Building up Trust in a Dynamic Game

A study on Collusive Price-fixing in the Chilean Pharmaceutical Retail Industry

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Job Market Seminar

Motivation

- Collusion theory focus on how collusive agreements are **implemented** but not how they are **initiated** (Green et al. (2015)).
  - Implementation: prevent deviation, monitor operation.
  - Initiation: build up collusion.
- Why **initiation**?
  - Firms **learn-to-coordinate** is not well-understood.(Whinston (2003) Chapter 2).
  - Post-cartel tacit collusion.(Harrington (2015); Sproul (1993)) Collusion Cycle
- Model **learning-to-coordinate**.

Movitation - Background

- Based on price-fixing case in Chile pharmacy retailing in 2006 - 2008.
  - 3 chains sell almost every purchase of drugs.
  - Different strategies across time.
  - Rebuild cooperation after change of ownership of Salcobrand(smallest chain).
- Gradual in collusion. Price Trend
  - Raise price on over 200 drugs during 5 months.
- Finding: evidence of **learning-to-coordinate**.

Price Leadership

Motivation - Model

- Model under the **dynamic game** with **relaxed beliefs**.
  - demand side: simple logit
  - supply side: strategy interaction and belief evolution.
- Issue: under-identification
- Restriction: each firms' belief about **other firms' action** is valued by a firm-specific time-varying **belief parameter**
  - between 0 and 1
    - 1: collusive belief
    - 0: competitive belief
  - evolve with signal of others firms' williness to collude

Motivation - Collusion Theory

- First to model the **initiation** and **diffusion** of collusion with *multi-market contact*,
  - **incentive problem**: sustainability.
  - **coordination problem**: coordinate with other firms' strategy.
- Propose a parsimonious model with relaxed belief.
  - **partly endogenize** beliefs: "belief parameter" capture learning.
  - **identification** Aguirregabiria and Magesan (2019).

Motivation - Policy Relevance

- Harrington (2018) structural remedy: **divesture**, introduce additional competitor
  - force each chain to sell 25 % of the assets.
  - form a new retailer chain.
- Qualitative analysis: divesture.
  - harder to monitor deviation.
  - hinder coordination in multiple equilibria.
- This framework allow us to evaluate the structural remedy.
  - quantify coordination difficulty.

Counterfactual Policies

Contribution

- First structural model for **collusion initiation** with **learning-to-coordinate**.
  - Finding: the gradualism in collusion explained by learning-to-coordinate.
  - Counterfactual: introduce more player to hinder coordination.
- First **biased-belief equilibrium** framework for dynamic game.
  - Counterfactual analysis.
  - Clear identification results.
  - Can test whether belief is biased.

Related Literature I

- Empirical study of collusion initiation.
  - Measure incentive to collude.
    Igami and Sugaya (2019) Private monitoring, repeated game.
  - Multi-market contact facilitates collusion.
    Empirical evidence: Ciliberto and Williams (2014); Theory: Sekiguchi (2015), Choi and Gerlach (2013).
- Dynamic game of non-equilibrium beliefs.
  - Biased-belief equilibrium.
  - Empirical evidence of firms' nonequilibrium beliefs after market change.
    Goldfarb and Xiao (2011), Hortaçsu and Puller (2008).

Market Overview

- *Oligopolistic* retail pharmaceutical distribution market (Data Source: Expert report Núñez et al. (2008)).
  - 92 % of the drugs sales are concentrated Farmacias Ahumada S.A. ("FASA"), Farmacias Cruz Verde S.A. ("Cruz Verde") and Farmacias Salcobrand S.A. ("Salcobrand").
  - 8 % independent drug stores that do not carry branded drugs.
- Prices not regulated.
- Physicians prescribe on brands.
- Insurance cover very limited, listed price reflects out-of-pocket price.

Data

- Daily level data, from Jan 1st, 2006, to Dec 31st, 2008.
- 222 brands that the chains were accused of colluding.
- For each chain, each brand:
  - Nationwide sales volume (q_{imt});
  - Nationwide sale-weighted average price (p_{imt}) .
- Among the products:
  - Mostly are prescription drugs;
  - 70 % of the drugs are treatments for chronic diseases.
- Data source: Competition Tribunal of Chile.

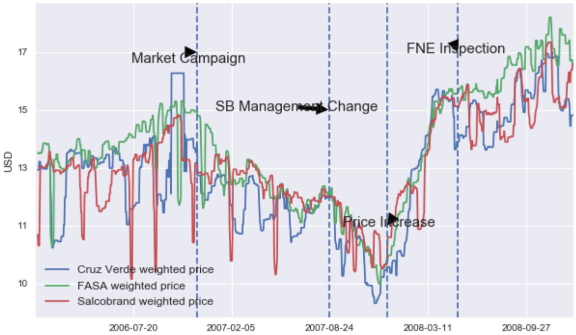
Price Evolution

- January 2006 - December 2006: *Loss leadership*.
- December 2006 - August 2007: *Price war*.
- August 2007: Salcobrand 100% ownership sold to Juan Yarur Companies for 130 million dollars.
- November 2007 - April 2008: *Gradual Price increase*.
- April 2008: FNE investigation started.
- The Competition Tribunal sentence Farmacias Cruz Verde Salcobrand to pay fines of approximately US$19 million each.

