Sentimental Business Cycles

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Introduction

Sources of fluctuations in the economy: Much work estimates impact of '**fundamental shocks**' on the economy:

- Technology shocks / investment specific shocks.
- Monetary/ fiscal/ credit/ trade policy shocks.
- Oil price / commodity price shocks.
- TFP uncertainty / policy uncertainty shocks.

Other shocks: Large share of the variances of macro aggregates remains unaccounted for:

- News (about fundamentals) shocks.
- Animal spirits / expectational shocks / non-fundamental shocks.

Non-Fundamental Shocks

This paper: Focus on contribution of non-fundamental "demand shocks."

- Do they matter?

Key Challenge: How to estimate causal effects?

- Sentiments hard to translate into observables.
- **Multiple equilibria**: Some attempts using structural models.
- **Animal spirits**: Variety of recent attempts
  - Barsky and Sims (2012),
  - Levchenko and Pandalai-Nayar (2018), Forni et al. (2013)
  - Mian, Sufi and Khouskou (2015), Benhabib and Spiegel (2016), Feve and Guay (2018), Lagerborg (2017)

This paper: Central Contributions

1. **Empirics**: Estimate the dynamic causal effects of **sentiment** shocks:
   - Propose IV strategy for estimation.
   - Combine IV with SVAR to estimate dynamic causal effects.
2. **Theory**: Build model and apply it for structural analysis:
   - Incomplete information and Bayesian learning.
   - Heterogeneous Agents New Keynesian with Search and Matching.
   - HANK&SAM provides amplification mechanism.
3. **Quantification**: Estimate key structural parameters:
   - Simulation based estimates of structural parameters.

Empirics

Sentiments: Draw data from **University of Michigan Survey of Consumer Confidence**:

- Conducted since late 1940's;
- Monthly since 1977 (quarterly since 1952);
- 500 randomly drawn persons are interviewed per month;
- Asked about own situation and about US economy;

Three broad **indices**:

- **Index of Consumer Sentiment** (**ICS**): A mix of:
- **Index of Current Economic Conditions** (**ICC**), and
- **Index of Consumer Expectations** (**ICE**).

Empirics

ICE is derived from answers to three questions (each given 1-5 score):

1. **PEXP**: "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

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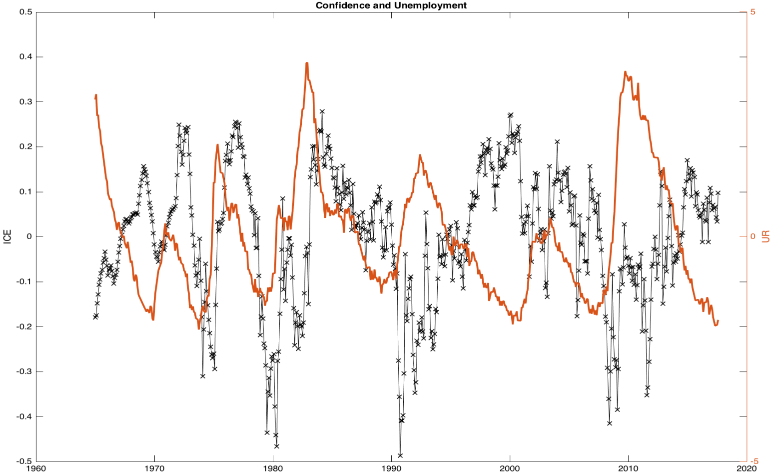
- **ICE** = 100 + "% positive respondents" - "% negative respondents" (normalized to 1966 base).

ICE ICE B...


Confidence and Unemployment
ICE
UR
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
5
0
-5
1960
1970
1980
1990
2000
2010
2020

Empirics

Does Consumer Confidence indices contain valuable information?

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- **Ludvigson** (2004): ICE has predictive power for aggregate consumption growth (but not after controlling for the consumption-wealth ratio).
- **Problem**: Predictive power / Granger causality - no causal interpretation, could be due to news about fundamentals.

Empirical Approach

Consumer confidence and sentiments: Generic model of ICE:

$$\mathbf{CI} = \mathbf{F}(\quad \text{fundamentals,news,noise,} \quad \text{sentiments})$$

- How do we isolate non-fundamental component?

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- Can be estimated with 2SLS or 3SLS.

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Assume that the dynamics of observables is:

$$\mathbf{X}_t = \mathbf{A}(L)\,\mathbf{X}_{t-1} + \overbrace{\mathbf{u}_t}^{\text{innovations}}$$

$$\mathbf{u}_t = \mathbf{B}\underbrace{\mathbf{e}_t}_{\text{structural shocks}}$$

- Structural shocks not observed.

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- Order **CI** (wlog) first

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- Proxy needs to be *correlated* with true shock but not equal to it
- Allows for measurement errors and one can correct for scaling issues

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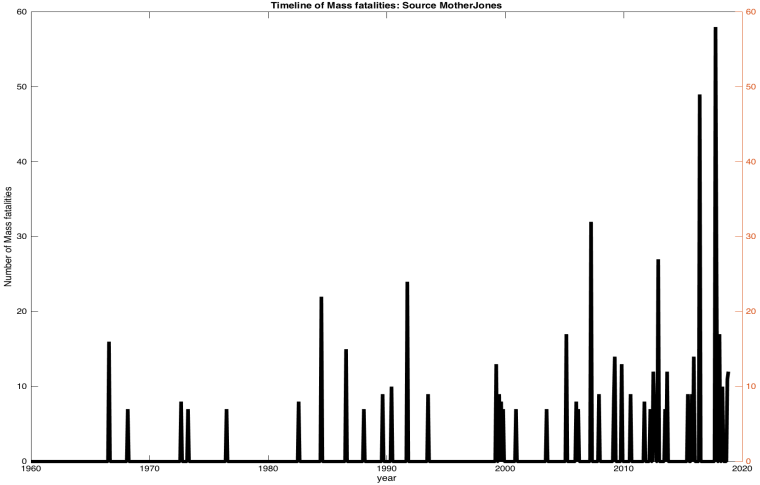
- Mass shootings are unpredictable over time.
- Each event unlikely to bear much in terms of direct costs.

