The Real Effects of Monetary Shocks: Evidence from Micro Pricing Moments

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[1]The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System.

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- Initiative launched by the Federal Reserve Bank of Cleveland in December 2018
- Focus on improving the understanding of policymakers, researchers, and the general public about inflation and its dynamics
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  - Enhanced external communications
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Motivation: Monetary Non-Neutrality

- Long-standing question in macroeconomics:
  To what extent can monetary policy shocks affect real output and consumption?
  - Depends on prices acting as shock absorbers
  - Small changes in pricing assumptions may have different implications
    - For example: menu cost vs. Calvo pricing

- A recent literature proposes a sufficient statistic approach for monetary non-neutrality:
  - Focus on kurtosis of price changes
  - Kurtosis of price changes embodies "selection effect" (Golosov and Lucas, 2006; Midrigan, 2011):
    - If prices are very far from desired prices, a monetary shock triggers disproportionately large price and small output responses
    - Kurtosis embodies low selection effect: small price, large output response
  - Most distilled in Alvarez et al. (2016): kurtosis over frequency is sufficient in a wide class of models

Motivation: Monetary Non-Neutrality

One proposal sufficient statistic:

> *"We analytically solve a menu cost model that encompasses several models, such as Taylor (1980), Calvo (1983), Reis (2006), Golosov and Lucas (2007), Nakamura and Steinsson (2010), Midrigan (2011) and Alvarez and Lippi (2014). The model accounts for the positive excess kurtosis of the size-distribution of price changes [. . .] We show that the ratio of kurtosis to the frequency of price changes is a sufficient statistics for the real effects of monetary shocks [. . .]"*
>
> *"We [. . .] conclude that a model that successfully matches the micro evidence produces persistent real effects that are about 4 times larger than the Golosov-Lucas model, about 30% below the effect of the Calvo model [. . .]"*

Alvarez, Le Bihan, Lippi (AER, 2016)

This paper

- Using producer micro price data from Bureau of Labor Statistics (BLS), empirically evaluate what price-setting moments are informative for monetary non-neutrality
  - Higher frequency means more responsiveness of prices
  - Higher kurtosis has ambiguous effects:
    - No association with prices, or:
    - Positive association with prices
  - Higher kurtosis over frequency decreases responsiveness of prices
    ✓Alvarez et al. (2016)

- Results are robust across monetary policy shock identification schemes
  - Romer and Romer (2005)
  - High-frequency identification
  - FAVAR

- Both DSGE menu cost and Calvo models can accommodate these results when matching micro price moments from the data:
  - Generate a positive association between kurtosis and price responses.

This paper

- Challenge to fundamental notion that kurtosis embodies the selection effect?
  - Empirically, kurtosis is not informative about monetary non-neutrality or even has the wrong posited sign: But does kurtosis not capture selection at all? Counter-intuitive.
  - Empirically, kurtosis over frequency is informative for monetary non-neutrality - how should we intuitively, correctly think about the underlying mechanism in menu cost models? A pure frequency effect?
- Resolution:

  Menu cost models predict a positive relationship between kurtosis and monetary non-neutrality if random menu costs lead to a large fraction of free price changes.
  - Intuition: raises "Calvo-ness" - more random small price changes

This paper: structure

- Recap: Sufficient statistic in Alvarez et al. (2016)
- Construct "micro-macro moments": aggregate IRFs jointly conditional on a monetary shock *and* micro moments

  Goal: evaluate informativeness of micro moments for monetary non-neutrality (wider applicability)
- Compare empirical to theoretical IRFs from models

Pricing Moment - Sufficient Statistic

- What is the sufficient statistic in Alvarez et al. (2016)?

Pricing Moment - Sufficient Statistic

Setup and main result in Alvarez, Le Bihan, Lippi (2016):

- Economy of multiproduct firms
- Second-order, continuous time approximation of profits
- Economies of scope in price-setting, free price changes
- No strategic complementarities, normal shocks, no trend inflation
- Aggregation following small, one-time monetary shock δ, ignoring GE effects

- **Sufficient statistic:**

$$\mathrm{M} = \frac{\delta}{6\epsilon}\frac{Kur(\Delta p_i)}{N(\Delta p_i)} \tag{1}$$

  where $\frac{1}{\epsilon}$ is the supply elasticity of labor to the real wage, and δ a small, one-time monetary shock.
- Intuition: Kurtosis embodies low selection effect.

