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 shocks/ commodity price shocks.
- TFP uncertainty shocks/ 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

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 in labor market.
   - HANK&SAM provides amplification mechanism.
3. **Quantification**: Estimate key structural parameters:
   - Simulation based estimates of structural parameters.

This paper: Key Findings

1. **Empirics**: A deterioration in consumer confidence:
   - raises unemployment, decreases industrial production and consumption persistently
   - reduces the nominal interest rate and is non-deflationary

Sentimental Business Cycles: Sentimental shocks explain between 16 and 28 % of variance of unemployment and 10 to 20 % of fluctuations in industrial production at business cycle frequencies.

2. **Theory**: Shocks to sentiments induces a powerful supply-demand feedback mechanism:
   - Countercyclical risk wedge important for amplification of negative demand effects.
   - Monetary policy can moderate demand effects.
   - Non-deflation results from interaction of supply-demand feedback.

Empirics

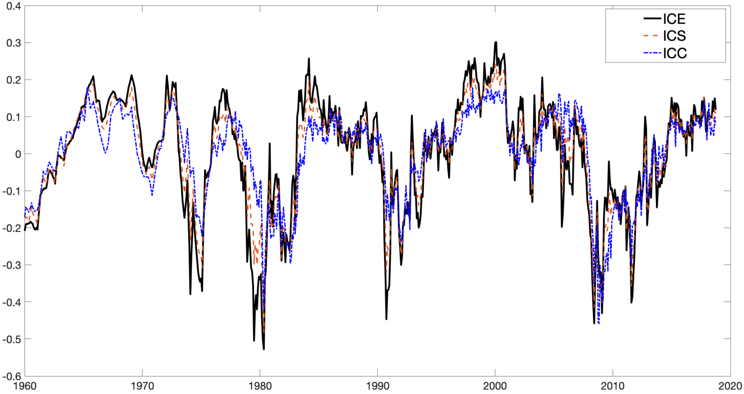
Sentiments: Draw data from **University of Michigan Survey of Consumer Confidence**:

- 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**:

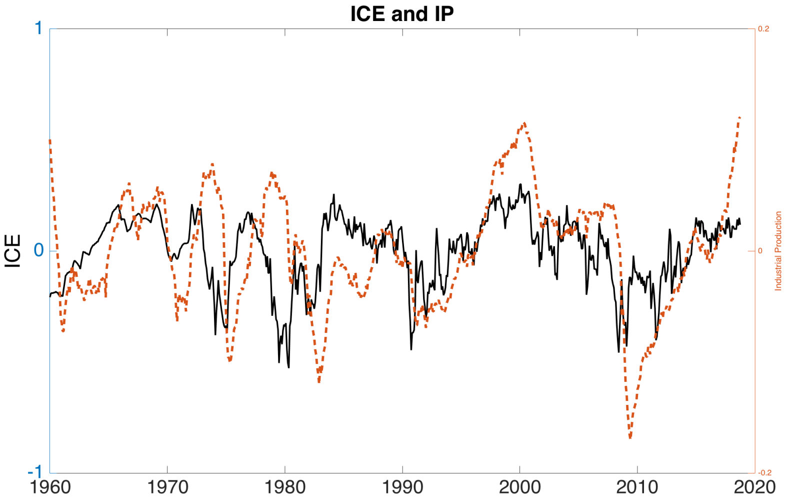
- **Index of Consumer Sentiment** (**ICS**): A mix of:
- **Index of Current Economic Conditions** (**ICC**), and
- **Index of Consumer Expectations** (**ICE**).

Empirics



ICE
ICS
ICC
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
1960
1970
1980
1990
2000
2010
2020