Sentence Coordination Mechanism

Price Trend

Figure: Weighted Average Price Level from Jan 2006 - Dec 2008



Sentence Coordination Mechanism Background Price Leadership

Stylized Facts

1. Post-collusion: coordinations happen more frequently.
   Definition | Coordinated Price Increase
2. The smallest chain, Salcobrand, is the **price leader**.
   Price Leader
3. First collude on more **differentiated** market.
4. The collusion on other markets without demand link increase firms' incentive to collude.
   Firms' Incentive | Robustness Check

Motivating example - Game

- Two players: Cruz Verde and Salcobrand,
- Two markets: Folisanin(suplement) and Eranz(treatment for Alzheimer).
  - Easier to collude on Folisanin.
- Incomplete information:

$$\Pi_{imt} = \sum_m \left(\pi_{im}(\mathbf{a}_{mt}) + \theta_{MC} \mathbb{1}\{a_{imt} \neq a_{imt-1}\} + \epsilon_{imt}(a_{imt}) \right),$$

- $\pi_{im}, \theta_{FC}, \theta_{MC}$ common knowledge, ϵ_{imt} known distribution.

Motivating Example - Coordination

- The two markets are not connected on demand/supply, write as separate decisions.
- Market outcome.
  - **Static competition**.
  - **Price leadership**(Mouraviev and Rey (2011)).
- **Problem**: firms may be uncertain how other firms will respond.
- **Firms' learning**: firms update their beliefs given past history.

Motivating Example - Decision Rule

Decision depend on payoff-relevant state variables(Maskin and Tirole (1987)) with relaxed belief.
Strategy on market m:

$$\sigma_{im}(\underbrace{y_{im,t-1}, \quad a_{jm,t-1}, \quad \epsilon_{imt},}_{\text{Payoff related}} \quad \underbrace{h_t}_{\text{No payoff related}} \quad)$$

h_t is a function of history, for example,

- collusion on the other market;
- whether other firms have deviated(Fershtman and Pakes (2000))

Diffusion of collusion: If firms collude on Eranz, may collude on Folisanin.

Dynamic Game: Identification of Belief

Define the associated conditional choice probabilities(CCPs)(Magnac and Thesmar (2002)):

$$\mathbf{P}_{imt}(a_{imt}, \mathbf{y}_{mt}, \mathbf{h}_t) = \int \sigma_{im}(a_{imt}, \mathbf{y}_{mt}, \mathbf{h}_t) d\epsilon_{imt}. \tag{1}$$

- Let h denote firms' collusion status on the other market.
- $\mathbf{P}_{imt}(a_{imt}, \mathbf{y}_{mt}, \mathbf{h}_t) = \Lambda(\mathrm{v}_{it}^{\mathbf{B}_{it}}(a_{im}, \mathbf{y}_{mt}, h_t))$,
  - $\Lambda(\cdot)$ is the CDF of ϵ_{imt},
  - $\mathrm{v}_{it}^{\mathbf{B}_{it}}(a_{im}, \mathbf{y}_{mt}, h_t)$ choice dependent value function

Value Function CCP

- Identify a the **ratio of beliefs** from ratio of $\Lambda^{-1}(\mathbf{P}_{imt}(a_{imt}, \mathbf{y}_{mt}, h))$ across h. (Aguirregabiria and Magesan (2019))

Exclusion Restrictions

Dynamic Game: Flow Payoff

$$\Pi_i(\mathbf{x}_{mt}, \mathbf{a}_{mt}) = \sum_{m \in \mathcal{M}} \left[\mathrm{R}_{im}(\mathbf{x}_{mt}, \mathbf{a}_{mt}) + \mathrm{F}_{im}(\mathbf{x}_{mt}, \mathbf{a}_{mt}) + \epsilon_{imt}(a_{imt}) \right],$$

where

- $\mathrm{R}_{im}(\mathbf{x}_{mt}, \mathbf{a}_{mt})$: estimated profit, level of differentiation;
- F_{im} fixed cost, unknown to economist;
  - Menu cost
  - Fixed cost
  - Leadership cost
- $\epsilon_{imt}(a)$ i.i.d across players, markets, states and actions.(Magnac and Thesmar (2002))

Fixed Cost Specification

Dynamic Game: Overview

Goal: Estimate **beliefs** $\mathbf{B}_{im}$, **profit** R_{im} and **fixed cost** F_{im}.
The dimensionality of the state is **huge**($2^{(3*200)} \approx 4 * 10^{180}$).
Make the following restrictions:

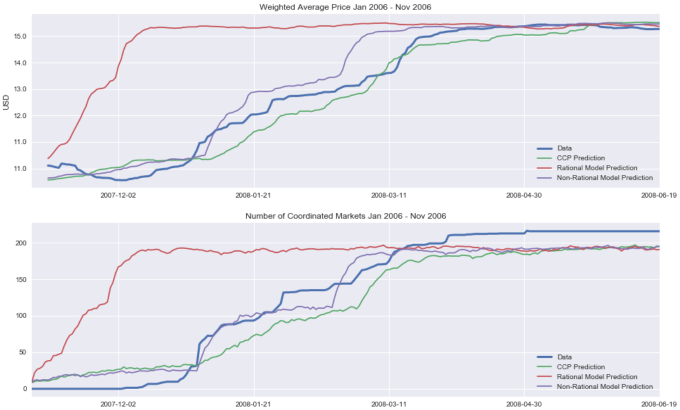
- The decision of prices is restricted to two price levels: low and high.
- A market manager (i, m) make separate decision from other markets.
- Beliefs are biased by a single firm-history-specific parameter $\lambda_i(h_t) \in [0, 1]$.
  - $\lambda_i(h_t) = 0$, player i believe in competitive equilibrium.
  - $\lambda_i(h_t) = 1$, player i believe in sub-game perfect equilibrium of price leadership.
- h_t is number of colluded markets. $h_t \in \{[0, 30], [31, 90], [91, 150], [151, \infty)\}$.