Empirical Analysis

- Construct "micro-macro moments":

  Aggregate IRFs jointly conditional on a monetary shock *and* micro moments

Step 1: Slicing the Data

- Calculate sectoral pricing moments from BLS producer price (PPI) micro data
  - Time horizon: 1998-2005
  - 154 sectors at 6-digit NAICS
  - Key data steps:
    - Pool price changes at 6-digit month-NAICS level to mitigate outlier effects
    - Drop price changes $< |\$0.01|$ as in Alvarez et al. (2016)
    - Compute statistics at month-NAICS level, then average over time
  - Frequency, kurtosis, kurtosis over frequency, average size, and fraction small price changes

Step 1: Slicing the Data

- Construct two subsets of data:
  above and below median pricing statistic
- Calculate empirical aggregate IRFs for each subset
- Pricing moments of the subsets:

	Median Value	Below Median Average	Above Median Average
Frequency	0.10	0.06	0.28
Kurtosis	3.5	2.4	5.6
$\frac{\text{Kurtosis}}{\text{Frequency}}$	28.1	16.6	50.9
N	154	77	77

Table: Pricing Moment Slices

Step 2: Construct Price IRFs

- Construct (potentially) differential price responses to monetary shock
- Three identification schemes:
  - Narrative approach (R&R 2004)
  - High-frequency approach (Karadi and Gertler 2015)
  - FAVAR (BBE 2005, BGM 2009)
- Narrative approach model-free
- Very clean identification from high-frequency approach
- FAVAR uses data rich environment
- Next: Examine empirical price IRF of two subsets of data

Empirical IRF - Narrative Approach

- Narrative approach
  - Constructed using Greenbook forecasts
  - Regresses change in FFR around FOMC on lag of FFR and Fed's information set
  - Purging monetary shock series of forecastable variation
  - Narrative series free from endogenous and anticipatory actions

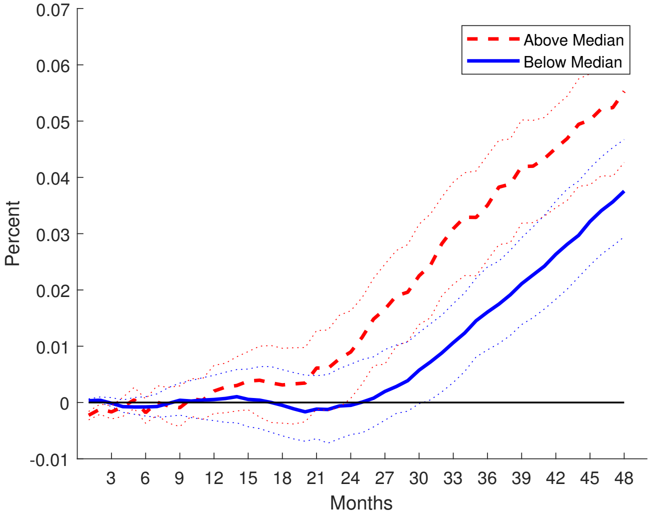
Empirical IRF - Narrative Approach

- Run baseline regression in Romer and Romer (2004)

$$\pi_t^c = \alpha^c + \sum_{k=1}^{11} \beta_k^c D_k + \sum_{k=1}^{24} \eta_k^c \pi_{t-k}^c + \sum_{k=1}^{48} \theta_k^c MP_{t-k} + \epsilon_t \qquad (2)$$

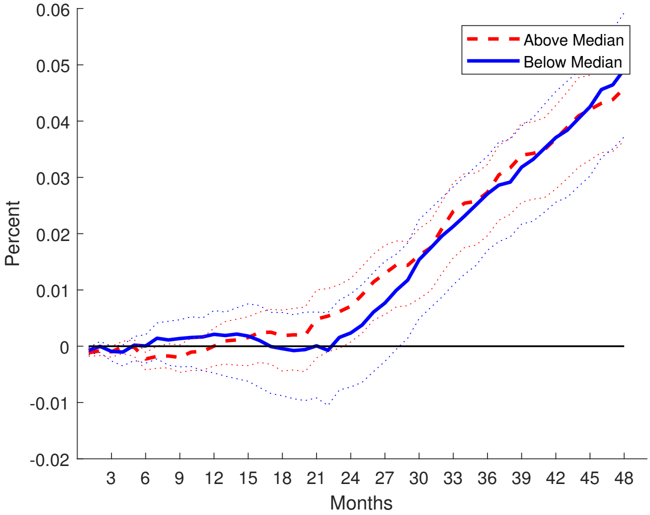
- Monthly data from 1969.3-2007.12
- 154 PPI data series
- Calculate as dependent variable the average inflation rate above and below median statistic

Empirical IRF - Narrative Approach



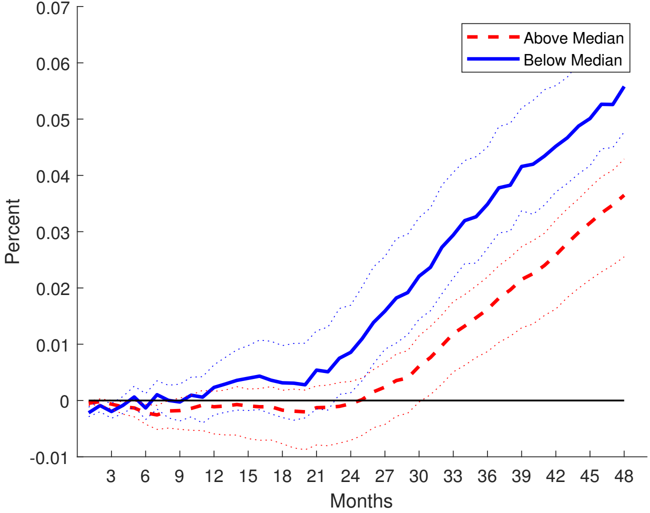
- High frequency of price changes: large price response.

