The Macroeconomics of Sticky Prices with Generalized Hazard Functions

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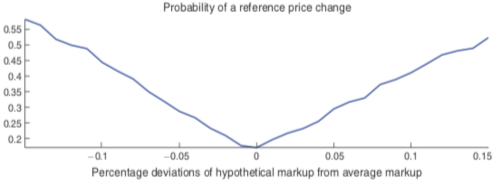
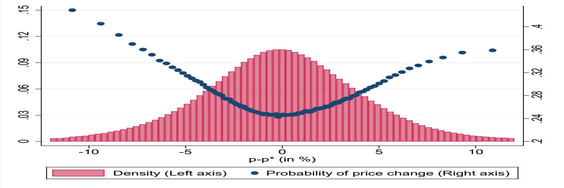
Motivation: state-dependent price changes

Prob. of price-change depends on "gap" from ideal price $x \equiv p - p^*$

Eichenbaum, Jaimovic, Rebelo (AER 2011)



Gautier and Le Saout (JMCB 2015)



Caballero-Engel's : Generalized Hazard Function (GHF): $\Lambda(x)$

Relation to literature and new results

- Caballero-Engel's : Generalized Hazard Function (GHF) : $\Lambda(x)$
  Prob. of price-change depends on gap from ideal price

- Random Menu Cost model w/ idiosyncratic shocks:

  Caballero-Engel (1993,1999,2007), Dotsey-King-Wolman (1999)

- Several applications: Berger-Vavra (2018), Petrella et al. (2018), Woodford (2008), Constain-Nakov (2011), others

- Three new analytic results :

  (T1) GHF increasing $\Longrightarrow$ Dist. menu cost, (so $\Longleftrightarrow$),

  (T2) Dist. of price changes $\Longrightarrow$ GHF & dist. price gaps f, (so $\Longleftrightarrow$).

  (T3) Sufficient statistic for monetary shock; $\text{CIR}^{Y} = \frac{\text{Kurtosis}}{6\ \text{Frequency}} \times$ shock,

  - - - Max CIR (kurtosis): Constant GHF (Calvo), Min: Golosov-Lucas.

Firm's Problem: Bellman equation Caballero-Engel

- uncontrolled price gap x: driftless random walk w/variance $\sigma^2 dt$

$$r\,v(x) = \min\Big\{ \underbrace{B\,x^2}_{\text{flow cost}} + \frac{\sigma^2}{2} v''(x) + \kappa \int_0^{\Psi} \min\{\psi + v(0) - v(x)\,,\, 0\} dG(\psi)\,,\; r(v(0) + \Psi) \Big\}$$

  - Random cost ψ drawn w/prob.: $\kappa\, dG(\psi)$ each period of length dt
  - Pay Ψ and adjust at any time.

- Optimal decision rule $\bar{x}(\psi)$ and X
  - If $|x| < X \rightarrow$ **adjust w/ prob.** $\Lambda(x) = \kappa\, G\,(v\,(x) - v\,(0))$ per dt
  - If $|x|$ reaches $X \rightarrow$ **adjust w/certainty**, $\Lambda(X)dt = 1$ standard sS.
  - Generalized Hazard Function $\Lambda(x)$, increasing in $|x|$

- Calvo: $\kappa > 0$, G mass point at $\psi = 0$, and $\Psi = \infty$

- Golosov Lucas: $\kappa = 0$ and $\Lambda(x) = 0, x \in (-X, X)$ and $\Psi < \infty$

(T1) – Inversion Result

- Caballero Engel: CDF $G \implies \Lambda$ increasing and symmetric GHF.

- **New result:** Take Λ increasing and symmetric $\implies G$

  Fix volatility $\sigma^2 = Var(\Delta p)\, N_a$, curvature B, and discount rate r.

  Consider an upper bd X & symmetric, weakly increasing GHF Λ.

  Then there is a unique Ψ and CDF G that rationalizes X, Λ.

- **Importance:** can use any weakly increasing symmetric GHF Λ

  to fit data or write models.

- Solving Bellman equation and policy is hard, non-linear o.d.e.
  Solving for G given Λ **easy and constructive**: linear o.d.e.
  (discrete values on $G \implies$ linear system of eqns).

- Results holds if there is a drift μ on price gap x.

Steady State: invariant gaps f & price changes q

- Intermediate step: $f(x)$ invariant distribution of price gaps x

  Solves the KFE for all $x \in [-X, X]$, $x \neq 0$:

  $$f(x)\Lambda(x) = \frac{\sigma^2}{2} f''(x) \quad \text{and } f \text{ continuous at all } x$$

  with $f(-X) = f(X) = 0$ and $\int_{-X}^{X} f(x)dx = 1$.

