The Effects of Screen Quotas on the Movie Exhibition Market: Evidence From Brazil

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Outline

Introduction

Context and Motivation

- What are screen quotas?
- Where? Argentina, Spain, Mexico, South Korea, plus Brazil
- Few quantitative analyses, in Brazil or otherwise, none with admin data
- Many other quota-like policies (trade quotas, national content requirements)
- Question: **what is the effect of quotas on movie theater revenues, ticket sales, and other variables of interest**?

Main Results

- **Reduced-form** results:
  - → Negative effects of quotas on **foreign** movie theater revenue and ticket sales
  - → Small positive (but non-robust and statistically insignificant) effects on **domestic movie** revenues and ticket sales
  - → **Overall** impacts on box-office and sales are negative
  - → Quotas do seem to prompt movie theaters to screen **more Brazilian movies**
- Then build a **dynamic discrete-choice model** to emulate programming choices
- **Structural parameters estimates** for quotas have small magnitudes, but:
  - → Quota coefficient sign probably confounded by co-linearity with screening foreign films
  - → Heterogeneous effects (negative for larger multiplexes)

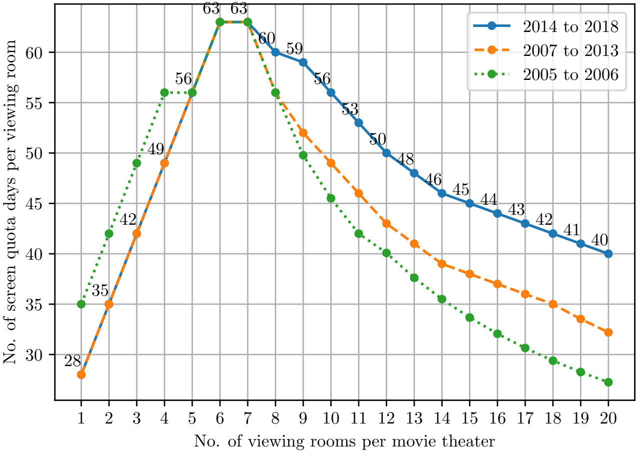
Institutional Setting

Screen quotas in Brazil

- Screen quotas 1932, many incarnations: educational; week/weekend; *Lei da Dobra*;
- Since 2001, quotas have **two major requirements**:
  1. Yearly minimum number of **days** as a (non-linear) function of the number of viewing rooms per multiplex (see Figure 1);
  2. Yearly minimum number **titles** per year, also non-linear function multiplex viewing rooms;
- We **ignore title requirements**, since they are non-binding relative to day requirements (see Figure 2)

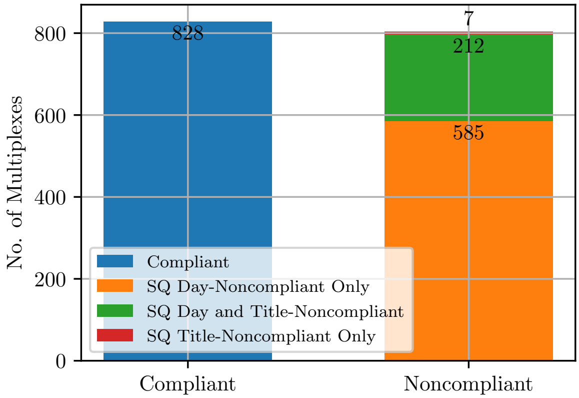
Screen quotas in Brazil

Figure 1: Screen quotas per viewing room by movie theater size



Screen quotas in Brazil

Figure 2: Screen quotas per viewing room by movie theater size (pooled sample 2017 and 2018)