History ▸ Price Leadership

Dynamic Game: Estimation of Variable Payoff

- Estimation of R_{im}.
  - Demand / Marginal cost estimated using Jan 2006 - Nov 2006 (competition episode);
    Latin America Price Trend | Quantity Change
  - Simple logit demand, market is brand level, no demand linkage;
    Demand Estimation
  - Constant marginal cost, first order condition from Bertrand-Nash competition; Marginal Cost Estimation
    Estimated Demand | Demand Check | Demand Check IV | Demand Check OLS
- Estimation of λ_i and F_{im}
  - Revealed preference based on high/low price choice from Nov 2007 - April 2008(coordination episode).
    Estimation Steps
- Monte Carlo

Prediction of the price level of Jan 2006 - Nov 2006



Estimated λ | Estimated Costs | Non-equilibrium Prediction | Equilibrium Prediction

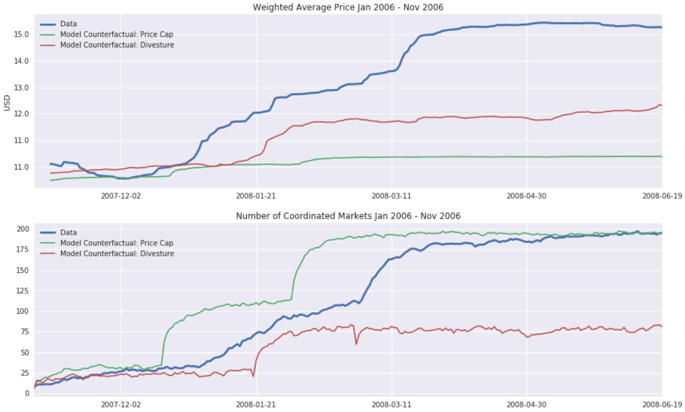
Counterfactuals

Consider two counterfactuals

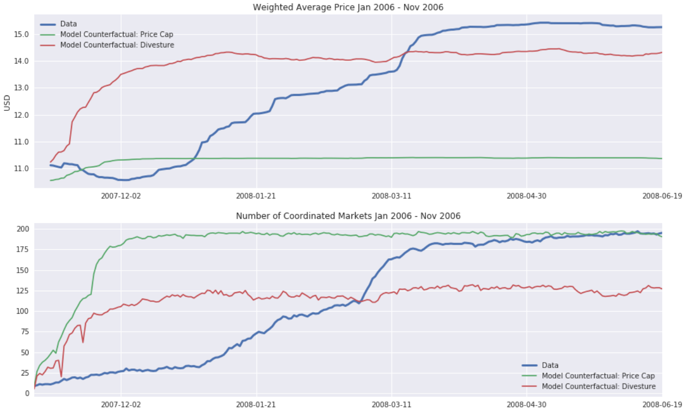
1. Impose a cap for the price increase(10%);
2. Divest the industry by enforcing the act such that each chain divests 25% of their stores and create a new firm with the assets. (Harrington (2018)(pp.234)).

Policy Relevance

Counterfactuals: The Model Counterfactual With Non-Rational Belief



Counterfactuals: The Model Counterfactual With Rational Belief



Conclusion

The contribution of this project:

- First structural model for **collusion initiation** with **learning-to-coordinate**.
  - Finding: the gradualism in collusion explained by learning-to-coordinate.
  - Counterfactual: introduce more player to hinder coordination.
- First framework for transition between equilibria.
  - No assumption on how firms are learning.
  - Clear identification results.
  - Can test whether belief is biased.

Thank You

Price Leadership

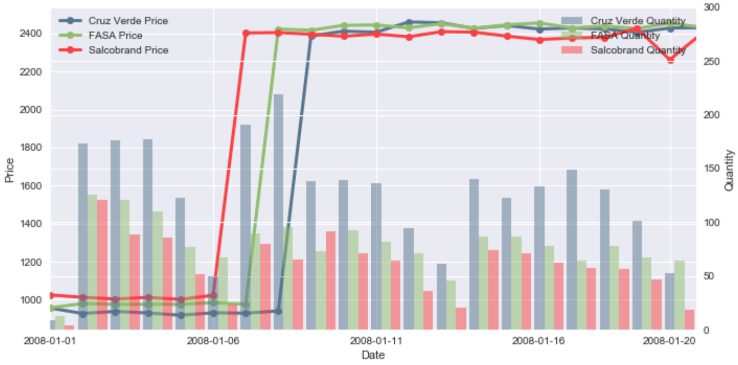


Figure: Example of Price Increase of *Marvelon-20 Caja 21 Comp.*

Background Price Trend Dimensionality

Collusion News

Home › ECONOMY › 'New Case of Collusion in Chilean Medicine Market'

ECONOMY

'New Case of Collusion in Chilean Medicine Market'

by Boris van der Spek 20 January, 2020 0 1221

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Reading Time: 2 minutes

SANTIAGO – A recent investigation shows that the three major pharmacies in Chile are holding prices of at least 120 medicines artificially high. According to one of the journalists involved, the study shows that pharmacies are still colluding, over 10 years after a major collusion scandal struck the Chilean medicine market. The journalists in charge have handed the details to the National Prosecutor.