Empirical IRF - Narrative Approach



- Irrelevance of kurtosis for impulse response.

Empirical IRF - Narrative Approach



- High kurtosis over frequency of price changes: lower price response.

Empirical IRF - Narrative Approach 2.0

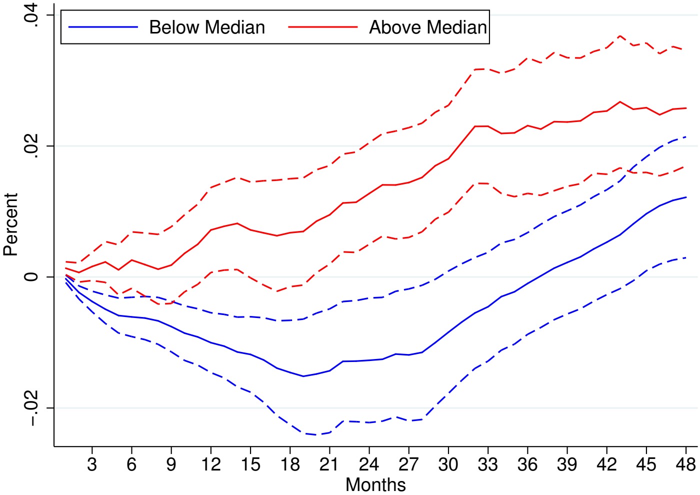
- Alternative specification also using Romer and Romer narrative identification:
  - Local projection method following Jorda (2005)
  - Regression specification:

$$log(ppi_{t+h})^c = \beta_h^c + \theta_h^c * MPshock_t + controls_t + \epsilon_{t+h}^c \quad (3)$$

  where controls include 2 lags of the shock, 2 lags of the Fed Funds rate, current and 2 lags of the unemployment rate, and industrial production.

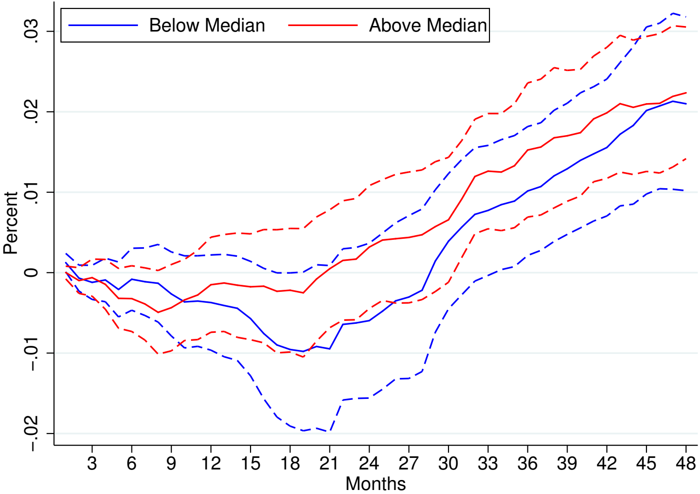
- Identical results continue to hold

Empirical IRF - Narrative Approach 2.0



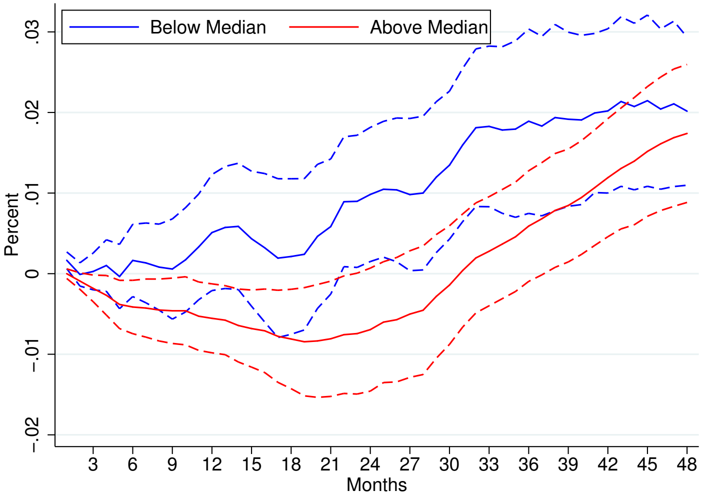
- High frequency of price changes: large price response.

Empirical IRF - Narrative Approach 2.0



- Irrelevance of kurtosis for impulse response. If anything, larger price response for higher kurtosis.

Empirical IRF - Narrative Approach 2.0



- High kurtosis over frequency of price changes: low price response.

