Price Rigidities in U.S. Business Cycles

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Levels, Trends & Cycles in Nominal Rigidities?

- How severe are nominal rigidities in the U.S. economy?
- Has this severity changed over time?
- Does it exhibit any meaningful cyclical variation?

– Important for understanding economy's response to shocks & effectiveness of demand stabilization policy

Our Contribution

- An estimated time series of the degree of nominal price rigidities in the U.S.

- Using a GE model with flexibly specified pricing frictions + time series of real economic activity, inflation, and moments of the distribution of price changes, between 1978.1 and 2014.12

– Along the way: reassess some aspects of the conventional wisdom on price rigidity

Status Quo

- Research has linked the degree of nominal rigidities $\mathcal{R}$ to moments of the steady state distribution of price changes, constructed using micro price data

  ..., Golosov & Lucas Jr (2007), Nakamura & Steinsson (2010), Midrigan (2011), Vavra (2013), Berger & Vavra (2018), ...

- In particular, frequency and frequency / kurtosis are sufficient statistics for non-neutrality in a wide class of models with time-dependent and state-dependent price adjustment

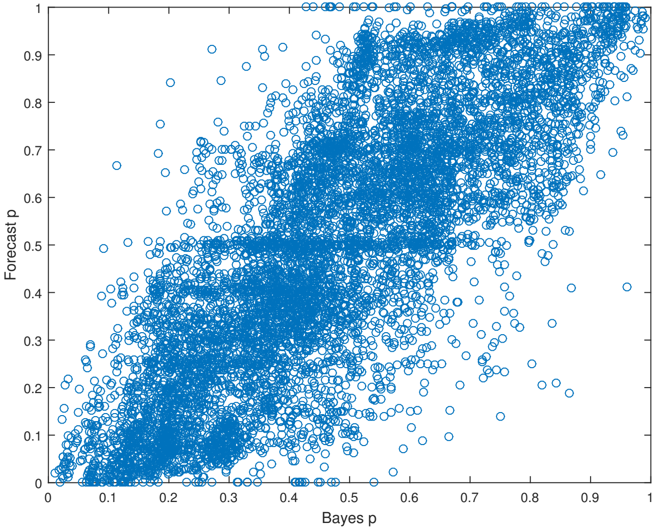
  Alvarez, Le Bihan & Lippi (2016), Alvarez, Lippi & Oskolkov (2022)

Status Quo: Perfect Repricing

- Status quo models: once a firm decides to reprice, the new price (or path) is the deterministic full info optimal choice

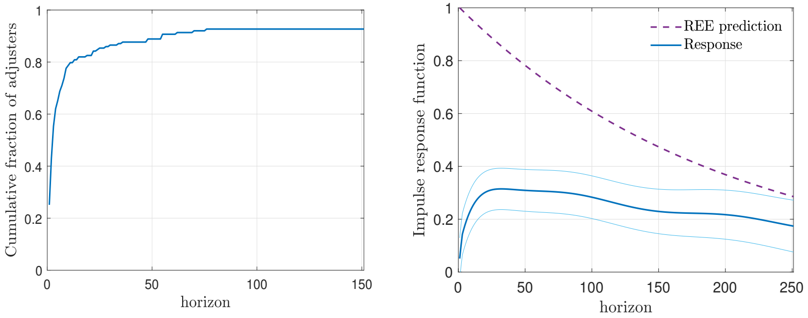
- At odds with overwhelming evidence that actions are based on dispersed beliefs and are only noisily related to optima in numerous contexts
  - neuroscience & cognitive psychology evidence on perception, numerosity, probability estimation
  - economics evidence from games, forecasting, ...
    - surveys ..., Coibion & Gorodnichenko (2012), ...
    - the lab ..., Khaw, Stevens & Woodford (2017), ...
  - dispersion & stochasticity *conditional* on adjusting

Khaw, Stevens & Woodford (2017) Experiment



individual forecasts noisily related to Bayes-optimal forecasts

Khaw, Stevens & Woodford (2023) Experiment



noisy individual forecasts aggregate to systematically sluggish adjustment

What We Do

- We consider a stochastic price-setting model
- Allowing for imprecision in both the timing of price changes and the chosen price levels
- Endogenizing stochasticity by nesting menu and information costs, the two main ways of generating nominal rigidities
- Precursors:
    - Costain & Nakov (2019): control cost pricing in GE
    - Khaw, Stevens & Woodford (2017): individual forecasting