ICE



ICE and IP
1
0
-1
ICE
0.2
0
-0.2
Industrial Production
1960
1970
1980
1990
2000
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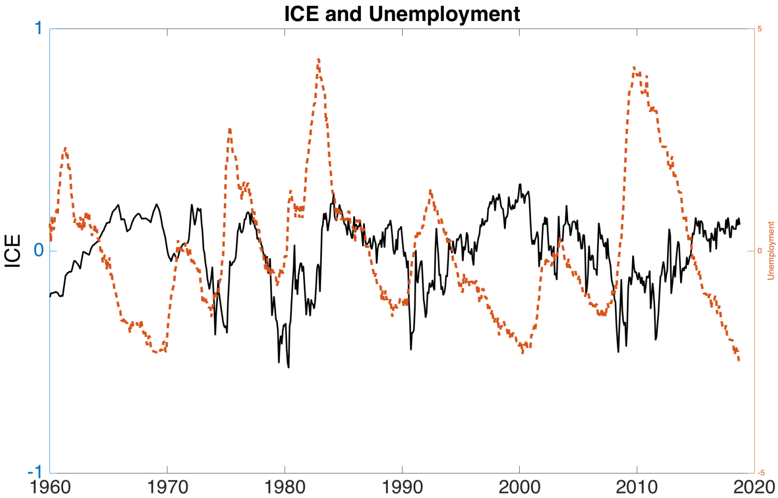
ICE


ICE and Unemployment
ICE
Unemployment
1
0
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5
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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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- Use an external instrument to proxy for the sturctural shock.
- Can be estimated with 2SLS or 3SLS.

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Assume that the dynamics of observables is:

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

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

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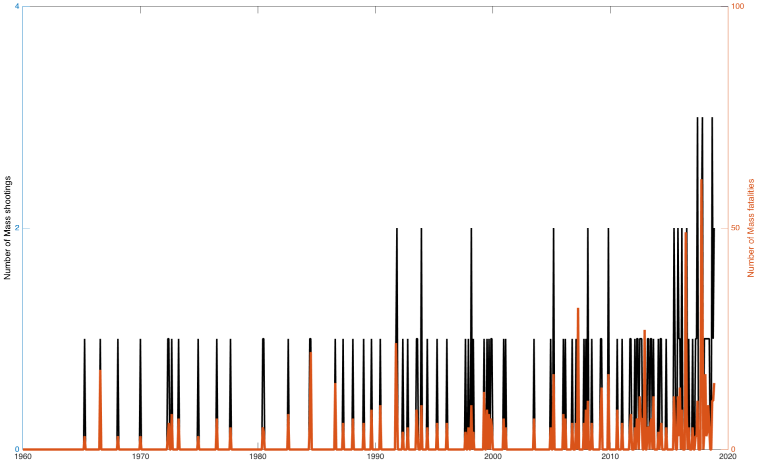
- Mass shootings are unpredictable over time.
- Each event unlikely to bear much in terms of direct costs.

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

Fatalities in Mass Shootings



Mechanism: Shooting -> News -> Confidence

Incident	Year	TV cov.	TV time	Articles	Words
Sandy Hook	2012	168	15:57:10	130	118,354
Fort Hood sh.	2009	31	05:05:00	36	35,097
Virginia Tech shooting	2007	59	06:12:12	36	33,473
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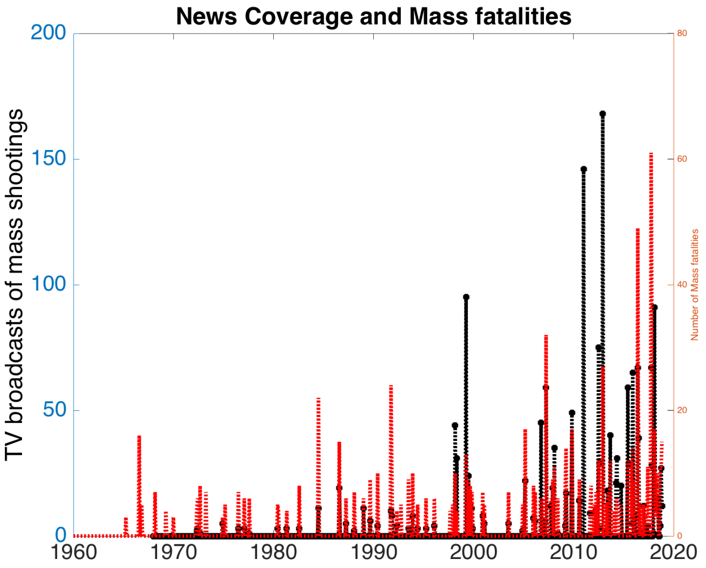
- Lankford (2018): Mass killers (7 biggest shootings since 2012) received more news coverage than top sports stars and celebrities.
- Mass shootings impact on psychological well-being: PTSD symptoms (Hughes et al, 2011), subjective well-being (Clark and Stancanelli, 2017) - potential for direct impact on confidence.