- Number of price changes per unit of time

  $$N_a = \underbrace{\int_{-X}^{X} f(x)\Lambda(x)dx}_{\#\text{with } x \ \Pr(\text{change})} + \underbrace{\sigma^2 |f'(X)|}_{\Pr(\text{change at barrier})}$$

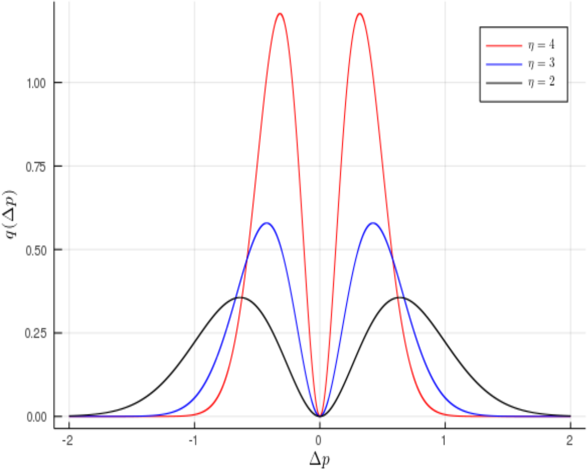
- Price changes have *mass point(s)* at $\pm X$ if $X < \infty$

- Symmetric *density* of price changes q for all $x \in (-X, X)$

  $$\Delta p = \begin{cases} -x & \text{w/ density } q(x) = \frac{\Lambda(x) f(x)}{N_a} \text{ provided that } |x| < X, \\ -X & \text{w/ probability mass } \frac{\frac{\sigma^2}{2}|f'(X)|}{N_a} \end{cases}$$

Example of density price changes: $q(\Delta p)$

Quadratic Hazard: $\Lambda(x) = \kappa x^2$, $X = \infty$, different $\eta \equiv \left(\frac{2\kappa}{\sigma^2}\right)^{\frac{1}{4}}$



(T2) – Recovering f, Λ and G from dist. $q(\Delta p)$

- Price changes have density $\Delta p \sim q(\cdot)$ for $x \in (-X, X)$.
- Assume q is symmetric., let Q be its CDF, so $q = Q'$.
- Using equations above: $q \implies f \implies \Lambda$:

  Invariant distribution f:

  $$f(x) = \frac{2}{Var(\Delta p)} \left[\int_x^{\infty} (1 - Q(z)) \, dz \right] \text{ for all } x \geq 0$$

  and Generalized Hazard Function Λ:

  $$\Lambda(x) = \frac{N_a \, Var(\Delta p)}{2} \; \frac{q(x)}{\int_x^{\infty} (1 - Q(z)) \, dz} \text{ for all } x > 0$$

- Given Λ & previous recovery results, we get:

  $q \implies f \implies \Lambda \implies G$ (distribution of menu cost)
  Recovery result can be extended to model with drift

- Easily extend case w/drift (Bailey-Blanco data by Lippi-Lotti)

- Sketch of proof for case w/no drift
  - Model gives us:

$$\frac{\Lambda(x) f(x)}{N_a} = q(-x) \quad , \quad \frac{\sigma^2}{2} f''(x) = \Lambda(x) f(x) \quad \text{for all } x \geq 0$$

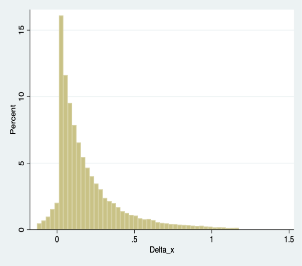
  - Replace KFE into eqn for q and recall $\sigma^2 = Var(\Delta p)\, N_a$:

$$\frac{\sigma^2}{2} \frac{f''(x)}{N_a} = q(-x) \;\; \text{all } x \geq 0$$

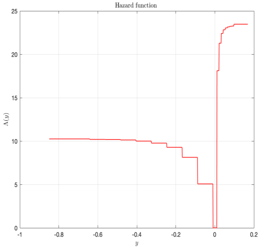
    - Integrate w.r.t x twice gives $f(x)$.
    - Use f and definition of q again to get Λ.
- Similar argument where there is drift for (T1) and (T2).
- **Summary:** Model $\sim G \iff \Lambda \iff q \sim$ Data

A problem with investment data (large drift)

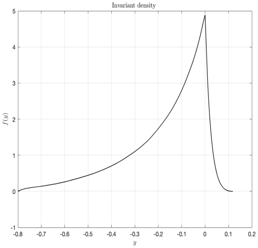
Data from Baley & Blanco $Q(-\Delta x)$



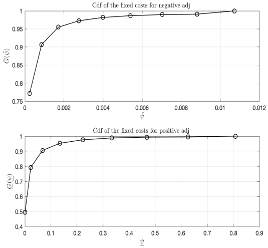
Hazard function $\Lambda(\Delta x)$



Invariant density $f(\Delta x)$



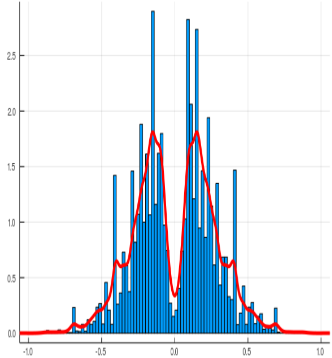
Cost CDF $G(\psi)$



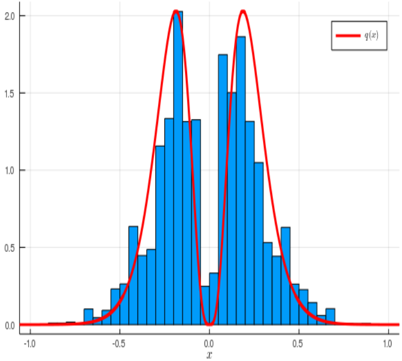
Application to Cavallo's online prices (zero drift)