Fatalities in Mass Shootings



Mechanism: Shooting -> News -> Confidence

Incident	Year	TV cov.	TV time	Articles	Words
Sandy Hook	2012	99	11:27:56	130	118,354
G. Clifford shooting	2011	133	11:19:28	89	91,715
Fort Hood sh.	2009	31	05:05:00	36	35,097
Virginia Tech shooting	2007	59	06:12:12	36	33,473
Aurora sh.	2012	70	08:49:48	31	23,715
Red Lake massacre	2005	15	00:48:40	19	18,519

(Vanderbilt TV News Archive, Schildkraut, Elsass and Meredith, 2017)

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- Mass shootings impact on psychological well-being: PTSD symptoms (Hughes et al, 2011), subjective well-being (Clark and Stancanelli, 2017) - potential for direct impact on confidence.

Estimation

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- Benchmark VAR:

$$\mathbf{X}_t = \begin{pmatrix} CI_t & \text{(log consumer confidence)} \\ Y_t & \text{(log industrial production)} \\ U_t & \text{(unemployment rate)} \\ P_t & \text{(log CPI)} \\ R_t & \text{(Federal funds rate)} \\ SP_t & \text{(SP 500 / CPI)} \\ \Phi_t & \text{(Uncertainty, Jurado et al)} \end{pmatrix}$$

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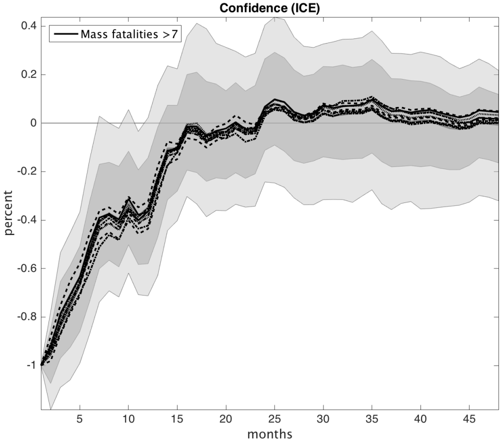
- Detrend all apart from R_t with 4th order time polynomial.
- Instrument: Detrended fatalities in shootings with $\geq$7 fatalities

Relevance

A. Benchmark VAR			
	Proxy	F-test value	
Sample		F^{HOM}	F^{MOP}
1965:1-2007:8	MassFat_7	11.3	17.6
1965:1-2015:12	MassFat_7	11.8	6.3
1965:1-2018:11	MassFat_7	5.4	2.4
1965:1-2007:8	MassFat_3	8.9	7.3

- Use Montiel Olea, Stock and Watson (2017) parametric bootstrap with Newey-West HAC-robust covariance matrix

Relevance



- Significant drop in ICE for approximately 2 years.
- **Relevance** $\surd$

Impulse Responses

Dynamic Causal Effects: Now look at dynamic causal effects of autonomous changes in consumer sentiments.

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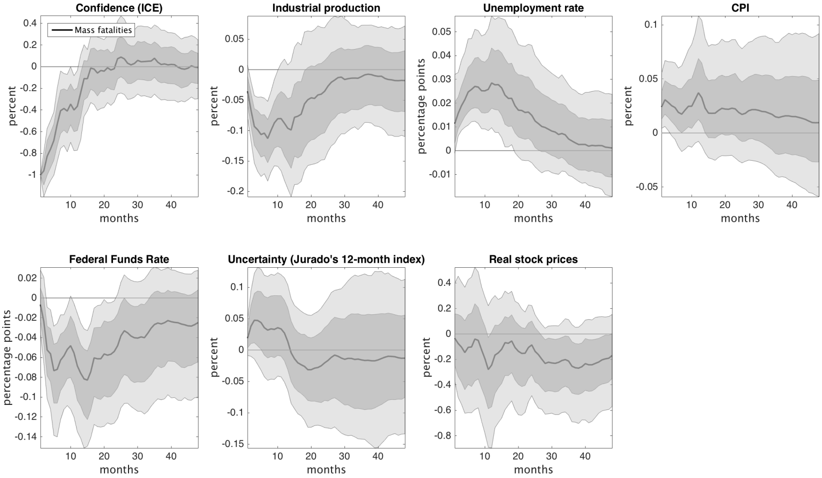
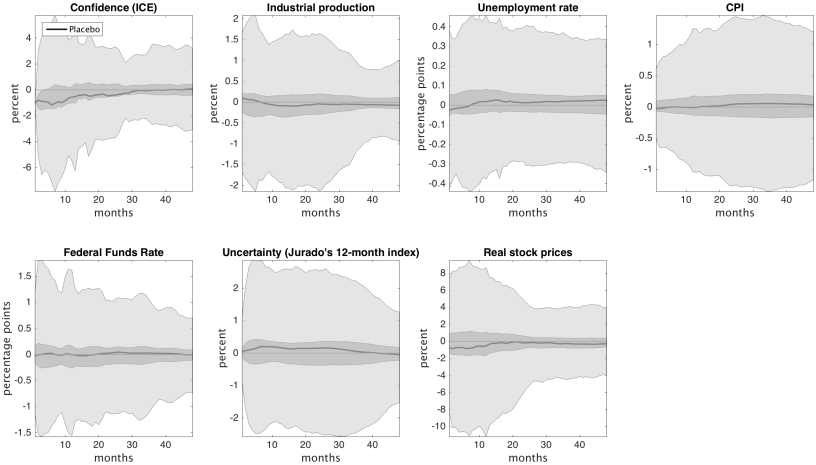
- Augment with other variables.
- Look at relationship to other shocks.

Benchmark VAR



IV with random reshuffling of mass fatalities



More Results

Dynamic Causal Effects: Robustness and impact on other variables:

- Robust to using news coverage.

Other variables:

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- Drop in consumption.

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- TFP: No impact.