News Coverage and Mass fatalities
TV broadcasts of mass shootings
Number of Mass fatalities
200
150
100
50
0
80
60
40
20
0
1960
1970
1980
1990
2000
2010
2020

Estimation

Implementation: US time series data:

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- Instrument: Detrended fatalities or TV media coverage

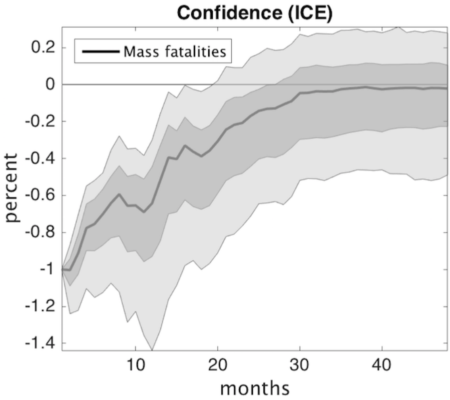
Relevance

Weak Instrument tests, VAR with 18 lags				
	Instrument			
	Fatalities		News coverage*	
Sample	F^{hom}	F^{MOP}	F^{hom}	F^{MOP}
1960-2015:1	12.43	6.76	-	-
1968-2015:1	-	-	15.83	52.20
1960-2017:6	11.13	6.36	-	-
1968-2017:6	-	-	11.15	3.53
1960-2007:9	5.50	4.30	-	-
1968-2007:9	-	-	3.5	34.82

*Logistic transformation

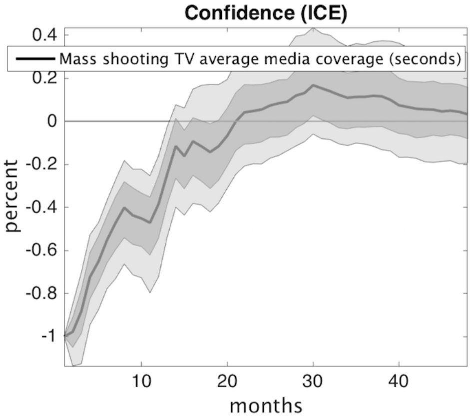
- Use Montiel Olea, Stock and Watson (2017) parametric bootstrap with Newey-West HAC-robust covariance matrix

Relevance



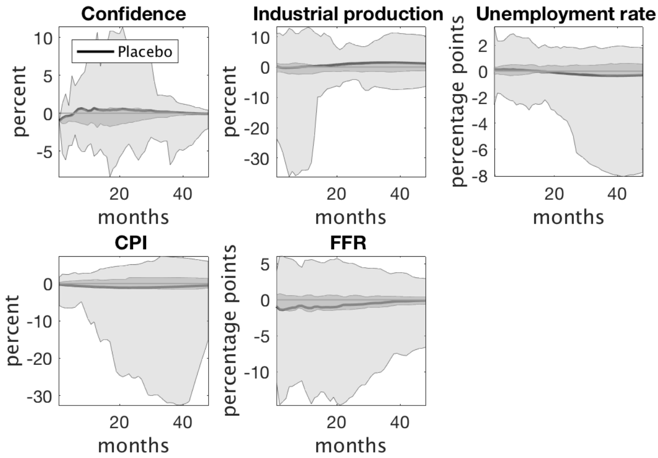
- Significant drop in ICE for approximately 2 years.
- **Relevance** $\surd$

Relevance



- Slightly more precisely estimated for full sample
- **Relevance** $\surd$

IV with random reshuffling of mass fatalities



Impulse Responses

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

- Normalization: 1 percent drop in consumer confidence.