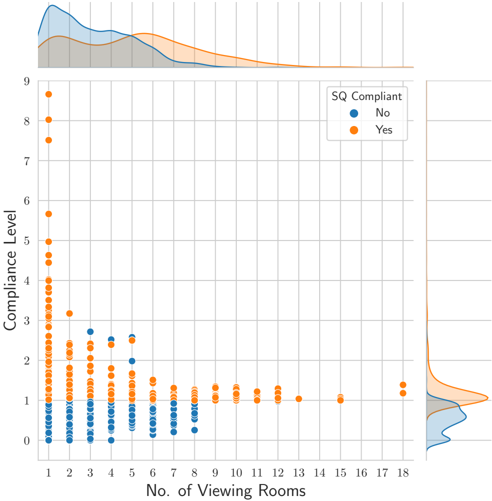


Screen quotas in Brazil

- Additional sources of **heterogeneity** of quotas:
  - → Intra-chain **"swaps"** — so we look at chain-level (results are robust when we look at multiplex level);
  - → Quotas are a **function of days open**, so just add controls;
  - → 2019 had no quota in effect;
  - → **"Predatory occupancy"**.
- **Exogeneity of quotas** per VR:
  - → Regulatory assessment report "On screen quota distortions" (see Figure 3), quotas penalize medium-sized theaters;
  - → Linear quotas set to begin in 2020 postponed.

Screen quota compliance

Figure 3: Multiplex Size vs. Screen Quota Compliance (pooled sample 2017 and 2018)



Data

Data

- Three main data sources:
  - → **Ticket sales session-level** data from exhibitors, from 2017 to 2019, obtained through Brazilian FOIA request;
  - → **Inspection reports** regarding SQ fulfillment, publicly available from 2009 to 2018;
  - → **Registry** data comprising companies, movie theaters, chains and movies.
- All data comes from **Ancine**. Data is submitted by regulated agents and submission is mandatory.

Data

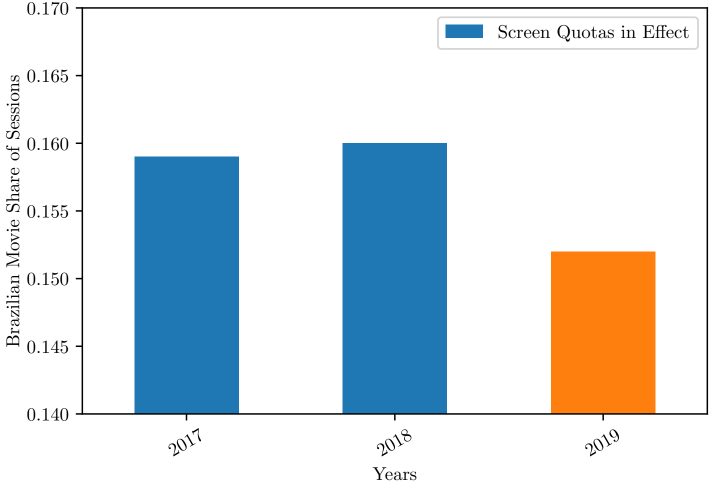


Figure 4: Brazilian Share of Movie Sessions (Source: SCB/Ancine)

Reduced-Form Regressions

- **Naïve** approach: SQ per VR as independent variables Go
  - → Problem: quotas may be non-biding for some (some fulfill 10x due quotas, while others ignore it);
  - → Compliance levels are not uncorrelated with SQ size (see Figure 5)
  - → Results non-robust to inclusion/exclusion of 2019.

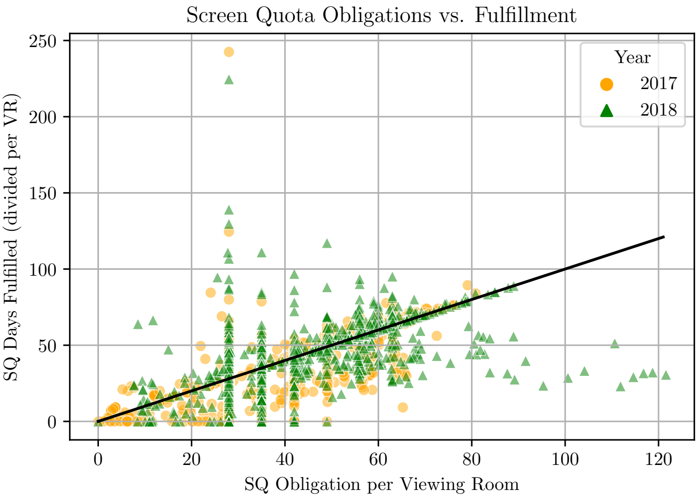


Figure 5: Screen quota obligation vs. fulfillment (2017 and 2018). Source: Ancine