Figure: Distribution of price changes - Histogram

Fitting Kernel density for *q*



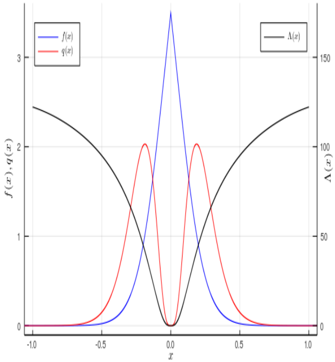
Fitting a Gamma distribution for *q*



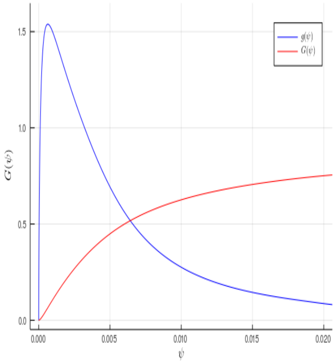
Pooling all products for category 561, COICOP label "Non-durable household goods"

Application: data corrected for Unobs. Heterogeneity

Recovered Hazard Λ and density f



Recovered cost distr. $g(\psi), G(\psi)$

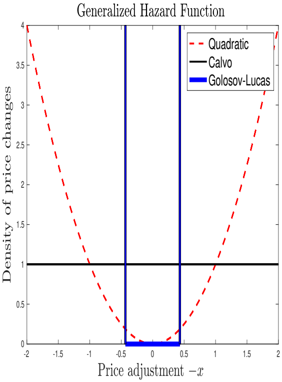


Pooling all products and correcting for heterogeneity

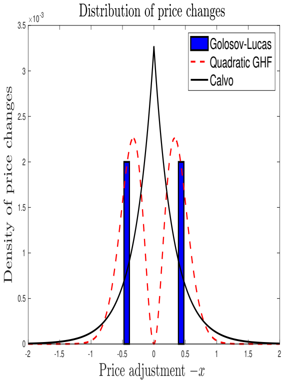
Comparison of three models

Same frequency of price changes $N_a = 1$
Same standard deviation of price changes $Std(\Delta)$

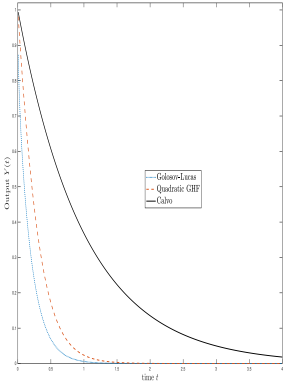
Generalized Hazard Function $\Lambda(x)$



Distribution price changes $q(x)$



Output IRF $Y(t)$

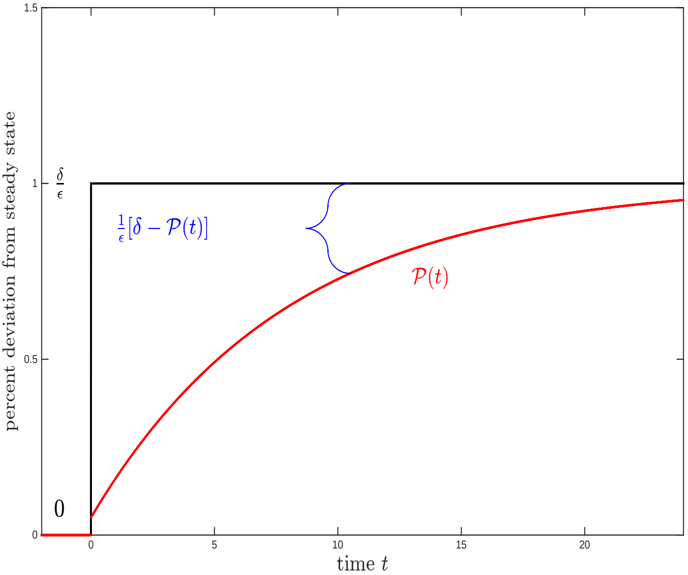


(T3) – Cumulative Response to Aggregate Shock

- Once and for all monetary (cost) shock of size δ
- GE model with NO strategic complementarity (as original GL)
- Effect of aggregate price level $\mathcal{P}(t;\delta)$ at horizon t
- Effect on output $Y(t;\delta) = (1/\epsilon)\,[\delta - \mathcal{P}(t,\delta)]$ at horizon t.
- Output Cumulative IRF to δ shock: $\mathcal{M}(\delta) = \int_0^\infty Y(t,\delta)dt$
- Small shock $\mathcal{M}(\delta) \approx \mathcal{M}'(0)\delta$ since by definition $\mathcal{M}(0) = 0$.
- Keep same decision rules (extension using MFG's)
- Show that: $\mathcal{M}(\delta) = \frac{1}{\epsilon}\frac{Kurt(\Delta p)}{6N_a}\delta + o(\delta^2)$

  ϵ GE elasticity unrelated to price setting –labor supply, etc.