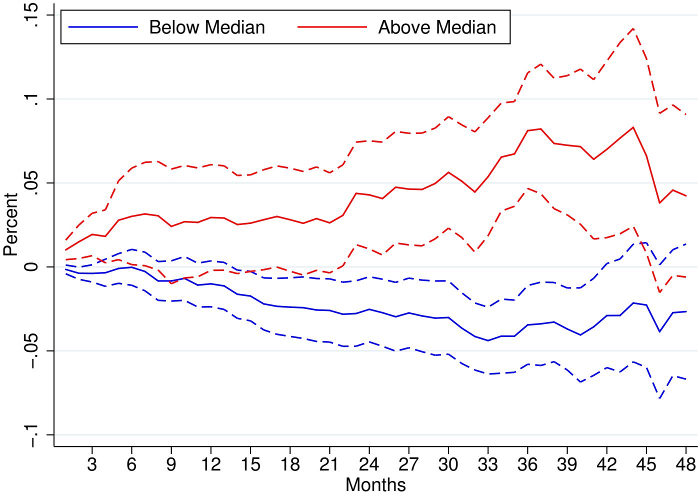
Empirical IRF - High-Frequency Approach

- High-frequency approach (Karadi and Gertler 2015)
- Monthly data from 1990.1-2012.6
- Run baseline regression

$$log(ppi_{t+h})^c = \beta_h^c + \theta_h^c * MPshock_t + controls_t + \epsilon_{t+h}^c \quad (4)$$

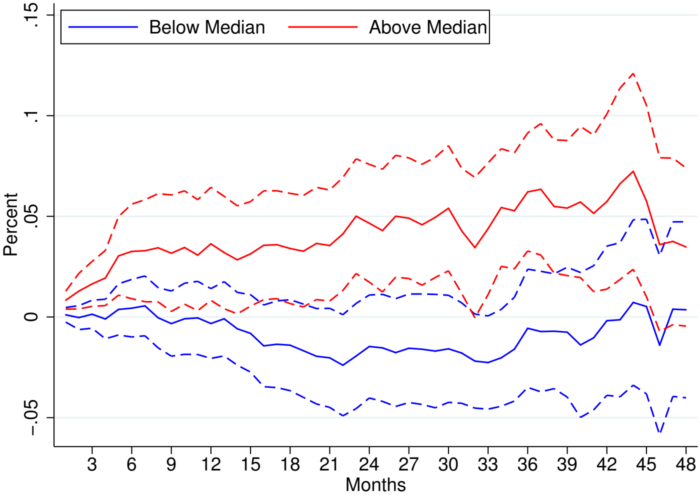
with previous set of controls.

Empirical IRF - High-Frequency Approach



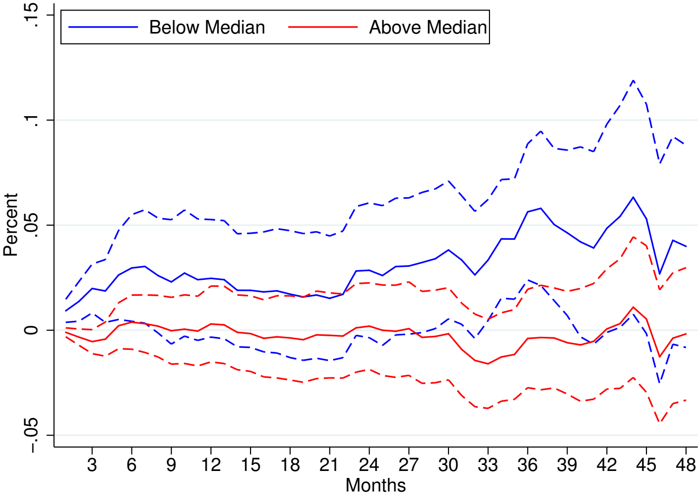
- High frequency of price changes: large price response.

Empirical IRF - High-Frequency Approach



- Wrong response: larger price response for higher kurtosis.

Empirical IRF - High-Frequency Approach



- Kurtosis over frequency: No significant difference.

Empirical IRF - FAVAR Approach (BGM 2009)

- Assume economy is affected by vector C_t of common components

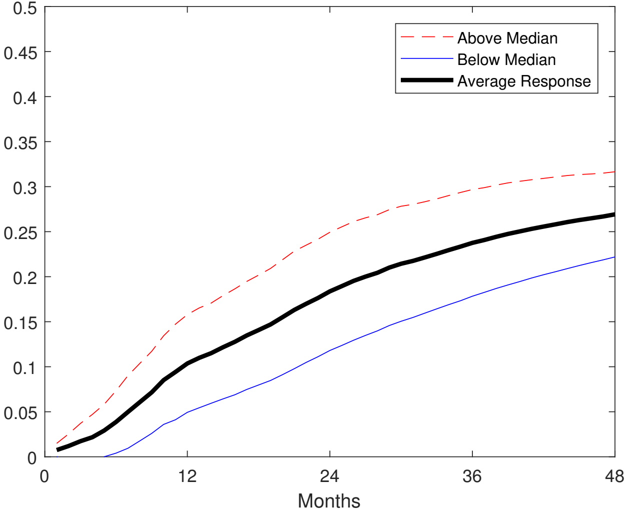
$$C_t = \Phi(L) C_{t-1} + \nu_t \tag{5}$$

