligations altogether are less likely to have had their behavior affected by policy. Results point to small but negative effects on overall and foreign film revenues and ticket sales.

Next, we build a dynamic discrete choice model of exhibitor choices to consolidate reduced-form results, following models by Rust (1987) and estimation techniques by Bajari et al. (2007). Overall, the model does a poor job predicting screening decisions, since heterogeneity is mostly driven by private shocks at the exhibitor-title level. Further extensions are necessary to capture and predict exhibitor behavior more fully, thereby allowing us to construct policy counterfactuals. Crucially, however, our model estimates imply a negative but small effect of screen quotas on firm value functions, in line with reduced-form regression results.

Policy takeaways from our work are: screen quotas, in their present form, do not seem to have large impacts on exhibitor behavior; effects seem to be small and negative on overall income and ticket sales, and have no discernible effect on Brazilian movies, the main policy targets.

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A Appendix: Reduced-Form Regression Tables

In this appendix, we present several regression tables with alternative specifications. Its purpose is to present robustness checks to results presented in section 4 and other relevant results left out not to take up too much space.

Table 6 presents what one might call raw regression results. The only explanatory variable used is nominal screen quota per chain, that is, before penalty increases and weighting by opening days. Overall, results are non-significant.

TABLE 6: Raw Regression Coefficient Results

	Dependent variable:					
	log(Box Office)			log(Ticket Sales)		
	All Movies	Foreign	Brazilian	All Movies	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Nominal SQ per VR	0.006	0.007	0.006	0.007	0.008*	0.009
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Chain Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
2019?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	629	625	602	629	625	602
R^2	0.960	0.961	0.930	0.958	0.959	0.931
Adjusted R^2	0.935	0.937	0.886	0.932	0.934	0.888

*p<0.1; **p<0.05; ***p<0.01

Table 7 looks at the interaction between screen quotas as opening days, to help ascertain whether opening days constitute a "bad control". Once again, coefficients point to null results, whether we include 2019 or not. This allows us to include opening days as a control, while allaying concerns that this may bias point estimates.

Table 8 displays omitted results for higher tranches of compliance. Note the extremely small samples that causes the 120 – 160% to become fully saturated.

Tables 9 and 10 tinker with alternative thresholds for the central bin, i.e. the bin that comprises 100% compliance. Sample sizes indicate that most chains are clustered around 100% compliance. We experiment with 85 – 125%, 95 – 105%, 90 – 110% and 99 – 101% compliance tranches. We can see that results are non-significant for all specifications except

TABLE 7: Regression Coefficient Results

	Dependent variable:	
	Opening Days	
	(1)	(2)
Nominal Screen Quota per VR	−5.613	−1.199
	(6.503)	(13.743)
Compliance (squared dist)	−28.791	−232.869
	(225.041)	(293.793)
Comp × Quota	2.437	8.796
	(7.010)	(9.296)
Chain FE	Yes	Yes
Year FE	Yes	Yes
2019?	Yes	No
Observations	626	406
R^2	0.998	0.999
Adjusted R^2	0.996	0.997

*p<0.1; **p<0.05; ***p<0.01

for 90 – 110% thresholds, in the foreign movie category. Futhermore, coefficients are surprisingly positive. Results likely hint at sample bias in this specific slice of compliance.

TABLE 8: Segmented Regression

	Dependent variable:					
	log(Box Office)					
	120-160% Compliance			>160% Compliance		
	All Movies	Foreign	Brazilian	All Movies	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Screen Quota per VR	0.060	0.232	−1.018	−0.005	0.036	−0.009
				(0.012)	(0.059)	(0.010)
Opening Days	0.0005	0.0004	0.001	0.014^{***}	0.018	0.012^{***}
				(0.003)	(0.015)	(0.002)
Chain FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
2019?	No	No	No	No	No	No
Observations	37	37	37	33	31	33
R^2	1.000	1.000	1.000	0.998	0.976	0.997
Adjusted R^2				0.987	0.824	0.984

*p<0.1; **p<0.05; ***p<0.01

TABLE 9: Alt Bins Segmented Regression Coefficient Results

	Dependent variable:					
	log(Box Office)					
	85 – 125% Compliance			95 – 105% Compliance		
	All Movies	Foreign	Brazilian	All Movies	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Screen Quota per VR	0.002	0.003	−0.0003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.006)
Opening Days	0.0002**	0.0002**	0.0003	0.0001*	0.0001*	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Chain Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
2019?	No	No	No	No	No	No
Observations	355	353	349	257	255	251
R^2	0.994	0.995	0.981	1.000	1.000	0.998
Adjusted R^2	0.984	0.986	0.948	0.997	0.996	0.983

*p<0.1; **p<0.05; ***p<0.01

TABLE 10: Alt Bins Segmented Regression Coefficient Results (2)

	Dependent variable:					
	log(Box Office)					
	90 – 110% Compliance			99 – 101% Compliance		
	All Movies	Foreign	Brazilian	All Movies	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Screen Quota per VR	0.004^{*}	0.005^{***}	0.002	0.011	0.013	−0.015
	(0.002)	(0.002)	(0.005)	(0.007)	(0.007)	(0.027)
Opening Days	0.0002^{**}	0.0001^{***}	0.0002	0.00004	0.00004	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0005)
Chain Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
2019?	No	No	No	No	No	No
Observations	304	302	298	228	226	222
R^2	0.999	0.999	0.992	1.000	1.000	0.999
Adjusted R^2	0.995	0.997	0.968	0.995	0.995	0.929

*p<0.1; **p<0.05; ***p<0.01

B Appendix: Estimation Algorithm

In this appendix we describe step-by-step the Conditional Choice Simulation (CCS) algorithm developed to tackle the estimation problem of the dynamic model discussed in section 6. The algorithm follows closely the procedure proposed by Bajari et al. (2007).

