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?

- News and sentiments non-observed and hard to translate into observables
- **News**: Use either information from asset prices or structural models
- **Multiple equilibria**: Some attempts using structural models.
- **Animal spirits**:
  - 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)
- None of the latter produce direct causal evidence on impact of sentiments

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 (HANK) model.
   - Search and Matching in labor market (SAM).
   - 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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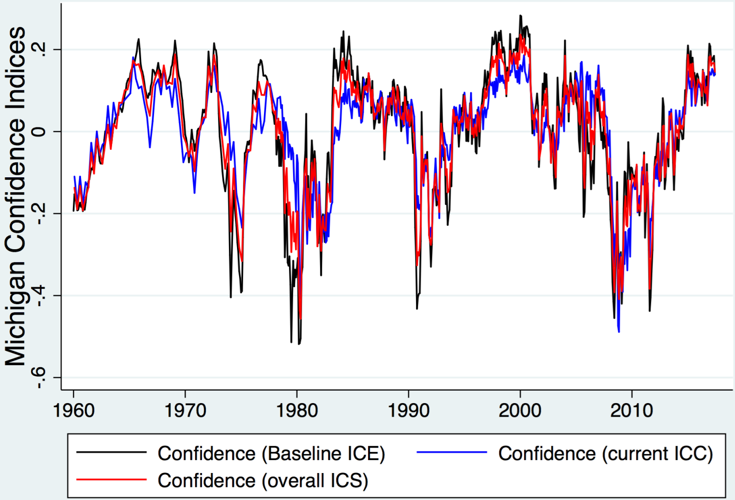
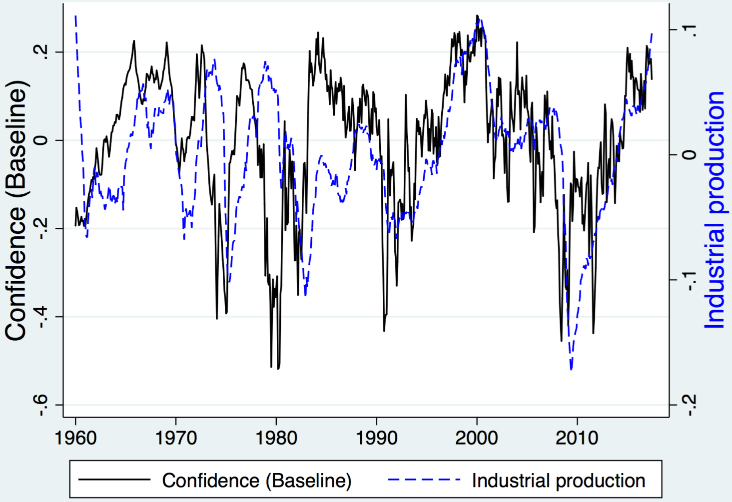
- **ICE** computed as 100 + "% positive respondents" - "% negative respondents" (normalized to 1966 base).

Empirics



Note: Both variables are detrended using a 4th order polynomial trend.

ICE ICE B...



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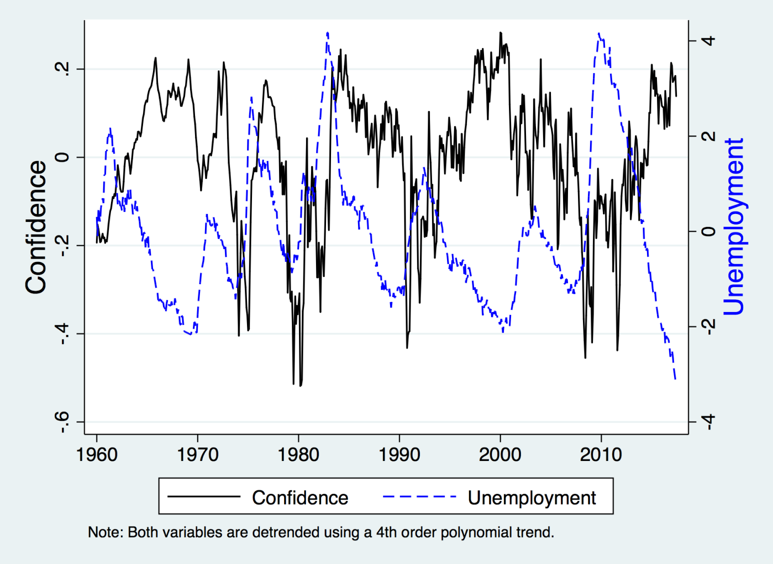

