The Effects of Screen Quotas on the Movie Exhibition Market: Evidence from 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 exhibitor choice. Reduced-form regressions point to negative effects of screen quotas on overall and foreign films' box-office and ticket sales, but impact on Brazilian movie revenue or public is either zero or very small. Nevertheless, quotas do seem to prompt movie theaters to screen more Brazilian movies. Structural parameter estimates still need further adjustments.
Keywords: *applied microeconomics*, *audiovisual*, *cinema*, *policy analysis*, *screen quotas*, *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 harkens 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 screens (or 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 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, because the sitting president the year before did not renew an executive order mandating quotas and specifying policy particulars. 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 exhibition industry.

The reduced-form identification strategy combines exogenous variation in quotas with compliance data, also available from the Brazilian regulatory body. We first show that a naïve approach, using simply screen quotas mandated days per screen as exogenous variables yields mostly non-significant results, highly sensitive to inclusion/exclusion of 2019. We then argue that screen quota effects are likely mediated by compliance, as simple microeconomic theory would imply: quotas are non-binding for multiplexes that screen much more Brazilian movie-days than mandated; likewise, policy effects are to be ignored in multiplexes that are fully non-compliant (i.e., that screened 0 Brazilian movies throughout the year). To capture "compliance effects", 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 negative effects of screen quotas on overall ticket sales and box-office, driven by a larger adverse impact in foreign movie revenue and public. Effects on Brazilian feature films are non-significant. At the same time, screen quotas do seem to increase the number of Brazilian feature film sessions. This suggests policy elicits supply-side effects, but with weaker (or null) demand-side response. In other words, the marginal Brazilian feature film screened as a result of quotas is unable to draw in significant moviegoers or revenues.

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. 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

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

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 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 already discussing 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 issues regarding first-stage Conditional Choice Probability (CCP) estimators with large state spaces.

Finally, this paper contributes to a larger (but also sparse) literature on industrial and trade policy quota requirements' effects. The literature on quotas mostly focuses on trade-related settings. Kiyota et al. (2013) analyses the effects of lifting trade quotas in postwar Japan and finds positive productivity effects following their removal. De Bromhead et al. (2019) investigates the role of quotas and trade policy in shifting the composition of imports in 1930s Great Britain. This paper expands the literature by looking at a domestic quota policy in a non-trade-related setting.

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). Federal funding in 2019 amounted to R$ 243 million in tax breaks and R$ 500 million in direct funding, which roughly translates to $ 135 million dollars.[4] 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[5].

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

[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]See https://oca.ancine.gov.br/sites/default/files/repositorio/pdf/valores_execucao_fsa.pdf and https://oca.ancine.gov.br/sites/default/files/repositorio/pdf/810_0.pdf

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

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 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: a minimum amount of Brazilian movie screening days as a function of the number of screening rooms a movie theater has.

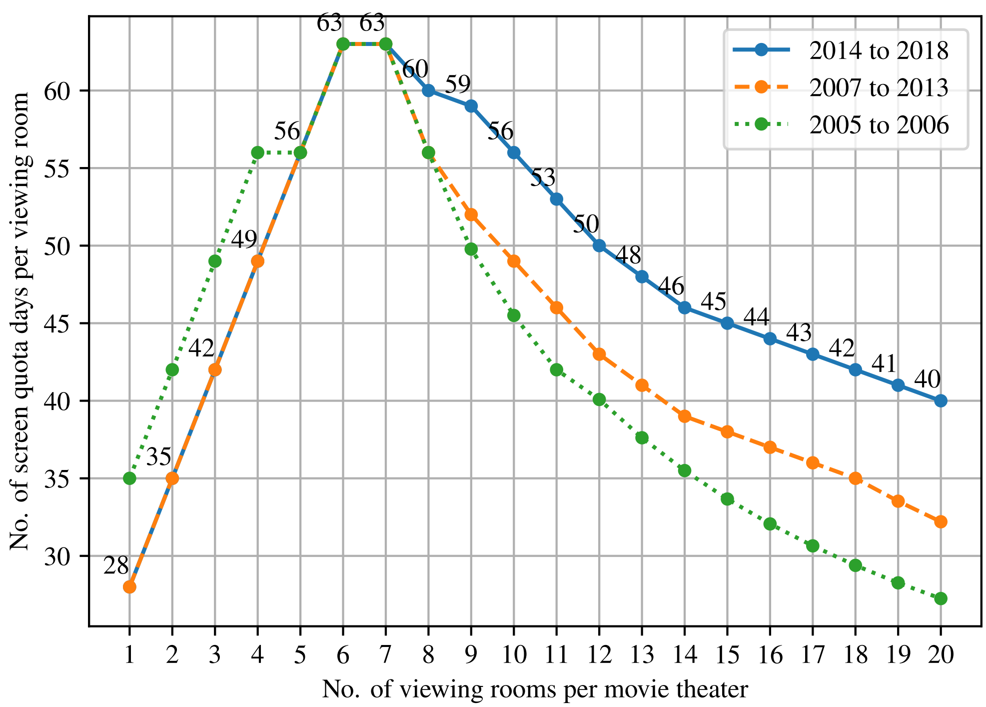
In 2001, the *Medida Provisória* 2228-1 of 2001 was put into law renewing screen quotas for more 20 years. These are the object of our analysis. Although no amendment affecting the policy has been made to the law in the last 20 years, screen quotas have been gradually changed by the yearly executive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

Unfortunately, the Ancine has no comprehensive data on ticket sales or box-office per multiplex going back to 2005. 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[6]; and the possibility of swapping obligations between movie theaters belonging to the same chain.