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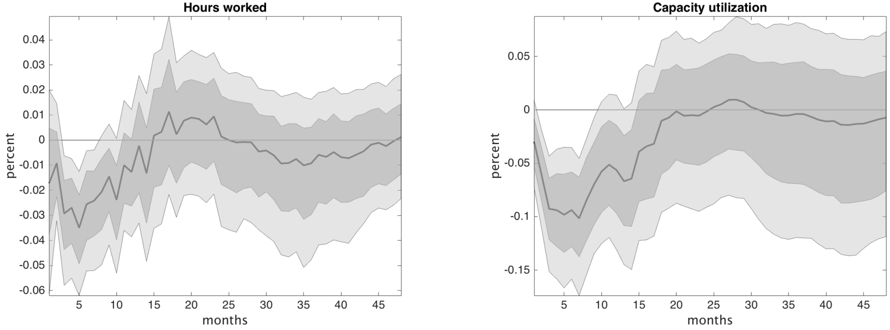
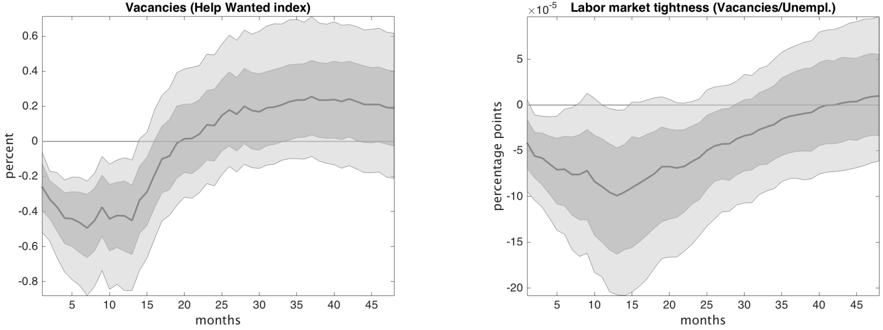
- Nominal exchange rate depreciates.
- TFP: No impact.
- Relationship to uncertainty: No significant impact.

Inputs

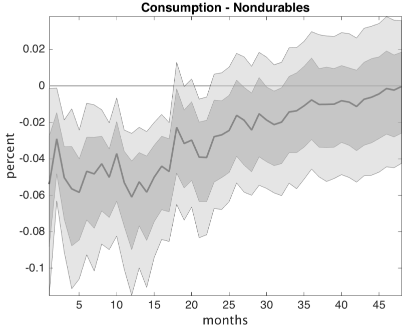


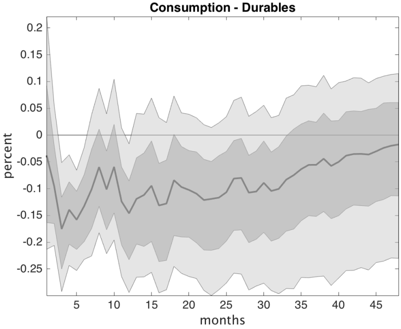
Hours worked
percent
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
5 10 15 20 25 30 35 40 45
months
Capacity utilization
percent
0.05
0
-0.05
-0.1
-0.15
5 10 15 20 25 30 35 40 45
months

Labor Market

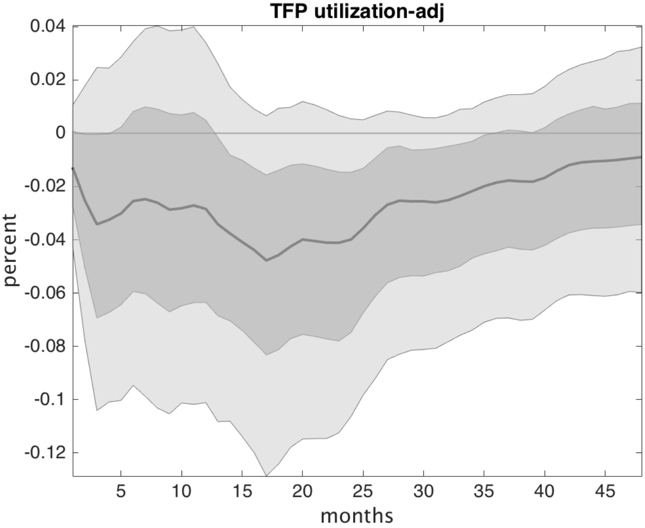


Consumption





Fernald Capacity Util. Adj. TFP



Nominal Exchange Rate

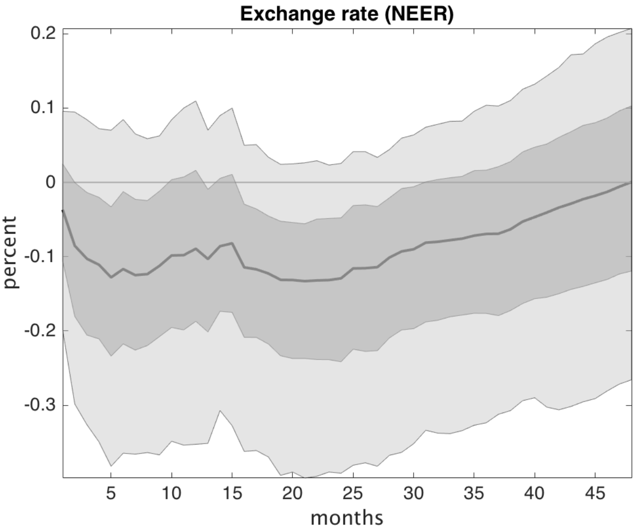


Table 3: Forecast Error Variance Decomposition

Variable	Forecast horizon (months) 1	3	6	12	48	120
Index of consumer expectations	75	70	59	49	36	28
Unemployment rate	26	34	40	44	25	20
Vacancies	39	40	37	34	17	13
Labor market tightness	20	20	19	18	16	15
hours worked per worker	3	15	19	16	7	8
Capacity utilization	11	18	21	19	7	7
Industrial production	12	19	25	25	14	13
Consumption of non-durables	16	28	31	37	38	32
Consumption of durables	8	21	23	18	20	15
Inflation rate	25	20	14	11	4	4
Federal funds rate	3	9	17	20	18	15
Stock prices	3	4	4	5	12	13
Uncertainty	9	7	6	4	3	4

Theory

Households:

- Search for jobs.
- Face uninsurable unemployment risk.
- Save in bonds and equity.

Firms:

- Monopolistically competitive.
- Face Rotemberg (1982) quadratic price adjustment costs.
- Hire labor in frictional matching market.

Monetary Authority:

- Sets short term nominal interest rate.

Theory

Fundamental Shocks:

- Persistent aggregate productivity shocks.
- Transitory aggregate productivity shocks.
- Monetary policy shock.