  - Where $C_t = [F_t \; R_t]'$ and F_t are a small number K of common factors
- Common factors link to large set of observable series X_t

$$X_t = \Lambda C_t + e_t \tag{6}$$

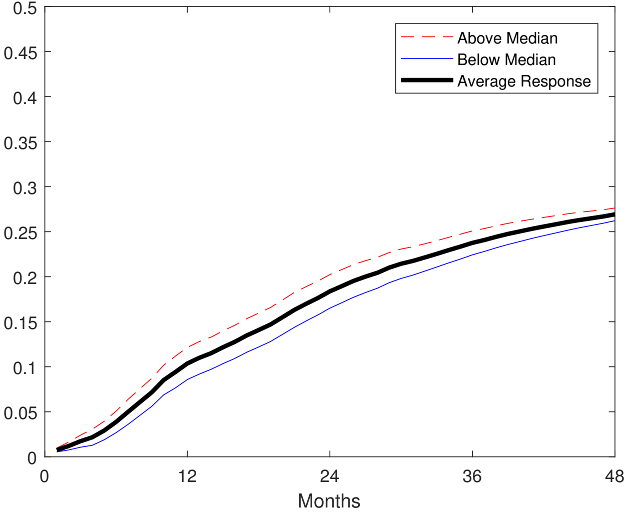
- Monthly data for 653 monthly series 1976.1-2005.6
- 154 PPI price series
- Calculate sector-specific IRFs, then use average response

Empirical IRF - FAVAR - Frequency



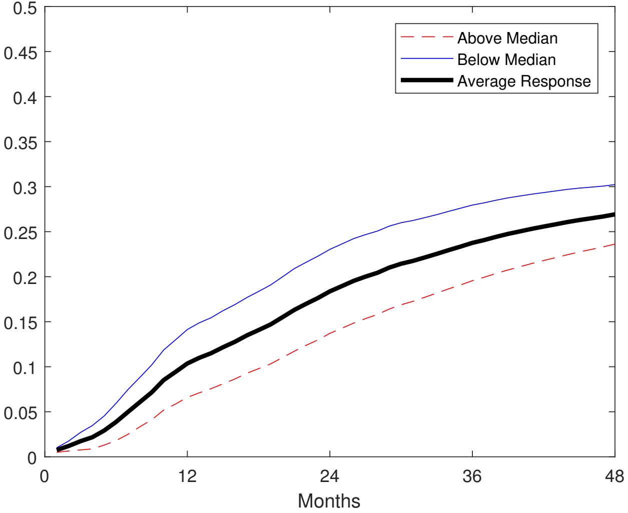
- High frequency of price changes: large price response.

Empirical IRF - FAVAR - Kurtosis



- Kurtosis of price changes: Higher kurtosis has larger price response.

Empirical IRF - FAVAR - Kurtosis/Frequency



- High kurtosis over frequency price changes: low price response.

Empirical IRF - FAVAR - Kurtosis vs. Frequency

- Decompose price response into frequency and kurtosis
- Controlling for frequency, kurtosis is not driving monetary non-neutrality
- Regress cumulative sectoral price response on both frequency and kurtosis, taking into account sectoral fixed effects:

$$log(IRF_{k,h}) = \beta_1 log(frequency_k) + \beta_2 log(kurtosis_k) + FEs + \epsilon_{k,h} \quad (7)$$

Empirical IRF - FAVAR - Kurtosis vs. Frequency

Cross-Sectional Determinants of Sectoral Price Response								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Kurtosis/	-.137*	-0.134						
Frequency	(0.076)	(0.081)						
Log Frequency			0.152**	0.160**			0.170**	0.186**
			(0.063)	(0.072)			(0.071)	(0.081)
Log Kurtosis					0.090	0.070	-0.058	-0.079
					(0.116)	(0.117)	(0.131)	(0.130)
Industry FE		X		X		X		X
R^2	0.019	0.035	0.036	0.053	0.004	0.021	0.037	0.055
N	148	148	148	148	148	148	148	148

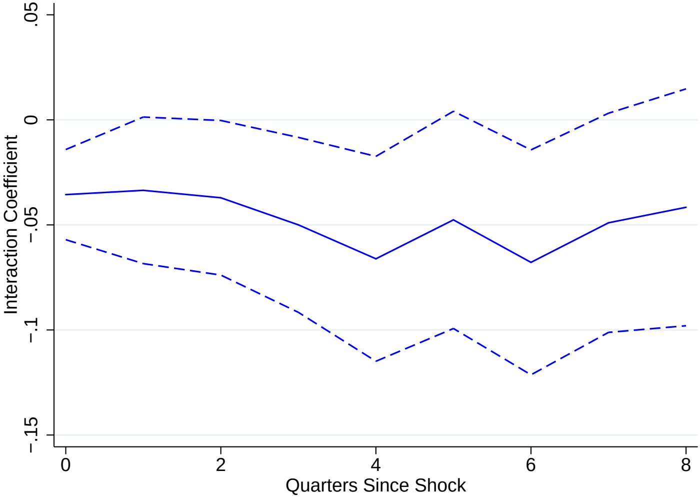
- Kurtosis over frequency matters
- Result driven by frequency