First, we calculate Conditional Choice Probabilities (CCP) of choosing a movie in a given state, namely, having fulfilled $x\%$ of quota obligations at time t. Recall that time is defined as the chronological index of a movie theater's sessions throughout the year. Thus $t = 1$ represents the first session a multiplex has screened, in any of its viewing rooms, in the year of 2018.

Our first approach to obtain Gaussian kernel density estimates (KDE) and use them to calculate probabilities. We proceed as follows:

1. We divide observations into movies/weeks, and then place them on a 2-dimensional space with attributes of quota fractional fulfillment (x_t) and day. So for movie A in week 1, a session is placed on a day — say Monday — and x_t — say 0.1 — grid. We choose to lump observations by day because index t is not directly comparable between multiplexes. Some may have more session than others, and distribution may vary throughout the year.
2. Bandwidth for kernel density estimates is obtained through maximum likelihood cross validation of randomly selected movie/week pairs. We use the mode of best bandwidth obtained via cross validation: 0.52. This is a usual approach in machine learning to deal with bias/variance trade-offs in KDEs. In essence, is leaves a part of observations out of the sample and chooses bandwidth that produces best out of sample fits.[17]. We did not cross validate all samples because the procedure is computationally expensive for the number of movie/week pairs.
3. We get KDEs for each movie/week using bandwidth obtained in (2.)

The second approach is to run a flexible multinomial Logit regression also on a weekly basis. Recall that our model constrains agents to screen a movie that was screened at least once that week according to the data:

$$m_t = \frac{\exp(x_{mt} + d_{mt} + c_{mn} + x_{mt} * c_{mn} + x_{mt} * d_{mt})}{\sum_{j_t} \exp(x_{jt} + d_{jt} + c_{jn} + x_{jt} * c_{jn})} \tag{17}$$

Where m_t is movie m at session t, x_{mt} denotes fractional fulfillment of quota, d_{mt} and c_{mn} are day and multiplex fixed-effects.

We then go on to simulate paths as described in section 6 for each exhibitor i. The algorithm works the following way:

1. At $t = 1$, $x_1 = 0$. The algorithm gets week and day for $t = 0$. With week information, it accesses all movies that were screened said week.

[17]For details check the documentation for Python's Sklearn GridSearchCV function

2. Having movies, day and x_t information, we get kernel density estimates for each movie according to day/x_t pair. Densities of all movies are summed up, such that probabilities are given by densities relative to total. In the Logit cases, relevant observation attributes are plugged in the model to get a probability prediction.
3. An extreme value error type I distribution is used to draw one shock for each movie.
4. Results for (2) and (3) are added together and the highest sum determines the "winner" movie
5. The expected occupation of the movie chosen in 4. is stored in an array
6. Private shock relative to the movie chosen in 4. is also stored in an array.
7. We record values for $\max(0, 1 - x_t)$. When $t = 0$, this equals 1.
8. Finally, state transition is effected, according to Equation 3.
9. Repeat steps $1 - 9$ until we reach terminal state $t = T$.

Then, we repeat these steps 20 for each of the 6 multiplexes with the KDE conditional probabilities. Logit CCPs computations are much more efficient, thereby allowing us to run 100 simulations for each multiplex. To compute the disturbed value function, we introduce slight modifications. We multiply step (2) by $(1 + X)$ where $X \sim \mathcal{N}(0, 1)$ to get the "noisy" estimate. In the systematic bias case, we add or subtract 10 and 20% to Brazilian movies in step (4) before computing the winner. In total, we get 4 noisy estimates for each CCP method, and 4 systematically biased value functions with 10 and 20% upwards or downwards bias.

Note that parameters are not required to operate the algorithm. In the second stage, we just get the stored arrays, weight them by a daily discount factor, such that the yearly interest rate make up to 6.5% and multiply the results by a vector of parameters:

$$V_{i0}(0, \theta) = \begin{bmatrix} o_{w_1 1} & \varepsilon_1(w_1) & \max(0, 1 - x_1) \\ o_{w_2 2} & \varepsilon_2(w_2) & \max(0, 1 - x_2) \\ \vdots & \vdots & \vdots \\ o_{w_T T} & \varepsilon_T(w_T) & \max(0, 1 - x_T) \end{bmatrix} \cdot \begin{bmatrix} \theta_1 \\ 1 \\ \theta_2 \end{bmatrix}$$

We use the exact same procedure for computing the disturbed value functions. This allows us to quickly calculate minima for Equation 14.