Information:

- Imperfect common information: Only sum of productivity shocks observed.

Non-fundamental shock:

- Noisy signal about persistent productivity shock.

Agents and Markets:

Unemployed	**Households** (Lack of insurance)	**Employed**
↓	↑	↓
Matching market	**Goods market** (price rigid)	Rigid wage
↑		↑
Vacancies	↑	**Jobs**
	Firms	

Theory: The main mechanism

Countercyclical Endogenous Risk:

$$\text{Noise shock(-)} \quad \xrightarrow{\text{(filtering)}} \quad \text{Confused with } \mathbf{A}^P \downarrow$$

Theory: The main mechanism

Countercyclical Endogenous Risk:

$$\begin{array}{ccc} \text{Noise shock(-)} & \xrightarrow{\text{(filtering)}} & \text{Confused with } \mathbf{A}^P \downarrow \\ & & \downarrow \\ & & \text{goods demand} \downarrow \end{array}$$

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Noise shock(-) $\xrightarrow{\text{(filtering)}}$ Confused with $\mathbf{A}^P \downarrow$

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$\searrow$ (NK) **Firms** labor demand $\downarrow$

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$\swarrow$ (SAM)

u $\uparrow$, real wages $\downarrow$

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Countercyclical Endogenous Risk:

$$\begin{array}{ccccccc}
 & \text{(filtering)} & & & & & \\
\text{Noise shock(-)} & \rightarrow & \text{Confused with } \mathbf{A}^P \downarrow & & & & \\
 & & \downarrow & & & & \\
 & & \text{goods demand} \downarrow & & & & \\
\textbf{Households} & \text{(HA)} \nearrow & & & \searrow \text{(NK)} & & \textbf{Firms} \\
\text{precautionary} & & & & & & \text{labor} \\
\text{saving} \uparrow & & & & & & \text{demand} \downarrow \\
 & \text{(HA)} \nwarrow & & & \swarrow \text{(SAM)} & & \\
 & & \text{u} \uparrow \text{, real wages} \downarrow & & & &
\end{array}$$

Households - Preferences

Composition: Continuum of single-member households.
Preferences:

$$\mathcal{V}_{it} = \max \widehat{\mathbb{E}}_t \sum_{s=t}^{\infty} \beta^{s-t} \left(\frac{\mathbf{c}_{i,s}^{1-\mu} - 1}{1-\mu} - \zeta \mathbf{n}_{i,s} \right),$$

Consumption:

$$\mathbf{c}_{i,s} = \left(\int \left(c_{i,s}^{j} \right)^{1-1/\gamma} dj \right)^{1/(1-1/\gamma)}$$

Employment Status and Earnings:

$$\mathbf{n}_{i,s} = \begin{cases} 0 \text{ if not employed at date } s, \textbf{ home production } \vartheta \\ 1 \text{ if employed at date } s, \text{ earns wage } w_{i,s} \end{cases}$$

Technology - Production and Hiring

Technology:

$$\mathbf{y}_{j,s} = \exp\left(\mathbf{A}_s\right)\left(\mathbf{z}_{js}\mathbf{k}_{js}\right)^{\tau}\mathbf{n}_{j,s}^{1-\tau}$$

Employment Dynamics:

$$\mathbf{n}_{j,s} = (1-\omega)\mathbf{n}_{j,s-1} + \mathbf{h}_{j,s}$$

Hiring:

$$\mathbf{h}_{j,s} = \mathbf{q}_s\mathbf{v}_{j,s}$$

- $v_{j,s} \geq 0$, flow cost $\kappa > 0$ per unit.

Capital accumulation:

$$\mathbf{k}_{j,s+1} = \left(1 - \delta\left(\mathbf{z}_{j,s}\right)\right)\mathbf{k}_{j,s} + \mathbf{i}_{j,s}$$

Matching technology

Timing: (i) job losses, (ii) hiring, (iii) production.

Matching function:

$$\mathbf{M}_s = \overline{m}\mathbf{u}_s^{\alpha}\mathbf{v}_s^{1-\alpha},$$
$$\mathbf{v}_s = \int_j \mathbf{v}_{j,s}dj$$

Matching rates: Let $\theta_s = \mathbf{v}_s/\mathbf{u}_s$ denote labor market tightness:

$$\textbf{job finding rate}: \eta_s = \frac{\mathbf{M}_s}{\mathbf{u}_s} = \overline{m}\theta_s^{1-\alpha}$$

$$\textbf{vacancy filling rate}: \mathbf{q}_s = \frac{\mathbf{M}_s}{\mathbf{v}_s} = \overline{m}^{1/(1-\alpha)}\eta_s^{-\alpha/(1-\alpha)}$$

Prices, Wages, Interest Rates

Price Setting: Monopolistically competition firms, price adjustment costs:

$$\max \widehat{\mathbb{E}}_t \sum_{s=t}^{\infty} \Lambda_{j,t,s} \left[\frac{\mathbf{P}_{j,s}}{\mathbf{P}_s} \mathbf{y}_{j,s} - \mathbf{w}_s \mathbf{n}_{j,s} - \kappa \mathbf{v}_{j,s} - \mathbf{i}_{j,s} - \frac{\phi}{2} \left(\frac{\mathbf{P}_{j,s} - \mathbf{P}_{j,s-1}}{\mathbf{P}_{j,s-1}} \right)^2 \mathbf{y}_s \right]$$

subject to:

$$\begin{aligned}
\mathbf{y}_{j,s} &= \exp\left(\mathbf{A}_s\right) \left(\mathbf{z}_{j,s} \mathbf{k}_{j,s}\right)^{\tau} \mathbf{n}_{j,s}^{1-\tau} \\
\mathbf{n}_{j,s} &= (1-\omega) \mathbf{n}_{j,s-1} + \mathbf{h}_{j,s} \\
\mathbf{k}_{j,s+1} &= (1 - \delta\left(\mathbf{z}_{j,s}\right)) \mathbf{k}_{j,s} + \mathbf{i}_{j,s} \\
\mathbf{y}_{j,s} &= \left(\frac{\mathbf{P}_{j,s}}{\mathbf{P}_s} \right)^{-\gamma} \mathbf{y}_s
\end{aligned}$$

- $\Lambda_{j,t,s}$: firm owners' intertemporal discount factor.

