Pricing Under Distress

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Motivation

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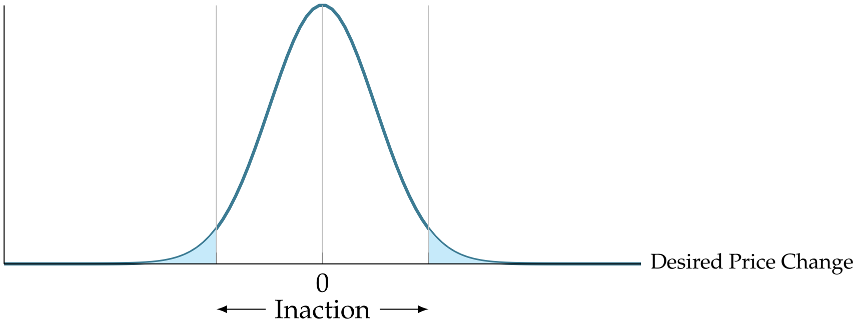
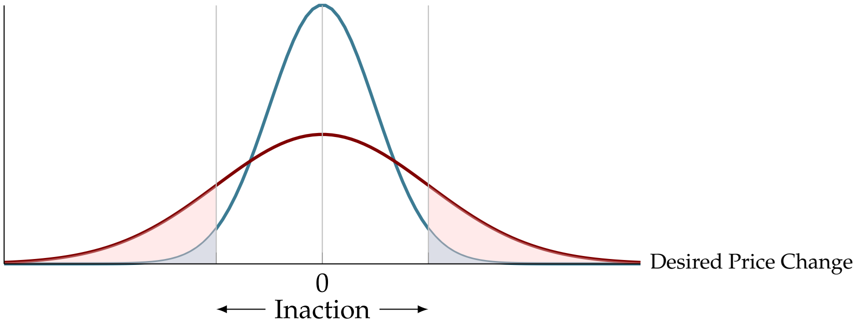
  - Typical model of uncertainty: time variation in dispersion of a fundamental distribution: **realization** vs. **anticipation**. [Bloom (2009) : volatility effect vs. uncertainty effect]
  - Vavra (2014): **Realized** uncertainty $\Rightarrow$ **more** price changes $\Rightarrow$ MP **less** effective.

Literature Review

Menu Cost: Inaction Bands

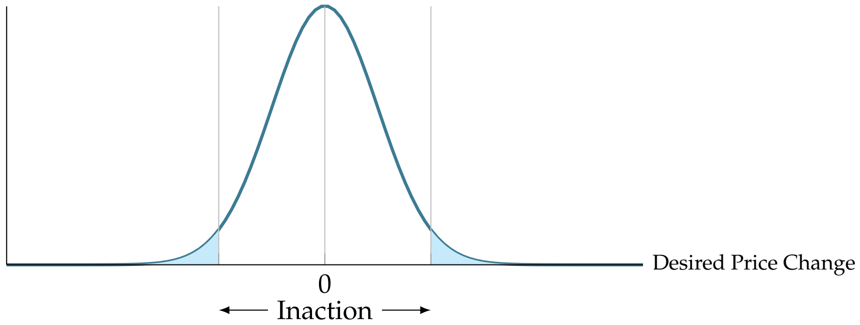


Menu Cost: Inaction Bands, **Realized** Dispersion, and MP



- 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



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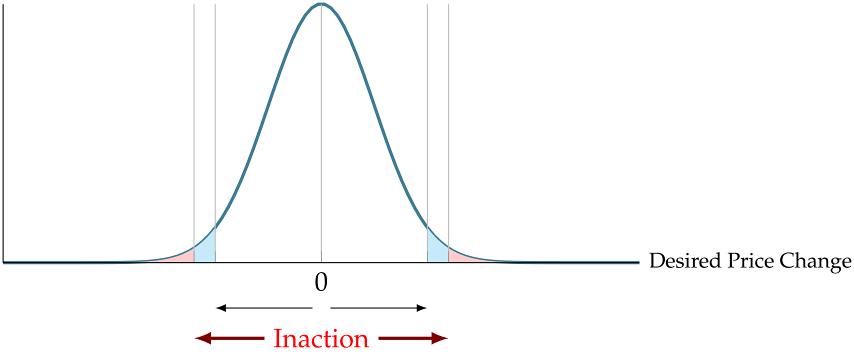