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

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

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



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.[7]

Our analysis ignores minimum title requirements, since compliance with day quotas goes hand in hand with compliance of title requirements.[8] 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.[9]

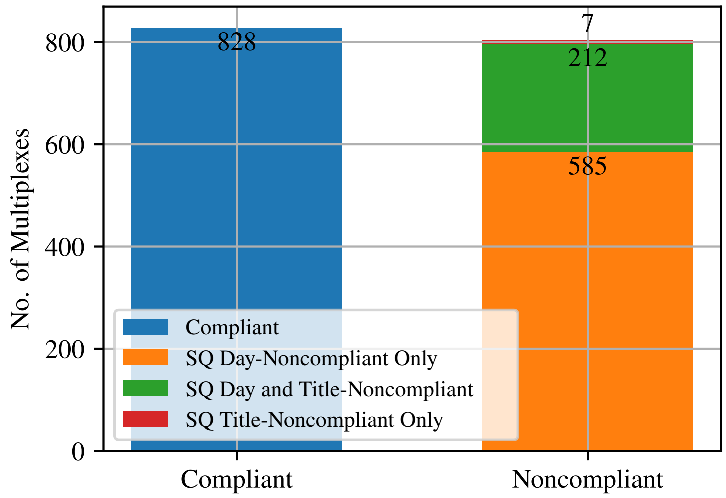
Non-linear screen quotas (coupled with compliance levels) are thus the main source of variation used to tease out causal policy effects in reduced form regressions. Additional sources of variation come from the penalty increases mentioned before. Heterogeneity also arises from the number of days open: if a movie theater operates for half a year, only half of its nominal obligation is due. This 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 quotas per viewing room in relation to operating days. Finally, we handle

[7]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.

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

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

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



variation stemming from swaps by looking at chain-level 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, before the pandemic set in, 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 a robustness check on results excluding/including 2019.

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.[10]

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.

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[11], 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 might be 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.

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 (see section 2); transfers between movie theaters; final net screen quotas; number of quota

[10] *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*

[11] 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

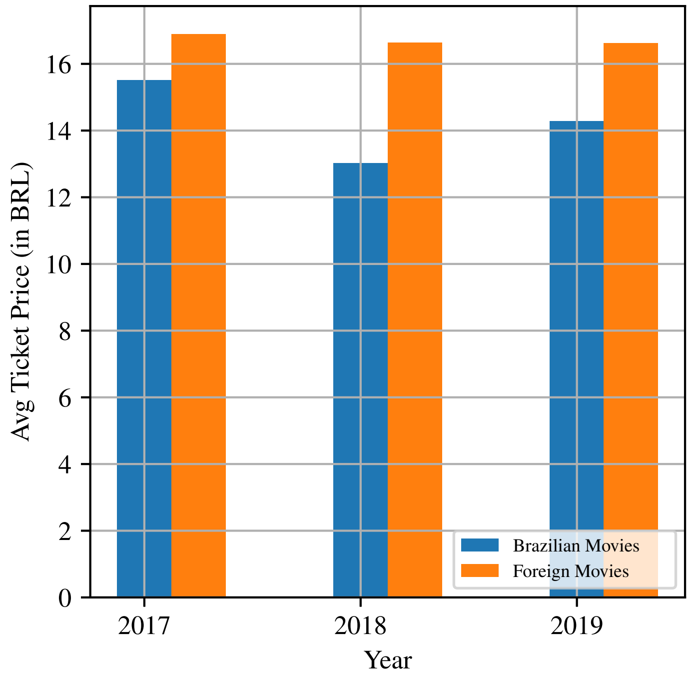
Note: *Nationality* is a dummy variable coded 1 for Brazilian films and 0 otherwise.

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

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



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 the Brazilian price consumer index data (IPCA).

4 Reduced-Form Regressions

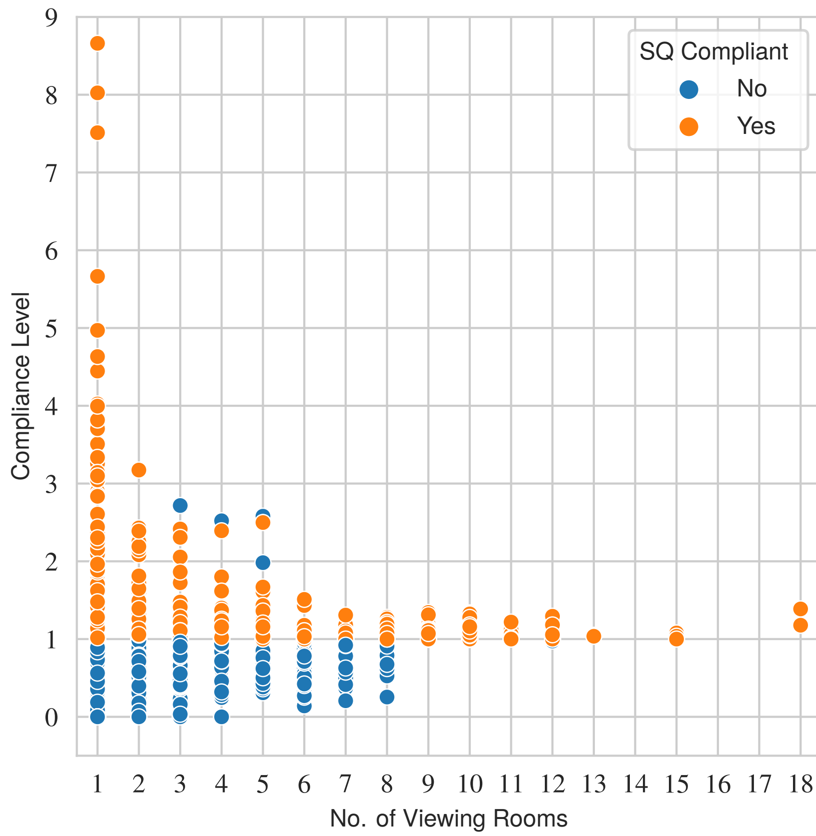
In this section, we specify and run least squares regressions to identify policy effects on two several dependent variables: box-office, ticket-sales, number of movie sessions, and session occupancy. As discussed in section 3, dependent variables were chosen to identify possible effects of screen quotas 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. In the first set of regressions, we run a simple reduced-form regression using yearly quota days per screen:

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

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



Where y_{nit} are the dependent variables for chain i, year t, and nationality n — meaning we are either looking at Brazilian films, foreign films, or both. 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 days open, year and movie theater chain fixed-effects.[12]

Table 2 displays results of the naïve regressions for box-office as dependent variable. Observations represent aggregated sessions per nationality of a movie theater chain per year. Nominal screen quotas per viewing room do seem like a natural explanatory variable since they are plausibly exogenous. However, coefficients signs and magnitudes are highly sensitive to the exclusion/inclusion of 2019. As we discussed before, it is unclear how movie theaters responded to the thwarted expectation of screen quotas in 2019. Appendix A also shows similar results hold for ticket sales.

Furthermore, 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,

[12]It is possible that days open 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 operating days.