Confidence
Unemployment
.2
0
-.2
-.4
-.6
4
2
0
-2
-4
1960
1970
1980
1990
2000
2010
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- **Ludvigson** (2004): ICE has predictive power for aggregate consumption growth (but not robust to allowing for control variables such as the consumption-wealth ratio).
- **Problem**: Predictive power / Granger causality may simply be due to confidence data reflecting news about future fundamentals and not necessarily due to sentiments.

Empirics

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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- **Barsky and Sims**: Estimate VAR:

$$\begin{aligned} \mathbf{X}_t &= \begin{bmatrix} \mathbf{CI}_t \\ \mathbf{C}_t \\ \mathbf{Y}_t \end{bmatrix} \\ \mathbf{X}_t &= \mathbf{A}\left(L\right)\mathbf{X}_{t-1} + \mathbf{u}_t \end{aligned}$$

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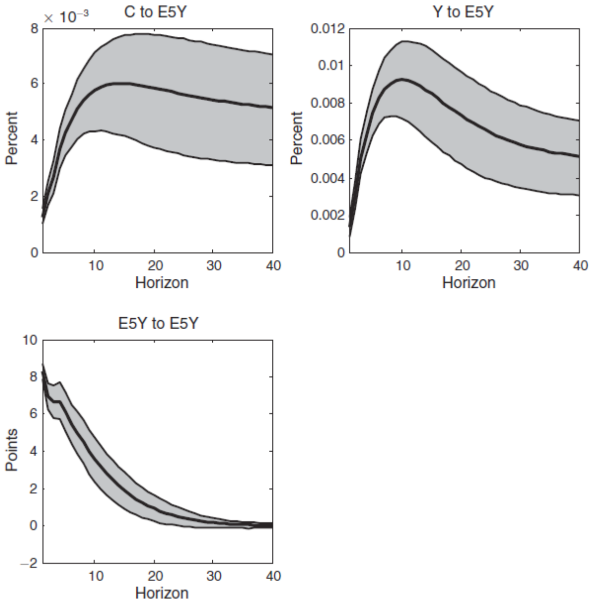
- Do not claim causality

Empirics: Barsky and Sims



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Barsky and Sims: Construct NK model with imperfect information.

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

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

Theory: Barsky and Sims

TABLE 3—MODEL VARIANCE DECOMPOSITION

	$h = 1$	$h = 4$	$h = 8$	$h = 16$	$h = 20$
News					
E5Y	0.52	0.71	0.75	0.77	0.77
C	0.11	0.25	0.36	0.47	0.49
Y	0.02	0.11	0.31	0.46	0.49
Animal spirits					
E5Y	0.25	0.09	0.06	0.05	0.04
C	0.06	0.01	0.00	0.00	0.00
Y	0.01	0.01	0.00	0.00	0.00
Technology					
E5Y	0.01	0.01	0.00	0.00	0.00
C	0.43	0.48	0.50	0.48	0.47
Y	0.13	0.54	0.57	0.50	0.48
Noise					
E5Y	0.22	0.19	0.19	0.18	0.18

- Confidence innovations are news shocks, animal spirits don't matter.

Empirical Approach

Our **approach**: Dynamic causal analysis:

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

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- Can be estimated with 2SLS or 3SLS.

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Assume that the dynamics of observables is:

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- Order **CI** (wlog) first

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- From this can compute identified impulse responses etc.
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- Allows for measurement errors and one can correct for scaling issues