- Expected volatility next period makes future adjustments more likely.
- Firms delay adjustment to avoid paying the cost twice: **wait and see** $\Rightarrow$ more inaction

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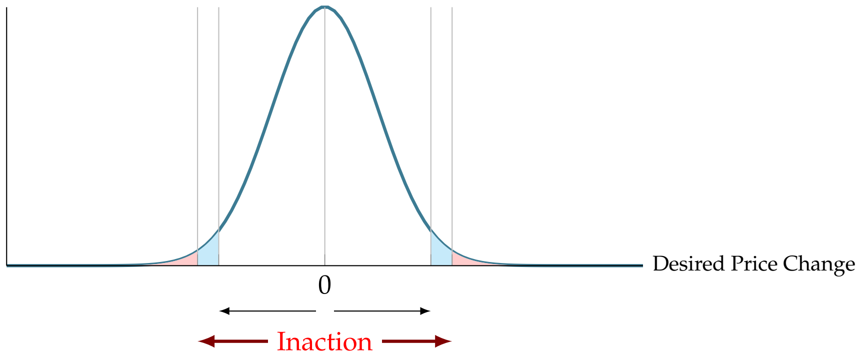

- Expected volatility next period makes future adjustments more likely.
- Firms delay adjustment to avoid paying the cost twice: **wait and see** $\Rightarrow$ more inaction
- Less firms adjust their prices $\Rightarrow$ A contemporaneous MP shock is more effective.

This Paper

- Anticipation without realization (**news** about future changes in dispersion) empirically relevant in a quasi natural experiment. (Chilean Riots in 2019)

    1. Supermarkets in Chile during the Riots: lower frequency of price changes, and conditional on a price change, the size of price changes increased.
    2. We rule out any supply-based forces; show changes are uniform across riot intensity.
    3. Quantitative heterogeneous-firms pricing model based on Vavra (2014) with all possible demand shocks (level, dispersion, news / aggregate, idiosyncratic)
    4. In the context of this model, the **only** way to explain change in pricing during the riots is by using a news shock about idiosyncratic demand dispersion.

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  4. In the context of this model, the **only** way to explain change in pricing during the riots is by using a news shock about idiosyncratic demand dispersion.
- **Timing** is crucial to understand MP effectiveness: More effectiveness under anticipation, less effectiveness upon realization.

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- **Business to Business (B2B) VAT Invoices**
  - Daily Frequency from 2015 to 2019. Universe of B2B transactions.
  - Description of product, buyer, seller, price and quantity

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- **Baseline Dataset**: 27,109 products across 67 supermarket

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- **Unit of observation**: supermarket-location-product Sample details
- **Price**: Intra-day maximum price. Continuity. Remove short-lived fluctuations. examples
- **Baseline Dataset**: 27,109 products across 67 supermarket
- **Matched Subsample**: Supplier prices for a subset of the products analyzed in the baseline dataset using fuzzy matching, 8,777 products across 37 supermarkets details

The Riots in Chile: An Unexpected Event

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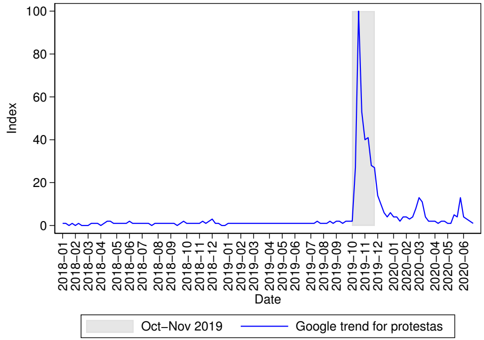