Impulse response of output



Sufficient Statistic for CIR

- Reminder is of third order:

$$\mathcal{M}(\delta) = \mathcal{M}(0) + \mathcal{M}'(0)\delta + \frac{1}{2}\underbrace{\mathcal{M}''(0)}_{=0}\delta^2 + o(\delta^2) = \frac{1}{\epsilon}\frac{Kurt(\Delta p)}{6N_a}\delta + o(\delta^2)$$

- Only weakly increasing Λ can be rationalized as random menu cost or optimal adjustment intensity model.

- Among the weakly increasing Λ the inverted-L hazard Λ (i.e. Golosov and Lucas) has the smallest $Kurt(\Delta p) = 1$.

- Among the weakly increasing Λ the constant hazard Λ (i.e. Calvo) has the largest $Kurt(\Delta p) = 6$.

- non-monotone Λ may yield $Kurt(\Delta p) > 6$; can be arbitrarily large.

- $Kurt(\Delta p)$ measures lack-of-selection selection for price increases after a positive aggregate shock.

Scope & limitations of sufficient statistic result

- Sufficient statistic $\mathcal{M}'(0) = \frac{1}{\epsilon} \frac{Kurt(\Delta p)}{6 \, N_a}$
  - holds in Calvo$^+$ w/Multiproduct, and w/arbitrary Time dependent.
  - Insensitive, up to first order, to :
    - steady state inflation μ: $\frac{\partial \left(\mathcal{M}'(0) \right)(\mu)}{\partial \mu} \Big|_{\mu=0} = 0$
    - asymmetries in objective function
  - In relative terms w/strategic complementarities θ

    $$\mathcal{M}'(0;\theta) = \mathcal{M}'(0;0)\,(1 + \Upsilon(\theta))$$

    where θ weight of optimal price on aggregate price.

    $\Upsilon(\theta)$ independent of price setting statistics (Kurt & Freq.)
- Does NOT hold:
  - Large inflation/drift (Sheshinsky-Weiss, Blanco-Baley)
  - Firms do not close gap - “sales” (Alvarez-Lippi AEJ20, ERJ AER11)

Test sufficient statistic using cross industry data

- Empirical Strategy:
  3 main steps (using granular French data on PPI and CPI):

  1) Construct measures of the effect of a monetary shock for different **sectors**, using a FAVAR (Bernanke, Boivin and Eliasz, 2005) estimated on **sectoral** and aggregate time series. Different identification strategies.

  2) Using CPI/PPI **micro data**, calculate moments of the price change distribution at the product level for each **sector**: frequency, kurtosis, mean and skewness

  3) Relate - across sectors - product-level moments and the Cumulative Impulse Response to a monetary shock (i.e. $\mathcal{M}$)

- Findings:
  - Expected sign & magnitudes of coefficients across industries.
  - Other moments (inflation, variance, skewness) not significant.
  - Significant for PPI, borderline for CPI.

Extensions and future work

- Alternative foundations for GHF (inattention), as Woodford.
- Equivalent identification using spell durations
- Computation of entire IRF using eigenfunctions-eigenvalues
- Example: Flexibility Index: not sufficient statistic for CIR.
- Future Work: models with strategic complementarities (MFG)

The slides below are based upon

Empirical Investigation of a Sufficient Statistic for Monetary Shocks

Fernando Alvarez, Andrea Ferrara, Erwan Gautier, Hervé Le Bihan, and Francesco Lippi

Empirical Implication of Sufficient Statistic

- Output's IRF at time s for **sector** j :
  $Y^j(s) = \frac{1}{\varrho_j}\left[\delta - P^j(s)\right]$
- Cumulated Impulse Response:
  Output $CIR_T^{Y_j} \equiv \int_0^T Y^j(s)ds$ & Prices $CIR_T^{P_j} \equiv \int_0^T P^j(t)ds$
- Thus, for large horizon T, we have:
  $CIR_T^{Y_j} = \frac{1}{\varrho_j}\left(\delta T - CIR_T^{P_j}\right) \approx \frac{\delta}{\varrho_j 6}\frac{Kurt_j}{Freq_j}$
- Main theoretical prediction to be tested:

$$CIR_T^{P_j} = \delta T - \frac{\delta}{6}\frac{Kurt_j}{Freq_j} + \epsilon_j \tag{1}$$

- Using a first order Taylor expansion around means $\bar{F}, \bar{K}$:

$$CIR_T^{P_j} \approx CIR_T^{\bar{P}} - \frac{\delta}{6}\frac{\bar{K}}{\bar{F}}\frac{Kurt_j}{\bar{K}} + \frac{\delta}{6}\frac{\bar{K}}{\bar{F}}\frac{Freq_j}{\bar{F}} + \epsilon_j \tag{2}$$

Data (France)

- **Macro time series**:
  - More than 300 sectoral-level price indices: CPI products at COICOP5 and PPI NACE Rev2 at 4-digits
  - Aggregate Inflation, Industrial production, Unemployment rate, Consumption, 3-month Euribor
  - Benchmark: all series over 2005-2019 period (monthly)
- **Micro price data sets**:
  - PPI micro data set (1994-2005, manufacturing sector), 118 NACE rev2 4-digit products (Gautier 2008)
  - CPI micro data set (1994-2019, 60% CPI), 223 products at COICOP5 (Berardi et al. 2015)