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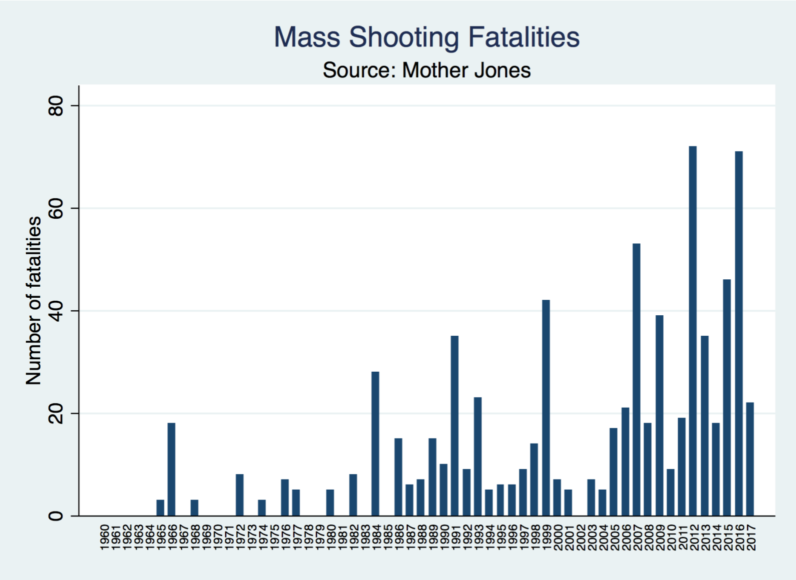
- Mass shootings are unpredictable over time.
- Each event unlikely to bear much in terms of direct costs.

Mass Shootings with 10 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
GMAC massacre	Jacksonville, Fla	Jun 1990	10	4
Luby's massacre	Killeen, TX	Oct 1991	24	20
Columbine High massacre	Littleton, Col	Apr 1999	13	24
Red Lake massacre	Red Lake, Minn	Mar 2005	10	5
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, Fla	Jun 2016	49	53

Fatalities in Mass Shootings



Mechanism: Shooting -> News -> Confidence

Incident	Year	Articles	Words
Sandy Hook	2012	130	118,354
Shooting of Gabrielle Clifford	2011	89	91,715
Fort Hood military base sh.	2009	36	35,097
Virginia Tech shooting	2007	36	33,473
Aurora Co. movie theatre sh.	2012	31	23,715
Red Lake massacre	2005	19	18,519
Santana High School sh.	2001	17	14,045
University of Alabama-High sh.	2010	12	12,872
Northern Illinois Univ. shooting.	2008	12	7,524
Binghampton, NY shooting	2009	11	10,729

(source: Schildkraut, Elsass and Meredith, 2017)

- In addition to electronic news coverage.

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- **Conclusion**: Many (most) Americans would be aware of mass shooting events.
- 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.

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- Benchmark VAR:

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

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- Detrend all apart from R_t with 4th order time polynomial.

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- Monthly data.
- Sample period 1960:1 - 2017:6.
- Estimate VAR with 18 lags.
- Benchmark VAR:

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

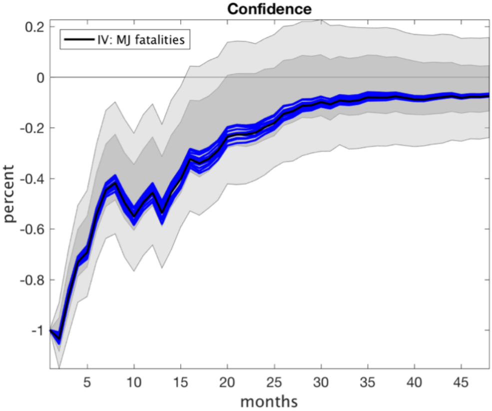
- Detrend all apart from R_t with 4th order time polynomial.
- Instrument: Detrended fatalities.

Relevance

F tests for Alternative Confidence Indices

Instrument	Mass fatalities coefficient	IV exclusion F- statistic
MotherJones Fatalities		
ICE	-1.73***	10.83
ICS	-1.07***	7.35
BUS5	-1.40***	3.35
BUS12	-0.86**	4.35
PEXP	-0.27**	4.25