TABLE 2: Naïve Regression Coefficient Results

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Nominal SQ per	0.0088**	0.0100**	0.0083	-0.0391	-0.0394	0.0402
Viewing Room	(0.0043)	(0.0042)	(0.0056)	(0.0683)	(0.0667)	(0.0454)
Days Open	0.0011**	0.0011**	0.0007**	0.0013**	0.0013*	0.0007*
	(0.0005)	(0.0004)	(0.0003)	(0.0007)	(0.0007)	(0.0004)
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	628	624	602	408	406	388
R^2	0.9645	0.9656	0.9320	0.9698	0.9700	0.9391
Adjusted R^2	0.9421	0.9437	0.8886	0.9347	0.9350	0.8669

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

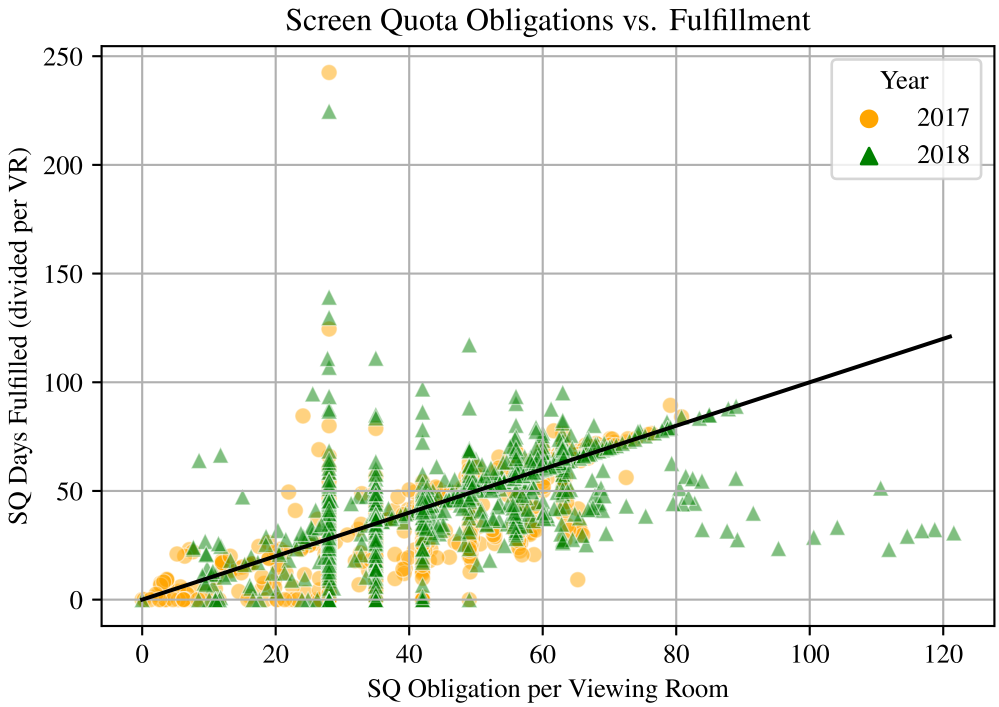
regulations may not be binding on the opposite end: it could be so profitable to feature Brazilian films that they'd do it even in the absence of quotas.

This might not be a problem if compliance levels are uncorrelated with screen quota size, such that, on average, the quota's effects are proportional to its size.[13] But Figure 5 shows not only variance is higher at lower quota levels, but also that large quotas are systematically not fulfilled. The line represents points where quotas fulfilled equal quotas due.

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.

[13]It is important to note that this might still be a problem even if compliance levels are uncorrelated with screen quota size. This is because it estimates implicitly assume high compliance levels balance out low ones in cases where variance is high for a given quota level. But this is not the case. If a multiplex fulfills 2x his due quota and another one fulfills no quota at all, this means both multiplexes were likely *not* affected at all — and not affected correctly "on average". In such cases, a naïve reduced-form would be treating two observations as having the same quota, whereas it should be taking the average treatment effect to be zero. This is also a problem for any non-linear fit mapping from treatment sizes to average effect sizes.

FIGURE 5: Screen quota obligation vs. fulfillment (2017 and 2018). Source: Ancine



Moreover, the impact is likely correlated with screen quota size. If two movie theaters fulfilled 100% of their quotas, but one had twice as many quota-days to fulfill, the policy likely induced him to screen more days of Brazilian films — presumably twice as many, on average.

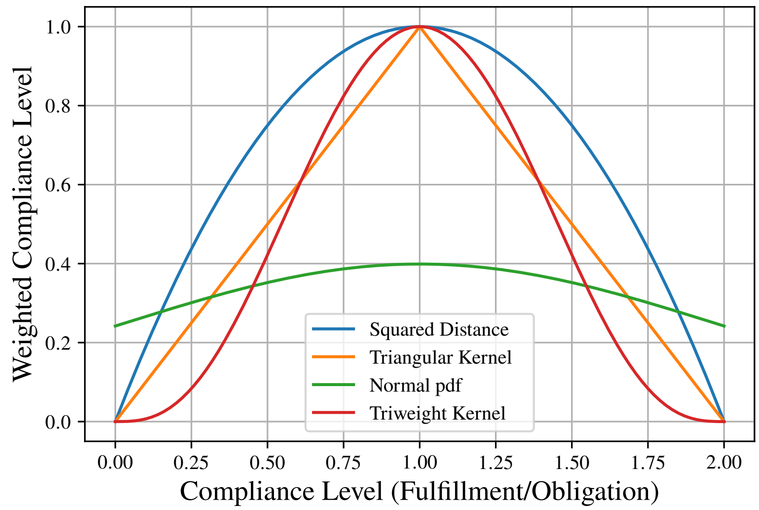
A first approach to deal with this problem would be to segment according to the level of compliance. We could divide observations into compliance bins and look at effects bin-wise. But this approach has several problems: (a) each bin will have few observations, costing us statistical power; (b) pooling thresholds are arbitrary; and (c) because the pooled sample is binned according to compliance, sometimes the same chain will shift bins across years, preventing us from calculating entity fixed-effects. Appendix A explores binned regressions and shows that results are highly non-significant across the board. Additionally, only 13-40% of chains stay in the same bin, depending on the specification.

Our preferred approach is to weight compliance levels to account for the fact that narrowly compliant agents are more likely to be influenced by policy. This allows us to harness compliance effects in the full available sample. We choose different kernel functions, shown in Figure 6, to emulate the theoretical intuition that narrowly compliant movie theaters should be more affected by the policy.[14]

To emulate this effect, we apply different non-linear functions to compliance levels

[14]Technically, these are not kernels because areas under the curves are not normalized to 1. In most cases, we choose the functions such that a fully compliant agent would have a compliance level of 1.