Step 1: Measure sectoral CIR to monetary shocks

FAVAR methodology (Bernanke Boivin, Eliasz, QJE 2005)

- Y_t is the 3 month Euribor; X_t matrix of M information variables
- F_t **unobserved** factors (principal components of X_t) $<< M$
- Estimate a VAR on $[F_t \; Y_t]$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \quad (3)$$

- **Impulse response function** of **each** X_t for a shock on Y_t

- Replace F_t by estimated Factors $\hat{F}$, using X_t containing a large number of aggregate and sectorial time series in:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \quad (4)$$

- **Estimated factors** $\hat{F}_t$ are the principal component of X_t

Step 1: Measure sectoral CIR to monetary shocks

- Identification
  - Recursive Cholesky identification strategy, as in BBE-2005
  - Add a long term "neutrality" restriction: output comes back to its original level + all sectoral prices have the same response in the long run
- Normalisation of the shock so that the MP shock generates a 1% response in the price level, ie $\delta = 1\%$
- Alternative identifications: Cholesky with no long run restriction, high-frequency instrumental variable (Altavilla et al. 2019)
- Filtering the Euribor

Details on filtering

Step 3: Results Constrained Regression (PPI)

▸ Scatter plot

$$CIR_T^{P_j} = -T\delta + \frac{\delta}{6}\frac{Kurt_j}{Freq_j}$$

Identification	Cholesky Long-run Restriction $T = 24m$	Cholesky Long-run Restriction $T = 36m$	Cholesky No Long-run Restriction $T = 24m$	Cholesky No Long-run Restriction $T = 36m$	High-Frequency IV Long-run Restriction $T = 24m$	High-Frequency IV Long-run Restriction $T = 36m$
Kurt/Freq	0.0669**	0.0974***	0.690***	1.124***	0.192***	0.242***
	(0.0326)	(0.0355)	(0.220)	(0.341)	(0.0614)	(0.0801)
Constant	-20.57***	-35.16***	-48.02***	-81.88***	-34.27***	-52.21***
	(2.130)	(2.199)	(13.43)	(20.51)	(3.638)	(4.799)
Obs.	118	118	118	118	118	118
R^2	0.041	0.082	0.117	0.135	0.131	0.118

- The **evidence** is supportive of the sufficient statistic result:
  - Coefficient of *kurt*/*freq*: positive and statistically significant
  - Constant term: negative and statistically significant

▸ Tests

Results Unconstrained Regression (PPI)

$$CIR_T^{P_j} \approx CIR_T^{\bar{P}} - \frac{\bar{K}}{\bar{F}} \frac{\delta}{6} \frac{Kurt_j}{\bar{K}} + \frac{\bar{K}}{\bar{F}} \frac{\delta}{6} \frac{Freq_j}{\bar{F}}$$

Identification	Cholesky Long-run Restriction		Cholesky No Long-run Restriction		High-Frequency IV Long-run Restriction	
	$T = 24m$	$T = 36m$	$T = 24m$	$T = 36m$	$T = 24m$	$T = 36m$
$Freq/\bar{F}$	-2.501*	-3.153**	-23.65***	-37.41***	-6.004**	-7.239*
	(1.279)	(1.314)	(8.897)	(13.96)	(2.776)	(3.761)
$Kurt/\bar{K}$	3.663*	4.665**	28.83**	45.17**	6.662**	7.922*
	(1.897)	(1.995)	(11.66)	(17.59)	(3.100)	(4.010)
Constant	-18.82***	-32.42***	-23.13*	-40.64**	-26.56***	-42.36***
	(2.208)	(2.166)	(12.73)	(18.61)	(3.011)	(3.960)
Obs.	118	118	118	118	118	118
R^2	0.106	0.161	0.240	0.259	0.217	0.179

- Kurtosis and frequency are statistically significant
- F-test null: coefficients of $Freq/\bar{F} = -Kurt/\bar{K}$

Tests

More Tests on the Model's Predictions

Back1 Back2

- Under a strict interpretation, predicted coefficients are:
- In constrained version of model: $\beta = 1/6$ and $\alpha = -T$
- In unconstrained version of model: $\beta^k = -\beta^f = \frac{\delta}{6}\frac{\bar{K}}{\bar{F}}$

Identification	Cholesky LRR $T = 24$	Cholesky LRR $T = 36$	Cholesky No LRR $T = 24$	Cholesky No LRR $T = 36$	High-Freq. IV LRR $T = 24$	High-Freq. IV LRR $T = 36$
Constrained model						
P-val $\beta = 1/6$	0.003	0.053	0.019	0.006	0.681	0.351
P-val $\alpha = -T$	0.111	0.702	0.076	0.027	0.006	0.000
Unconstrained model						
P-val $\beta_f = -\beta_k$	0.566	0.457	0.648	0.643	0.819	0.857
P-val $\beta_f = -\frac{\bar{K}}{6\bar{F}}$	0.130	0.325	0.033	0.020	0.577	0.460
P-val $\beta_k = \frac{\bar{K}}{6\bar{F}}$	0.679	0.915	0.039	0.022	0.477	0.389

- If mismeasurement, the estimated coefficient can be downward biased ie ranging between 0 and 1/6