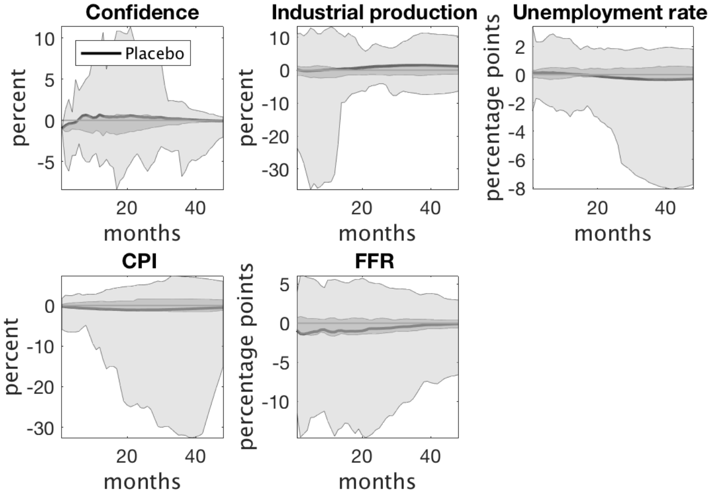
Relevance



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

Placebo: Random Reshuffling of Shootings

IV with random reshuffling of mass fatalities



Impulse Responses

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

- IV so normalization needed: 1 percent drop in consumer confidence.

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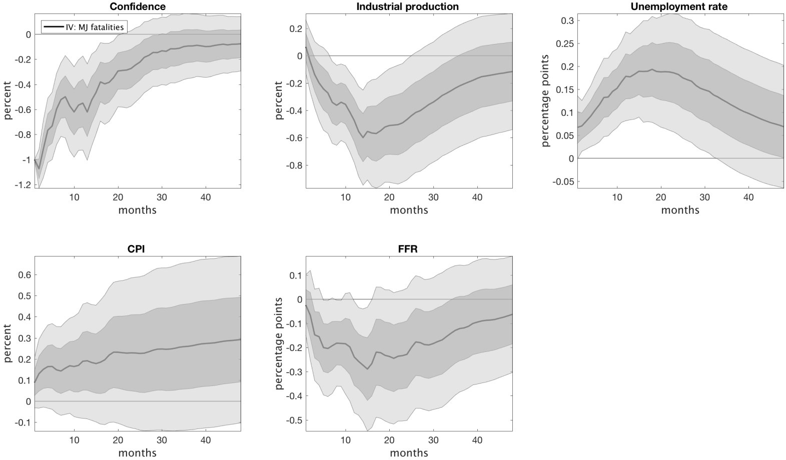
- Look at relationship to other shocks.

Benchmark VAR



Benchmark VAR

Dynamic Causal Effects: Results indicate:

- Long-lived slump in output.

Benchmark VAR

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- Increase in price level and drop in interest rates: Suggests monetary policy shock accompanying the drop in sentiments.

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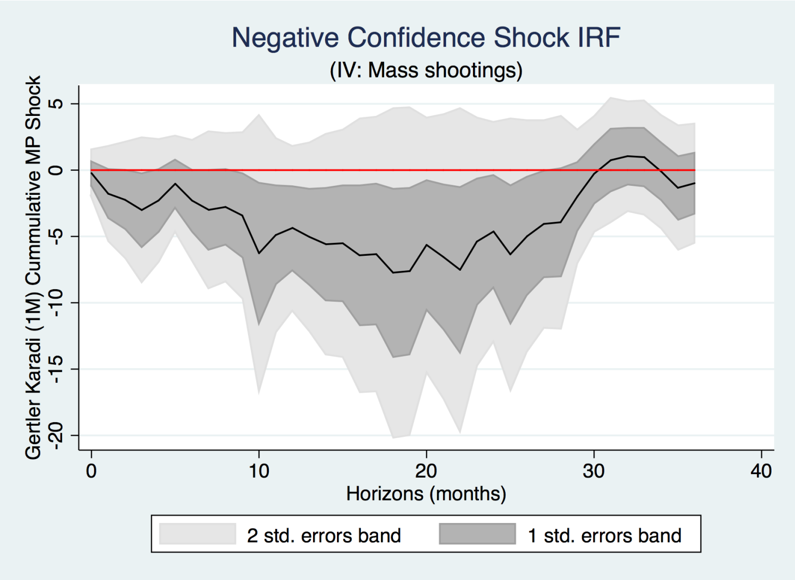
- Increase in price level and drop in interest rates: Suggests monetary policy shock accompanying the drop in sentiments.
- Check this with local projection of Gertler-Karadi MP shock on identified sentiment shock.

Impact on Gertler-Karadi MP Shock



More Results

Dynamic Causal Effects: Robustness and impact on other variables:

- Robust to 12 lags instead of 18.