▸ Motivation

Definition of Expected Payoff

- Given current beliefs, we can represent a firm's best response at time t using solution from a single agent Dynamic Programming(DP) problem following Bellman's principle.

$$V_{it}^{B_{it}}(\mathbf{x}_t) = \max_{a_{it}}\{\pi_{it}^{B_{it}}(a_{it}, \mathbf{x}_t, \epsilon_{it}) + v_{it}^{B_{it}}(a_i, \mathbf{x}_t)\}$$

- The current epxected payoff

$$\pi_{it}^{B_{it}}(a_{it}, \mathbf{x}_t, \epsilon_{it}) = \sum_{\mathbf{a}_{-it}} B_{it}(\mathbf{a}_{-it}|\mathbf{x}_t)\Pi_{it}(a_{it}, \mathbf{a}_{-it}, \mathbf{x}_t, \epsilon_{it}).$$

- And the expected continuation value

$$v_{it}^{B_{it}}(a_i, \mathbf{x}_t) = \sum_{\mathbf{a}_{-it}} \beta B_{it}(\mathbf{a}_{-it}|\mathbf{x}_t) \sum_{\mathbf{x}_{t+1}} f(\mathbf{x}_{t+1}|a_{it}, \mathbf{a}_{-it}) V_{it+1}^{B_{it}}(\mathbf{x}_{t+1}).$$

Equilibrium Strategy

Competition Tribunal Sentence

- The Competition Tribunal sentence Farmacias Cruz Verde Salcobrand to pay approximately US$19 million each (Maximum applicable fine).
- Collusive agreement to increase prices of at least 206 pharmaceutical drugs between December 2007 and March 2008.
- The price in real values before vs. after the break it was 16.4% for SB, 18.6% for CV and of 16.9% for FASA.

Price Trend

coordination Mechanism

(Núñez et al. (2008)) Salcobrand's business manager emailed the CFO at the onset of the conspiracy period, on December 19, 2007, explaining the actions they were undertaking:

> *[In order to coordinate the price increases] we offered to be the chain that raised its prices first ([every week] on Monday or Tuesday) so that the other two chains would have three or four days to 'detect' these [price] increases and absorb them. Until now, [we have] succeeded in raising the prices of five of the most important products of four pharmaceuticals companies. Due to the good results, we hope to repeat the 'procedure' with more products and with more pharmaceuticals in the coming weeks.*

Price Trend

1-2-3 Price Increase

Define the coordinated price increase as:

1. The increase of price ($> 15\%$ or more than 1500 peso) is happened for a certain product for 3 firms.
2. The increase is started by one firm, and the other two firms follow within at most 4 days.
3. The price levels before and after increases should be reasonably close($< 15\%$).
4. The price level is maintained for at least 3 days.

▸ Number of coordinated price increase ▸ Facts

Coordinated Price Increase

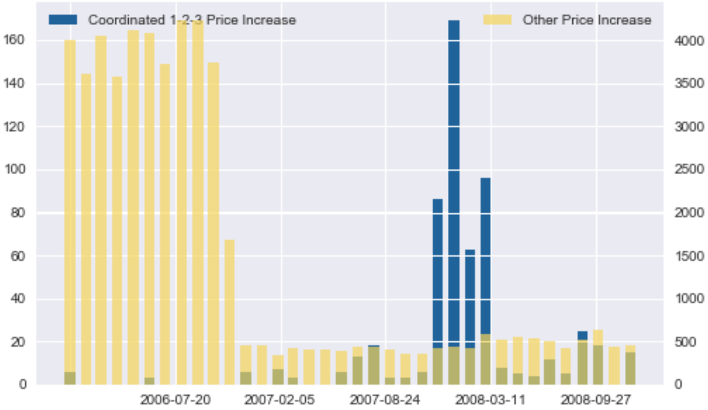


Table: The Coordinated Price Increase Frequency

Time periods	Frequency	Percentage	Monthly average
Jan,2006 - Nov, 2007	24	12.8%	1.04
Dec,2007 - Apr, 2008	137	72.9%	27.40
May,2008 - Dec, 2008	27	14.4%	$\boxed{3.86}$
Total	188	100%	5.22

[1] The coordinated price increase is defined by the action such that one firm make a price increase on a certain product, and the other firms follow within a reasonable short time period.

[2] The table recomputed using the method in the expert report requested by FNE. Núñez et al. (2008).

▸ Definition of coordinated price increase ▸ Facts

Table: The 1-2-3 Price Increase/ Decrease Frequency

Sequence	Jan,2006 -Nov,2007	Dec,2007 -Apr,2008	May,2008 -Dec,2008	Total
	1-2-3 Price Increase			
SB lead	11	$\boxed{126}$	10	147
FA lead	12	8	10	30
CV lead	10	0	12	31
Total	32	$\boxed{143}$	32	188

[1] The table is recomputed according to the method reported in the expert report Núñez et al. (2008)

[2] Based on the foregoing, the relevance of SB on the subject is highlighted, because of the total increases 1-2-3 accounted for, 75% of them (162 increases) are made in the first movement.

▶ Definition of coordinated price increase ▶ Facts

Time Varying Incentive

Estimate a Cox survival(Cox, 1972) model following that of Chilet (2016).