Generalizing the Basic TD and SD Models

- Calvo: optimal policy is characterized by
  - adjustment rule: adjust w.p. $\bar{\Lambda}\ \forall$ state
  - repricing rule: $p^* = \arg\max_p V(p, a, \Gamma)$
  - workhorse model, sizable non-neutrality

- Menu cost model: optimal policy is characterized by
  - adjustment rule: adjust w.p. 1 if $V^{adj} - V^{non} > \kappa$, 0 o/w
  - repricing rule: $p^* = \arg\max_p V(p, a, \Gamma)$
  - advantage of optimizing foundations

- Here: generalize to stochastic version:
  - adjust w.p. Λ increasing in $V^{adj} - V^{non} - \kappa$
  - charge price p w.p. $f(p|\cdot)$ increasing in $V(p, a, \Gamma)$

What We Find

In this model:

1. Pricing frictions interact

2. Weak selection is no longer necessary for large $\mathcal{R}$

3. Calvo is no longer upper bound on the degree of nominal rigidities $\mathcal{R}$, as is the case with models of perfect repricing

   $\rightarrow$ Depart from conventional wisdom on sources and dynamics of nominal rigidities embedded in standard models

What We Find

In the estimation on U.S. data:

1. Menu cost is very small & stable, small contribution to $\mathcal{R}$

2. Timing of adjustments has been fairly accurate (strongly SD prob. adj., though asymmetrically so)

3. Inaccurate repricing has significantly contributed to $\mathcal{R}$ (weakly SD pricing rule)

4. Variation in efficiency of info processing has generated volatility in $\mathcal{R}$, and hence in effectiveness of m.p.

Plan

Model

Stats & Simulations

Estimation

Monopolistic Retailers

- A unit mass of retailers indexed by j sell a continuum of differentiated varieties
- Retailers are monopolistically competitive price-setters in their product market, and are price-takers in the input market
- Once a retailer sets a price, they stands ready to purchase whatever quantity of the intermediate good is needed to satisfy the demand at that price

Monopolistic Retailers

- Demand:

$$y_{jt} = \; p_{jt}^{-\varepsilon_t} Y_t$$

- Technology:

$$y_{jt} = \; e^{a_{jt} + a_t} x_{jt}$$

- Operating profits:

$$\pi_{jt} = \; p_{jt} y_{jt} - p_t^x x_{jt}$$

Retailers' Problem

- Retailers acquire information and set prices to solve

$$\max_{\left\{I_{jt}^a, I_{jt}^p, \delta_{jt}, p_t\right\}} E_{0j} \sum_{t=0}^{\infty} M_{0,t} \left[\pi_{jt} - \theta^a I_{jt}^a - \delta_{jt}\theta^p I_{jt}^p - \delta_{jt}\kappa\right],$$

$M_{0,t}$ is the stochastic discount factor

π_{jt} is the retailer's flow operating profit

I_{jt}^a and I_{jt}^p are the info flows for the adjustment and pricing decisions

θ^a and θ^p are the unit costs of information for the two decisions

κ is the menu cost

δ_{jt} is 1 if the retailer changes its price, 0 otherwise

Information Choice

- Information acquisition : rational inattention
  (Sims, 2003; Woodford, 2009)
  - firms understand environment but do not have free real-time knowledge of the realized state
  - information is abundant but hard to process, use
  - its acquisition is a choice that responds to incentives
  - firms obtain signals about desirable course of action
  - any signal structure is allowed, at a cost
  - signals that are more informative cost more

Information Choice

- From prior work in RI signals directly indicate action: adjust vs. don't adjust price; if adjust, which price to choose Woodford (2009); Stevens (2020)

- Their cost is linear in Shannon mutual information (1948, 1959): how much the actions condition on the state, on average, relative to actions drawn from a reference distribution that the firm "has" for free (a default action distribution)

- Shannon mutual info is the average Kullback-Leibler divergence of the choice from the reference distribution (equivalently, it is the reduction in the entropy of the state)

  $\mathcal{D}\left(p \parallel q\right) = \sum_x p(x) \ln \frac{p(x)}{q(x)}$

Information Acquisition

- Deciding to adjust according to $\Lambda(\tilde{p}, a, \Gamma_t)$ vs. some reference probability $\bar{\Lambda}$ entails information flow

$$\mathcal{I}_t^a = E_t\left\{\mathcal{D}\Big(\Lambda(\tilde{p}, a, \Gamma_t) \parallel \bar{\Lambda}\Big)\right\}$$

$$\mathcal{D}\big(\Lambda \parallel \bar{\Lambda}\big) = \Lambda \ln\left(\frac{\Lambda}{\bar{\Lambda}}\right) + \big(1-\Lambda\big)\ln\left(\frac{1-\Lambda}{1-\bar{\Lambda}}\right)$$

