Pricing Under Distress

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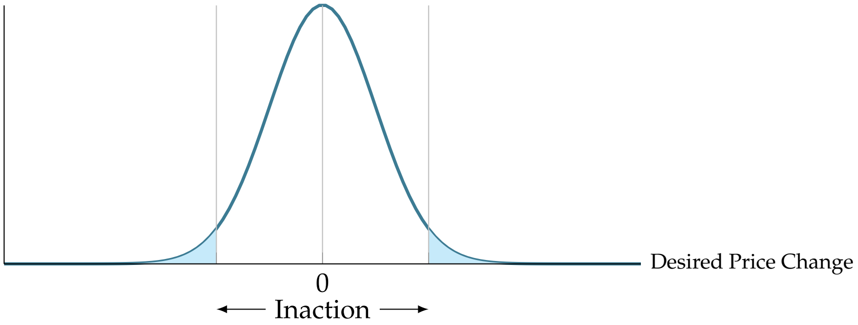
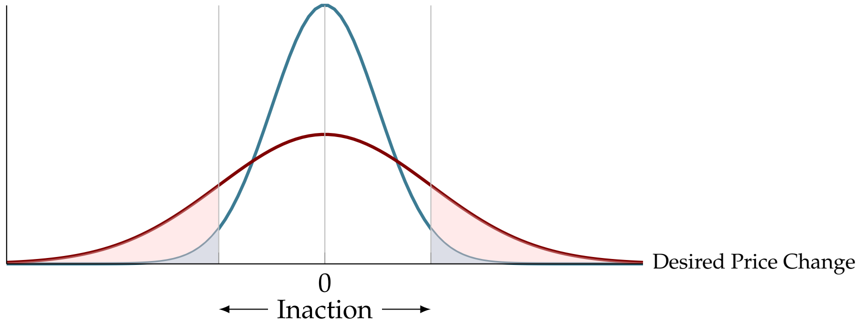
  - Typical model of uncertainty: time variation in dispersion of a fundamental distribution: **realization** vs. **anticipation**. [Bloom (2009) : volatility effect vs. uncertainty effect]
  - Vavra (2014): **Realized** uncertainty $\Rightarrow$ **more** price changes $\Rightarrow$ MP **less** effective.

Literature Review

Menu Cost: Inaction Bands

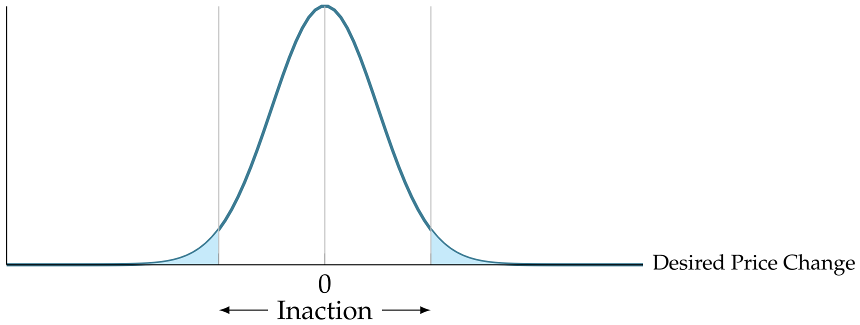


Menu Cost: Inaction Bands, **Realized** Dispersion, and MP

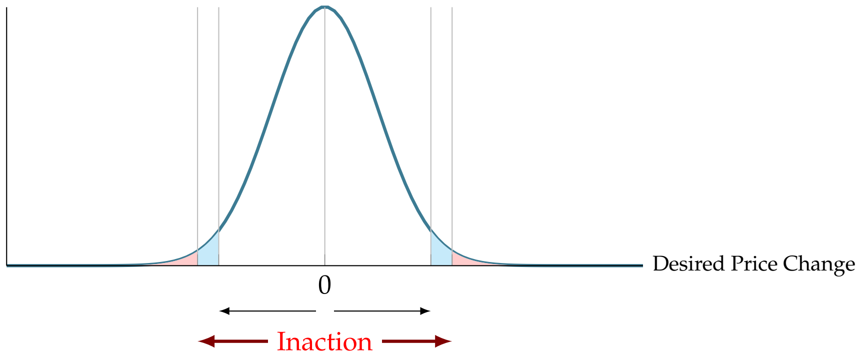


- Pure realized volatility increase the mass outside the bands.
- More firms adjust their prices $\Rightarrow$ A contemporaneous MP shock is less effective.