FIGURE 6: Weighting functions for compliance levels



(normalized to 1 as 100%). Then, we can define regression equations:

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

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.

This approach naturally raises questions regarding the endogeneity of compliance levels. It is plausible that weighted compliance levels correlate with omitted variables that influence our variables of interest. This is certainly possible, but we note that by adding the non-interacted compliance term $f(c_{it})$, we are controlling for this kind of endogeneity.

Regressions using the squared distance kernel are displayed below in Tables 3 and 4, respectively for box-office and ticket sales. Compliance levels are normalized to 1 and weighted accordingly. Robust standard errors are displayed in parenthesis.

Results indicate quotas have an adverse effect on box-office revenues and ticket sales. As expected, ticket sales closely follow box-office revenues, but 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 maybe these coefficients are somehow capturing firm size effects 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 with lower quotas per screen. Fixed effects should account for this, but shifting composition of movie theater chains throughout the years, however small, could be driving observed estimates.

Results are robust to the alternative kernel function choices displayed in Figure 6 or to the inclusion of other covariates, such as number of viewing rooms. We use bunching

TABLE 3: Weighted Regression Coefficient Results (Box Office)

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Compliance	1.8657***	1.9062***	0.4965	2.5027***	2.5718***	1.3092
(Squared Distance)	(0.6751)	(0.7095)	(0.9098)	(0.9455)	(0.9353)	(1.6410)
Quota per	0.0487**	0.0545**	-0.0104	0.0625***	0.0696***	-0.0027
Viewing Room	(0.0206)	(0.0221)	(0.0235)	(0.0233)	(0.0246)	(0.0376)
Days Open	0.0009***	0.0009**	0.0007***	0.0010**	0.0009**	0.0008*
	(0.0004)	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0005)
Compliance	-0.0478**	-0.0523**	0.0154	-0.0682**	-0.0748**	-0.0027
× **Quota**	(0.0226)	(0.0240)	(0.0264)	(0.0326)	(0.0332)	(0.0479)
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	628	624	602	408	406	388
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

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

estimators to provide further robustness checks regarding the choice of functional forms (for a review of bunching estimators, see Kleven 2016). These do not avoid the problems of choosing effect thresholds, but avoid some assumptions regarding effects according to compliance level. Results are presented in Appendix A and closely follow the ones presented for the kernel specifications below. In fact, the results confirm our intuition that quota effects are stronger (i.e., more negative) for movie theater chains close to 100% compliance, and results wane as we move away from 100% compliance.

Surprisingly, however, quotas do not seem to significantly increase revenues or ticket sales of Brazilian movies. To investigate further what may be driving results, we present Table 5, where we look at number of sessions and movie session occupancy (tickets sold divided by total seat capacity) as dependent variables.

TABLE 4: Weighted Regression Coefficient Results (Ticket Sales)

	Dependent variable:					
	log(Ticket Sales)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Compliance	1.8106***	1.8985***	0.4028	2.3471***	2.4410***	1.1560
(Squared Distance)	(0.6481)	(0.6871)	(0.8533)	(0.8582)	(0.8709)	(1.4568)
Quota per	0.0490**	0.0552**	-0.0095	0.0634***	0.0707***	-0.0005
Viewing Room	(0.0200)	(0.0217)	(0.0228)	(0.0220)	(0.0237)	(0.0355)
Days Open	0.0009***	0.0009***	0.0007***	0.0010**	0.0009**	0.0008**
	(0.0003)	(0.0003)	(0.0002)	(0.0005)	(0.0004)	(0.0004)
Compliance	-0.0458**	-0.0513**	0.0175	-0.0621**	-0.0692**	0.0004
× **Quota**	(0.0219)	(0.0234)	(0.0250)	(0.0296)	(0.0310)	(0.0425)
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	628	624	602	408	406	388
R^2	0.9700	0.9705	0.9388	0.9787	0.9778	0.9489
Adjusted R^2	0.9507	0.9515	0.8992	0.9534	0.9513	0.8871

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

The results above suggest a simple micro story. Quotas add a restriction to movie theaters' screening decision problems. This leads them to screen more Brazilian movies, increasing the number of Brazilian film sessions, as seen in Table 5. As a consequence, occupancy of Brazilian movies falls, whereas occupancy for foreign films increase, since the marginal Brazilian movie screened as a result of quotas is less appealing to moviegoers, while the marginal foreign film de-screened as a result of quotas is less desirable than the other ones that remained. Finally, this all leads to lower overall revenues and ticket sales, since we are adding a restriction to the exhibitor problem. We should note that other regressions suggest no effects on ratio between foreign and Brazilian movie ticket prices.[15],

[15]Check Appendix A for results.

TABLE 5: Weighted Regression Coefficient Results (Other variables)

	Dependent variable:					
	No. of Sessions			Session Occupancy		
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Compliance	666.4578	2383.2641	-2478.4195**	-0.0106	-0.0152	0.0945
(squared dist)	(1836.7657)	(2019.6112)	(992.3284)	(0.0304)	(0.0243)	(0.0887)
Quota per	9.1731	35.0042	-49.2760**	-0.0005	-0.0004	0.0005
Viewing Room	(30.6587)	(29.5818)	(23.0908)	(0.0009)	(0.0007)	(0.0025)
Compliance	-27.0820	-90.7394	89.1496**	0.0005	0.0005	-0.0015
× **Quota per VR**	(67.7877)	(75.3754)	(34.9722)	(0.0010)	(0.0007)	(0.0027)
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	628	624	602	628	624	602
R^2	0.9992	0.9988	0.9976	0.9295	0.9317	0.7882
Adjusted R^2	0.9987	0.9980	0.9960	0.8846	0.8880	0.6521

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

so it does not seem that exhibitors are responding by changing prices.

The somewhat surprising fact that we do not see a significant increase in Brazilian movie revenues or ticket sales as a result of quotas could be explained by the fact that our sample is not large enough (under-powered) to capture small effects. Maybe the marginal Brazilian movie featured because of quotas has little appeal to moviegoers, explaining the small (non-significant) increases we see.

Unfortunately, the presence of (statistically significant) coefficients without a clear causal interpretation, namely the compliance and quota per viewing room residual coefficients, prevents us from extrapolating the reduced-form to at least attempt a simple welfare analysis of quota effects.