Wages: Wage function:

$$\mathbf{w}_s = \overline{\mathbf{w}} \left(\frac{\eta_s}{\overline{\eta}} \right)^{\chi}$$

- Simplifies marginally by avoiding having wealth dependent wages.
- Correspond to Nash bargaining solution depending on parameters.

Monetary Policy: Interest Rate Rule:

$$\mathbf{R}_s = \mathbf{R}_{s-1}^{\delta_R} \left(\overline{R} \left(\frac{\Pi_s}{\overline{\Pi}} \right)^{\delta_\pi} \left(\frac{\theta_s}{\overline{\theta}} \right)^{\delta_\theta} \right)^{1-\delta_R} \exp \left(\mathbf{e}_s^R \right)$$

Assets and Borrowing Constraints: Limited participation

Bonds: $b_{i,s}$ - in zero net supply.

Equity: $x_{i,s}$ - positive net supply - only held by small subset of rich entrepreneurs

Tractable Equilibrium

Euler Equations:

$$\mathbf{c}_{r,s}^{-\mu} \geq \beta \widehat{\mathbb{E}}_s \frac{\mathbf{R}_s}{\Pi_{s+1}} \mathbf{c}_{r,s+1}^{-\mu},$$

$$\mathbf{c}_{u,s}^{-\mu} \geq \beta \widehat{\mathbb{E}}_s \frac{\mathbf{R}_s}{\Pi_{s+1}} \left(\left(1 - \eta_{s+1}\right) \mathbf{c}_{u,s+1}^{-\mu} + \eta_{s+1} \mathbf{c}_{e,s+1}^{-\mu} \right),$$

$$\mathbf{c}_{e,s}^{-\mu} \geq \beta \widehat{\mathbb{E}}_s \frac{\mathbf{R}_s}{\Pi_{s+1}} \left(\omega \left(1 - \eta_{s+1}\right) \mathbf{c}_{u,s+1}^{-\mu} + \left(1 - \omega \left(1 - \eta_{s+1}\right)\right) \mathbf{c}_{e,s+1}^{-\mu} \right),$$

- Entrepreneurs face no idiosyncratic risk.
- Asset poor unemployed will be in a corner.
- Asset poor employed will be on their Euler equation.
- Asset poor employed price the bonds.

Shocks and Information

Technology: Sum of persistent and transitory component:

$$\mathbf{A}_s = \mathbf{A}_s^P + \varepsilon_s^T, \;\; \varepsilon_s^T \sim \text{nid}\left(0, \sigma_T^2\right)$$
$$\mathbf{A}_s^P = \rho_A \mathbf{A}_{s-1}^P + \varepsilon_s^P, \;\; \varepsilon_s^P \sim \text{nid}\left(0, \sigma_P^2\right)$$

Information: Imperfect common information.

- $\mathbf{A}_s \in I_s$ but $\mathbf{A}_s^P, \varepsilon_s^T \notin I_s$.
- Agents receive a signal on $\mathbf{A}_s^P$:

$$\Psi_s = \mathbf{A}_s^P + \varepsilon_s^S, \;\; \varepsilon_s^S \sim \text{nid}\left(0, \sigma_S^2\right)$$

- ε_s^S : sentiment / expectational shock.

Monetary Policy:

$$\mathbf{e}_s^R = \varepsilon_s^R, \;\; \varepsilon_s^R \sim \text{nid}\left(0, \sigma_R^2\right)$$

- Sentiments impact **directly** and **indirectly** on monetary policy.

The Endogenous Risk Channel

Endogenous earnings risk: log-linearized Euler equation:

$$-\widehat{c}_{e,t} + \beta\overline{R}\widehat{\mathbb{E}}_s\widehat{c}_{e,t+1} = \frac{1}{\mu}\left(\widehat{R}_t - \mathbb{E}_t\widehat{\Pi}_{t+1} - \beta\overline{R}\Theta^F\mathbb{E}_t\widehat{\eta}_{t+1}\right)$$

1. **Discounting**: $\widehat{c}_{e,s+1}$ enters with coefficient $\beta\overline{R} < 1$.

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- **acyclical** if $\Theta^F = 0$: No endogenous risk feedback.

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- recession $\Rightarrow$ lower job finding rate $\Rightarrow$ higher precautionary savings demand $\Rightarrow$ demand contracts at the current real interest rate $\Rightarrow$ real interest rate must decline $\Rightarrow$ inflation must decline $\Rightarrow$ marginal costs must decline $\Rightarrow$ firms post fewer vacancies $\Rightarrow$ job finding rate declines - diabolical loop.

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- Hence, key to the endogenous risk channel is whether unemployment risk or wage risk matters most.

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- $\widehat{\Lambda}_T^d$: Moments that are matched:

$$\widehat{\Lambda}_T^d = \left[\mathbf{F} - \mathbf{stat}, \sigma^2_{\mathbf{Solow}}, \mathbf{IRF}_{nfore} \right]$$
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- $\Lambda_T^m (\Theta_2 | \Theta_1)$: Model equivalents of $\widehat{\Lambda}_T^d$ obtained by simulation.

Simulation estimator

1. Assume (Barsky-Sims, 2012):

$$\mathbf{CI}_t = \zeta_1 \left(a_t - a_{t-1} - g_{t|t-1} \right) + \zeta_2 \left(g_{t|t} - \rho_a g_{t|t-1} \right) + \zeta_2 \varepsilon_{c,t}$$

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2. Simulate model to generate:

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$$\Lambda_T^m \left(\Theta_2 | \Theta_1 \right) = \frac{1}{N} \sum_{i=1}^{N} \Lambda_T^m \left(\Theta_2 | \Theta_1 \right)_i$$

Calibrated parameters (monthly)