- Pricing according to $f(p \mid a, \Gamma_t)$ vs. $\bar{f}(p)$ entails info flow

$$\mathcal{I}_t^p = E_t\left\{\mathcal{D}\Big(f(p \mid a, \Gamma_t) \parallel \bar{f}(p)\Big)\right\}$$

$$\mathcal{D}\left(f(p \mid a, \Gamma) \parallel \bar{f}(p)\right) = \sum_p f(p \mid a, \Gamma) \ln\left(\frac{f(p \mid a, \Gamma)}{\bar{f}(p)}\right)$$

Choice & Reference Distributions

- For a given reference, the choice distribution max firm value
- How to specify the reference distributions $\bar{\Lambda}$ and $\bar{f}$, relative to which the cost of conditioning on the state is measured?
- Exogenous? E.g., control costs (Costain & Nakov, 2019)
- But DMs have strong incentives to use sophisticated defaults
- Well-chosen reference distributions lower both value of conditioning actions on the state in real time (because they improve the default action) and the avg cost of doing so

Reference Distributions

- So DMs would want to use their knowledge of the structure of their environment to choose well-adapted reference distributions

- From the information-theoretic point of view, the optimal reference distribution is the one that minimizes the choice distribution's average KL divergence from it, integrating over the states to be encountered ("pure RI")

Reference Distributions

- Consider a less efficient, though still endogenous information structure in which the reference distributions are the steady state cross-sectional distributions
- Motivated by the idea that DMs with prior experience across a range of states may find it “easy” or “intuitive” to implement default rules that are optimal on average
- These defaults should be quite useful, especially in the case of small aggregate shocks

Cross-Sectional Distributions

- Let $\tilde{\Omega}(p, a)$ be the SS pre-adj. cross-sectional distribution

  The reference adjustment probability is

$$\bar{\Lambda} = \int_a \sum_p \tilde{\Omega}(p, a) \Lambda(p, a, \Gamma_{ss}) \, da$$

- Let $\Omega(p, a)$ denote the SS joint distribution post-adjustment

  The pricing reference distribution is

$$\bar{f}(p) = \int_a \Omega(p, a) \, da$$

  where

$$\Omega(p, a) = [1 - \Lambda(p, a, \Gamma)] \cdot \tilde{\Omega}(p, a) + \left[\textstyle\sum_{\hat{p}} \Lambda(\hat{p}, a, \Gamma) \, \tilde{\Omega}(\hat{p}, a)\right] \cdot f(p \mid a, \Gamma)$$

Solving the Firm's Problem

Consider choosing information acquisition for any state $(\tilde{p}, a, \Gamma)$:

$$V^*(\tilde{p}, a, \Gamma) = \max_\Lambda \Big\{ \Lambda \cdot [V^a(a, \Gamma) - \kappa] + (1 - \Lambda) \cdot V(\tilde{p}, a, \Gamma) - \theta^a \, \mathcal{D}\left(\Lambda \parallel \bar{\Lambda}\right) \Big\}$$

$$V^a(a, \Gamma) = \max_f \left\{ \sum_p f(p \mid a, \Gamma) V(p, a, \Gamma) - \theta^p \mathcal{D}\left(f(p \mid a, \Gamma) \parallel \bar{f}(p)\right) \right\}$$

where

$$V(p, a, \Gamma) = \pi(p, a, \Gamma) + E\Big\{ M' \, V^*\left(\tilde{p}', a', \Gamma'\right) \;\Big|\; a, \Gamma \Big\}$$

$$\sum_p f(p \mid a, \Gamma) = 1$$

Optimal Choices

Optimality yields

$$\ln\left(\frac{\Lambda(\tilde{p},a,\Gamma)}{1-\Lambda(\tilde{p},a,\Gamma)}\right)=\ln\left(\frac{\bar{\Lambda}}{1-\bar{\Lambda}}\right)+\frac{1}{\theta^a}\left[V^a(a,\Gamma)-V(\tilde{p},a,\Gamma)-\kappa\right]$$

and

$$f(p\,|\,a,X)=\frac{\bar{f}(p)\exp\left\{\frac{V(p,a,X)}{\theta^p}\right\}}{\sum_{\hat{p}\in\mathcal{P}}\bar{f}(\hat{p})\exp\left\{\frac{V(\hat{p},a,X)}{\theta^p}\right\}}$$