Conceptual Framework

- Preferred approach: weight compliance levels using kernel functions, and then interact it with SQ per VR.
- Intuition: **policy effects should be stronger on narrowly compliant chains**
- We run the following regression:

$$y_{it} = \beta_0 + \beta_1 q_{it} + \beta_2 f(c_{it}) + \beta_3 q_{it} * f(c_{it}) + \theta \mathbf{x}_{it} + \varepsilon_{it} \tag{1}$$

- y_{it}: dependent variable (total box-office, ticket sales, ...);
- c_{it}: normalized compliance (days fulfilled / days due);
- q_{it}: yearly quota per viewing room;
- $f(.)$: weighting function (see Figure 6);
- $\mathbf{x}_{it}$: vector of controls with movie-chain FE, year FE and opening days.

Weighting Kernels

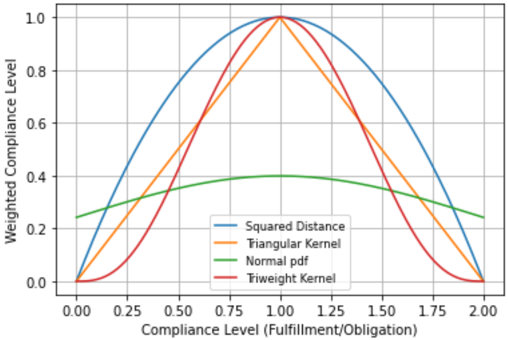


Figure 6: Weighting functions for compliance levels

Naïve Regression Results

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Screen Quota 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

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Weighted Regression Results I

	Dependent variable:					
	log(Box Office)					
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Near 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)
Screen 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)
Near Compliance	-0.0478**	-0.0523**	0.0154	-0.0682**	-0.0748**	-0.0027
$\times$ **SQ per VR**	(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

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

Weighted Regression Results II

	Dependent variable:					
	No. of Sessions			Session Occupancy		
	All	Foreign	Brazilian	All	Foreign	Brazilian
	(1)	(2)	(3)	(4)	(5)	(6)
Near Compliance	666.4578	2383.2641	-2478.4195**	-0.0106	-0.0152	0.0945
(Squared Distance)	(1836.7657)	(2019.6112)	(992.3284)	(0.0304)	(0.0243)	(0.0887)
Screen 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)
Near Compliance	-27.0820	-90.7394	89.1496**	0.0005	0.0005	-0.0015
× **SQ 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

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Reduced-form results — interpretation

- Results are robust to inclusion/exclusion of 2019 and to different kernel choices, plus bunching estimates Go
- **Negative effects** on overall and foreign revenues and public as expected, but **insignificant** for Brazilian movies (point estimates are small and non-robust to alternative specs)
  - → At the same time, quotas seem increase session availability
- **Simple micro story**:
  - → Add restriction to optimization, income and moviegoers fall
  - → Quotas may prompt more Brazilian movie sessions, but box-office and ticket sales do respond weakly (if at all)
  - → Moviegoer numbers might fall less than incomes because theaters respond by lowering ticket prices (weak evidence)

Reduced-form results — interpretation

- Problems: coefficients without causal interpretation
  - $\rightarrow$ Near Compliance
  - $\rightarrow$ Screen Quotas per Viewing Room
- Omitted variable bias suggests **Near Compliance** might be confounded by better management, for example
- Interpretation unclear for SQ per VR
- Consequence: we cannot extrapolate reduced-form coefficients to assess marginal policy effects

Dynamic Model

Dynamic discrete-choice model

- Why model? Assess “welfare” effects, counterfactuals
- Programming is a clear **discrete-choice problem**:
  - $\rightarrow$ **Only one movie** per session;
  - $\rightarrow$ Movie **attributes** partly observable, partly not.
- Screen quotas introduce a **dynamic** feature
- Simple dynamic discrete-choice model for multiplexes in 2018:
  - $\rightarrow$ Observables: avg occupancy of movie in given week and quota requirements;
  - $\rightarrow$ Strong assumptions: exogeneity, perfect foresight