In the next section, we develop a dynamic discrete choice model to enable us to run counterfactuals and obtain some estimates of lost revenues and ticket sales to the screen quota policy.

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 set available options M_t. In our simplified model, we will assume m_{it} to be a binary variable, as if the exhibitor only had the alternative to choose between a representative "Brazilian" or "foreign" feature film.

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:

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

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 $\varepsilon_t(j)$ which is known by the firm, but unbeknownst 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 binary choice m and state x_t and with $o_{mt} \equiv E(o_m|t)$, the average occupancy of Brazilian or foreign movies conditional on t.

If $t < T$, where T represents the terminal state or last session screened each year, we have:

$$\pi(m_t, x_t, \varepsilon_t(m); \theta) = o_{mt} - \theta[\mathbb{1}_{t=T} \max(0, 1 - x_t)] + \varepsilon_t(m) \tag{4}$$
$$= \tilde{\pi}(m_t, x_t; \theta) + \varepsilon_t(m) \tag{5}$$

Equation (4) breaks down the profit function into two non-stochastic components: the expected seat occupancy of movie m in time t, o_{mt}, and the remaining screen quota fraction of the movie theater by the end of the year, when fines are tallied and levied, $\max(0, 1 - x_t)$, multiplied by a parameter, θ, that measures the sensibility to quota requirements. The indicator function $\not\Vdash_{t=T}$ equals 0 when $t < T$ and 1 when $t = T$, because penalties are tallied and charged only by the end of each year, or in the terminal state T. The expression $\max(0, 1 - x_t)$ represents the quota left unfulfilled by time t.

Before we move on, a remark regarding the choice of explanatory variable o_{mt} is needed. Session occupancy 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 occupancy (or any other closely related variable) to select titles. Figure 7 displays the distribution of viewing room occupancy 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 occupancy decreases 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 :

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

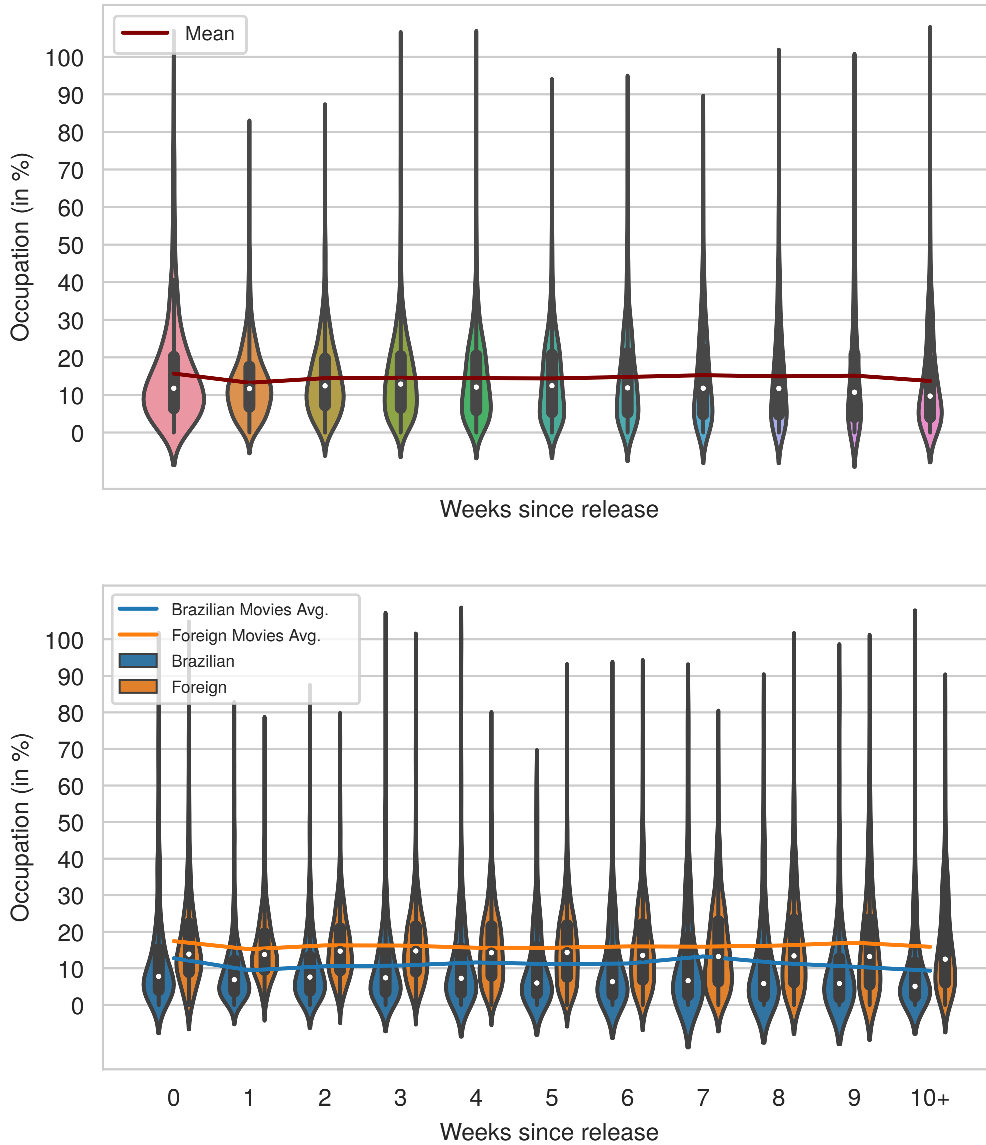
Where $\beta \in (0, 1)$ is the discount factor of future states. We assume that future errors, ε_{t+1}, are independent from state t variables.[16] Now, we define a policy (or control) function that maps from the state to the movie choice, $\delta_t(x_t, \varepsilon_t) = \arg\max_m [\tilde{\pi}(m_t, x_t) + \varepsilon_t(m) + \beta E(V_{t+1}(x_{t+1}, \varepsilon_{t+1})]$. 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

[16] 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 7: Viewing Room Occupation Per Weeks Since Release. Source: Distributor Data/Ancine



— 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, $p(m_t|x_t)$, is the result of integration over the policy function in all areas where $\delta_t(x_t, \epsilon) = m_t$:

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

Our distributional assumption regarding vector ϵ allows us to express this probability conditional probability in the familiar Logit form[17]:

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

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 known.