Parameter	Meaning	Value
$\overline{\mathbf{u}}$	st.st. unemployment rate	6 percent
$\overline{\eta}$	st.st. job finding rate	34 percent
α	matching function parameter	0.6
$(\kappa/\overline{\mathbf{q}})\ /\ (3\overline{\mathbf{w}})$	st.st. hiring cost	4.5 percent
ζ	price contract length	6 months
γ	elasticity of substitution	8
τ	output elasticity to capital	0.35
$\xi_{\delta,z}$	elast. of depr. rate to cap.ut.	1
δ	depreciation rate (annually)	7.1 percent
$\overline{\mathbf{R}}/\overline{\Pi}$	st.st. gross real rate	$1.04^{1/12}$
$\overline{\Pi}$	st.st. gross inflation rate	1
δ_R	interest rate smoothing	0.5
σ_m	st. dev., monetary pol. shock	0.1 percent
μ	CRRA parameter	2
$(c_e - c_u)\ /\ c_e$	st.st. cons. drop upon unempl.	15 percent

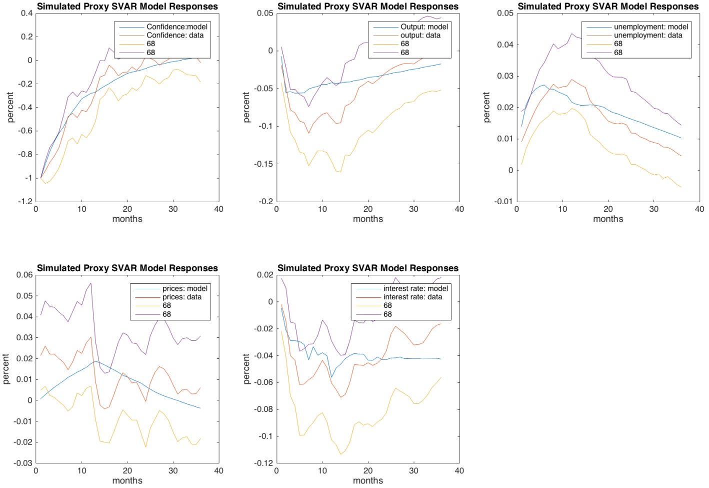
Estimated Parameters

Parameter	Meaning	Estimates
χ	real wage elasticity	0.0211
ρ_A	persistence of TFP shocks	0.9165
δ_Π	interest rate resp. to infl.	1.166
δ_θ	interest rate resp. to tightness	0.0005
β	implied disc. factor (annually)	0.87
Θ^F	implied risk wedge	0.0034

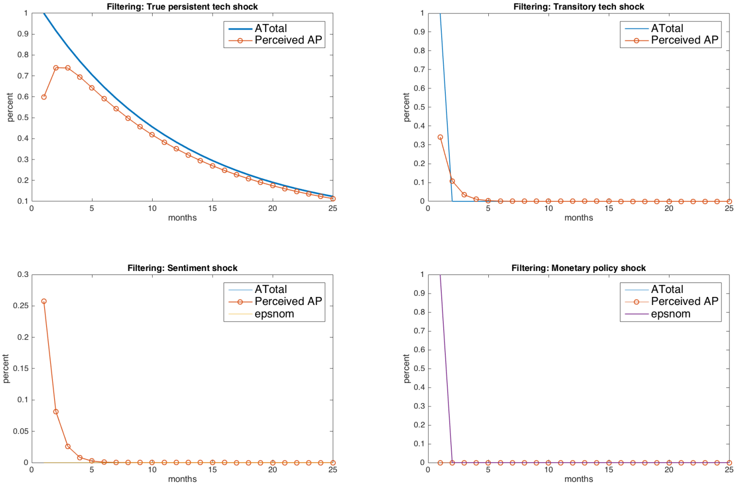
Estimated Parameters

Parameter	Meaning	Estimate
σ_P	std., persistent TFP shock	0.09 percent
σ_T/σ_P	std., trans. TFP shock	1.144 percent
σ_S/σ_P	std., sentiment shock	1.318 percent
$\rho_{\mathbf{CI}}$	confidence persistence	0.923
ϑ_1	confidence parameter	3..42
ϑ_2	confidence parameter	28.4
σ_{CI}	measurement error, confidence	0.01 percent

Matched VAR IRFs (1)



True Model IRFS



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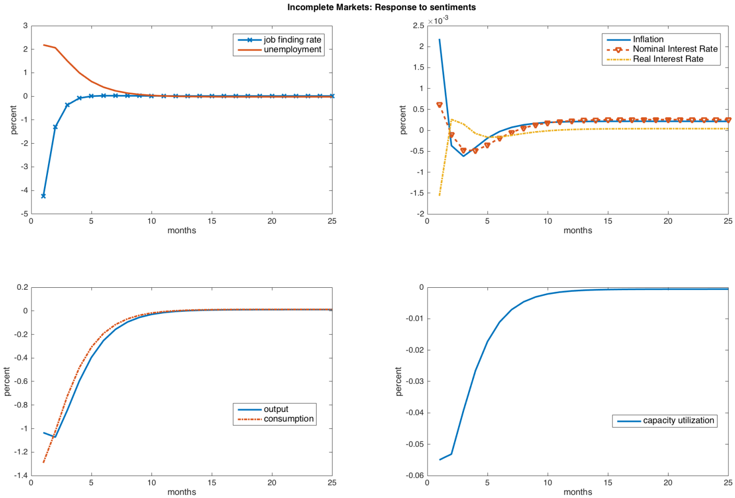
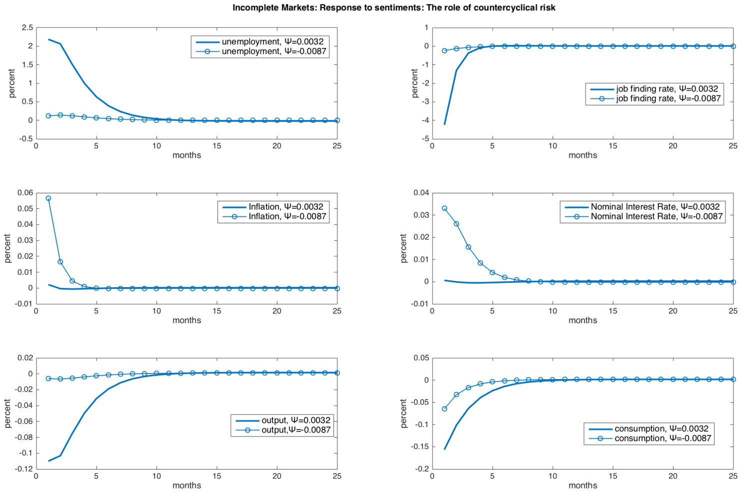
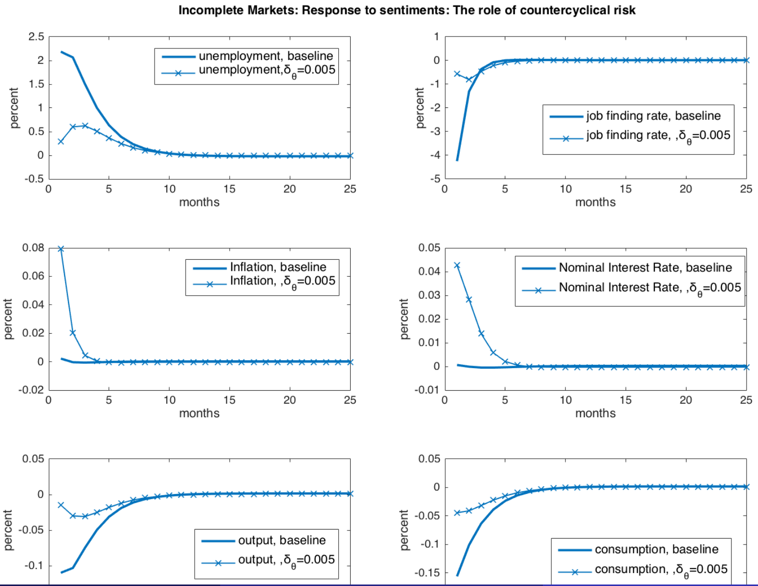