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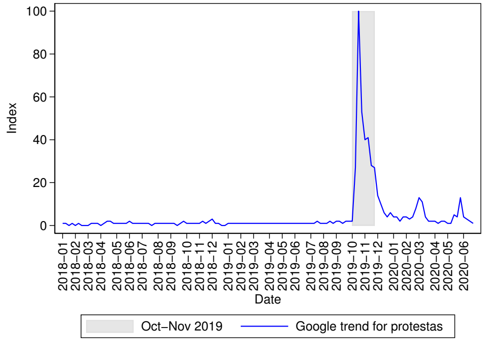

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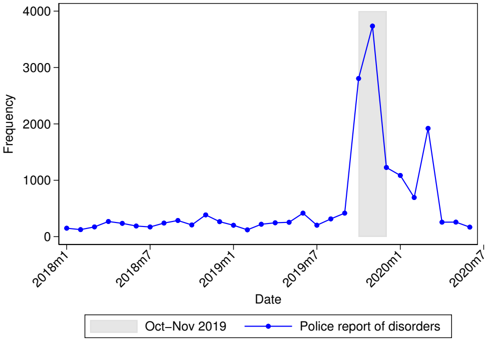
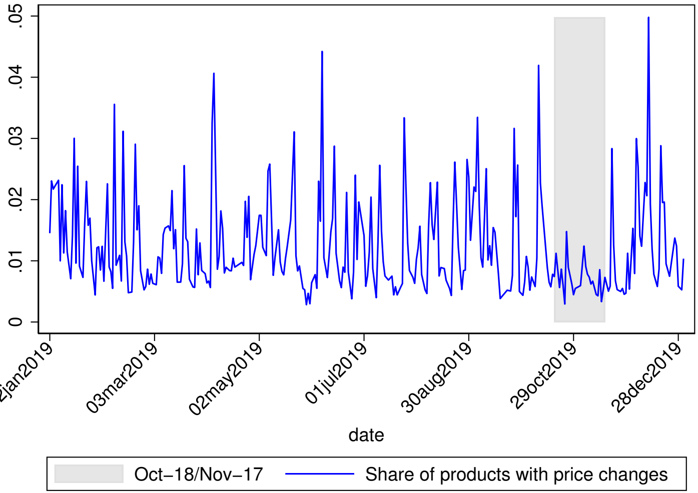


Police Reports of *"desórdenes"*

Raw Data: Fraction of Prices That Change (Daily)



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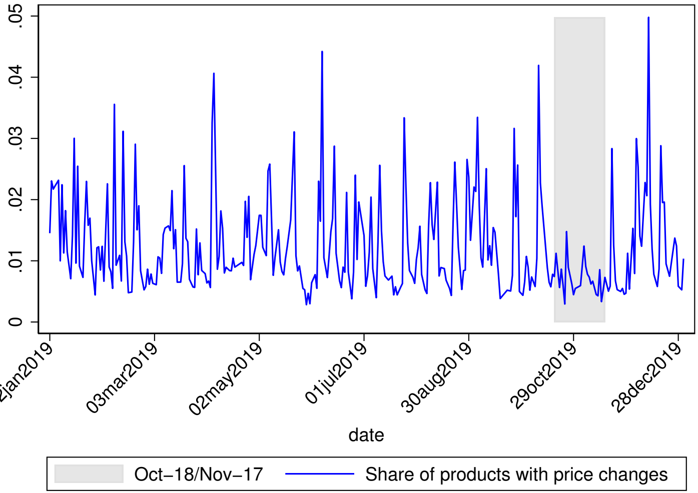

- Frequency of price changes drops during the Riots.