Other variables:

More Results

Dynamic Causal Effects: Robustness and impact on other variables:

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- TFP: No impact.

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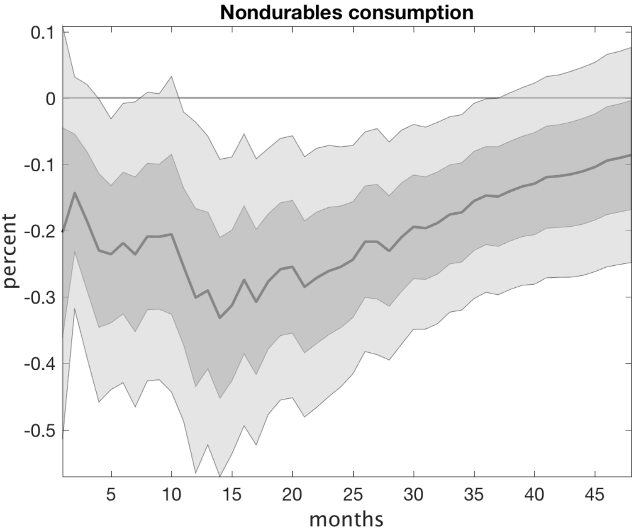
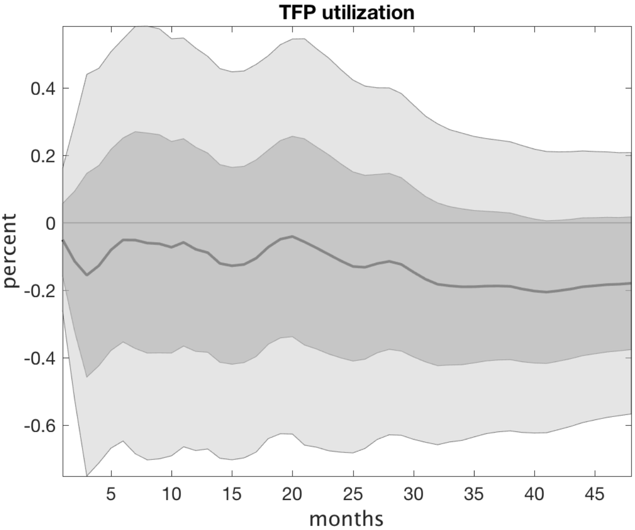
Other variables:

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

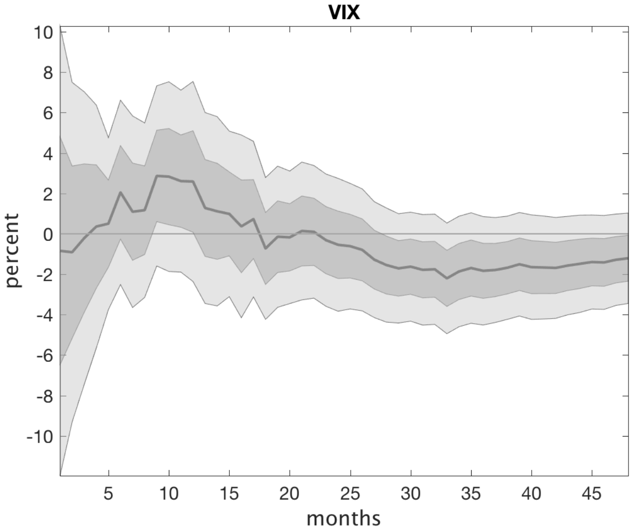
Consumption



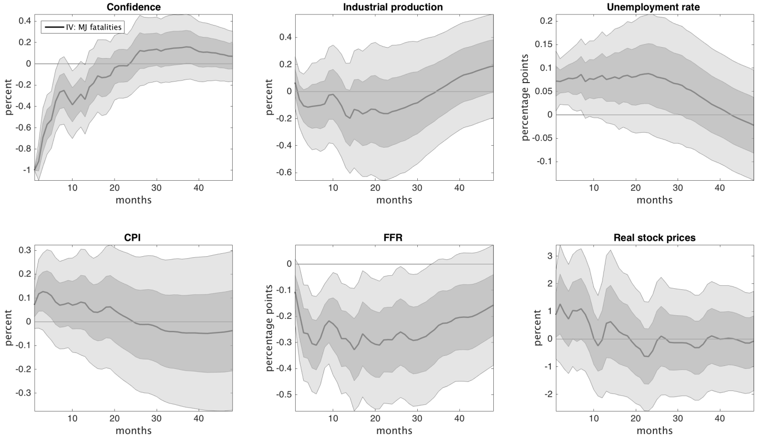
Fernald Capacity Util. Adj. TFP



VIX



Controlling for Stock Prices



Contribution to Business Cycles:

	Variable					
Horizon	**CI**	**Y**	**U**	**P**	**R**	**Q**
1	42.5	0.6	23.2	12.6	8.3	5.8
2	37.5	1.2	22.4	12.6	11.5	4.8
3	36.4	1.4	21.5	11.2	12.8	4.0
6	31.5	1.3	17.5	7.4	17.4	4.3
12	25.9	1.1	12.6	4.3	18.0	2.8
24	19.6	1.6	10.0	1.7	20.2	1.8
48	18.5	1.9	6.6	0.8	21.9	1.2
120	18.0	3.5	6.4	1.1	21.4	1.0

- sizeable contribution!

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:

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

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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 & & \downarrow & & \\
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 & & & \searrow \text{(NK)} & \textbf{Firms} \text{ labor demand} \downarrow
\end{array}
$$

Countercyclical Endogenous Risk:

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

$\downarrow$

goods demand $\downarrow$

$\searrow$ (NK)

Firms labor demand $\downarrow$

$\swarrow$ (SAM)

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

Theory: The main mechanism

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 & & \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:

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

Matching technology

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

Matching function:

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

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

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

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

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:

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

- $\Lambda_{j,t,s}$: 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:

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

- 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:

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

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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- ε_s^S : sentiment / expectational shock.

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Monetary Policy:

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

- 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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$$\Theta^F \equiv \underbrace{\omega\eta\left(\left(\vartheta/w\right)^{-\mu} - 1\right)}_{\text{unemployment risk}} - \underbrace{\chi\mu\omega\left(1-\eta\right)}_{\text{wage risk}}$$

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

The Endogenous Risk Channel

- **Countercyclical risk**: **Amplification**

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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- Can also generate inflationary impact of technology shocks.

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5. Repeat N times and average:

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

Calibrated parameters (monthly)

Parameter	Meaning	Value
$\bar{\mathbf{u}}$	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

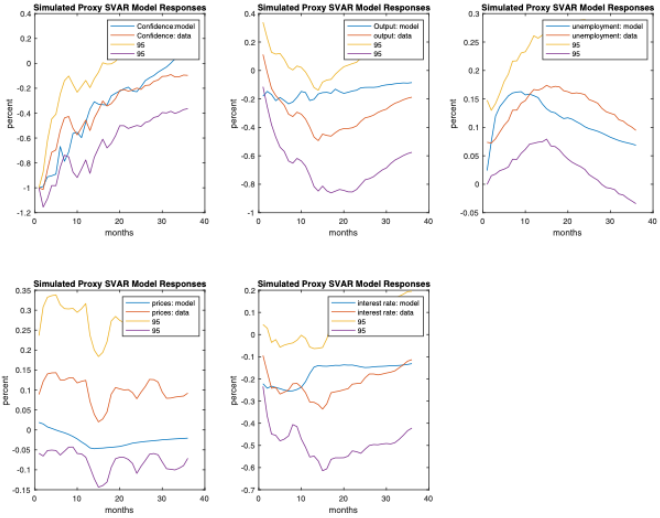
Estimated Parameters - Preliminary

Parameter	Meaning	Estimate
ϕ	price adj. cost	282.9
χ	real wage elasticity	0.016
ρ_A	persistence of TFP shocks	0.987
δ_Π	interest rate resp. to infl.	2.09
ψ	impact of noise on mon.pol.	0.145
β	implied disc. factor (annually)	0.892
Θ^F	implied risk wedge	0.0026$>$0
ξ	average price contract length	6.62 months