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 to get estimates by maximum likelihood.[18]

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,

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

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

we follow the Conditional Choice Probability (CCP) methods pioneered by Hotz & Miller (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[19] 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 full set of 785 multiplexes that had quotas due in 2018. Together, they comprise 4,232,361 movie sessions. We restrict estimation to 2018 due to the computational burden of adding more years — running all simulations takes a whole week with our available resources — and because 2018 had an unrestricted fractional fulfillment quota rule, as explained in session 2.2. Computing the fraction of quota fulfilled per day in 2017 would require knowing all sessions screened in a day, and this would substantially complicate how to calculate the state transition.

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

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

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

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

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

of errors and the observable variables, with θ_1 being merely the inverse of the standard 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. A first attempt was 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, but simulations were extremely slow to run. Alternatively, we choose use a flexible binary Logit regression using the state x_t, the squared state x_t^2, the number of screens of the multiplex, the number of seats in the viewing room, and movie theater, day, and hour fixed effects as independent variables.

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 "nationality" dummy 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.
5. After T is reached, we multiply the quotas unfulfilled, $\max(0, 1 - x_T)$, by each multiplex's total quotas due in days to get non-fulfillment in days, which is used to tally penalties.

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 80 simulated paths[20] 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, for the expected occupancy and quotas not fulfilled, respectively. 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 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 $N = 6$, with disturbances introducing systematic bias for and against Brazilian movies conditional probabilities. Note that because our period

[20]We restricted simulations to 80 due to computational constraints.

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.

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:

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

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

Table 6 presents estimates for the dynamic model using the conditional choice forward simulation algorithm. Standard errors are in parenthesis obtained from Hessian inverse matrix. As expected, estimates for $\hat{\theta}_1$ are positive and show that exhibitors do take expected occupancy into account — recall that extreme type I shocks have zero expected value and are concentrated between -2 and 2. Unfortunately, results for the screen quota parameter take positive values. This would mean that having quotas left unfulfilled is valuable for agents, which makes no sense — quotas would lead to foreign films being more desirable.[21] To investigate what may be driving these estimates we restrict estimation to the sub-sample of multiplexes that fulfill screen quotas according to the simulations. We then get radically different values for the unfulfilled quota parameter. Of course, this procedure is highly *ad hoc*, but may point to some problems. Simulations lead to much higher compliance than observed in data: 467 out of 785 multiplexes are compliant in data, whereas 731 out of 785 are compliant in simulations. This means our first stage conditional probabilities are likely doing a poor job of reproducing movie theater behavior.

It could be that non-compliant movie theater ignore screen quota requirements because there are few costs in doing so. Or maybe just adding more disturbed value functions will do. Whatever the case, further investigation and simulations are required to get a better picture.

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

[21] Note that values are positive but quite small since unfulfilled quotas just appear in the last state T, whereas the expected occupancy enters the value functions in every period

TABLE 6: Dynamic Model Parameter Estimates

	All Multiplexes	*Compliant-Only Multiplexes*
	(1)	(2)
Expected occupancy ($\hat{\theta}_1$)	5.467	4.729
	(0.0007)	(0.0008)
Screen quota unfulfilled ($\hat{\theta}_2$)	3.992	−4,773.466
	(0.0013)	(48.3001)

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 negative effects on overall and foreign film revenues and ticket sales, whereas effects on Brazilian film revenues are either positive or zero, but too small to be precisely estimated by our sample.

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 still does a poor job simulating actual movie theater behavior in the first stage. Coefficients for quota unfulfilled are positive, which make no sense given our prior knowledge. Further investigations and adjustments are necessary for the model to work, thereby allowing us to construct policy counterfactuals and calculate welfare effects.

References

(2018). *Box-Office Control System Manual*. Available at https://www.gov.br/ancine/pt-br/assuntos/atribuicoes-ancine/regulacao/cinema/cota-de-tela/manual-cota-de-tela-22-02-2018.pdf/view.

Angrist, J. D. & Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Arcidiacono, P. & Ellickson, P. B. (2011). Practical methods for estimation of dynamic discrete choice models. *Annu. Rev. Econ.*, *3*(1), 363–394.

Bajari, P., Benkard, C. L., & Levin, J. (2007). Estimating dynamic models of imperfect competition. *Econometrica*, *75*(5), 1331–1370.

Courtney, C. (2015). O Efeito da Cota de Tela Sobre o Cinema Brasileiro. Master's thesis, Department of Economics/PUC-Rio, Brazil.

De Bromhead, A., Fernihough, A., Lampe, M., & O'Rourke, K. H. (2019). When Britain turned inward: the impact of interwar British protection. *American Economic Review*, *109*(2), 325–52.

Hotz, V. J. & Miller, R. A. (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies*, *60*(3), 497–529.

Hotz, V. J., Miller, R. A., Sanders, S., & Smith, J. (1994). A simulation estimator for dynamic models of discrete choice. *The Review of Economic Studies*, *61*(2), 265–289.

Keane, M. P. & Wolpin, K. I. (1994). The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence. *the Review of economics and statistics*, (pp. 648–672).

Kiyota, K., Okazaki, T., et al. (2013). *Effects of Industrial Policy on Productivity: The case of import quota removal during postwar Japan*. Technical report, Institute of Economic Research, Hitotsubashi University.

Kleven, H. J. (2016). Bunching. *Annual Review of Economics*, *8*, 435–464.

Messerlin, P. & Parc, J. (2014). The effect of screen quotas and subsidy regime on cultural industry: A case study of french and korean film industries. *Journal of international business and economy*, *15*(2), 57–73.

Orbach, B. Y. & Einav, L. (2007). Uniform prices for differentiated goods: The case of the movie-theater industry. *International Review of Law and Economics*, *27*(2), 129–153.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica: Journal of the Econometric Society*, (pp. 999–1033).

Santos, A. (2019). A Cota de Tela é Uma Medida que Atende Às Necessidades do Cinema Nacional? Master's thesis, School of Communication and Arts/Universidade de São Paulo, Brazil.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Zubelli, L. M. R. A. (2017). *A Systemic Vision of Public Policies for the Audiovisual Sector: Understanding the Trajectory since the 1990s in Brazil*. PhD thesis, Economics Institute/Federal University of Rio de Janeiro, Brazil.