Menu Cost: Inaction Bands



Menu Cost: Inaction Bands, **Expected** Dispersion, and MP



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- Firms delay adjustment to avoid paying the cost twice: **wait and see** $\Rightarrow$ more inaction

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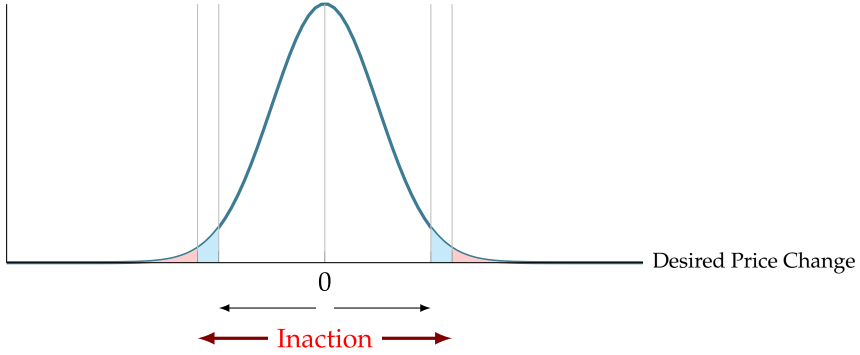

- Expected volatility next period makes future adjustments more likely.
- Firms delay adjustment to avoid paying the cost twice: **wait and see** $\Rightarrow$ more inaction
- Fewer firms adjust their prices $\Rightarrow$ A contemporaneous MP shock is more effective.

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- Business to Business (B2B) VAT Invoices from Chilean Tax Authority provided to the Central Bank of Chile
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- **Baseline Dataset**: 39,829 products across 183 supermarkets at 768 locations (14M+ observations)
- **Matched Subsample**: Supplier prices for a subset of the products analyzed in the baseline dataset using fuzzy matching, 6,540 products across 94 supermarkets at 491

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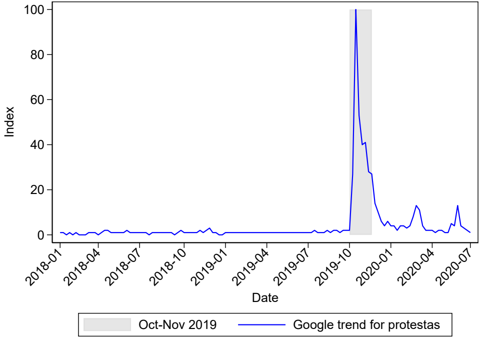

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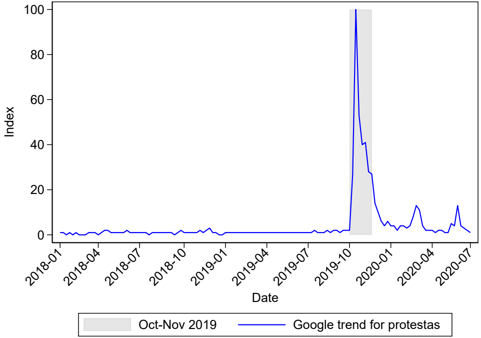
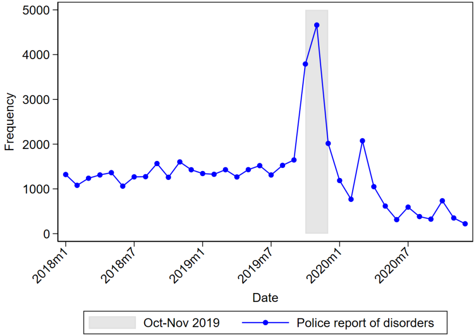
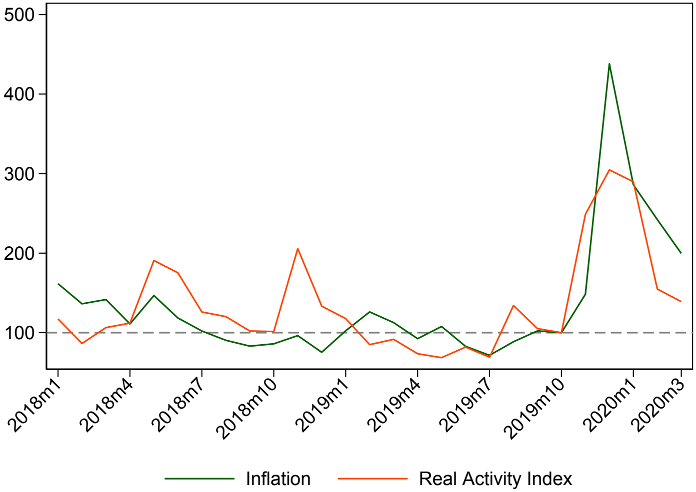