Baseline Specification

$$y_{it} = \alpha + \beta * D_{riots} + \text{Fixed Effects} + \text{Other Controls} + \varepsilon_{it}^{y}$$

- Two dimensions of pricing behavior captured in y_{it}:
  - Occurrence and Sign of price change ("break") in product i in day t
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- Two dimensions of pricing behavior captured in y_{it}:
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  - Size and Sign of price change ("delta") in product i in day t
- D_{riots}: 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: Size, sign, and days since the last price change

details

- Errors are clustered at seller-location level

Baseline Results

Supermarket Pricing Behavior

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_{riots}	-0.00296***	-0.00346***	0.0188***	0.0200***
	(0.000458)	(0.000346)	(0.00656)	(0.00601)
Observations	7,246,966	7,246,966	43,646	34,204
Adjusted R-squared	0.002	0.002	0.390	0.432
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00694	0.00559	0.114	0.0987

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

- Identification: more than 3000 daily products sold before and during the Riots.
- During the Riots the frequency of price changes decreased by around 50%.
- The size of price changes increases by around 20%.

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) Delta Positive Breaks	(4) Delta Negative Breaks
D_{riots}	0.000575	0.000670	-0.0460*	-0.00996
	(0.00232)	(0.00138)	(0.0240)	(0.0254)
Observations	1,982,065	1,982,065	12,063	8,718
Adjusted R-squared	0.008	0.010	0.354	0.495
Controls	Yes	Yes	Yes	Yes
FE	yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00700	0.00517	0.159	0.136

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

- Suppliers did not change their pricing behavior during riots.

Is It About Now? Intensity of Riots

Supermarket Analysis and Intensity of Riots

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_{riots}	-0.00315***	-0.00355***	0.0158***	0.0140**
	(0.000647)	(0.000473)	(0.00592)	(0.00678)
D_{riots}*$Intensity$	0.000431	0.000183	0.00694	0.0155
	(0.000914)	(0.000571)	(0.0143)	(0.0128)
Observations	7,246,775	7,246,775	43,646	34,204
Adjusted R-squared	0.002	0.002	0.390	0.432
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
mean of Dependent Variable	0.00694	0.00559	0.114	0.0987

Note: *Intensity* is a dummy for municipalities above median of No. of Social Disorders by 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.

Map

Taking Stock

- Chilean Riots decreased the frequency and increased the size of price changes.
- Supply factors cannot explain these changes:
  - No change in behavior of suppliers.
- It seems supermarkets are not reacting to something that's happening contemporaneously:
  - Supermarkets that were not directly affected by Riots exhibit the same behavior.
- Turn to the structural model to confirm that it is indeed **news about future dispersion in idiosyncratic demand** that is responsible for these empirical results.

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 changes:
  - Add idiosyncratic demand shocks (n_t^i) and anticipated news about their dispersion

$$
\begin{aligned}
\log\left(n_{t+1}^i\right) &= \rho_n \cdot \log\left(n_t^i\right) + v_{t+1} \cdot \sigma_n \cdot \epsilon_{t+1}^{n,i} \\
\log\left(v_{t+1}\right) &= \rho_v \cdot \log\left(v_t\right) + \sigma_v \cdot \epsilon_{t+1}^{v} + \sigma_{\text{news}} \cdot u_t^{\text{news}}
\end{aligned}
$$

  - Use Kimball (1995) aggregator instead of CES in order to have a role for idiosyncratic demand.
- We also consider versions with: first and second moment of nominal expenditures, and news about each.

Model

- Production: $y_t^i = z_t^i l_t^i$.
- n_t^i: idiosyncratic demand shock.
- CES / Dixit-Stiglitz: constant markup, n_t^i irrelevant for pricing
- Kimball (1995) aggregator to combine $n_t^i y_t^i$ into Y_t.

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

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

- ω_p is related to desired markup, ψ_p captures the how demand elasticity changes with market share.

Profit Function with Kimball Value Function

Calibration

- Use direct measurements from Chilean micro data when possible.
  - Use supplier price dynamics to calibrate the leptokurtic idiosyncratic TFP process.
  - Set ω_p to match average markup of 34%.
  - Set $\psi_p = -1.5$ to match cost pass-through from suppliers to supermarkets.
  - Match time series properties of dispersion of prices.