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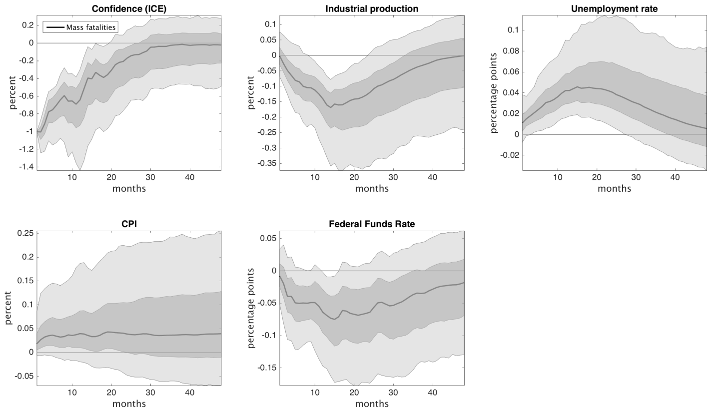
Impulse Responses

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

- Normalization: 1 percent drop in consumer confidence.
- Augment with other variables.
- Look at relationship to other shocks.

Benchmark VAR



More Results

Dynamic Causal Effects: Robustness and impact on other variables:

- Robust to using news coverage.

Other variables:

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Other variables:

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- TFP: No impact.

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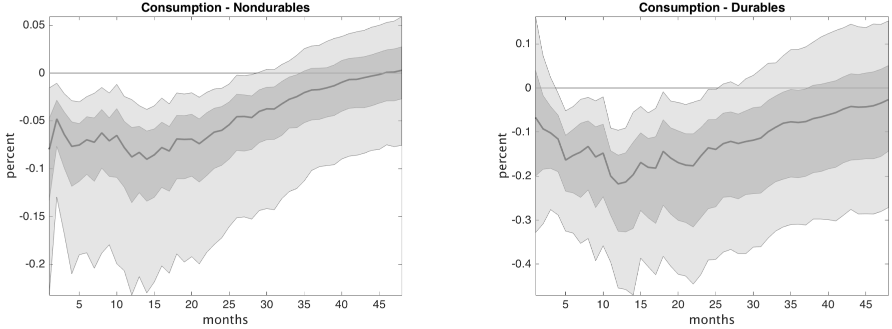
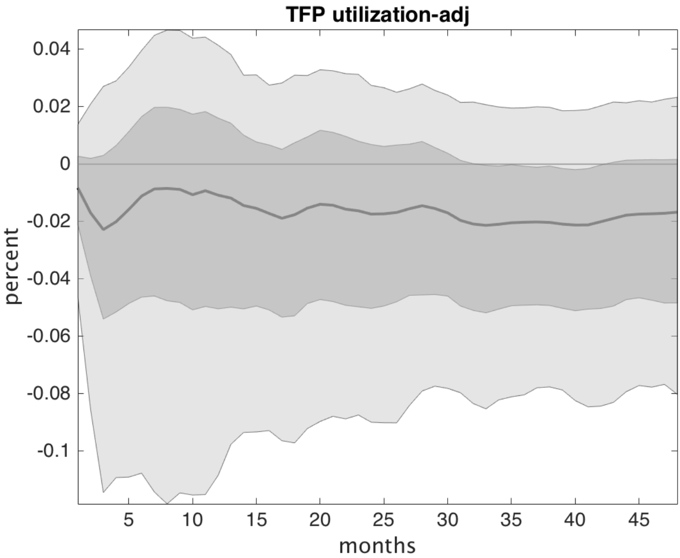
Other variables:

- Drop in consumption.
- Labor market variables: Hours worked down, tightness down.
- Capacity utilization drops.
- Nominal exchange rate depreciates.
- TFP: No impact.
- Relationship to uncertainty: No significant impact.