- A market is defined as a product j, where three firms compete on.
- A failure is defined as the market starting to collude.
- Explanatory variables
  - History is the number of drugs that firms have already colluded on.
  - The elasticity is estimated in the first stage with logit demand model.
  - Market size is the daily average quantity sold by three firms before collusion(Oct, 2007).
  - Price dispersion is the average weekly price standard deviation(Jan, 2006 - Oct, 2007).
  - Share dispersion: the median of weekly share dispersion. Reflects the asymmetry of the firms' shares.

Facts

Firms' Incentive

	Cox Prop. Hazard	Time Varying Effect
number of collusion	-0.8638**	-0.0236***
	(0.4374)	(0.0065)
cross elas	0.0006	0.0938
	(0.0006)	(0.0915)
cross elas $*$ *t*		- 0.014
		(0.0138)
market size	0.0411	-17.1882*
	(0.0987)	(9.3957)
market size $*$ *t*		2.5779*
		(1.4115)
price dispersion	12.1707***	1771.7916**
	(4.7055)	(840.5366)
price dispersion $*$ *t*		-265.5883**
		(127.0097)
share dispersion	0.8859	-718.1204*
	(2.5878)	(388.6157)
share dispersion $*$ *t*		107.7807*
		(58.3505)
N	1394	1394
log-likelihood	-825.0	-1025.0

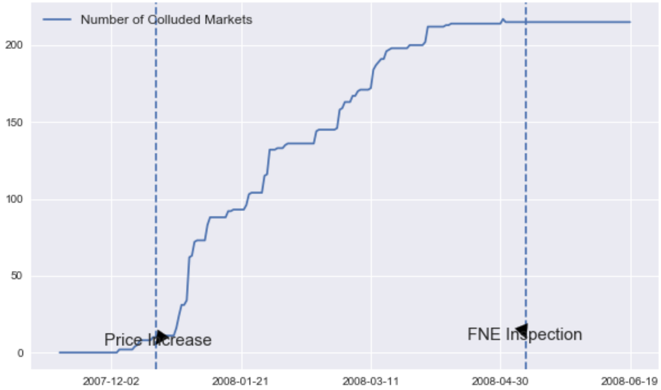
Robustness Check Facts

Table: Time of Collusion - Survival Model

	Dependent variable: Time to the First Coordinated Price Increase					
	Market Characteristics	Cumulative Past Events		Non-cumulative Past Events		
	(1)	(2)	(3)	(4)	(5)	(6)
Cross Elas	0.0248	0.0357	0.035	0.0244	0.0244	0.0247
	(0.0246)	(0.0315)	(0.0314)	(0.0246)	(0.0245)	(0.0246)
$Cross\ Elas * Ln(t)$	-0.0037	-0.0053	-0.0052	-0.0036	-0.0036	-0.0037
	(0.0037)	(0.0047)	(0.0047)	(0.0037)	(0.0037)	(0.0037)
Market Size	10.1006***	9.3913*	9.7513*	10.297***	9.8346***	10.1665***
	(2.553)	(5.257)	(5.2558)	(2.5748)	(2.5483)	(2.5561)
$Market\ size * Ln(t)$	-1.5065***	-1.4001*	-1.4538*	-1.5359***	-1.4664***	-1.5165***
	(0.3826)	(0.7894)	(0.7893)	(0.3859)	(0.3819)	(0.3831)
Share Disp	45.3541	52.9556	70.103	49.4483	45.4013	45.3579
	(56.7315)	(80.71)	(80.0564)	(57.1709)	(56.432)	(56.7494)
$Share\ Disp * Ln(t)$	-6.774	-7.8864	-10.4655	-7.3866	-6.7774	-6.7748
	(8.481)	(12.0943)	(11.9964)	(8.5473)	(8.4364)	(8.4836)
Sucess Coord		-0.0035	-0.0028			
		(0.0048)	(0.0048)			
Fail Coord		0.0109***				
		(0.0037)				
Price Dec CV				0.0084		
				(0.0176)		
Price Dec FA					-0.0626*	
					(0.0381)	
Price Dec SB						0.0142
						(0.0242)
N	16493	15270	15270	16493	16493	16493
log-likelihood	-3232.0	-3101.0	-3122.0	-3232.0	-3225.0	-3232.0

▸ Survival Model ▸ Facts

Number of Colluded Market



Dimensionality

Dynamic Game: Value Function

- *Choice dependent value function*:
$$\mathrm{v}_{it}^{\mathbf{B}_{it}}(a_{im}, \mathbf{x}_t) = \mathbb{E}_{\mathbf{B}_{it}}\Big[\pi_{im}(a_{imt}, \boldsymbol{a}_{-im}, \boldsymbol{x}_{mt}) + \beta f(\boldsymbol{x}_{j,t+1}|\boldsymbol{a}_{mt}, \boldsymbol{x}_{mt})\mathbf{V}_{im}(\boldsymbol{x}_{j,t+1})\Big],$$
- *Value function*: $\mathbf{V}_{im}(\boldsymbol{x}_{jt+1}) = \max_{a_{im}}\{\mathrm{v}_{it}^{\mathbf{B}_{it}}(a_i, \mathbf{x}_t) + \sum_{m\in\{Folisanin,Eranz\}} \epsilon_{imt}(a_{imt})\}$.

Dynamic Game Best Response

Dynamic Game Identification

Magnac and Thesmar (2002) propse the following assumptions to identify markov perfect equilibrium dynamic game.