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Internal Calibration (Monthly)

Moment	Data	Model
Freq. Price Change	0.31	0.29
Cost Pass-through	0.28	0.29
Frac. Small Price Change	0.45	0.35
Frac. Pos. Price Change	0.51	0.64
Size Price Change	0.106	0.090
Agg. disp. AR(1)	0.81	0.84
Agg. disp. AR(1)	0.018	0.016

More on Calibration

News Shock

- A one-time news about an increase in idiosyncratic demand dispersion tomorrow.

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

- $\sigma_{news} = 0.75 \cdot \sigma_v$
- 3 S.D. shock to news about demand dispersion
- Probability of demand volatility increase goes from 20% to 90% when current volatility is at the unconditional mean

Decision Rules

Matching the Qualitative Pattern in Pricing During the Riots

	Frac Up	Frac Down	Size Up	Size Down
Data - Riots	−	−	+	+
News on Idio. Demand Dispersion (+)	−	−	+	+

Matching the Qualitative Pattern in Pricing During the Riots

	Frac Up	Frac Down	Size Up	Size Down
Data - Riots	–	–	+	+
News on Idio. Demand Dispersion (+)	–	–	+	+
Idio. Demand Dispersion (+)	+	+	+	+
Nom. Expenditure Level (+)	+	–	–	+
Nom. Expenditure Dispersion (+)	0	0	0	0
News on Nom. Expenditure Level (+)	+	–	–	+
News on Nom. Expenditure Dispersion (+)	0	0	0	0
Aggregate TFP Shock (–)	+	–	–	+
Menu Cost Shock (+)	–	–	–	–

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	Frac Up	Frac Down	Size Up	Size Down
Data - Riots	–	–	+	+
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Nom. Expenditure Level (+)	+	–	–	+
Nom. Expenditure Dispersion (+)	0	0	0	0
News on Nom. Expenditure Level (+)	+	–	–	+
News on Nom. Expenditure Dispersion (+)	0	0	0	0
Aggregate TFP Shock (–)	+	–	–	+
Menu Cost Shock (+)	–	–	–	–

- In this model only news about future demand dispersion can replicate the empirical patterns.

One-Time Monetary Shock

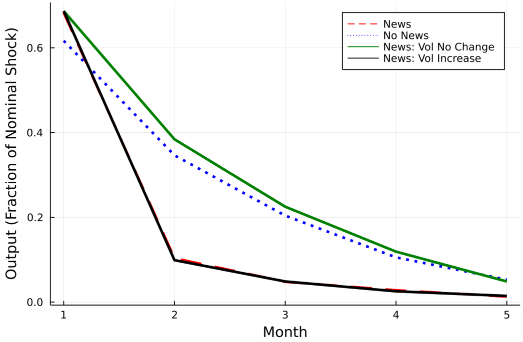
- Nominal expenditure $S = P \cdot C$

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

- One-time unanticipated shock to S of size μ (monthly growth of 0.37%)
- 4 cases:
  1. No news shock
  2. Positive news about demand volatility in $t+1$ and unanticipated component drawn ...
     a) ... unconditionally
     b) ... such that volatility stays constant in $t+1$
     c) ... such that volatility increases in $t+1$

One-Time Monetary Shock with and without News

Pass-through of Nominal Expenditure Shock to Real Output



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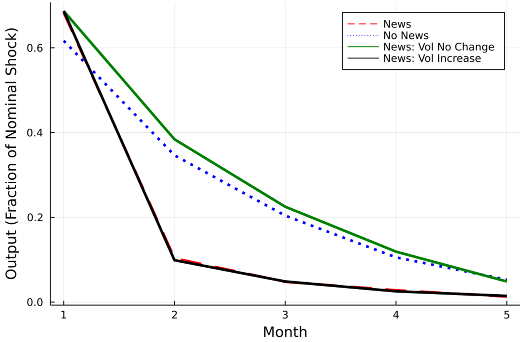
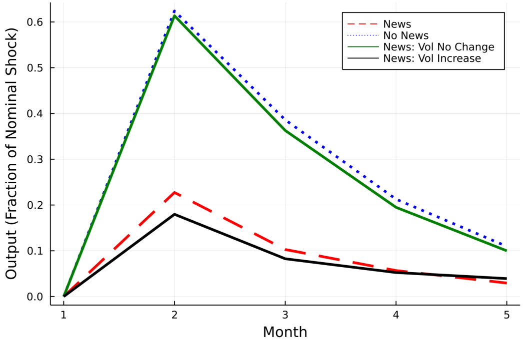