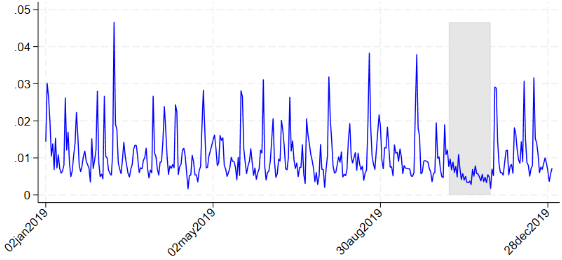


The Riots in Chile: Spike in Uncertainty



Uncertainty as Proxied by Standard Deviation Across Forecasters

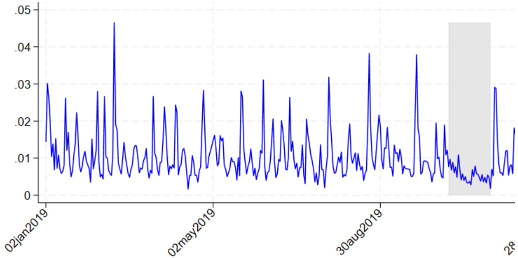
Raw Data



Fraction of Prices That Change

- Frequency of price changes drops during the Riots.

Raw Data



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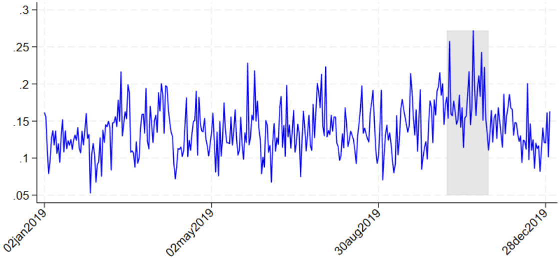

Average Size of Price Change

- Frequency of price changes drops during the Riots.
- The size of price changes increases during the Riots.

Baseline Specification

$$y_{it} = \text{Fixed Effects} + \beta D_t + \gamma_1 X_{1it} + \gamma_2 X_{2t} + \varepsilon_{it}^{y}$$

- Two dimensions of pricing behavior captured in y_{it}:
  - Occurrence and Sign of price change ("break") in product i in day t
  - Size and Sign of price change ("size") in product i in day t

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  - Occurrence and Sign of price change ("break") in product i in day t
  - Size and Sign of price change ("size") in product i in day t
- D_t: Riots Dummy, Oct. 18 - Nov. 17
- Fixed Effects:
  1. Product (supermarket-branch-category): **Must be sold before and during riots.**
  2. Week day $(1-7)$, Month $(1-12)$, Number of the week $(1-5)$, and Holidays.
- Other Controls: product-specific time-varying pricing dynamics and economic activity controls
- Errors are clustered at seller-location level

Baseline Results

Supermarket Pricing Behavior

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.00300***	-0.00305***	0.0313***	0.0462***
	(0.000298)	(0.000270)	(0.0121)	(0.00927)
Observations	14,135,650	14,135,650	81,439	64,648
Adjusted R-squared	0.002	0.003	0.426	0.472
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00647	0.00523	0.115	0.124

Note: Clustered Std. Errs. in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

- Identification: more than 6,000 daily products sold before and during the Riots.
- During the Riots the frequency of positive price changes decreased by around 46% and negative price changes by 58% relative to unconditional mean.
- The size of price changes increased by around 30%.

Were Supermarkets responding to changes in suppliers' behavior?

- Regression using pricing data of supermarkets' suppliers.

Supermarkets' Suppliers Pricing Behavior: Matched Sample

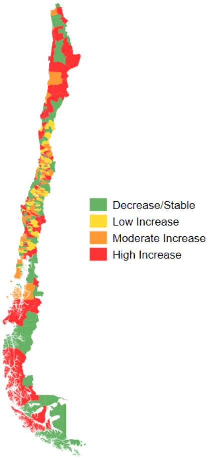
Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.000457	-0.00105	0.00979	-0.00790
	(0.000658)	(0.000824)	(0.0117)	(0.0196)
Observations	857,519	857,519	5,266	3,005
Adjusted R-squared	0.028	0.027	0.346	0.362
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00664	0.00389	0.0945	0.125

Note: Clustered Std. Errs. at supplier-supermarket link level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

- Suppliers did not change their pricing behavior during riots.