Zubelli, L. M. R. A., Gama, B. C., Barbosa, B. R., & Borges, D. d. S. (2017). *Relatório de Análise de Impacto: Cota de Tela*. Technical Report n.º 1/2017, Agência Nacional do Cinema (Ancine). Available at https://www.gov.br/ancine/pt-br/assuntos/atribuicoes-ancine/regulacao/relatorios-analise-impacto/relatorio-de-analise-de-impacto-viii-cota-de-tela.pdf/view.

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.

There are still many other regression specifications available at the GitHub repository.

A.1 Naïve Regressions

Table 7 displays results for naïve regressions using screen quotas per viewing room as main explanatory variable but with ticket sales as dependent variable. Results closely follow the ones on Table 2.

TABLE 7: Naïve Regression Coefficient Results (Ticket Sales)

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Nominal SQ per Viewing Room	0.0097**	0.0106**	0.0105*	-0.0431	-0.0436	0.0387
	(0.0042)	(0.0041)	(0.0055)	(0.0670)	(0.0653)	(0.0496)
Days Open	0.0011**	0.0010**	0.0007***	0.0013**	0.0012*	0.0008**
	(0.0004)	(0.0004)	(0.0003)	(0.0007)	(0.0006)	(0.0004)
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	628	624	602	408	406	388
R^2	0.9631	0.9638	0.9335	0.9695	0.9688	0.9431
Adjusted R^2	0.9398	0.9408	0.8912	0.9341	0.9324	0.8757

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

A.2 Segmented Regressions

As we've mentioned in Section 4, segmented regressions pose several problems. The following tables present results for alternative bin specifications, since pooling thresholds are chosen arbitrarily. Thresholds are chosen such that ranges are bigger rather than smaller, comprising more observations in each bin and avoiding fixed-effects issues mentioned before.

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.

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

$$\ln(y_{nit}) = \beta_0 + \beta_1 q_{it} + \theta \mathbf{x}_{it} + \varepsilon_{nit} \tag{17}$$

For details on what each variable represents, see Equation 1.

Results for our preferred specification are displayed in Table 8. 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 displayed in Table 9, but also display null results and very small samples. In some cases, like the $120-160\%$ tranche, samples are so small that regressions get fully saturated.

Tables 10 and 11 tinker with alternative thresholds for the central bin, i.e. the bin that comprises 100% compliance, since it is the one that interests us the most. 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 for $90-110\%$ thresholds, in the foreign movie category. Furthermore, coefficients are surprisingly positive. Results likely hint at sample bias in this specific slice of compliance.

A.3 Bunching Regressions

Table 12 presents the results of bunching regressions looking at revenues as dependent variable. An in-depth overview of bunching regressions is beyond the scope of this Appendix, but, in short, bunching creates categorical variables for each tranche of compliance. As with the segmented regressions, pooling thresholds are somewhat arbitrary. This, however, let's us use the full sample and does not impose a functional form of effects like the kernel approach.

Pooling thresholds chosen are: 0-30%; 30-60%; 60-90%; 90-120%; 120-150%; 150+%. Results shown are robust to alternative bin specifications. For other pooling thresholds, please check the GitHub repository.

Note that the table omits the first tranche (0-30%) dummy variable.

TABLE 8: 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)
S Quota per	0.002	0.003	−0.001	0.001	0.002	−0.015	0.043	0.046	−0.380
Viewing Room	(0.003)	(0.003)	(0.006)	(0.007)	(0.008)	(0.013)	(0.055)	(0.056)	(0.247)
Days Open	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

A.4 Alternative Kernel Specifications

Tables 13 and 14 present some alternative kernel specifications. They largely show results have similar coefficients whether compliance is weighted by the alternative squared distance function or one of the other kernels shown. Also, leaving 2019 out reveals mostly the same effects, and preserves signs.

Nevertheless, there are differences. Table 13 shows that, with a triangular kernel kernel, point estimates for our coefficient of interest are *negative*, and not positive for Brazilian movies, even though significance levels are so small that these probably should be regarded as zero. Moreover, when we combine coefficients for the isolated and interacted quota terms, we see that the interacted term has a bigger magnitude even when 2019 is included, which is not the case for the squared distance coefficient.

Table **??** tells much the same story as the other kernels, even though significance levels vary. Once more, when we combine coefficients for the isolated and interacted quota terms, we see that the interacted term has a bigger magnitude even when 2019 is included, which is not the case for the squared distance coefficient.

TABLE 9: Segmented Regression (cont.)

	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

A.5 Auxiliary Regressions

Table 15 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.

AAAAADD text

TABLE 10: Alternative 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 11: Alternative 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

TABLE 12: Bunching Regression Coefficient Results (Box Office)

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
30-60% Compliance	1.5552**	1.5145*	0.3592	2.0257**	2.0328**	0.3399
	(0.7927)	(0.8131)	(1.2211)	(0.8783)	(0.9224)	(2.1395)
60-90% Compliance	1.6587**	1.5445**	0.7258	2.1590***	2.0421***	1.1355
	(0.7396)	(0.7249)	(1.3010)	(0.7246)	(0.7568)	(2.1258)
90-120% Compliance	2.1464***	1.9496***	2.0935	2.9369***	2.5865**	2.8908
	(0.7521)	(0.7523)	(1.3180)	(0.9825)	(1.0186)	(2.2555)
120-150% Compliance	2.0875***	1.8604***	2.0254	2.9909***	2.6378***	2.9928
	(0.7025)	(0.6970)	(1.3487)	(0.8896)	(0.9396)	(2.4114)
150+% Compliance	1.7718	1.2663	1.3408	2.9540*	1.9606	2.0504
	(1.1972)	(1.8642)	(1.3766)	(1.7930)	(2.9183)	(2.2231)
30-60% Compliance × SQ per VR	-0.0439*	-0.0422	0.0114	-0.0575**	-0.0582**	0.0129
	(0.0258)	(0.0263)	(0.0388)	(0.0281)	(0.0296)	(0.0686)
60-90% Compliance × SQ per VR	-0.0459*	-0.0435*	0.0103	-0.0598**	-0.0592**	0.0038
	(0.0243)	(0.0242)	(0.0402)	(0.0240)	(0.0255)	(0.0680)
90-120% Compliance × SQ per VR	-0.0568**	-0.0528**	-0.0168	-0.0773**	-0.0726**	-0.0295
	(0.0242)	(0.0243)	(0.0398)	(0.0305)	(0.0319)	(0.0708)
120-150% Compliance × SQ per VR	-0.0549**	-0.0497**	-0.0163	-0.0778**	-0.0726**	-0.0328
	(0.0245)	(0.0244)	(0.0409)	(0.0304)	(0.0326)	(0.0735)
150+% Compliance × SQ per VR	-0.0473	-0.0288	0.0063	-0.0727	-0.0470	0.0056
	(0.0385)	(0.0627)	(0.0444)	(0.0537)	(0.0955)	(0.0728)
Days Open	0.0008***	0.0008**	0.0006**	0.0007**	0.0007**	0.0004
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Nominal SQ	0.0577**	0.0562**	0.0080	0.0745***	0.0731***	0.0079
per Viewing Room	(0.0236)	(0.0237)	(0.0384)	(0.0229)	(0.0238)	(0.0692)
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	628	624	602	408	406	388
R^2	0.9630	0.9638	0.9443	0.9705	0.9693	0.9600
Adjusted R^2	0.9380	0.9393	0.9062	0.9326	0.9297	0.9072