- **News** ⇒ inaction ⇒ less aggregate price flexibility ⇒ more response in output
- **Pass-through:** increases by 6.6 p.p with a concurrent news shock.

Persistent News

Timing of Monetary Shock

Pass-through of Nominal Expenditure Shock to Real Output



- Monetary policy shock hits in period 2, while the news still arrives in period 1.

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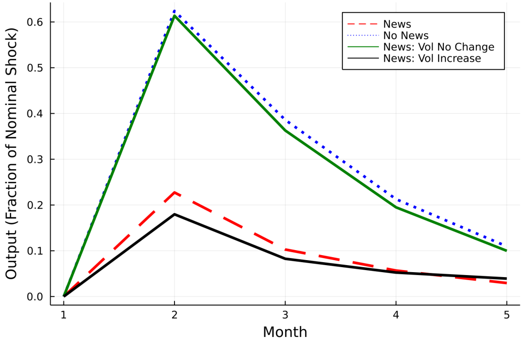

- Monetary policy shock hits in period 2, while the news still arrives in period 1.
- If volatility actually increases in period 2, the effectiveness disappears.

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

- **Uncertainty and pricing behavior**
  - *Vavra (2014), Baley and Blanco (2019), Drenik and Perez (2020), Ilut, Valchev, Vincent (2020), Klepacz (2021), Alvarez and Lippi (2021)*
  - We extend the workhorse menu cost models by adding news shocks (*Barsky and Sims, 2011*) to idiosyncratic demand dispersion under Kimball preferences (*Klenow, 2006*)
  - Separate the effects of anticipation and actual realization of increased dispersion (*Bloom 2009*)

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  - Separate the effects of anticipation and actual realization of increased dispersion (*Bloom 2009*)
- **Micro pricing data**
  - *Hobijn, Ravenna, Tambalotti (2006), Golosov and Lucas (2007), Gagnon (2009), Nakamura and Steinsson (2010, 2018), Midrigan (2011), Eichenbaum, Jaimovich, Rebelo (2014), Alvarez, Beraja, Gonzalez, Neumeyer (2019)*
  - We use the Chilean riots in 2019 as a laboratory to study firms' pricing behavior under distress.
  - Daily transaction data for supermarkets at the product level; observe both retail and supplier prices.
  - First paper to exploit daily price changes.

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

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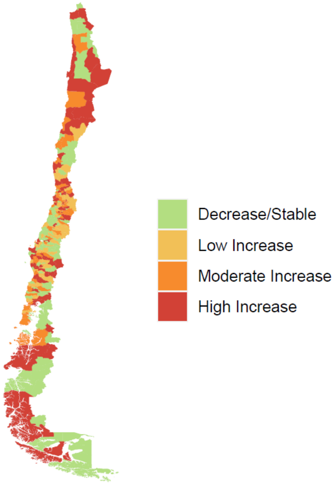
The Riots in Chile: Widespread & Heterogeneous

Intensity of Burglaries Across Regions During Riots



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Matched Subsample

- The baseline dataset: final prices of products sold by supermarkets
- The richness of the electronic invoice allows us to go 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**: 8.777 products across 37 supermarkets

details

return

A Transaction Level Dataset: Sample

- Because of anonymity of firms, use these **sampling criteria**:
  - Economic activity is *"Retail trade in non-specialized stores"* (CBC's classification)
  - Medium & large retailers (annual sales>USD$4M.); guarantees information since 2014
  - At least 50% of sales in a specific set of product categories (rice, eggs, milk, perfumery, etc)
- Supermarkets do not distinguish their **branch locations** (not audited by tax authority): set of criteria to identify unique branches,
  - Most important: a proper branch must have 95% of weeks registering the same municipality as the most recurrent among its buyers