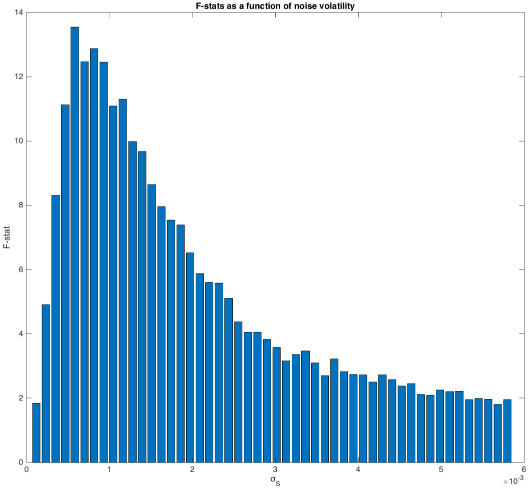
Role of Countercyclical Risk



Role of monetary stabilization



Role of Noise



Summary

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- Confidence matters for labor market

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- Find countercyclical risk wedge to be important

Empirics

Confidence and Sentiments: Think of consumer confidence as:

$$\mathbf{CI} = \mathbf{F}\,(\text{fundamentals,news,noise,sentiments})$$

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$$\mathbf{X}_t = \mathbf{A}\left(L\right)\mathbf{X}_{t-1} + \mathbf{u}_t$$

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- Do not claim causality

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Barsky and Sims: Construct NK model with imperfect information.

- TFP follows:

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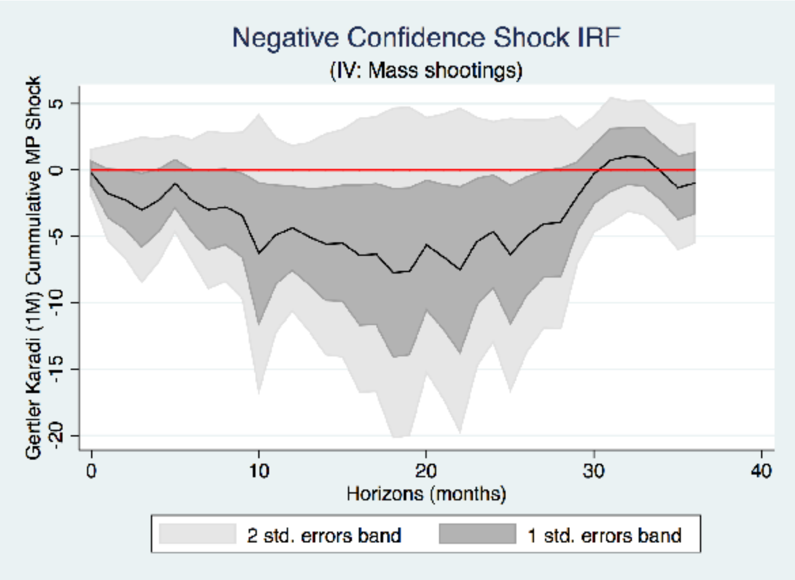
- Barsky-Sims model-equivalent of $\mathbf{CI}_t$ is:

$$\mathbf{CI}_t = \zeta_1 \left(a_t - a_{t-1} - g_{t|t-1}\right) + \zeta_2 \left(g_{t|t} - \rho_a g_{t|t-1}\right) + \zeta_2 \varepsilon_{c,t}$$

Impact on Gertler-Karadi MP Shock



Calibrated parameters (monthly)

Parameter	Meaning	Value
$\bar{\mathbf{u}}$	st.st. unemployment rate	6 percent
$\bar{\eta}$	st.st. job finding rate	34 percent
α	matching function parameter	0.6
$(\kappa/\bar{\mathbf{q}}) \,/\, (3\bar{\mathbf{w}})$	st.st. hiring cost	4.5 percent
ζ	price contract length	6 months
γ	elasticity of substitution	8
τ	output elasticity to capital	0.35
$\xi_{\delta,z}$	elast. of depr. rate to cap.ut.	1
δ	depreciation rate (annually)	7.1 percent
$\bar{\mathbf{R}}/\bar{\Pi}$	st.st. gross real rate	$1.04^{1/12}$
$\bar{\Pi}$	st.st. gross inflation rate	1
δ_R	interest rate smoothing	0.8
σ_m	st. dev., monetary pol. shock	0.1 percent
μ	CRRA parameter	2
$(c_e - c_u) \,/\, c_e$	st.st. cons. drop upon unempl.	15 percent