Closing the Model

Representative household with habits, preference shocks

Competitive intermediate good produced with labor

Monetary authority using Taylor rule

Fiscal authority funding spending with lump-sum taxes

Steady State Frictions

Steady State Pricing Frictions

- We estimate $\{\theta^a, \theta^p, \kappa, \rho_a, \sigma_a\}$ to target the averages of five pricing moments over the sample period (1978-2014)

	Model	Data
Frequency of price changes	0.108	0.108
Mean absolute value	0.072	0.073
Standard deviation	0.125	0.126
Skewness	-0.113	-0.113
Kurtosis	11.15	11.03

Steady State Pricing Frictions

- Parameter estimates:

θ^p	θ^a	κ	ρ_a	σ_a
1.86	0.10	0.004	0.924	0.239

- Small menu cost $\Rightarrow$ menu cost spending $=$ 0.05% of SS sales and yet only 11% frequency of price changes

- Larger info costs : info acquisition $=$ 2.1%

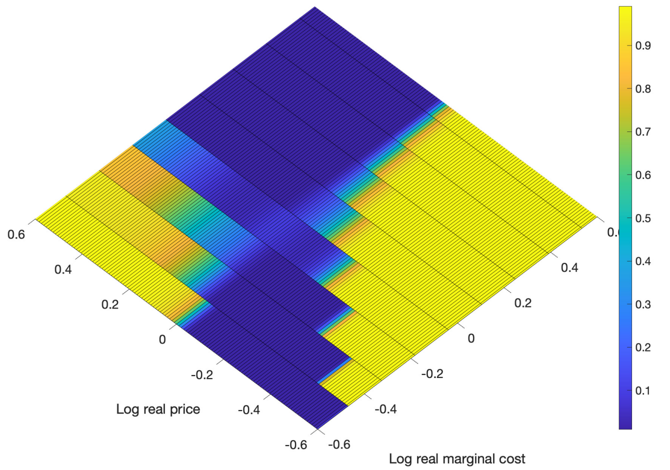
- Considerable share of which is to figure out what price to charge : repricing costs $=$ 1.3%

Steady State Pricing Frictions

- As a result of these pricing frictions
  - steady state price dispersion is 13% higher
  - steady state consumption is 7% lower