Results

Table 1: Dynamic Model Parameter Estimates

	All Multiplexes	*MX $\leq$ 5 VRs*	MX *6-10 VRs*	*MX $\geq$ 11 VRs*
	(1)	(2)	(3)	(4)
Expected occupancy ($\hat{\theta}_1$)	36.66	26.95	43.48	80.94
	(0.0000)	(0.0005)	(0.0001)	(0.0000)
SQ unfulfilled ($\hat{\theta}_2$)	0.001	0.013	-0.002	-0.011
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Dynamic Model Results — interpretation

- Positive coefficients for unfulfilled quotas (θ_2) make no sense
- Implies having unfulfilled quotas is good for multiplex
- Positive effects mainly driven by small-sized movie theaters
  - $\rightarrow$ Costs to disregard maybe quotas smaller, non-binding for some (screen much more than required)
- Magnitudes of θ_2 are small regardless of size
- Possible role for omitted vars: benefits of screening foreign films not capt by expected occupancy
- Extensions: try to add more covariates, but relevant observables are hard to get.

Conclusion

Conclusion

- Takeaways:
  - → Reduced-form regressions suggest effects on revenues and ticket sales are negative, but impacts on Brazilian movies indistinguishable from zero with available sample
  - → But quota does seem to prompt movie theaters to screen more BR movies
- Regressions suggest a simple story: movie theaters indeed respond to SQ by displaying more Brazilian movies, but demand-side responses are more muted
- Dynamic model suggests effects are heterogeneous across different multiplex sizes, but suggest magnitude of quota effects are small; further extensions are needed to get a better picture
- Data, code, and many other regressions available at https://github.com/pbragasoares/

Appendix: Additional Reduced-Form Regression Tables

Alternative kernels: Gaussian

Back

	Dependent variable:					
	log(Box Office)			log(Ticket Sales)		
	All Movies (1)	Foreign (2)	Brazilian (3)	All Movies (4)	Foreign (5)	Brazilian (6)
Compliance (Gaussian kernel)	4.8385***	6.4733***	0.0709	4.6590***	6.5440***	-0.0302
	(1.2052)	(1.3114)	(1.7934)	(1.1546)	(1.2593)	(1.7099)
Opening Days	0.0410	0.0390	0.0183	0.0476	0.0446	0.0265
	(0.0305)	(0.0303)	(0.0418)	(0.0292)	(0.0291)	(0.0399)
Quota per viewing room	0.0661***	0.0930***	-0.0258	0.0655***	0.0939***	-0.0238
	(0.0153)	(0.0167)	(0.0238)	(0.0147)	(0.0161)	(0.0227)
Compliance $\times$ **Quota per VR**	-0.1390***	-0.2087***	0.0853	-0.1321***	-0.2070***	0.0870
	(0.0421)	(0.0458)	(0.0635)	(0.0404)	(0.0440)	(0.0605)
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	0.9643	0.9664	0.9328	0.9634	0.9655	0.9345
Adjusted R^2	0.9414	0.9448	0.8893	0.9400	0.9433	0.8921

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Alternative kernels: Triangular

Back

	Dependent variable:					
	log(Box Office)			log(Ticket Sales)		
	All Movies (1)	Foreign (2)	Brazilian (3)	All Movies (4)	Foreign (5)	Brazilian (6)
Compliance (Triangular kernel)	2.0112***	1.9793***	1.1049**	1.9504***	1.9819***	0.9950*
	(0.3147)	(0.3219)	(0.5447)	(0.3012)	(0.3089)	(0.5202)
Opening Days	0.0362	0.0360	0.0166	0.0428	0.0417	0.0250
	(0.0296)	(0.0298)	(0.0410)	(0.0283)	(0.0286)	(0.0391)
Quota per viewing room	0.0479***	0.0515***	0.0049	0.0491***	0.0531***	0.0066
	(0.0067)	(0.0069)	(0.0122)	(0.0064)	(0.0066)	(0.0117)
Compliance × **Quota per VR**	-0.0522***	-0.0543***	-0.0043	-0.0508***	-0.0541***	-0.0025
	(0.0092)	(0.0094)	(0.0160)	(0.0088)	(0.0091)	(0.0153)
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	0.9663	0.9675	0.9355	0.9656	0.9667	0.9369
Adjusted R^2	0.9447	0.9466	0.8938	0.9435	0.9452	0.8961