Reverse regression

Placebo Test: Sufficient Statistic

- Theory: zero derivative of CIR w/respect to odd moments,
  $\frac{\partial}{\partial \pi} CIR^{P_j}(\delta, \pi_j)\big|_{\pi_j=0} = 0$
  where π_j is sector *j* steady state inflation, or skewness
- Include other moments (mean and skewness of price changes) in the restricted regression
- These moments should not change the sign, nor be significantly different from zero

$$CIR_T^{P_j} = \alpha + \beta^r \frac{Kurt_j}{Freq_j} + \beta^m mean_j + \beta^s skew_j + \epsilon_j \quad (5)$$

Results of a Placebo Test (PPI)

Identification	Cholesky Long-run Restriction $T = 24m$	Cholesky Long-run Restriction $T = 36m$	Cholesky No Long-run Restriction $T = 24m$	Cholesky No Long-run Restriction $T = 36m$	High-Frequency IV Long-run Restriction $T = 24m$	High-Frequency IV Long-run Restriction $T = 36m$
Kurt/Freq	0.0849*	0.110**	0.715**	1.130**	0.168**	0.202**
	(0.0477)	(0.0488)	(0.284)	(0.432)	(0.0750)	(0.0989)
Mean	-0.418	-0.479	-6.211	-9.930	-1.212	-1.408
	(0.905)	(1.000)	(5.311)	(8.251)	(1.432)	(1.857)
Skewness	1.759	1.006	-5.014	-12.47	-4.613	-6.889*
	(3.434)	(3.100)	(15.18)	(21.06)	(2.783)	(4.109)
Standard dev.	-0.940	-0.749	-4.317	-5.494	0.219	0.726
	(1.016)	(1.083)	(7.037)	(10.86)	(1.964)	(2.535)
Constant	-16.65***	-31.95***	-27.65	-54.88	-34.44***	-54.26***
	(4.669)	(4.791)	(26.68)	(40.24)	(7.221)	(9.552)
Obs.	118	118	118	118	118	118
R^2	0.054	0.089	0.125	0.142	0.140	0.130

- Mean and skewness not statistically relevant
- Constant remains negative and statistically significant
- Coeff. *Kurt / Freq* very close to the one in constr. regression

Unconstrained

CPI Results: Weaker than PPI

Identification	Cholesky Long-run Restriction $T=24m$	Cholesky Long-run Restriction $T=36m$	Cholesky No Long-run Restriction $T=24m$	Cholesky No Long-run Restriction $T=36m$	High-Frequency IV Long-run Restriction $T=24m$	High-Frequency IV Long-run Restriction $T=36m$
Constrained Model						
Kurt/Freq	-0.0170	-0.0025	0.115*	0.233**	0.0495**	0.0720**
	(0.0165)	(0.0199)	(0.0658)	(0.105)	(0.0242)	(0.0315)
Constant	-11.64***	-27.36***	-21.20*	-47.72***	-34.43***	-54.70***
	(2.809)	(3.285)	(10.81)	(17.13)	(3.434)	(4.419)
R^2	0.004	0.000	0.014	0.023	0.019	0.024
Unconstrained Model						
$Freq/\bar{F}$	-4.920*	-8.540**	-54.17***	-91.14***	-16.36***	-21.30***
	(2.809)	(3.331)	(13.77)	(21.32)	(3.894)	(4.812)
$Kurt/\bar{K}$	4.359*	5.657**	6.648	8.581	7.132***	9.175***
	(2.328)	(2.594)	(4.523)	(7.023)	(2.201)	(2.806)
Constant	-12.61***	-24.70***	36.70***	55.84***	-20.74***	-36.08***
	(3.684)	(4.267)	(13.17)	(20.40)	(4.907)	(6.274)
R^2	0.065	0.132	0.477	0.529	0.350	0.342
Observations	223	223	223	223	223	223

Reverse regression: PPI

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Identification	Cholesky Long-run Restriction $T=24m$	Cholesky Long-run Restriction $T=36m$	Cholesky No Long-run Restriction $T=24m$	Cholesky No Long-run Restriction $T=36m$	High-Frequency IV Long-run Restriction $T=24m$	High-Frequency IV Long-run Restriction $T=36m$
CIR	0.612***	0.845***	0.170***	0.120***	0.681***	0.488***
	(0.220)	(0.186)	(0.0320)	(0.0227)	(0.130)	(0.103)
Constant	54.38***	69.69***	46.64***	47.52***	61.22***	63.92***
	(5.117)	(7.050)	(2.665)	(2.698)	(4.765)	(5.781)
Observations	118	118	118	118	118	118
R^2	0.041	0.082	0.117	0.135	0.131	0.118

- Coefficient expected to be equal to 6
- If mismeasurement of CIR, then coef between 0 and 6