Assumption (Identification of MPE Dynamic Game)

1. a_{it}, x_{it} *have finite supports.*
2. $\epsilon_{it}(a_i)$ *is additive seperable.*
3. ϵ_{it} *is conditionally independent of* $\mathbf{x}_t | \mathbf{x}_{t-1}$.
4. *Firms' private information* $(\epsilon_{1t}, \ldots, \epsilon_{Nt})$ *are drawn from* $T1EV$ *distribution* $G_i(\cdot)$, ϵ_{it}*'s are independently distributed over time.*

Dynamic Game Best Response

Assumption: Exclusion Restrictions

Assumption (Exclusion Restriction)

The vector of state variables $\mathbf{x}_{mt}, h_t$ satisfy the following conditions:
(A) $\pi_{im}(\boldsymbol{a}_{mt}, \boldsymbol{x}_{mt}, h_t) = \pi_{im}(\boldsymbol{a}_{mt}, \boldsymbol{x}_{mt})$,
(B) $\pi_{im}(a_{imt}, a_{-imt}, x_{imt}, x_{-imt}, h_t) = \pi_{im}(a_{imt}, a_{-imt}, x_{imt}, x'_{-imt}, h_t)$,
(C) $f(\mathbf{x}_{m,t+1}|(a_{imt}, a_{-im}), \mathbf{x}_{mt}) = \Pi_{i\in\mathcal{I}} f(\mathbf{x}_{im,t+1}|a_{imt})$. ■

▸ Dynamic Game Best Response

Table: Average Quantity Level Before and After the Price Increase

	Before	After
All drugs	215.5	200.3
By Prescription		
Prescription Drugs	214.4	201.2
Over-the-Counter Drugs	221.0	195.5
By Chronic Disease		
Chronic Disease	165.8	154.0
Non-Chronic Disease	308.1	286.1

[1] For each drug, I compute the average daily sale from 14 days to 7 days before the price increase, and 7 days to 14 days after the price increase.

[2] The daily average were computed using the Dec 2007 - Apr 2008 period.

Dynamic Game Estimation

Average Drug Prices in Latin America

Table: Drug Price in Latin America in year 2006 - 2008

Country	2006 (USD)	2007 (USD)	2008 (USD)	2006 - 2007 (%)	2007 - 2008 (%)
Argentina	5.93	6.36	7.3	7.4	14.7
Bolivia	4.73	4.9	5.98	3.6	22
Brazil	6.86	8.03	8.97	17.1	11.7
Chile	4.15	4.12	4.73	$\boxed{-0.6}$	$\boxed{14.8}$
Colombia	4.4	5.41	5.93	23.1	9.5
Ecuador	4.35	4.57	4.77	5.2	4.3
Paraguay	3.65	4.17	4.73	14.2	13.4
Peru	5.81	6.34	7.22	9	14
Uruguay	3.3	3.47	4.05	5	16.8
Venezuela	6.14	7.4	9.42	20.5	27.4

[1] Data source: IMS, Vasallo C. The medicine market in Chile: characterization and recommendations for economic regulation. Final report for the Ministry of Health Economics of MINSAL, Chile. 2010 Jun.

Dynamic Game Estimation

Bootstrap Specification

Table: Dynamic Game Structural Parameters

Number of markets	200	Number of Time Periods	50
Number of Player	2	Discount Factor	0.99
Market Size		15	
High Price	(1,1)	Lower Price	(0.8,0.8)
Menu Cost	(2,2)	Leading Cost	(-5,-5)
Fixed Cost		(0,0)	
Biased belief model	$\lambda_1(1) = \lambda_2(1) = 0.5$		$\lambda_1(2) = \lambda_2(2) = 1.0$
Unbiased belief model	$\lambda_1(1) = \lambda_2(1) = 1.0$		$\lambda_1(2) = \lambda_2(2) = 1.0$

Dynamic Game Estimation

Bootstrap Coverage

Table: Monte Carlo Experiment: Biased Belief Model Coverage

Parameter	Bootstraped Std.Err	Estiamted Std.Err	95 % CI Coverage
θ_1^{MC}	0.0939	0.0881	0.9100
θ_1^{FC}	0.0939	0.0906	0.9700
θ_1^{LC}	0.9174	0.7927	0.8200
θ_2^{MC}	0.0934	0.0817	0.9400
θ_2^{FC}	0.0939	0.0900	0.9700
θ_2^{LC}	0.9304	0.6859	0.8600

Dynamic Game Estimation

Consumer Demand Model

Market defined as each brand. Consumers are homogeneous, market size is fixed. Each t, the consumer on the market choose to buy from a firm i.
For each consumer who buys drug j, firm i at time t, the utility is

$$u_{imt} = \beta_m - \alpha_m p_{imt} + \xi_{mt}^{(1)} + \xi_{imt}^{(2)}, \tag{2}$$

- β_m is the utility parameter,α_j is the *price paramters*,
- $\xi_{mt}^{(1)}$ is the firm-product fixed effect, and $\xi_{imt}^{(2)}$ is the time-varying demand shock.
- $\xi_{imt}^{(2)}$ follows AR(1) process: $\xi_{imt}^{(2)} = \rho_m \xi_{im,t-1}^{(2)} + \epsilon_{imt}$.
- ϵ_{imt} i.i.d across i, m, t.