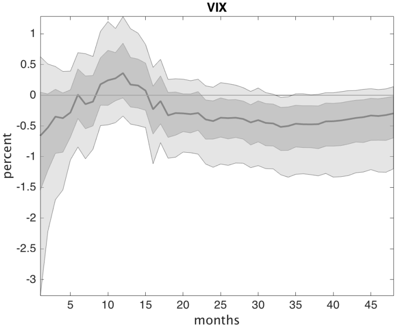
Consumption

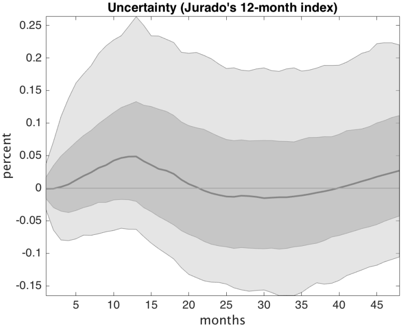


Fernald Capacity Util. Adj. TFP

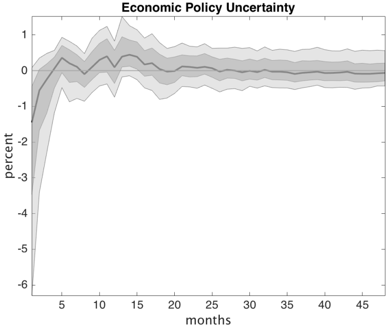


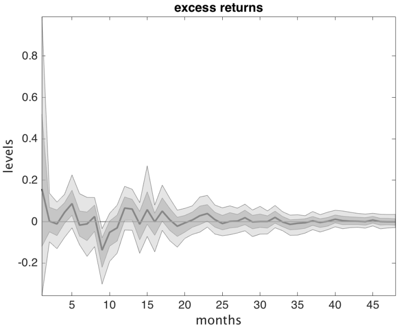
Uncertainty





EPU and Stock Market Returns





Contribution to Business Cycles:

	Variable							
Horizon	**ICE**	**IP**	**U**	**CPI**	**FFR**	**Hrs**	**TIGHT**	**V**
1	65	3	21	21	3	1	38	9
3	61	6	19	24	6	1	35	7
6	59	9	20	21	8	2	35	7
12	59	17	26	16	11	6	37	13
24	49	21	28	11	15	6	35	14
48	45	13	16	8	12	6	30	13

- Important for labor market

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.

Theory: The main mechanism

Countercyclical Endogenous Risk:

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

Countercyclical Endogenous Risk:

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

Theory: The main mechanism

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

$\downarrow$

goods demand $\downarrow$

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

Theory: The main mechanism

Countercyclical Endogenous Risk:

$$
\begin{array}{ccccc}
\text{Noise shock(-)} & \xrightarrow{\text{(filtering)}} & \text{Confused with } \mathbf{A}^P \downarrow & & \\
& & \downarrow & & \\
& & \text{goods demand} \downarrow & & \\
& & & \searrow \text{(NK)} & \textbf{Firms} \\
& & & & \text{labor} \\
& & & & \text{demand} \downarrow \\
& & & \swarrow \text{(SAM)} & \\
& & u \uparrow \text{, real wages} \downarrow & &
\end{array}
$$

Theory: The main mechanism

Countercyclical Endogenous Risk:

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

$\downarrow$

goods demand $\downarrow$

Households precautionary saving $\uparrow$ (HA) $\nearrow$ $\searrow$ (NK)   **Firms** labor demand $\downarrow$

(HA) $\nwarrow$ $\swarrow$ (SAM)

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

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, Interest Rates, Asset Markets

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:

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

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:

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

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

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

- 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 $\mathbf{A}_s^P, \varepsilon_s^T \notin I_s$.

Monetary Policy:

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

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

The Endogenous Risk Channel

Endogenous earnings risk: log-linearized Euler equation:

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

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- **countercyclical** if $\Theta^F > 0$: **Amplification/Propagation**
- **acyclical** if $\Theta^F = 0$: No endogenous risk feedback.

The Endogenous Risk Channel

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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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- **Procyclical risk**: **Stabilization**
- recession $\Rightarrow$ lower real wage $\Rightarrow$ less precautionary savings demand $\Rightarrow$ demand expands at the current real interest rate $\Rightarrow$ stabilization.
- 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. Simulate model to generate:

$$\mathbf{X}_t^{theory} = \begin{pmatrix} CI_t & \text{(log consumer confidence)} \\ Y_t & \text{(log industrial production)} \\ U_t & \text{(unemployment rate)} \\ P_t & \text{(log CPI)} \\ R_t & \text{(Federal funds rate)} \end{pmatrix}$$

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5. Repeat N times and average:

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

Calibrated parameters (monthly)