The Riots in Chile: Widespread & Heterogeneous

Change in Frequency of Public Disorder Reports across Regions During Riots



Intensity

Taking Stock

- Chilean Riots decreased the frequency (50-60%) and increased the size of price changes (30%) in supermarkets relative to pre-Riots period.
- Supply factors cannot explain these changes: No change in behavior of suppliers.
- Supermarkets seem not to react to something happening contemporaneously:
  - Supermarkets that were not directly affected by Riots exhibit the same behavior.
- Disagreement among professional forecasters (proxy for uncertainty) increases drastically in the months that follow the Riots.
- Turn to the structural model to show that **news about future dispersion in idiosyncratic demand** can explain these empirical results.

Model

- Builds on off-the-shelf menu-cost model (Vavra, 2014).
- Intermediate producers setting prices subject to a fixed adjustment cost, facing leptokurtic idiosyncratic TFP
  - Matched to suppliers changing prices occasionally in the data
- They face persistent idiosyncratic demand shocks.
- Kimball (1995) demand system
  - Demand shocks affect prices

Model Details

Calibration

- To the extent possible we use calibration targets from the Chilean micro data
  - Supplier prices used for calibration firm-level TFP process.
  - Average product-level markup (supermarket prices over supplier prices)
  - Pass-through of changes in supplier prices to supermarket prices
  - Frequency and size of price changes

Calibration Details

News Shock

- Start at the steady state and receive an unanticipated news shock
  - With probability $\mathcal{P}$, dispersion of idiosyncratic demand shock will increase by a factor of D in the next period.

$$
\begin{aligned}
\log\left(n_{t+1}^{i}\right) &= \rho_n \cdot \log\left(n_t^i\right) + v_{t+1} \cdot \sigma_n \cdot \epsilon_{t+1}^{n,i} \\
v_{t+1} &= \begin{cases} D & \text{with prob. } \mathcal{P} \\ 1 & \text{with prob. } 1-\mathcal{P} \end{cases}
\end{aligned}
$$

- Today firms learn that shocks to idiosyncratic demand tomorrow may become more dispersed, prompting a wait-and-see effect on price adjustment. Decision Rules

- A news shock today in the model leads to a decrease in price adjustment frequency and increase in the average size of adjustments immediately.

Solution Method

Pricing Responses to the News Shock (Various D and $\mathcal{P}$)

Data (Monthly)

	Frequency	Size
Data	–0.107***	0.020***
	(0.0172)	(0.00605)

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Model: Frequency

D\\$\mathcal{P}$	0.5	0.75	1.0
2	–0.017	–0.025	–0.032
3	–0.020	–0.031	–0.042
4	–0.022	–0.032	–0.045

Model: Size

D\\$\mathcal{P}$	0.5	0.75	1.0
2	0.006	0.009	0.012
3	0.006	0.011	0.014
4	0.007	0.011	0.015

Policy Implications

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- Output response as a fraction of the shock (CIR: cumulative response)

		$t = 1$	$t = 2$	CIR
No News	MP in $t = 1$	0.40	0.16	0.11
News (realized in $t = 2$)	MP in $t = 1$	0.60	-0.01	0.12
News (not realized in $t = 2$)	MP in $t = 1$	0.60	0.28	0.21

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News (not realized in $t = 2$)	MP in $t = 1$	0.60	0.28	0.21
News (realized in $t = 2$)	MP in $t = 2$	0.00	0.05	0.00
News (not realized in $t = 2$)	MP in $t = 2$	0.00	0.42	0.12

- MP in $t = 1$: Effectiveness increases by 50% on impact and persistent if no realization.
- MP in $t = 2$: If realized very little effect (Vavra's result), if not as effective as normal times.