Robustness: Firm-Level Sales Evidence

- Calculate pricing moments at firm level to help us control for additional, highly disaggregated factors
  - Pricing moments calculated for 2005-2014 pooled firm data
  - Merge pricing characteristics with quarterly Compustat data (N=550 representative firms, see Gilchrist et al. (2017))
- High-frequency identification following Karadi and Gertler (2015)
- Data from 1990Q2-2012Q2
- Study differential sales response h periods ahead across firms based on pricing statistics following expansionary monetary surprise:

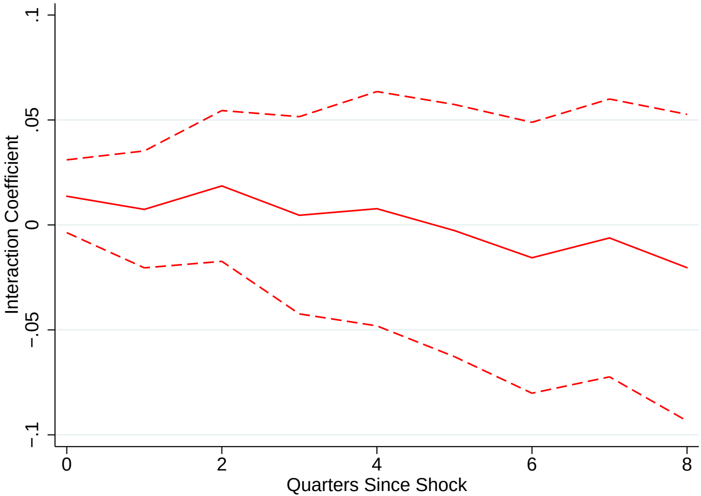
$$
\begin{aligned}
Log(sales_{j,t+h}) &= TimeFE + FirmFE + MPshock * frequency_j \\
&+ MPshock * kurtosis_j + controls + \epsilon_{j,t+h}
\end{aligned}
$$

Firm-Level Results - HF Approach - Frequency



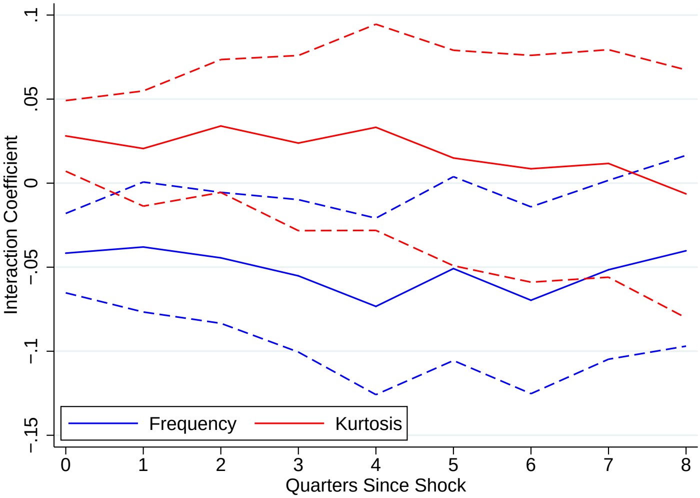
- Firms with high frequency have lower sales growth following expansionary shock

Firm-Level Results - HF Approach - Kurtosis



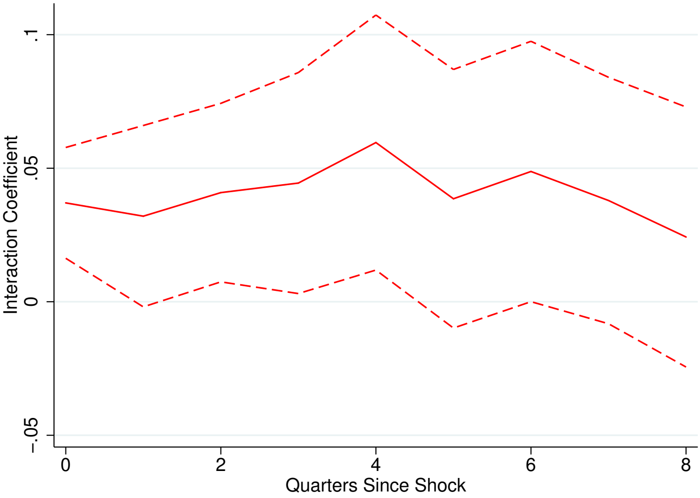
- Kurtosis of price change has insignificant sales effect

Firm-Level Results - HF Approach - Kurtosis/Frequency



- Including kurtosis and frequency jointly, frequency lowers sales.

Firm-Level Results - HF Approach - Kurtosis/Frequency



- Higher kurtosis over frequency increases sales.