Parameters: $\{\beta_m, \alpha_m, \rho_m, (\xi_{mt}^{(1)})_{i \in \mathcal{I}}\}_{m \in \mathcal{M}}$ Dynamic Game Estimation

Identification of α_j

- The demand model implies for drug j

$$\log(s_{imt}/s_{omt}) = \beta_m - \alpha_m p_{imt} + \xi_{mt}^{(1)} + \xi_{imt}^{(2)} \quad (3)$$

- Endogeneity: $cov(p_{imt}, \epsilon_{imt}) \neq 0$.
- Define Δ as the time difference opetarator: $\Delta x_{imt} = x_{imt} - x_{im,t-1}$.
- Identification of price sensitivity parameter α_j:

$$\Delta \log(s_{imt}/s_{omt}) - \rho_j \Delta \log(s_{imt}/s_{omt}) = -\alpha_j(\Delta p_{imt} - \rho \Delta p_{im,t-1}) + \Delta \epsilon_{imt}. \quad (4)$$

- $E[\Delta \epsilon_{imt} | p_{imt-k}] = 0$ for $k \geq 2$(Arellano and Bond (1991)).

Dynamic Game Estimation

Marginal cost

- The three big chains have similar wholesale costs as suggested Chilet (2016); Núñez et al. (2008).
- The specification of constant marginal cost is product specific and does is not time-varying:

$$c_{imt} = c_m + \omega_{im}^{(1)} + \omega_{imt}^{(2)}, \tag{5}$$

  where

  - c_m is the average cost of firm,
  - $\omega_{im}^{(1)}$ is the firm-product fixed effect,
  - $\omega_{imt}^{(2)}$ is the i.i.d time-varying cost shocks.

- Parameters: $\{c_m, (\omega_{mt}^{(1)})_{i \in \mathcal{I}}\}$.

Dynamic Game Estimation

Marginal Cost Identification

Marginal cost is identified from

- Assume firms compete in price.
- From Jan 2006 - Nov 2006, the firms are in Bertrand-Nash equilibrium.

The firms are maximizing the variable profit by setting price, and the first order condition

$$\hat{c}_{im} = \frac{1}{T_{data}} \sum_t \left(p_{imt} - \frac{1}{\alpha}(1 - s_{imt})^{-1} \right). \tag{6}$$

Dynamic Game Estimation

Fixed Cost Specification

$$F_{imt} = MC_{im}\mathbb{1}(a_{imt} \neq x_{imt}) + a_{imt}FC_{im} + a_{imt}\mathbb{1}(\mathbf{a}_{-imt} = \mathbf{o})LC_{im};$$

- Menu cost: $MC_{im} = \gamma_i^{MC,\mathrm{o}}$,
- Fixed cost: $FC_{im} = \gamma_i^{FC,\mathrm{o}} + \gamma_i^{FC,Profit}\widehat{\Delta\pi}_{im} + \gamma_i^{FC,Size}\overline{MS}_m$,
- Leadership cost: $LC_{im} = \gamma_i^{LC,Profit}\widehat{\Delta\pi}_{im} + \gamma_i^{LC,Size}\overline{MS}_m$.

Parameter of interest $\boldsymbol{\theta}_i = \{\gamma_i^{MC,\mathrm{o}}, \gamma_i^{FC,\mathrm{o}}, \gamma_i^{FC,Size}, \gamma_i^{FC,Profit}, \gamma_i^{LC,Size}, \gamma_i^{LC,Profit}\}$. ▸ Dynamic Game Estimation

▸ Dynamic Game Flow Payoff

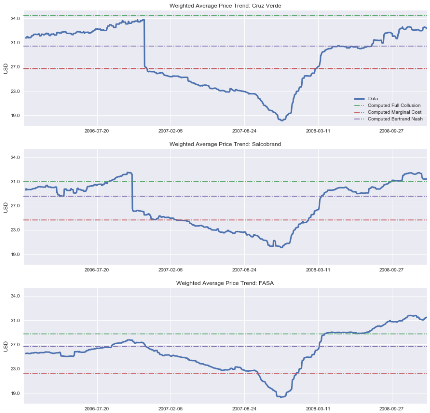
Check the demand estimation

After obtain the demand parameters: $\{\beta_j, \alpha_j, \rho_j, (\xi_{mt}^{(1)})_{i\in\mathcal{I}}\}_{m\in\mathcal{M}}$ and $\{c_j, (\omega_{mt}^{(1)})_{i\in\mathcal{I}}\}$, check the price level:

1. Solve the first order condition of $\max_{p_{imt}} s_{imt}(p_{imt}, \boldsymbol{p_{-i,mt}})(p_{imt} - c_{im})$ to obtain $\{p_{im}^{Nash}\}_{i,m}$.
2. Solve the first order condition of $\max_{p_{imt}} \left[s_{imt}(p_{imt} - c_{im}) + \sum_{i'} s_{i'mt}(p_{i'mt} - c_{i'j})\right]$ to obtain $\{p_{im}^{Collusion}\}_{i,m}$.
3. Use the marginal cost as $\{p_{im}^{War}\}_{i,j}$.