Parameter	Meaning	Value
$\bar{\mathbf{u}}$	st.st. unemployment rate	6 percent
$\bar{\eta}$	st.st. job finding rate	34 percent
$(\kappa/\bar{\mathbf{q}})\ /\ (3\bar{\mathbf{w}})$	st.st. hiring cost	4.5 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	0.25
σ_m	st. dev., monetary pol. shock	0.1 percent
γ	elasticity of substitution	8
μ	CRRA parameter	2
α	matching function parameter	0.5
τ	output elasticity to capital	0.35
$\xi_{\delta,z}$	elast. of depr. rate to cap.ut.	1
δ	depreciation rate (annually)	7.1 percnet
$(c_e - c_u)\ /\ c_e$	st.st. cons. drop upon unempl.	12 percent

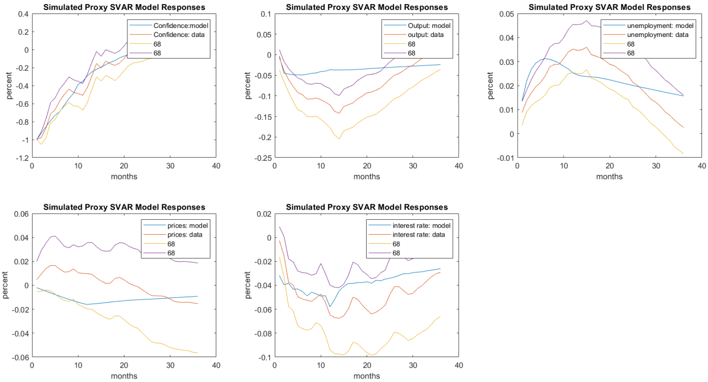
Estimated Parameters - Preliminary

Parameter	Meaning	Estimate
ϕ	price adj. cost	401
χ	real wage elasticity	0.04
ρ_A	persistence of TFP shocks	0.99
δ_Π	interest rate resp. to infl.	1.32
ψ	impact of noise on mon.pol.	0.004
β	implied disc. factor (annually)	0.870
Θ^F	implied risk wedge	$0.0026>0$
ξ	average price contract length	7.82 months

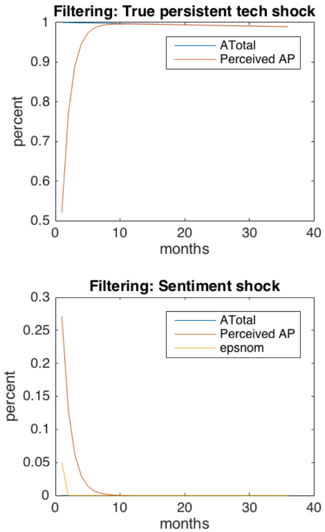
Estimated Parameters - Preliminary

Parameter	Meaning	Estimate
σ_T	std., transitory TFP shock	0.50 percent
σ_P	std., innov. to perst. TFP	0.05 percent
σ_S	std., sentiment shock	0.19 percent
$\rho_{\mathbf{CI}}$	confidence persistence	0.960
ϑ_1	confidence parameter	1.019
ϑ_2	confidence parameter	7.968
σ_{CI}	measurement error, confidence	0.15 percent
σ_{m_2}	measurement error, proxy	1.6 percent

Matched VAR IRFs - Preliminary



True Model IRFS - Preliminary



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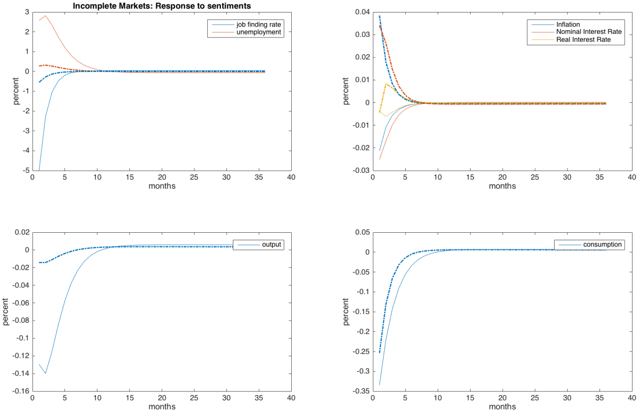

Model FEVD

Contribution to Business Cycles: Forecast error variance decomposition

	Variable						
Horizon	**ICE**	**IP**	**U**	**CPI**	**FFR**	**TIGHT**	**V**
1	30	0.7	19	34	0.3	18	18
3	18	1.3	16	28	0.6	9.3	8.2
6	10	8.4	12	19	0.8	2.7	2.9
12	2.5	0.7	4.2	5.7	1.1	0.7	1.0
24	0.7	0.2	0.8	1.2	0.7	0.2	0.3
48	0.2	0.1	0.2	0.3	0.3	0.1	0.1

Summary

Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks

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- Proposed dynamic causal estimation of consumer sentiment shocks
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- Find countercyclical risk wedge to be important

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).