Conclusion

1. We use microdata from Chile to identify the effect of Riots on price dynamics.
   - Frequency of price changes – both positive and negative – decreased
   - Conditional on changing prices, the size of price changes increased, for *both* positive and negative changes
   - Supply shocks cannot explain the empirical patterns

2. Using a quantitative menu cost model we show that news about future demand volatility can rationalize the effect of Riots on price dynamics

3. In periods of anticipation of uncertainty (without realization), monetary policy is more effective, unlike when uncertainty is realized

4. When pricing under distress, timing of policy is everything!

Appendix

Literature

1. **Uncertainty and firm-level decisions:**
   - Uncertainty drives business cycle fluctuations:
     - Bloom (2009, 2014) [anticipated idiosyncratic volatility causes wait-and-see behavior], and
     - Fernández-Villaverde (2011, 2015) [aggregate uncertainty amplify BC fluctuations].
   - Aggregate uncertainty impacts the effectiveness of monetary policy:
     - Vavra (2014) [price changes $\uparrow$, real policy effects $\downarrow$],
     - Baley and Blanco (2019), Ilut et al. (2020) [price changes $\downarrow$, real policy effects $\uparrow$], and
     - Klepacz (2021) [aggregate uncertainty $\uparrow$, price changes $\downarrow$].
   - Potential micro-foundations for firm-level decisions under uncertainty:
     - Rotemberg (2002) [consumer anger], and
     - Maćkowiak et al. (2023) [rational inattention].
   - **Empirical Challenge:** Identifying the effects of anticipated uncertainty vs. realized volatility.
     - Dew-Becker et al. (2017), Berger et al. (2019) [evidence for realization effect],
     - Drenik and Perez (2020) [price dispersion $\uparrow$], and
     - Kumar et al. (2023) [survey evidence].

   $\Longrightarrow$ Quasi-natural experiment disentangles **anticipation** and **realization channel.**

Literature

2. **Menu cost model:**
   - Monetary non-neutrality due to fixed costs of changing prices is well established theoretically:
     - Barro (1972), Sheshinki and Weiss (1977), Caplin and Spulber (1987), Caballero and Engel (1993), and Dotsey et al. (1999) **+ Kimball (1995)**.
   - Quantitative models support sizable monetary non-neutralities of menu costs:
     - Golosov and Lucas Jr (2007), Nakamura and Steinsson (2010), Midrigan (2011), and Vavra (2014) [product-level data].
     - Alvarez et al. (2016, 2023) [frequency of price changes crucial]
3. **Rare events and disasters in macroeconomics:**
   - Rare monetary events provide empirical insights:
     - Hobijn et al. (2006) [2022 introduction of Euro], Gagnon (2009) [1995 Mexico inflation], and Alvarez et al. (2019) [1990s Argentina hyper inflation].
   - Disasters as exogenous shocks:
     - Barro (1972), Gabaix (2012), Baskaya and Kalemli-Özcan (2016) [1999 Turkey earthquake], Acemoglu et al. (2018), Boehm et al. (2019) [Arab Spring], and Wieland (2019) [2011 Japan earthquake]

return

Riots: Timeline

- Oct 6, 2019: Santiago subway fare is raised by 30cs.
- Students' call to demonstrate against with limited success
- High Gov officials did not address the students' call
- **Oct 18: Disruptions in Santiago subway; police responded**
- **Night of Oct 18 onward: Widely spread mobs attacking, sacking and burning supermarkets, local businesses, etc.**
- Night of Nov 12: Mobs attacked military facilities
- Night of Nov 15: Turning point - Wide political agreement on course of action to change constitution

Return

Matched Subsample

- The baseline dataset: final prices of products sold by supermarkets
- The richness of the electronic invoice data allows us to go much further: we build an additional **matched subsample dataset with suppliers' prices** of a subset of the products analyzed in the baseline sample
  - Match done using non-standardized product descriptions across suppliers and supermarkets
  - Two parallel methods of fuzzy matching
  - A product: unique triplet + supplier's id + supplier's product description
- **Matched Subsample**: 6,540 products across 94 supermarkets

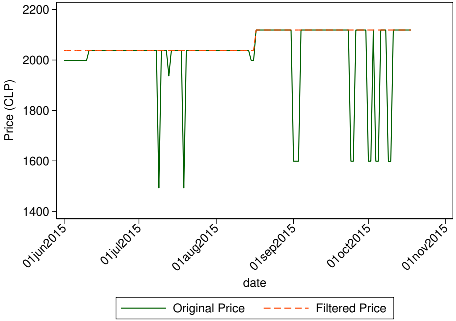
Details

Return

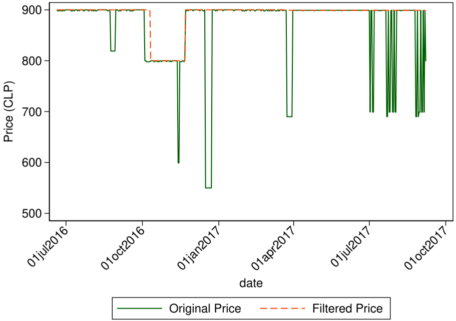
A Transaction Level Dataset: Product & Prices