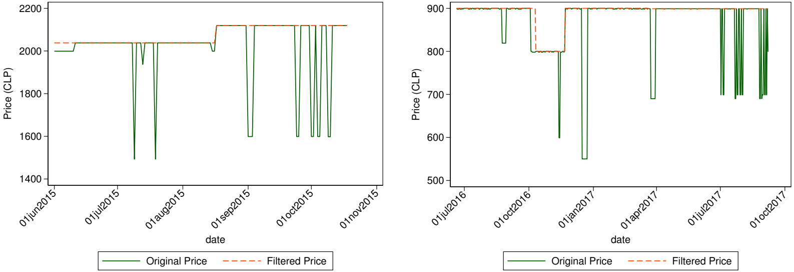
Criteria

return

A Transaction Level Dataset: Product & Prices

Original and Filtered prices: Two products in the Dataset

(a) Product X (b) Product Y



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A Transaction Level Dataset: Branch Definition

Tax authority does not audit the branch information. We impose four criteria on the branch information to ensure that the branch identifiers indeed refer to unique branches:

1. A proper branch must report positive sales on at least 50% of the days between their first and last observation in the dataset before October 18, 2019
2. A proper branch must have at least 80% of their weeks classified as valid weeks. We consider a valid week as one in which at least 50% of branch code's buyers were registered in the same municipality
3. We calculate the most common municipality for all costumers of a given branch in every week. A proper branch must have 95% of weeks registering the same municipality as the most recurrent among its buyers
4. A proper branch has to report at least 80 days with positive sales

return

Regression framework: Expanded

Our baseline specification, expanded with the set of controls is:

$$y_{it} = \alpha_0 + \beta_1 D_{riots} + \Gamma f(DSLB_{it}) + \Phi_1 SB_{it} + h(FE) + \varepsilon_{it}^{y} \tag{1}$$

- Where $h(FE)$ is the set of fixed effects explained before
- Where f(.) is a third order polynomial of the number of days since last break of the product ($DSLB$).
- SB indicates the numbers of price breaks in the last 30 days.

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.

return

Internal Calibration

- Aggregate price dispersion regression:
  - Normalize each product's price by its time-series mean
  - Compute standard deviation of normalized prices across products in every period
  - Estimate an AR(1) on the dispersion.
  - Run the same regression in the model to discipline (ρ_v, σ_v)

- 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.
  - Replicate the same regression in the model to discipline ψ_p

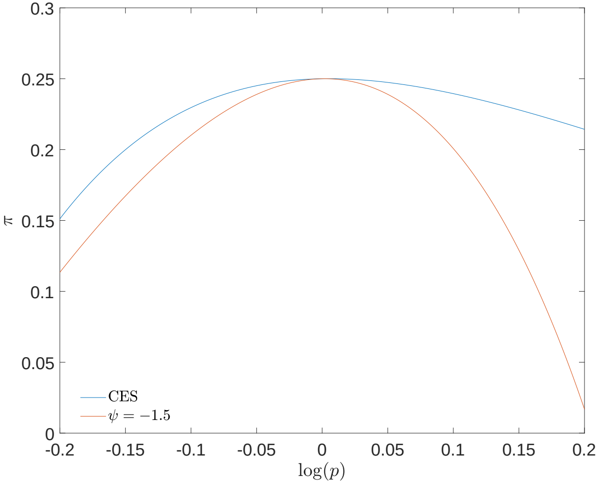
return

Solution Details

- Model features aggregate uncertainty
- Firms need to forecast P_t/S_t and λ_t before making their pricing decisions
  - Distribution of firms' states is an infinite-dimensional object
- Krusell-Smith algorithm: to forecast P_t/S_t and λ_t, firms use a regression on (v_t, χ_t, g_t) conditional on u_t^{news}
- Furthermore, firms need the law of motion of g_t, which is conjectured to be a regression on (v_t, v_{t+1}, g_{t+1}) conditional on u_t^{news}
- Given guesses for the law of motion, use VFI to solve for the Decision Rule. Then, search for the regression coefficients so that the simulated law of motion is well approximated by the conjectured law of motion.

return

Kimball Profit Function



Over-pricing' is more costly under Kimball demand.