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Confidence and Sentiments: Think of consumer confidence as:

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

- How can one isolate the expectational/non-fundamental component?

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- Do not claim causality

Empirics: Barsky and Sims

- Confidence innovation predicts future income and consumption growth.

Empirics: Barsky and Sims

Barsky and Sims: Construct NK model with imperfect information.

- TFP follows:

$$a_t = a_{t-1} + g_{t-1} + \varepsilon_{a,t}$$
$$g_t = (1 - \rho_a)\, g^* + \rho_a g_{t-1} + \varepsilon_{g,t}$$

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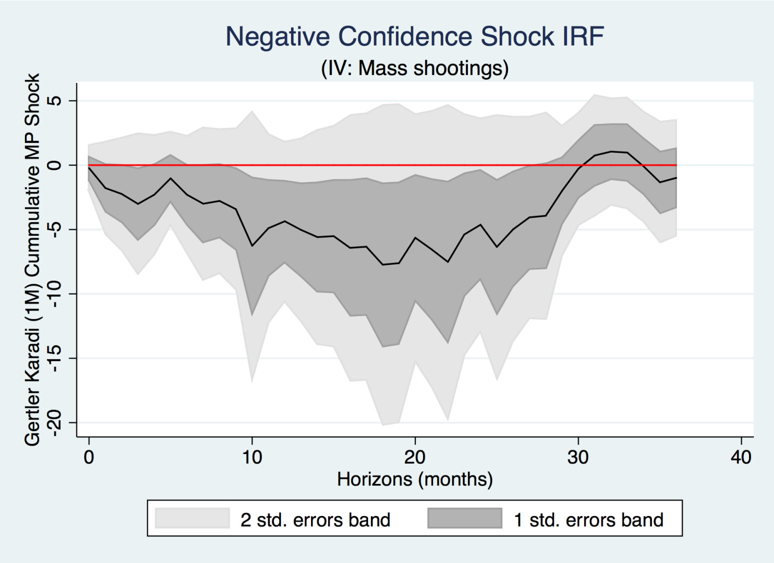
$$s_t = g_t + \varepsilon_{s,t}$$

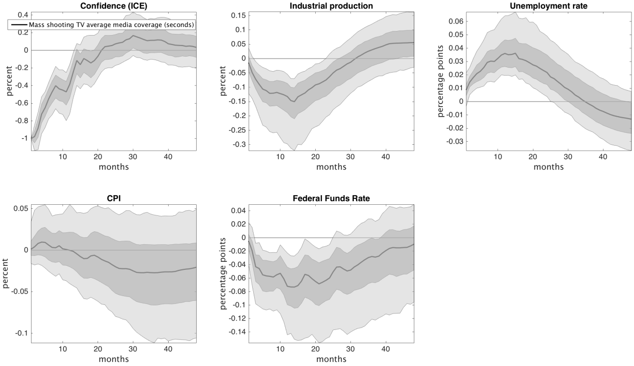
- $\varepsilon_{s,t}$: **Sentiments/animal spirits** (pure expectational shocks).
- Barsky-Sims model-equivalent of $\mathbf{CI}_t$ is:

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

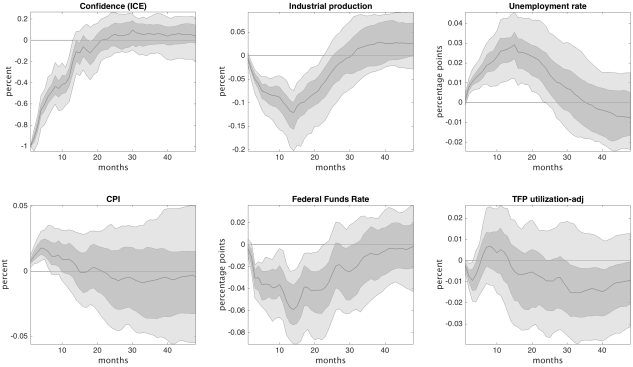
Impact on Gertler-Karadi MP Shock



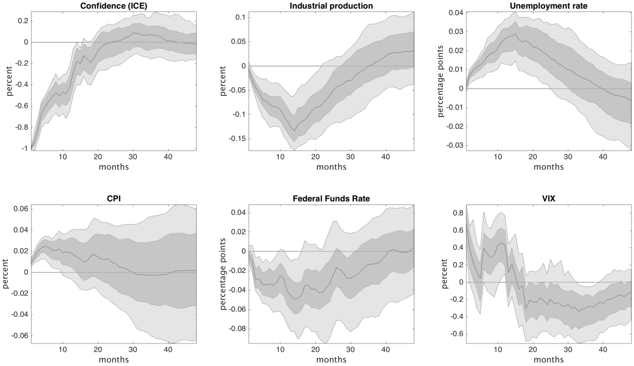
Alternative IV



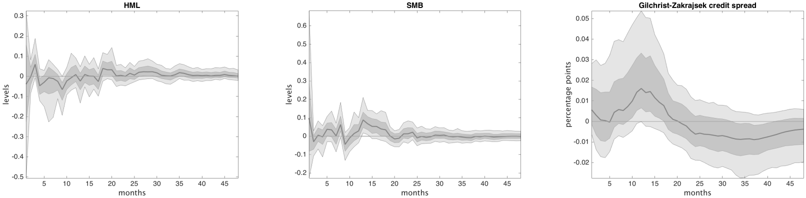
Cholseky TFP



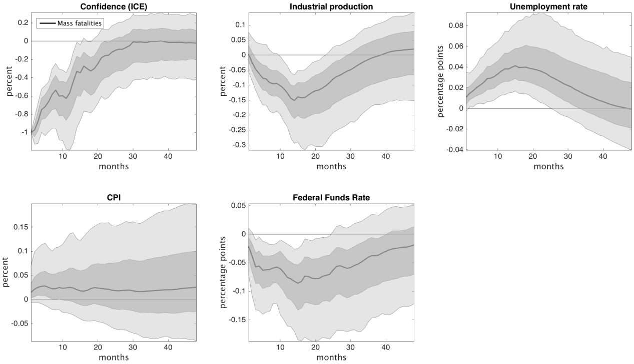
Cholseky VIX



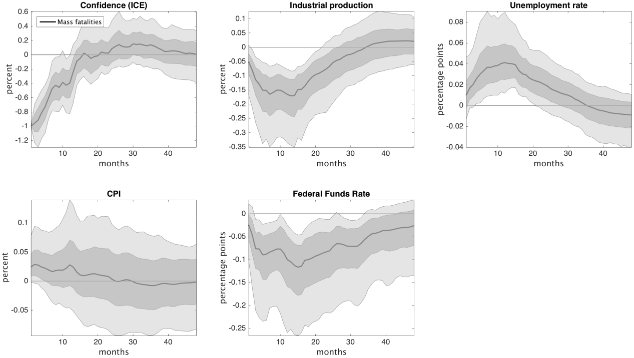
Other stock market variables



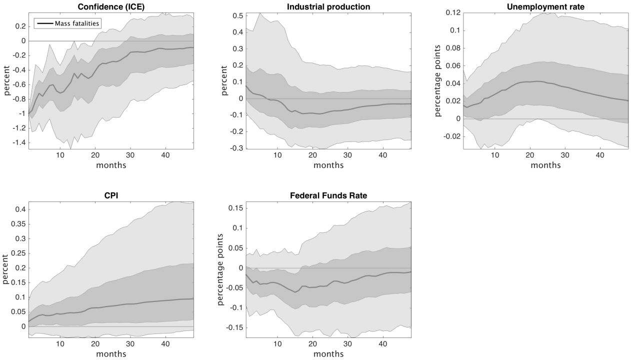
No detrending of mass fatalities



Before the Great Recession



Whole Sample



Whole Sample Alternative IV with TV coverage