Original and Filtered prices: Two products in the Dataset

(a) Product X



(b) Product Y



Return

Descriptive Statistics

	Baseline sample		Matched Sample		Suppliers Sample	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Price Setting						
Total Breaks	0.0117	0.1075	0.0126	0.1116	0.0105	0.1021
Positive Breaks	0.0065	0.0802	0.0067	0.0815	0.0066	0.0812
Negative Breaks	0.0052	0.0722	0.0059	0.0768	0.0039	0.0623
Size Positive	0.1153	0.1292	0.1006	0.1083	0.0945	0.1177
Size Negative	0.1239	0.1393	0.1059	0.1200	0.1254	0.1522
Sample Info						
No of Supermarkets	183		94		-	
No of Suppliers	-		298		298	
No of Supermarkets-locations	768		491		-	
No of Product ID	39,829		6,540		2,025	
No of Product Description	13,769		1,931		1,930	
No of Observations	14,135,650		2,025,729		857,519	

Return

Matched Subsample

- **Non-standardized product descriptions** across suppliers and supermarkets.
- Two parallel methods of fuzzy matching: **cosine similarity** and **1-gram distance**.
- Strict criteria for merge validation:
  1. Cosine distance $\leqslant 0.03$, 1-gram distance $\leqslant 3$, or Cosine distance $\leqslant 0.05$ and 1-gram distance $\leqslant 5$.
  2. At least 20 weeks observed.
- A product: unique triplet + supplier's id.
- In cases with multiple suppliers, the one with the longest overlap in the observation period with supermarket-location prices is selected.

Return

Is It About Now? Intensity of Riots - Dummy

Supermarket Analysis and Intensity of Riots

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.00310***	-0.00224***	0.0305**	0.0652**
	(0.000560)	(0.000461)	(0.0145)	(0.0253)
D * Intensity	0.000121	-0.000906*	0.000932	-0.0223
	(0.000657)	(0.000542)	(0.0197)	(0.0273)
Observations	14,135,650	14,135,650	81,439	64,648
Adjusted R-squared	0.002	0.003	0.426	0.472
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00647	0.00523	0.115	0.124

Note: *Intensity* is a dummy for municipalities above the median change in the number of police reports for public disorders in October and November 2019 relative to October and November 2018, adjusted for population. Clustered Std. Errs. in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

- *Intensity* in Riots not linked to differential changes in supermarkets' pricing behavior.

Is It About Now? Intensity of Riots - Continuous Measure

Supermarket Analysis and Intensity of Riots

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.00372***	-0.00333***	0.0228	0.0443***
	(0.000458)	(0.000455)	(0.0142)	(0.0134)
D * Intensity	2.93e-05*	1.17e-05	0.000309	7.31e-05
	(1.72e-05)	(9.68e-06)	(0.000457)	(0.000400)
Observations	14,135,650	14,135,650	81,439	64,648
Adjusted R-squared	0.002	0.003	0.426	0.472
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00647	0.00523	0.115	0.124

Note: *Intensity* is the change in the number of police reports for public disorders in October and November 2019 relative to October and November 2018, adjusted for population. Clustered Std. Errs. in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

- *Intensity* in Riots not linked to differential changes in supermarkets' pricing behavior.

Return

Model

- Start with the off-the-shelf menu-cost model (Vavra, 2014)
  - Intermediate producers setting prices subject to a fixed adjustment cost, ~~"Calvo-plus"~~
  - Shocks: leptokurtic idiosyncratic TFP, ~~aggregate TFP~~, ~~aggregate volatility of TFP~~, ~~nominal expenditure~~.
- Two departures:
  - Add idiosyncratic demand shocks (n_t^i); will introduce news later

$$\log\left(n_{t+1}^i\right) = \rho_n \log\left(n_t^i\right) + \sigma_n \epsilon_{t+1}^{n,i}$$

  - Kimball (1995) instead of CES, so idiosyncratic demand plays a role.
- Household standard: supply labor, consume, complete markets, own all the firms.