Estimated Parameters

Parameter	Meaning	Estimate
χ	real wage elasticity	0.043
ρ_A	persistence of TFP shocks	0.977
δ_Π	interest rate resp. to infl.	1.002
δ_θ	interest rate resp. to tightness	0.0004
β	implied disc. factor (annually)	0.87
Θ^F	implied risk wedge	$0.0024 > 0$

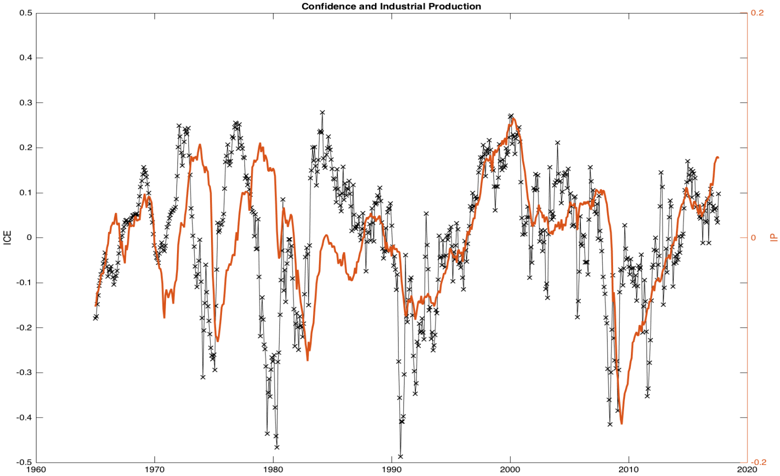
Estimated Parameters

Parameter	Meaning	Estimate
σ_T	std., transitory TFP shock	0.10 percent
σ_P	std., innov. to perst. TFP	0.07 percent
σ_S	std., sentiment shock	0.07 percent
$\rho_{\mathbf{CI}}$	confidence persistence	0.90
ϑ_1	confidence parameter	1.27
ϑ_2	confidence parameter	39.15
σ_{CI}	measurement error, confidence	2.5 percent

Mass Shootings with 12 or More Fatalities

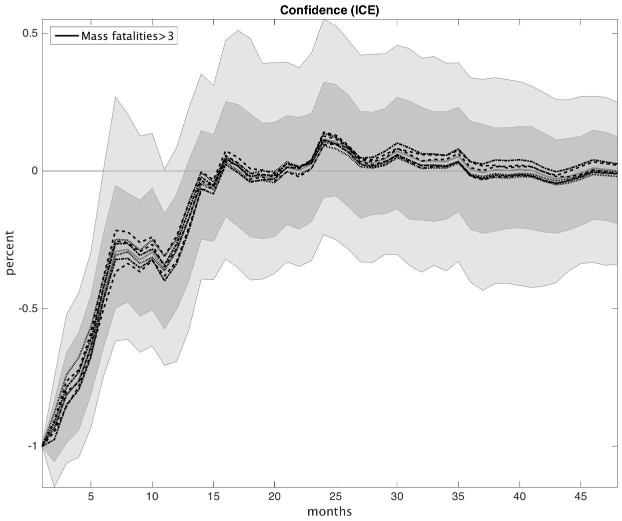
Incident	Location	Date	Fat.	Inj.
U. of Texas Tower shooting	Austin, Tx	Aug 1966	18	31
San Ysidro's McD massacre	San Ysidro, Cal	Jul 1984	22	19
U.S. Postal Service shooting	Edmond, Okl	Aug 1986	15	6
Luby's massacre	Killeen, TX	Oct 1991	24	20
Columbine High massacre	Littleton, Col	Apr 1999	13	24
Virginia Tech massacre	Blacksburg, VA	Apr 2007	32	23
Binghampton shootings	Binghampton, NY	Apr 2009	14	4
Fort Hood massacre	Fort Hood, TX	Nov 2009	13	30
Aurora Theatre shooting	Aurora, Col	Jul 2012	12	70
Sandy Hook massacre	Newtown, Conn	Dec 2012	28	2
Wash. Navy Yard shooting	Washington, D.C.	Sep 2013	12	8
San Bernadino mass shooting	San Bernadino, Cal	Dec 2015	14	21
Orlando Nightclub massacre	Orlando, FL	Jun 2016	49	53
Las Vegas Strip massacre	Las Vegas, Nevada	Oct 2017	58	546
Texas First Baptist Church mass.	Sutherland Springs, TX	Nov 2017	26	20
Marjory Stonemann Douglas High School	Parkland, FL	Feb 2018	17	17

ICE ICE B...



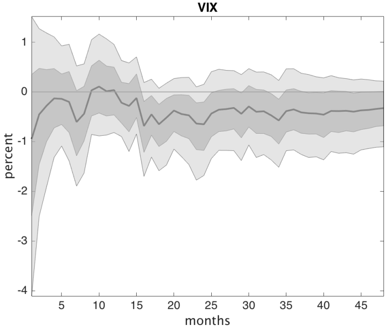
Confidence and Industrial Production
ICE
IP
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
0.2
0
-0.2
1960
1970
1980
1990
2000
2010
2020

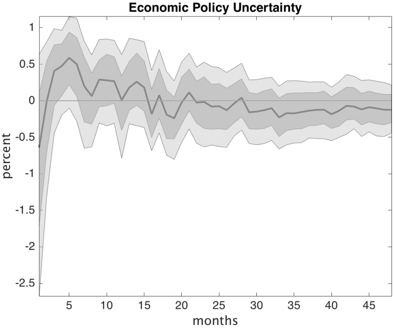
Relevance



- More noisy, less persistent

Uncertainty





Relevance

B. Alternative VAR-specifications, 1965:1-2007:8				
			F-test value	
Confidence	Observables	Lags	F^{HOM}	F^{MOP}
ICC	Benchmark	18	3.2	3.8
ICS	Benchmark	18	9.7	12.7
BUS5	Benchmark	18	5.3	5.6
BUS12	Benchmark	18	9.0	19.0
ICE	CPI inflation	18	10.1	13.4
ICE	no SP500	18	9.4	17.2
ICE	no U12	18	9.2	12.9
ICE	no SP500, U12	18	7.3	12.6
ICE	Benchmark	12	8.9	7.2

- Use Montiel Olea, Stock and Watson (2017) parametric bootstrap with Newey-West HAC-robust covariance matrix