New Pricing Facts

- Separating disaggregated sectors by pricing moments we find:
  - Lower frequency of price change leads to larger consumption response
  - Kurtosis of price changes does not affect consumption response ("irrelevance of kurtosis")
    or effect even goes in the wrong direction
  - Higher kurtosis over frequency leads to larger consumption response
    - But: only due to role of frequency of price changes
    - Jointly conditioning on frequency and kurtosis, only frequency relates to monetary non-neutrality
- Results robust to measurement of monetary shock

Model

- Construct general equilibrium pricing models that embed our pricing workhorse models, menu cost and Calvo
- Comparative static exercise varying pricing moments
- Can each model and calibration replicate ordering of empirical IRFs?

Model Setup

- Standard household side of model (log consumption, linear labor)
- Monopolistically competitive firms *i* set prices to maximize future expected profit subject to sticky price constraint
- Firms produce output subject to aggregate and idiosyncratic shock:

$$y_t(i) = A_t z_t(i) L_t(i) \tag{8}$$

- After choosing price, firms fulfill total demand of good i

$$y_t(i) = Y_t \left(\frac{p_t(i)}{P_t} \right)^{-\theta} \tag{9}$$

Firm Pricing

- Firms fulfill all demand at posted price $p_t(i)$
- Firms choose price to maximize future expected profit

$$\pi_t(i) = p_t(i)y_t(i) - W_t L_t(i) - \chi(i) W_t I_t(i) \tag{10}$$

- Random menu cost model embeds both pure menu cost and Calvo models
- Menu costs follow

$$\chi(i) = \begin{cases} 0 & \text{with probability } \alpha \\ \chi & \text{with probability } 1-\alpha, \end{cases} \tag{11}$$

- Set $\chi = \infty$ for Calvo model

Firm Productivity

- Firm productivity follows mean-reverting, leptokurtic shock process

$$logz_t(i) = \begin{cases} \rho_z logz_{t-1}(i) + \sigma_z \epsilon_t(i) & \text{with probability } p_z \\ logz_{t-1}(i) & \text{with probability } 1 - p_z \end{cases}$$

- Aggregate productivity follows AR(1) process

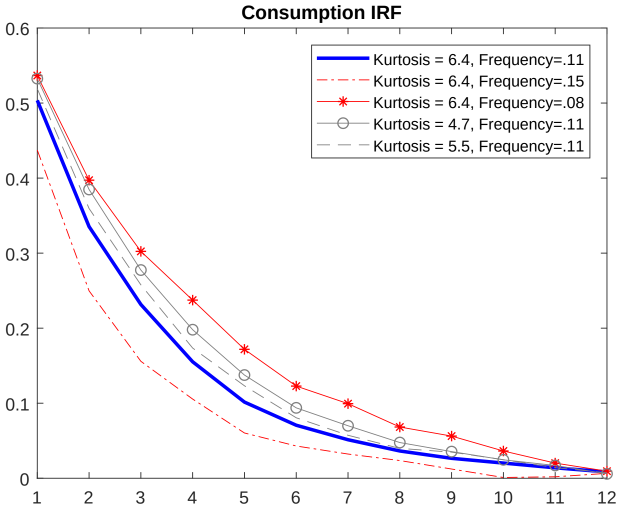
$$logA_t = \rho_A logA_{t-1} + \sigma_A \nu_t \tag{12}$$

- Close the model with a nominal aggregate spending process

$$logS_t = \mu + logS_{t-1} + \sigma_s \eta_t \tag{13}$$

CPI Calibration - Kurtosis Sufficiency

- Calibrate one sector model menu cost model to match CPI moments
- Is kurtosis a model sufficient statistic?



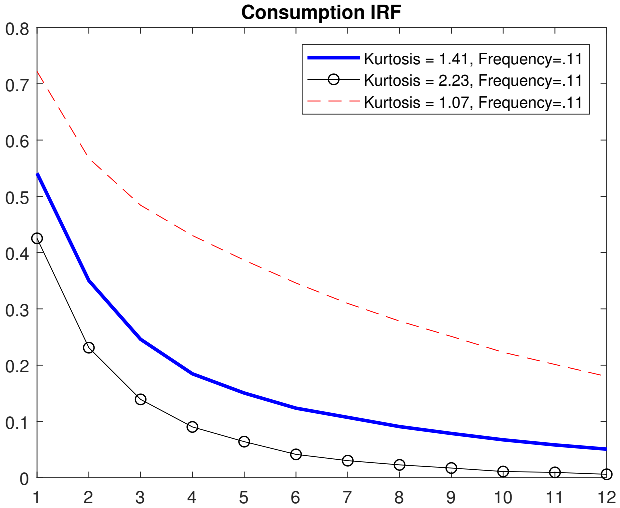
ALL (2016) Decomposition

- How can a baseline 2^{nd} generation menu cost model then show positive correlation between kurtosis and monetary non-neutrality?
- Start from most simple Golosov-Lucas model until ALL results emerge
- Change baseline model to Golosov Lucas (2007) in discrete time:
  - Remove aggregate productivity shocks
  - No leptokurtic productivity shocks
  - Random walk productivity shocks
  - No trend inflation

  Exercise: Vary kurtosis, plot impulse responses

ALL (2016) Decomposition - Golosov-Lucas

- Golosov-Lucas model with fixed menu cost
- Increased kurtosis leads to decreased monetary non-neutrality