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

TABLE 13: Weighted Regression Coefficient Results (Triangular Kernel)

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Compliance	1.8260***	1.7946***	1.0754	2.4363***	2.4021***	1.9219
(Triangular Kernel)	(0.6385)	(0.6717)	(0.8704)	(0.8892)	(0.8670)	(1.5604)
Quota per	0.0422***	0.0459***	0.0034	0.0562***	0.0610***	0.0071
Viewing Room	(0.0159)	(0.0171)	(0.0162)	(0.0191)	(0.0201)	(0.0273)
Days Open	0.0009**	0.0009**	0.0007***	0.0010**	0.0009*	0.0008*
	(0.0004)	(0.0004)	(0.0003)	(0.0005)	(0.0005)	(0.0004)
Compliance	-0.0460**	-0.0482**	-0.0028	-0.0664**	-0.0696**	-0.0217
× **Quota**	(0.0194)	(0.0205)	(0.0217)	(0.0277)	(0.0278)	(0.0409)
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	628	624	602	408	406	388
R^2	0.9697	0.9704	0.9374	0.9767	0.9766	0.9462
Adjusted R^2	0.9502	0.9513	0.8969	0.9490	0.9487	0.8811

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

TABLE 14: Weighted Regression Coefficient Results (Alternative Kernels)

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Compliance	4.4489*	6.0130**	0.0728			
(Normal pdf)	(2.4383)	(3.0199)	(1.9713)			
Compliance				1.8260***	1.7946***	1.0754
(Triweight Kernel)				(0.6385)	(0.6717)	(0.8704)
Quota per	0.0573*	0.0837**	-0.0278	0.0422***	0.0459***	0.0034
Viewing Room	(0.0339)	(0.0411)	(0.0291)	(0.0159)	(0.0171)	(0.0162)
Days Open	0.0010**	0.0009**	0.0007**	0.0009**	0.0009**	0.0007***
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Compliance × Quota	-0.1202	-0.1886*	0.0893			
(Normal pdf)	(0.0852)	(0.1052)	(0.0746)			
Compliance × Quota				-0.0460**	-0.0482**	-0.0028
(Triweight Kernel)				(0.0194)	(0.0205)	(0.0217)
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	628	624	602	628	624	602
R^2	0.9476	0.9500	0.8924	0.9502	0.9513	0.8969
Adjusted R^2	0.9681	0.9696	0.9347	0.9697	0.9704	0.9374

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

TABLE 15: Regression Coefficient Results (Days Open)

	Dependent variable:	
	Days Open	
	(1)	(2)
Nominal Screen Quota per Viewing Room	−5.613	−1.199
	(6.503)	(13.743)
Compliance (squared distance)	−28.791	−232.869
	(225.041)	(293.793)
Compliance (squared distance) × Quota per VR	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

Note: SE are clustered at the chain level. *p<0.1; **p<0.05; ***p<0.01.

TABLE 16: Weighted Regression Coefficient Results (Ticket Price Ratio)

	Dependent variable:					
	Foreign/Brazilian Movie Ticket Price Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Compliance	0.0181	0.0895				
(Squared Distance)	(0.2752)	(0.4653)				
Compliance			0.0408	0.1059		
(Triangular Kernel)			(0.2554)	(0.4364)		
Compliance					0.0408	0.1059
(Triweight Kernel)					(0.2554)	(0.4364)
Quota per	-0.0004	-0.0015	-0.0004	-0.0023	-0.0004	-0.0023
Viewing Room	(0.0078)	(0.0126)	(0.0058)	(0.0101)	(0.0058)	(0.0101)
Compliance × Quota per VR	-0.0002	-0.0045				
(Squared Distance)	(0.0087)	(0.0149)				
Compliance × Quota per VR			-0.0005	-0.0043		
(Triangular Kernel)			(0.0075)	(0.0132)		
Compliance × Quota per VR					-0.0005	-0.0043
(Triweight Kernel)					(0.0075)	(0.0132)
Chain Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
2019?	Yes	No	Yes	No	Yes	No
Observations	598	386	598	386	598	386
R^2	0.3993	0.5384	0.3994	0.5383	0.3994	0.5383
Adjusted R^2	0.0121	-0.0154	0.0123	-0.0157	0.0123	-0.0157

Note: SE are clustered at the chain level. *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 approach is to run a flexible binary Logit regressions divided by movie theater sizes (1-3; 4-5; 6; 7-8; and 9+ viewing rooms), due to memory constraints to run regressions.

$$m_t = \frac{\exp(x_{it} + x_{it}^2 + s_{ir} + d_t + c_i + h_i)}{\sum_{j_t} \exp(x_{jt} + x_{jt}^2 + s_{js} + d_t + c_j + h_t)} \tag{18}$$

Where m_t is movie nationality dummy (1 for Brazilian) at session t, x_{nt} denotes fractional fulfillment of quota of movie theater i at time t; d_t, c_i, h_t are day, multiplex, and hour fixed-effects; s_{ir} is the number of seats for movie theater i and screening room r.

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

1. At $t = 1$, $x_1 = 0$. The algorithm gets day, hour, and number of seats of session for $t = 0$
2. Relevant observation attributes are plugged in the model to get a log 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 occupancy 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 80 for each of the 785 multiplexes. To compute the disturbed value function, we introduce slight modifications. Before step (3) we add or subtract a value ranging from -3.5 to 1.5 to the Brazilian film probability. In total, we get 6 noisy estimates for value function.

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:

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

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