Placebo Test: PPI - unconstrained

Identification	Cholesky Long-run Restriction $T = 24m$	Cholesky Long-run Restriction $T = 36m$	Cholesky No Long-run Restriction $T = 24m$	Cholesky No Long-run Restriction $T = 36m$	High-Frequency IV Long-run Restriction $T = 24m$	High-Frequency IV Long-run Restriction $T = 36m$
$Freq/\bar{F}$	-2.865*	-3.337**	-24.17**	-37.39**	-5.488*	-6.347
	(1.454)	(1.491)	(10.35)	(16.28)	(3.258)	(4.406)
$Kurt/\bar{K}$	3.026	4.066	21.29*	33.52*	5.823*	7.153
	(3.048)	(2.796)	(12.09)	(17.14)	(3.177)	(4.673)
Mean	-0.254	-0.186	-4.946	-7.775	-0.855	-0.927
	(0.792)	(0.851)	(4.713)	(7.327)	(1.285)	(1.699)
Skewness	1.798	0.793	-5.560	-13.96	-4.708*	-7.159*
	(3.359)	(2.989)	(14.85)	(20.32)	(2.589)	(3.855)
Standard dev.	-0.916	-0.625	-5.324	-7.003	0.245	0.837
	(1.297)	(1.306)	(8.740)	(13.51)	(2.460)	(3.229)
Constant	-13.33*	-28.68***	9.428	2.375	-27.87*	-47.18**
	(7.379)	(7.539)	(48.08)	(75.03)	(14.08)	(18.59)
Observations	118	118	118	118	118	118
R^2	0.118	0.164	0.246	0.264	0.228	0.195

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Regression Results: Sector fixed effects (PPI)

Back

Identification	Cholesky Long-run Restriction		Cholesky No Long-run Restriction		High-Frequency IV Long-run Restriction	
	$T = 24m$	$T = 36m$	$T = 24m$	$T = 36m$	$T = 24m$	$T = 36m$
PANEL A: Constrained model						
Kurt/Freq	0.0366	0.0565*	0.393**	0.647***	0.119**	0.153**
	(0.0301)	(0.0321)	(0.157)	(0.239)	(0.0483)	(0.0662)
Constant	-14.93***	-27.83***	-23.02	-44.51**	-27.53***	-44.18***
	(2.701)	(3.153)	(14.04)	(20.87)	(3.258)	(3.918)
R^2	0.371	0.440	0.521	0.549	0.527	0.476
PANEL B: Unconstrained model						
$Freq/\bar{F}$	-1.705	-1.951	-11.87	-17.96	-2.621	-2.957
	(1.310)	(1.274)	(7.540)	(11.49)	(2.336)	(3.375)
$Kurt/\bar{K}$	2.562	2.722	21.48**	32.66**	3.630	3.823
	(1.964)	(1.984)	(10.41)	(15.38)	(2.902)	(3.963)
Constant	-14.62***	-26.72***	-18.73	-36.08*	-24.30***	-39.57***
	(2.986)	(3.177)	(13.94)	(19.64)	(2.908)	(3.588)
R^2	0.396	0.462	0.544	0.567	0.525	0.467
Observations	118	118	118	118	118	118

Regression Results: 2-year German Bond (PPI)

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Identification	High-Frequency IV		High-Frequency IV	
Long-run Restriction	Yes		No	
	24 months	36 months	24 months	36 months
PANEL A: Producer Prices - Constrained model				
Kurt/Freq	0.186***	0.244***	0.281***	0.446***
	(0.0669)	(0.0775)	(0.0923)	(0.149)
Constant	-20.34***	-34.78***	-24.42***	-43.44***
	(4.393)	(4.993)	(5.708)	(8.921)
R^2	0.069	0.091	0.092	0.095
PANEL B: Producer Prices - Unconstrained model				
$Freq/\bar{F}$	-5.148*	-6.623**	-8.765**	-14.20**
	(2.627)	(2.973)	(3.545)	(5.673)
$Kurt/\bar{K}$	8.553**	10.98**	7.425	8.914
	(3.931)	(4.451)	(4.794)	(7.257)
Constant	-15.64***	-28.50***	-10.82*	-18.71**
	(5.071)	(5.651)	(6.015)	(8.594)
R^2	0.104	0.131	0.144	0.149
Observations	118	118	118	118

Comparison with Hong et al. (2020) (1/3)

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Hong-Klepacz-Pasten-Schoenle "The Real Effects of Monetary Shocks: Evidence from Micro Pricing Moments" (2020) Banco Central Chile, WP 875

- HKPS (2020) carry out a similar empirical exercise to ours, using US cross sectoral PPI moments
- Compute IRF of prices using FAVAR and other approaches, and relate these to sectoral moments
- Main claim: hypothesis “kurtosis over frequency is a sufficient statistic” is rejected

However, several weaknesses and shortcuts

Comparison with HKPS (2020) (2/3)

Back

- Issue #1: The outcome variable in the regressions is the *level response of prices*, while the theory concerns the *cumulated response of output*: the dependent variable in their regressions is *not* the one that the theory focuses on.

- Issue #2: In most of their regressions, Kur/Freq ratio is a significant determinant or price (or sales) response to monetary policy shock, in line with theory! Ratio-Table 1 Ratio-Table 11

Comparison with HKPS (2020) (3/3)

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- Issue #3: When removing sectoral “fixed effects” in the cross sector regression (with N=148), both Freq and Kur, are separately significant with expected sign Table 12
- Issue #4: Claim by HKPS is (Kur/Freq) cannot be a ”sufficient statistic” because R^2 are $<<$ 1 .
  $R^2 = 1$ is an inadequate criterion. In most datasets, measurement errors weaken the fit of the relation between variables.