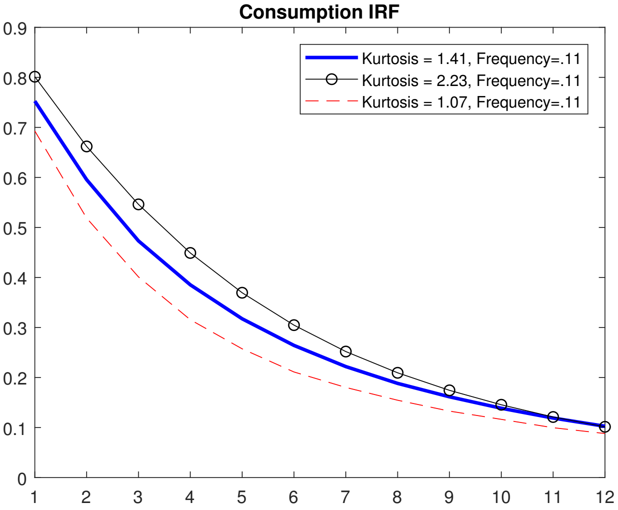
ALL (2016) Decomposition - Golosov-Lucas

- Raise kurtosis by decreasing size of productivity shocks
  - This lowers the average size of price changes, making monetary shocks relatively more important and increasing selection effect

Moment	Data	Baseline	High Kurtosis	Low Kurtosis
Frequency	0.11	**0.11**	**0.11**	**0.11**
Fraction Up	0.65	0.51	0.49	0.51
Average Size	0.077	**0.077**	0.033	0.23
Fraction Small	0.13	0.00	0.00	0.00
Kurtosis	6.4	1.41	**2.23**	**1.07**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	12.8	20.3	9.7

ALL (2016) Decomposition - Random Menu Costs

- Reintroduce random menu costs in ALL
- Result: A fraction $\mathcal{L}$ of price changes that are free
- Higher kurtosis leads to higher monetary non-neutrality



ALL (2016) Decomposition - Random Menu Costs

- A fraction $\mathcal{L}$ of price changes that are free is the key model ingredient to derive ALL results
- $\mathcal{L}$ controls the amount of kurtosis
- Increased $\mathcal{L}$ leads to higher kurtosis
  - But higher $\mathcal{L}$ also leads to more random Calvo price changes, decreasing overall selection effect

Moment	Data	Baseline	High Kurtosis	Low Kurtosis
Frequency	0.11	**0.11**	**0.11**	**0.11**
Fraction Up	0.65	0.51	0.51	0.51
Average Size	0.077	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	0.14	0.12
Kurtosis	4.9	2.74	**3.36**	**2.04**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	25.0	30.2	18.6
$\mathcal{L}$		*0.73*	*0.91*	*0.55*

ALL (2016) Decomposition - Random Menu Costs

- In a variety of models, kurtosis does not identify the amount of monetary non-neutrality.
- The degree of "Calvo-ness", embodied in the fraction of free price changes, $\mathcal{L}$, does
  - Only when kurtosis is identified by $\mathcal{L}$, does this relationship hold

Conclusion

- Using micro price data, we evaluate what price-setting moments are informative for monetary non-neutrality
  - Higher frequency means more responsiveness of prices
  - Higher kurtosis has ambiguous effects:
    - No association with prices, or:
    - Positive association with prices
  - Higher kurtosis over frequency decreases responsiveness of prices
- Results are robust across monetary policy shock identification schemes
- Both DSGE menu cost and Calvo models can accommodate these results when matching micro price moments from the data
- Cast doubt on the recent sufficient statistic approach in the data, and the notion that kurtosis embodies selection
- Resolution if random menu costs lead to a large fraction of random free price changes.

Calibration - Frequency Split

- Parameters common to all sectors calibrated the same for all exercises
  - Discount rate, nominal shock process, aggregate TFP, elasticity of substitution
- Second set of parameters calibrated to match sector-specific pricing moments

Frequency Calibration				
	Low Frequency Sector		High Frequency Sector	
Parameter	MC	Calvo	MC	Calvo
χ_j	0.2	∞	0.00045	∞
$p_{z,j}$	0.078	0.57	0.158	0.38
$\sigma_{z,j}$	0.095	0.23	0.089	0.091
α_j	0.036	0.06	0.062	0.28

Back

Pricing Moments - Kurtosis Split

Kurtosis Calibration						
	Low Kurtosis Sector			High Kurtosis Sector		
Moment	Data	MC	Calvo	Data	MC	Calvo
Frequency	0.11	0.11	0.11	0.23	0.24	0.24
Average Size	0.082	0.082	0.082	0.066	0.068	0.068
Fraction Small .01	0.15	0.11	0.11	0.16	0.16	0.16
Kurtosis	2.5	2.7	2.7	5.6	5.9	5.8
$\frac{\text{Kurtosis}}{\text{Frequency}}$	29.5	24.3	24.5	41.0	24.9	24.2

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