Firms

- Kimball (1995) aggregator to combine $n_t^i y_t^i$ into Y_t.

$$\int_0^1 G\left(\frac{n_t^i y_t^i}{Y_t}\right) di = 1$$

$$G\left(\frac{n_t^i y_t^i}{Y_t}\right) = \frac{\omega}{1+\psi}\left[(1+\psi)\frac{n_t^i y_t^i}{Y_t} - \psi\right]^{\frac{1}{\omega}} + 1 - \frac{\omega}{1+\psi}$$

- n_t^i: idiosyncratic demand shock.
- ω is related to desired markup, ψ captures how demand elasticity changes with market share.
- Intermediate-good production: $y_t^i = z_t^i h_t^i$.
- CES / Dixit-Stiglitz (when $\psi = 0$): constant markup, n_t^i irrelevant for pricing.

Exogenous Processes

- Productivity process

$$\log\left(z_t^i\right) = \begin{cases} \rho_z \log\left(z_{t-1}^i\right) + \sigma_z \epsilon_t^{z,i}; \quad \epsilon_t^{z,i} \sim N\left(0,1\right) & \text{with probability } p_z \\ \log\left(z_{t-1}^i\right) & \text{with probability } 1 - p_z \end{cases}$$

- Demand Process

$$\log\left(n_t^i\right) = \rho_n \log\left(n_{t-1}^i\right) + \sigma_n \epsilon_t^{n,i} \text{ with } \epsilon_t^{n,i} \sim N(0,1)$$

- Nominal expenditures $S_t \equiv P_t Y_t$

$$\log\left(S_t\right) = \mu + \log\left(S_{t-1}\right)$$

Profit Function with Kimball | Value Function

Return

External Calibration

Parameter	Description	Value	Source
β	Discount Rate	0.997	Vavra (2014)
μ	Trend Inflation	0.37%	Nominal and Real GDP Growth
p_z	Prob. change in idio. TFP	0.19	Prob. supplier price change
ρ_z	Idio. TFP Process	0.33	Supplier price dynamics
σ_z	Idio. TFP Process	0.10	Supplier price dynamics
ξ	Labor disutility	1.0	Normalization

- Use direct measurements from Chilean micro data when possible.
- Use supplier price dynamics to calibrate the leptokurtic idiosyncratic TFP process.

Internal Calibration

Parameter	Description	Value	Moment	Model	Data
ω	Kimball elasticity	1.33	Avg. Markup	0.37	0.37
ψ	Kimball super-elasticity	–1.67	Cost Pass-through	0.31	0.31
ρ_n	Idio. Demand AR(1)	0.76	Fraction up	0.55	0.53
σ_n	Idio. Demand AR(1)	0.088	Size	0.113	0.110
f	Menu Cost	0.042	Frequency	0.26	0.26

- Markup from matched dataset.
- Pass-through estimated from matched dataset

$$\Delta \log \left(p_t^i\right) = \beta \cdot \Delta \log \left(c_t^i\right) + \text{Firm FE}_i + \epsilon_t^i,$$

- Match time series properties of dispersion of prices.

More on Calibration

Return

Internal Calibration

- Pass-through Regression
  - Regress change in log-price for products on change in log-price of supplier prices between two periods when the product price change to get estimated cost pass-through $\hat{\Delta}$
  - Recover ψ using $\hat{\Delta} = \frac{-1}{\omega\psi - 1}$

return

Solution Details

- Stationary equilibrium

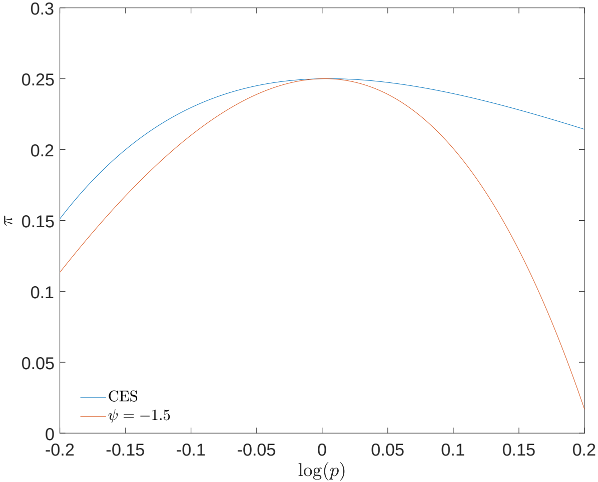
  1. Initialize guesses for aggregate prices $\left(\hat{\frac{P}{S}}, \hat{\lambda}\right)$ and use VFI to solve for the pricing decision rules.
  2. Initialize a firm distribution $H_0\left(\frac{p_{-1}}{S}, z, n\right)$. Iterate forward using the law of motion of z, n and the pricing decision rules until the mass of firms at each state is stationary.
  3. Compute $\frac{P}{S}$ and λ at the stationary distribution. Compute the absolute difference between the guesses and implied values. Repeat from step (1) until the differences are sufficiently small.