  compared with the full-info flexible price economy

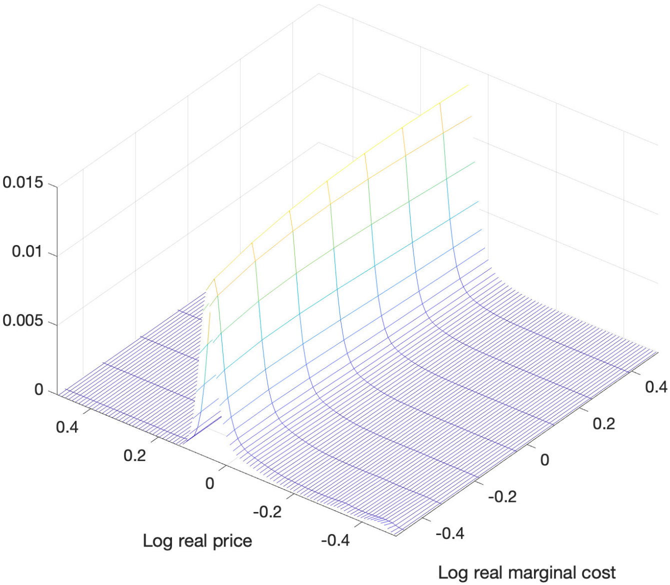
Adjustment Probability



stochastic adjustment decision

steep, asymmetric - Woodford (2009) - CE-07 - DKW-99

Pricing Policy



Interactions & Implications

1. Without mistakes in repricing, models need sizable menu cost or exogenously low prob. of adj. to get infrequent Δp

- Imperfect info $\Rightarrow$ infrequent adjustment despite $\kappa \approx 0$

2. Full info menu cost models also need mechanism to

   (i) mute selection to get meaningful $\mathcal{R}$

   (ii) match moments beyond freq and size of Δp

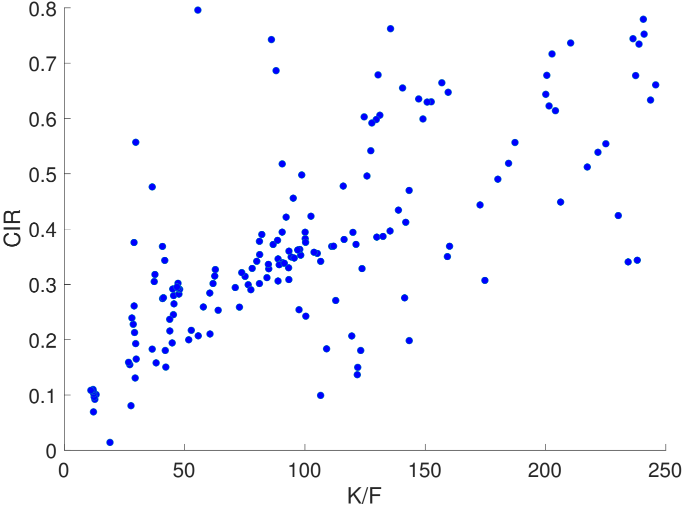
- Stochastic prices $\Rightarrow$ can end up with suboptimal price even if correctly decide when to adjust $\Rightarrow$ $\mathcal{R}$; can match higher moments of distribution of Δp

Statistics & Simulations

Model Simulations

- Suppose we solve model for different values of $\{\theta^p, \theta^a, \kappa^a\}$
- And compute the CIRs of output to a m.p. shock
- How well can pricing moments predict these CIR?

CIR and Kurtosis / Frequency



positive but imperfect correlation

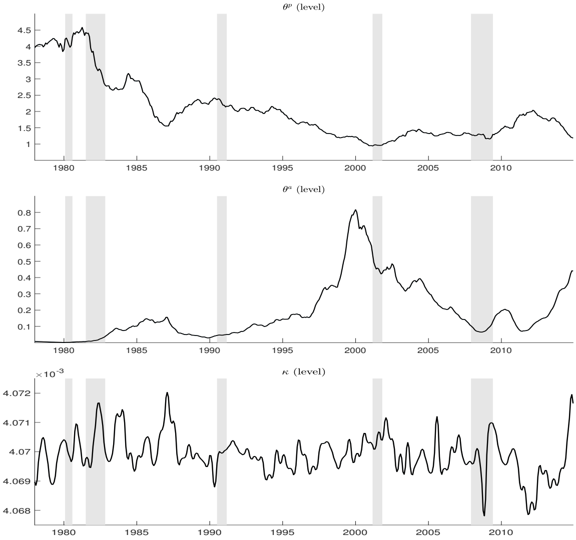
noisy for data-relevant range

Estimation

Estimation

- Data from Jan 1978 to Dec 2014 on macro aggregates (Y, π, r) + pricing moments – we thank Daniel Villar for sharing the CPI pricing moments that were first constructed by Nakamura, Steinsson, Sun & Villar (2018) and also studied by Luo & Villar (2021)
- We apply the sequence-space Jacobian method of Auclert, Bardóczy, Rognlie & Straub (2021) to this model with heterogeneous information → super fast, reliable solution
- Fundamental shocks to preferences, technologies, policies (unobservable for free by firms) + shocks to the pricing frictions, interpreted as shocks to attention/efficiency of information processing & implementation of decisions

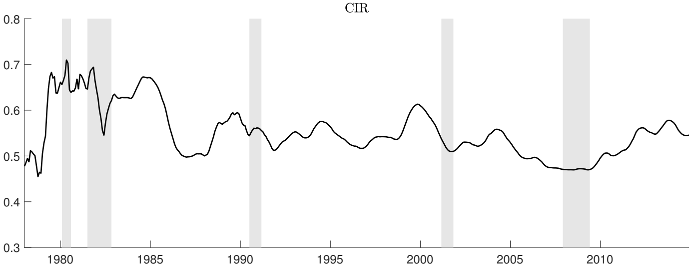
Estimated Series for Pricing Frictions



Estimation

Using the filtered shocks, we compute the implied CIR over time, when the choice distributions are reoptimized given the new parameter values (keeping the reference distributions at the baseline SS averages)

Implied Nominal Rigidity Over Time



cumulative consumption response to a 25 bp FFR shock
as a % of quarterly steady state C

Conclusions (1/2)