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Alternative kernels: Triweight

Back

	Dependent variable:					
	log(Box Office)			log(Ticket Sales)		
	All Movies (1)	Foreign (2)	Brazilian (3)	All Movies (4)	Foreign (5)	Brazilian (6)
Compliance (Triweight kernel)	2.0112***	1.9793***	1.1049**	1.9504***	1.9819***	0.9950*
	(0.3147)	(0.3219)	(0.5447)	(0.3012)	(0.3089)	(0.5202)
Opening Days	0.0362	0.0360	0.0166	0.0428	0.0417	0.0250
	(0.0296)	(0.0298)	(0.0410)	(0.0283)	(0.0286)	(0.0391)
Quota per viewing room	0.0479***	0.0515***	0.0049	0.0491***	0.0531***	0.0066
	(0.0067)	(0.0069)	(0.0122)	(0.0064)	(0.0066)	(0.0117)
Compliance $\times$ Quota per VR	-0.0522***	-0.0543***	-0.0043	-0.0508***	-0.0541***	-0.0025
	(0.0092)	(0.0094)	(0.0160)	(0.0088)	(0.0091)	(0.0153)
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	0.9663	0.9675	0.9355	0.9656	0.9667	0.9369
Adjusted R^2	0.9447	0.9466	0.8938	0.9435	0.9452	0.8961

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

Squared distance kernel: with and w/o 2019 Back

	Dependent variable:					
	log(Box Office)			log(Ticket Sales)		
	All Movies (1)	Foreign (2)	Brazilian (3)	All Movies (4)	Foreign (5)	Brazilian (6)
Compliance (Squared dist kernel)	2.0501***	2.0906***	0.5047	2.5331***	2.5937***	1.1897
	(0.2911)	(0.2991)	(0.5740)	(0.4452)	(0.4586)	(0.9132)
Opening Days	0.0348	0.0343	0.0187	0.0532	0.0539	0.0133
	(0.0293)	(0.0294)	(0.0411)	(0.0624)	(0.0638)	(0.0955)
Quota per viewing room	0.0553***	0.0609***	-0.0091	0.0705***	0.0770***	-0.0006
	(0.0079)	(0.0081)	(0.0161)	(0.0096)	(0.0101)	(0.0238)
Compliance × Quota per VR	-0.0541***	-0.0585***	0.0145	-0.0692***	-0.0755***	0.0005
	(0.0093)	(0.0096)	(0.0183)	(0.0146)	(0.0151)	(0.0291)
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	0.9671	0.9683	0.9351	0.9755	0.9759	0.9436
Adjusted R^2	0.9461	0.9480	0.8931	0.9464	0.9473	0.8753

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Dynamic model estimation

CCPs 1st stage estimation

- But how can we obtain CCP estimates?
- The literature suggests avoiding overly parametric assumptions, but state-space is too large for simple bin estimators (many possible state-choice pairs are not available in the data)
- We therefore try two approaches:
  - → Gaussian kernel density estimators in the x_t/day space, to get densities and compute probabilities from relative densities;
  - → Flexible Logit using movie-theater and day FE, and the state x_t.

Estimation Algorithm — 1st stage

- Having at our disposal the CCPs for every possible movie and state x_t, 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, $\hat{\bar{V}}_{0i}(0; \theta)$. We then average out the function over 20 simulated paths to get consistent estimates for $\hat{\bar{V}}_{0i}(0; \theta)$ for each agent

Estimation Algorithm — 2nd stage Back

- To get parameter estimates, we repeat 1st procedures with disturbed value functions (adding noise or systematic bias in 1st stage CCPs)
- We then get parameters such that they minimize Equilibrium violations (i.e., minimize the square error of disturbed functions having value bigger than proper val functions):

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