- Transition dynamics with news shock

  1. Set the number of periods that the transition takes denoted by T and solve for the stationary equilibrium.
  2. Initialize two sequences of guesses for $\frac{P}{S}$ and λ, for the case when the news shock is and is not realized.
  3. Assume that in period $T+1$, economy is at the stationary equilibrium. Iterate backward to solve for the value functions at each $t = T, T-1, ..., 2$. Do this for the case when news shock is and is not realized
  4. In period $t = 1$, solve for the value function using $V(\cdot) = \mathcal{P}\hat{V}(\cdot;2) + (1-\mathcal{P})\,\tilde{V}(\cdot;2)$
  5. Starting from the stationary distribution, iterate the firm distribution forward using the optimal decision rules. Compute the implied sequences of $\left(\frac{P_t}{S_t}, \lambda_t\right)$. Repeat from step (2) until the implied sequences of aggregate objects is sufficiently close to the guesses.

return

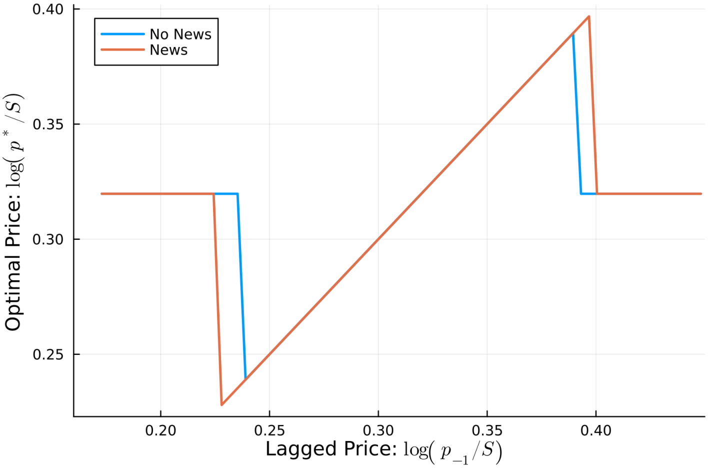
Kimball Profit Function



Over-pricing is more costly under Kimball demand.

Model Decision Rule

Decision Rules



- News about higher future demand dispersion: wait-and-see effect.

Return

Value Function

$$V\left(\frac{p^i_{t-1}}{S_t}, n^i_t, z^i_t; \frac{P_t}{S_t}, \lambda_t\right) = \max\left\{V_A\left(n^i_t, z^i_t; \frac{P_t}{S_t}, \lambda_t\right), V_N\left(\frac{p^i_{t-1}}{S_t}, n^i_t, z^i_t; \frac{P_t}{S_t}, \lambda_t\right)\right\}$$

$$V_N\left(\frac{p^i_{t-1}}{S_t}, n^i_t, z^i_t; \frac{P_t}{S_t}, \lambda_t\right) = \pi\left(\frac{p^i_{t-1}}{S_t}, n^i_t, z^i_t, \frac{P_t}{S_t}, \lambda_t\right) + \mathbb{E}_t\left[\Xi_{t,t+1} V\left(\frac{p^i_{t-1}}{S_t}\frac{1}{e^{\mu}}, n^i_{t+1}, z^i_{t+1}; \frac{P_{t+1}}{S_t}\frac{1}{e^{\mu}}, \lambda_{t+1}\right)\right]$$

$$\begin{aligned} V_A\left(n^i_t, z^i_t; \frac{P_t}{S_t}, \lambda_t\right) &= -f\frac{W_t}{P_t} \\ &\quad + \max_{\frac{p^i_t}{S_t}}\left\{\pi\left(\frac{p^i_t}{S_t}, n^i_t, z^i_t, \frac{P_t}{S_t}, \lambda_t\right) + \mathbb{E}_t\left[\Xi_{t,t+1} V\left(\frac{p^i_t}{S_t}\frac{1}{e^{\mu}}, n^i_{t+1}, z^i_{t+1}; \frac{P_{t+1}}{S_t}\frac{1}{e^{\mu}}, \lambda_{t+1}\right)\right]\right\} \end{aligned}$$

Solution Method Return