- Approach to estimating monetary non-neutrality has evolved to be disciplined by
  - aggregate data (*e.g.*, CEE, 2005)
  - micro data (*e.g.*, Midrigan, 2010)
- Moments from the distribution fo Δp help pin down $\mathcal{R}$
- Here we consider implications of the dynamics of these pricing moments using a stochastic generalization of standard models
- We find support for model in which both timing & especially repricing are noisily tied to conditions

Conclusions (2/2)

- Menu cost is very small, makes small contribution to $\mathcal{R}$
- Timing of adjustments has been fairly accurate (strongly state-dependent proba of adjustment)
- Inaccurate pricing (conditional on adjustment) has significantly contributed to $\mathcal{R}$ (weakly SD pricing rule)
- Estimation shows that $\mathcal{R}$ varies significantly over time

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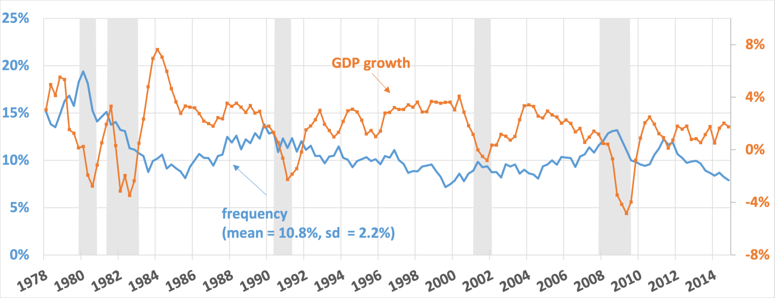
Time-Varying Frequency of Price Adjustment



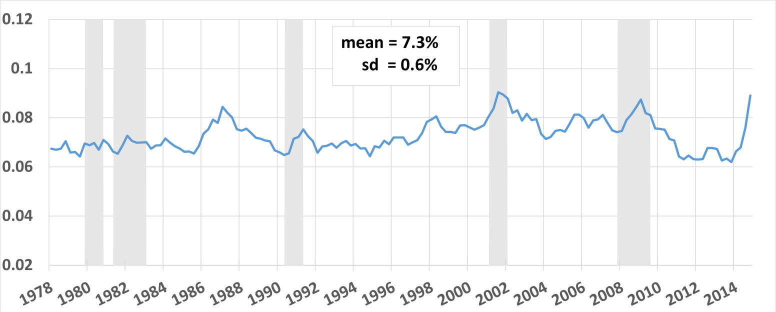
(correlation with real GDP growth = -0.25)

$\Rightarrow$ volatile, procyclical Calvo parameter

Note: Pricing moments are based on the micro data underlying the U.S. Consumer Price Index (CPI).

We thank Daniel Villar for these pricing series. GDP growth is from FRED.

Time-Varying Size of Price Adjustment



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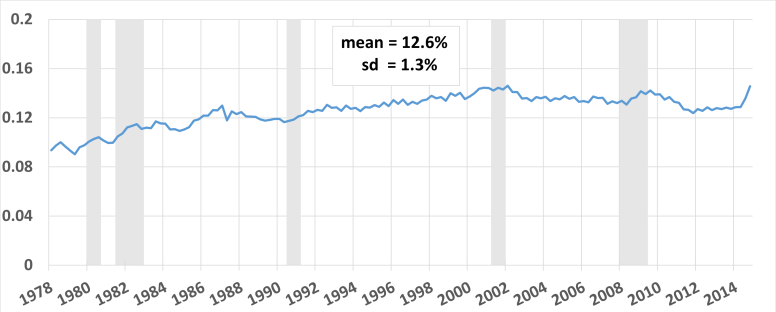
Time-Varying Dispersion of Price Adjustment



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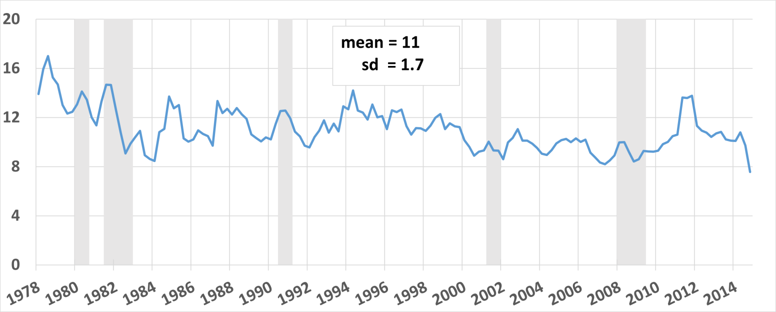
Time-Varying Kurtosis of Price Changes



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