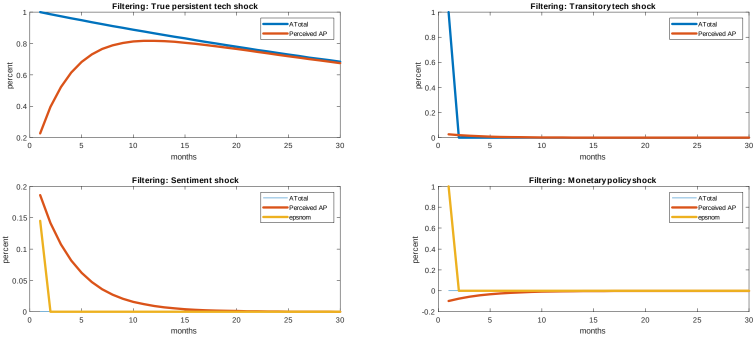
Estimated Parameters - Preliminary

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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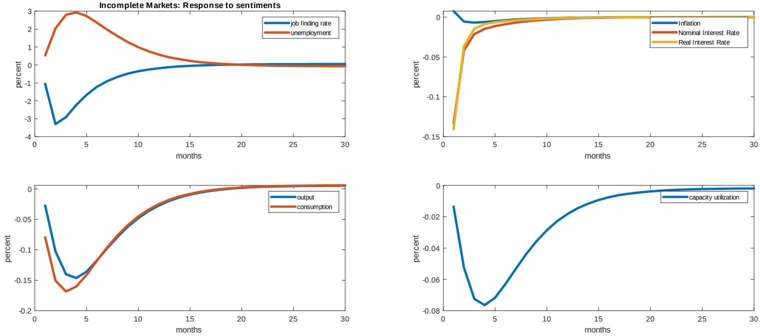
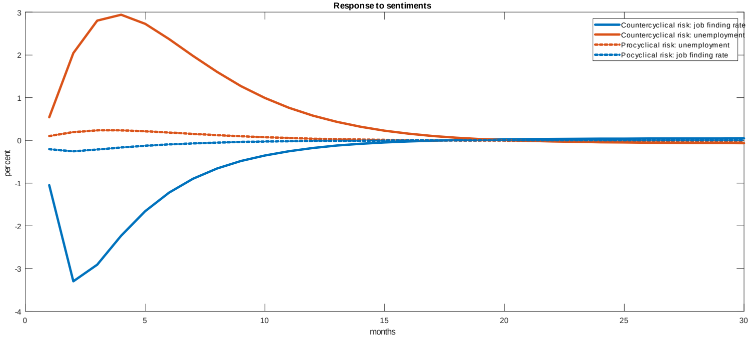
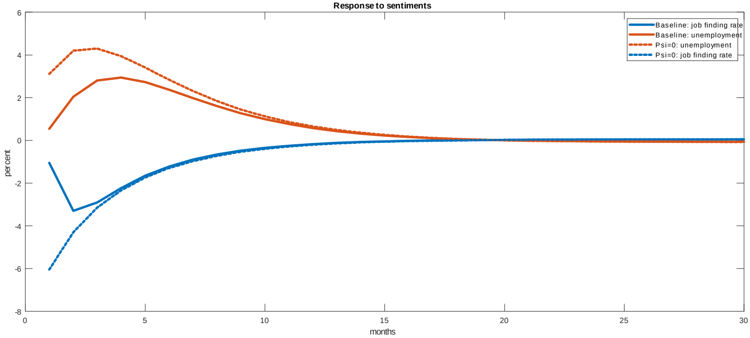


The Role of Countercyclical Risk - Preliminary



The Role of Monetary Policy - Preliminary



Contribution to Business Cycles: Forecast error variance decomposition

	Variable					
Horizon	**C**	**Y**	**U**	**V**	η	Π
1	1.5	0.0	0.3	0.3	0.3	0.6
3	4.1	0.1	1.7	3.4	2.8	1.2
6	6.7	0.4	3.7	6.2	6.0	2.3
12	9.7	1.5	8.1	6.4	8.9	5.4
24	5.0	1.3	5.1	3.1	4.2	5.7
	No Monetary Response ($\psi = 0$)					
1	13.3	0.2	9.3	9.3	9.3	2.1
3	18.5	0.9	14.0	17.6	16.5	4.5
6	22.1	2.0	18.1	18.5	21.6	7.0
12	22.3	4.0	21.9	13.5	20.6	12.2
24	9.8	2.8	11.1	6.3	8.8	11.3

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- Find countercyclical risk wedge to be important