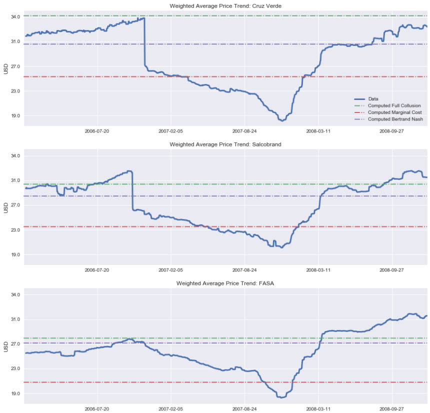
▸ Dynamic Game Estimation

Price Level Predicted Using IV



Dynamic Game Estimation

Price Level Predicted Using OLS



Dynamic Game Estimation

Estimated Elasticity

Table: Estimated Demand Price Coefficients

$\hat{\alpha}_m$	IV	OLS
$\hat{\alpha}_m$	0.8236	1.1828
	[0.2257, 1.6108]	[0.2508, 2.6102]
$s.e.(\hat{\alpha}_m)$		0.0630
		[0.0239, 0.1103]
R-square	0.4625	0.4931
	[0.0178, 0.7848]	[0.2608, 0.6614]
Durbin Test Stats	54.8629	-
	[7.6387, 109.1056]	-
No. $\hat{\alpha}_m$ negative	4	6
No. of Markets	214	214

[1] The first row shows the mean of the statistics averaged across markets.

[2] The second row shows the 10 %th and 90 %th quantile of the statistics.

Demand Check Demand Check IV Demand Check OLS

Dynamic Game - Estimation Steps

Make the following assumptions:

- β the discount factor is set to 0.9995.
- $\lambda_i(\bar{b}) = 1$, firms hold rational belief in the last episode.

I followed the following steps in order to obtain the structural parameters $\{\lambda_i, \boldsymbol{\theta}_i\}_{i=CV,FA,SB}$.

1. Obtain the non-parametric $\mathbf{P}^{o}_{im}$.
2. Estimate λ_i and compute the belief $\mathbf{B}^{o}_{it}$.
3. Given $\mathbf{P}^{o}_{i}$ and $\mathbf{B}^{o}_{i}$, estimate $\hat{\boldsymbol{\theta}}_i$ with Aguirregabiria and Mira (2002) estimator.
4. Update the probability of initializing a price increase.

Dynamic Game Estimation

Estimated $\lambda(b)$

Estimation of Belief Parameters $\lambda(b)$

b	*Cruz Verde*	*FASA*	*Salcobrand*
0 - 30	0.5187	0.3176	0.4699
	(0.1407)	(0.1527)	(0.1037)
30 - 90	0.6107	0.6291	0.4304
	(0.1858)	(0.1776)	(0.1049)
90 - 150	0.6183	0.6513	0.4791
	(0.1658)	(0.1727)	(0.1029)
150 +	1.	1.	1.

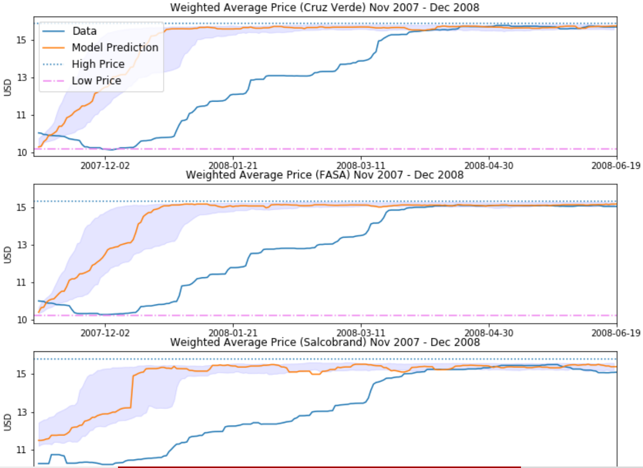
Insample Prediction

Estimation of Strucatural Costs *(Thousand of Pesos)*			
		Rational Belief	Non-rational Belief
Menu Cost	Cruz Verde	-232.4682	-7.6522
	FASA	-730.8975	-276.4451
	Salcobrand	-22.3094	-298.0671
Fixed Cost	Cruz Verde	-329.8713	-1.4162
		[-671.2018, 4.2168]	[-3.96 , 1.19]
	FASA	-645.5794	-114.1933
		[-1260.4551, -70.0513]	[-201.21, -32.75]
	Salcobrand	-74.6131	-31.8427
		[-135.4597, -0.0099]	[-56.29, -1.87]
Leader Cost	Cruz Verde	-9447.4493	-6884.5454
		[-16557.9705, 17.1637]	[-12219.71, -137.79]
	FASA	-12843.0407	-7683.2954
		[-25449.8779, 206.1243]	[-14242.44, -591.13]
	Salcobrand	-349.9771	-2667.0397
		[-834.9016, -10.2718]	[-4457.68, 40.50]

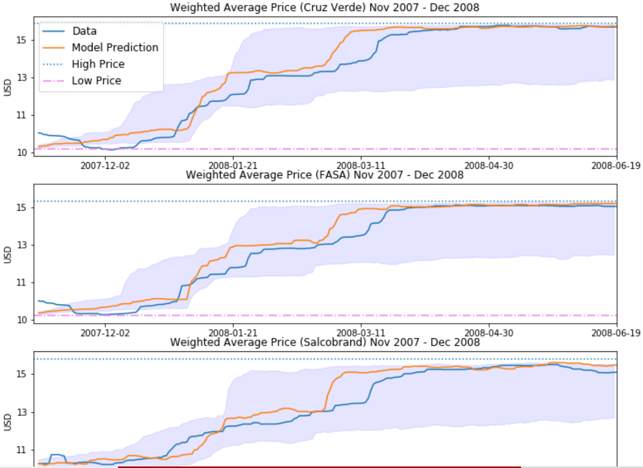
[1] In the bracket report 10-th and 90-th equantile of the estimated costs across products.

Insample Prediction

Prediction Under Equilibrium Belief Assumption



Prediction Under Non-Equilibrium Belief Assumption



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