HKPS 2020 - Table 1

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Cross-Sectional Determinants of Sectoral Price Response									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$	-0.250***								
	(0.074)								
Log Frequency		0.422***				0.476***	0.471***	0.385***	0.252**
		(0.073)				(0.074)	(0.084)	(0.093)	(0.123)
Log Kurtosis			0.138			-0.151	-0.163	-0.138	-0.096
			(0.119)			(0.112)	(0.122)	(0.113)	(0.120)
Log Avg. Size				-0.316**			-0.054	-0.097	-0.004
				(0.148)			(0.207)	(0.213)	(0.192)
Log Standard Dev.					-0.158		0.033	0.053	-0.115
					(0.127)		(0.138)	(0.149)	(0.124)
Log Profit								-0.341**	-0.228
								(0.154)	(0.145)
SD(e_k)									10.625
									(12.229)
$\rho(e_k)$									0.595***
									(0.119)
NAICS 3 FE	X	X	X	X	X	X	X	X	X
R^2	0.429	0.502	0.394	0.407	0.393	0.509	0.509	0.519	0.597
N	148	148	148	148	148	148	148	147	147

Table 1: Decomposing Monetary Non-Neutrality

NOTE: This tables uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: $log(IRF_{k,h}) = a + \alpha_j + \beta' M_k + \gamma' X_j + \epsilon_{k,h}$. Where $Log(IRF_{k,h})$ is the log of the 24-month cumulative sectoral response of prices to a monetary shock from our FAVAR analysis. M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, and standard deviation of price changes, or the full set of pricing moments. α_j are three-digit NAICS industry fixed effects and are included in all specifications. X_j are sector level controls including gross profit rate, the volatility of sector level shocks

HKPS 2020 - Table 11

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Cross-Sectional Determinants of Sectoral Price Response Univariate Specifications						
	Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1	
	(1)	(2)	(3)	(4)	(5)	(6)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$	-0.420***	-0.250***	-0.493***	-0.335***	-0.448***	-0.269***
	(0.060)	(0.074)	(0.066)	(0.074)	(0.071)	(0.077)
NAICS 3 FE		X		X		X
R^2	0.177	0.429	0.130	0.413	0.213	0.448
N	148	148	147	147	147	147
Log Frequency	0.448***	0.422***	0.470***	0.454***	0.507***	0.521***
	(0.056)	(0.073)	(0.060)	(0.078)	(0.067)	(0.094)
NAICS 3 FE		X		X		X
R^2	0.303	0.502	0.268	0.484	0.296	0.483
N	148	148	148	148	148	148
Log Kurtosis	0.289***	0.138	0.303**	0.072	0.301**	0.181
	(0.106)	(0.119)	(0.131)	(0.129)	(0.124)	(0.122)
NAICS 3 FE		X		X		X
R^2	0.042	0.394	0.035	0.395	0.026	0.382
N	148	148	147	147	147	147
Log Avg. Size	-0.594***	-0.316**	-0.497***	-0.313	-1.065***	-0.536**
	(0.120)	(0.148)	(0.182)	(0.231)	(0.205)	(0.234)
R^2	0.106	0.407	0.119	0.404	-0.095	0.373
N	148	148	148	148	148	148
Log Std. Dev.	-0.456***	-0.158	0.259	-0.031	0.865	0.743
	(0.141)	(0.127)	(0.412)	(0.474)	(0.536)	(0.595)
NAICS 3 FE		X		X		X
R^2	0.067	0.393	0.011	0.387	-0.028	0.355
N	148	148	147	147	147	147

Source: HKPS 2020, WP 875, Banco Central De Chile

HKPS 2020 - Table 12

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Cross-Sectional Determinants of Sectoral Price Response Multivariate Specifications						
	Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Frequency	0.520***	0.476***	0.561***	0.549***	0.623***	0.601***
	(0.056)	(0.074)	(0.062)	(0.074)	(0.072)	(0.099)
Log Kurtosis	-0.222**	-0.151	-0.237*	-0.223*	-0.313**	-0.220*
	(0.104)	(0.112)	(0.127)	(0.120)	(0.125)	(0.118)
NAICS 3 FE		X		X		X
R^2	0.320	0.509	0.277	0.481	0.331	0.501
N	148	148	147	147	147	147
Log Frequency	0.501***	0.471***	0.668***	0.610***	0.594***	0.581***
	(0.074)	(0.084)	(0.111)	(0.121)	(0.107)	(0.118)
Log Kurtosis	-0.165	-0.163	-0.062	-0.129	-0.307	-0.270
	(0.117)	(0.122)	(0.190)	(0.201)	(0.189)	(0.212)
Log Avg. Size	0.113	-0.054	0.298	0.212	-0.161	-0.107
	(0.212)	(0.207)	(0.278)	(0.326)	(0.296)	(0.279)
Log Std. Dev.	-0.213	0.033	-0.597	-0.387	-0.052	0.230
	(0.156)	(0.138)	(0.555)	(0.731)	(0.670)	(0.816)
NAICS 3 FE		X		X		X
R^2	0.327	0.509	0.132	0.428	0.327	0.492
N	148	148	147	147	147	147

Source: HKPS 2020, WP 875, Banco Central De Chile

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