Model Decision Rule

Main Mechanism

Main Mechanism

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

Profit Function with Kimball

return

Value Function

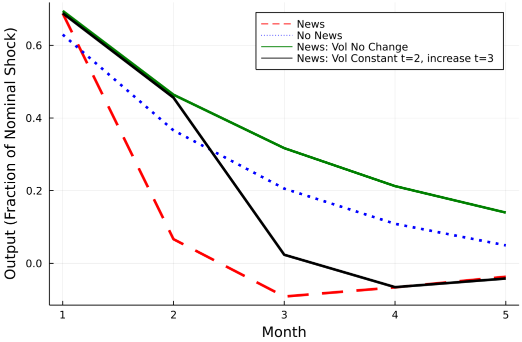
$$\chi_t \equiv \log\left(\frac{P_{t-1}}{S_t}\right), \quad g_t \equiv \int \frac{p^i_{t-1}/S_t}{n^i_t} di, \quad \mathbb{A}_t \equiv (\chi_t, g_t, v_t, u^{news}_t)$$

$$\begin{aligned}
V_N\left(\frac{p^i_{t-1}}{S_t}, n^i_t, z^i_t; \mathbb{A}_t\right) &= \pi\left(\frac{p^i_{t-1}}{S_t}, n^i_t, z^i_t; \chi_t, \lambda_t\right) + \mathbb{E}_t\left[\Xi_{t+1,t} V\left(\frac{p^i_{t-1}}{S_{t+1}}, n^i_{t+1}, z^i_{t+1}, f^i_{t+1}; \mathbb{A}_{t+1}\right)\right] \\
V_A\left(n^i_t, z^i_t, f^i_t; \mathbb{A}_t\right) &= -f^i_t \frac{W_t}{P_t} + \max_{p^i_t}\left\{\pi\left(\frac{p^i_t}{S_t}, n^i_t, z^i_t; \chi_t, \lambda_t\right) + \mathbb{E}_t\left[\Xi_{t+1,t} V\left(\frac{p^i_t}{S_{t+1}}, n^i_{t+1}, z^i_{t+1}, f^i_{t+1}; \mathbb{A}_{t+1}\right)\right]\right\} \\
V(\cdot) &= \max\left[V_A(\cdot), V_N(\cdot)\right]
\end{aligned}$$

Solution Method Return

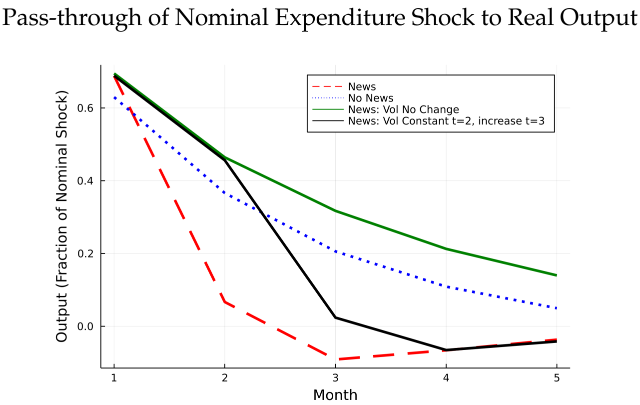
Persistent News

Pass-through of Nominal Expenditure Shock to Real Output



- 5 periods in a row of news: Anticipation increases effectiveness of MP.

Persistent News



- 5 periods in a row of news: Anticipation increases effectiveness of MP.
- As soon as volatility increases, MP loses all of its power. Return