Sentimental Business Cycles

Andresa Lagerborg, Evi Pappa, Morten O. Ravn
IMF, EUI, UCL, CEPR and CfM

ECB, Money Macro Workshop, 21st of March 2019
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.
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)
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).
ICE and Unemployment

ICE

Unemployment

Does Consumer Confidence indices contain valuable information?

- **Matsusaka and Sbordone (1995):** ICS Granger causes GDP.
Empirics

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**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:

\[ CI = F(\text{fundamentals, news, noise, sentiments}) \]

- How do we isolate non-fundamental component?
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- Propose a proxy:

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- We adopt **Proxy SVAR** estimator (Mertens & Ravn, AER, 2013).
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- We adopt **Proxy SVAR** estimator (Mertens & Ravn, AER, 2013).
- Use an external instrument to proxy for the structural shock.
- Can be estimated with 2SLS or 3SLS.
Empirical Approach

Assume that the dynamics of observables is:

\[ X_t = A(L)X_{t-1} + u_t \]

\[ u_t = B e_t \]

- Structural shocks not observed.
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- Order \( Cl \) (wlog) first
Empirical Approach

Identification

- **Aim**: Identify structural shock to CI and its effects

\[ \exists \text{st} - a \text{ proxy such that:} \]
\[ E(\text{st}, t) = \phi \neq 0 \text{ (Relevance)} \]
\[ E(\text{st} \neq \text{CI}, t) = 0 \text{ (Exogeneity)} \]
\[ \Rightarrow \text{st identifies CI, and BCI column.} \]
From this can compute identified impulse responses etc.

Implements IV with external instrument in a VAR

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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Empirical Approach

Identification

- **Aim**: Identify structural shock to CI and its effects
- **External instruments**: \( \exists s_t \) - a proxy - such that:

\[
\begin{align*}
\mathbb{E}(s_t e_{CI,t}) &= \varphi \neq 0 \quad \text{(Relevance)} \\
\mathbb{E}(s_t e_{\neq CI,t}) &= 0 \quad \text{(Exogeneity)}
\end{align*}
\]
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- From this can compute identified impulse responses etc.
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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
**Instrument:** Fatalities in mass shootings in the US.

- **mass shootings** = 3 fatalities or more (perpetrator excluded), lone shooter, public space.
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- **Source:** MotherJones 1982-2019, Duwe (2007)-News Archives-Wikipedia 1960-81
- 119 events in total, 21 had 10 fatalities or more.
- Most perpetrators (60%) had prior long term mental health problem.
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- Mass shootings are unpredictable over time.
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- Mass shootings are unpredictable over time.
- Each event unlikely to bear much in terms of direct costs.
<table>
<thead>
<tr>
<th>Incident</th>
<th>Location</th>
<th>Date</th>
<th>Fat.</th>
<th>Inj.</th>
</tr>
</thead>
<tbody>
<tr>
<td>U. of Texas Tower shooting</td>
<td>Austin, Tx</td>
<td>Aug 1966</td>
<td>18</td>
<td>31</td>
</tr>
<tr>
<td>San Ysidro’s McD massacre</td>
<td>San Ysidro, Cal</td>
<td>Jul 1984</td>
<td>22</td>
<td>19</td>
</tr>
<tr>
<td>U.S. Postal Service shooting</td>
<td>Edmond, Okl</td>
<td>Aug 1986</td>
<td>15</td>
<td>6</td>
</tr>
<tr>
<td>Luby’s massacre</td>
<td>Killeen, TX</td>
<td>Oct 1991</td>
<td>24</td>
<td>20</td>
</tr>
<tr>
<td>Columbine High massacre</td>
<td>Littleton, Col</td>
<td>Apr 1999</td>
<td>13</td>
<td>24</td>
</tr>
<tr>
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<td>Blacksburg, VA</td>
<td>Apr 2007</td>
<td>32</td>
<td>23</td>
</tr>
<tr>
<td>Binghampton shootings</td>
<td>Binghampton, NY</td>
<td>Apr 2009</td>
<td>14</td>
<td>4</td>
</tr>
<tr>
<td>Fort Hood massacre</td>
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<td>Oct 2017</td>
<td>58</td>
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<td>Texas First Baptist Church mass.</td>
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<td>Marjory Stonemann Douglas High School</td>
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Mechanism: Shooting -> News -> Confidence

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

**Conclusion:** Many (most) Americans would be aware of mass shooting events.
**Mechanism: Shooting -> News -> Confidence**

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Estimation

**Implementation**: US time series data:

- Monthly data.

\[
X_t = \begin{bmatrix} 
C_t & Y_t & U_t & P_t & R_t 
\end{bmatrix}
\]

Detrend all apart from \(R_t\) with 4th order time polynomial.

Instrument: Detrended fatalities or TV media coverage.
Implementation: US time series data:

- Monthly data.

Estimate VAR with 18 lags.

Benchmark VAR:

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- Instrument: Detrended fatalities or TV media coverage
Relevance

### Weak Instrument tests, VAR with 18 lags

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<tr>
<th>Sample</th>
<th>Fatalities</th>
<th></th>
<th>News coverage*</th>
<th></th>
</tr>
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<tr>
<td></td>
<td>$F^{\text{hom}}$</td>
<td>$F^{\text{MOP}}$</td>
<td>$F^{\text{hom}}$</td>
<td>$F^{\text{MOP}}$</td>
</tr>
<tr>
<td>1960-2015:1</td>
<td>12.43</td>
<td>6.76</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1968-2015:1</td>
<td>-</td>
<td>-</td>
<td>15.83</td>
<td>52.20</td>
</tr>
<tr>
<td>1960-2017:6</td>
<td>11.13</td>
<td>6.36</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1960-2007:9</td>
<td>5.50</td>
<td>4.30</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1968-2007:9</td>
<td>-</td>
<td>-</td>
<td>3.5</td>
<td>34.82</td>
</tr>
</tbody>
</table>

*Logistic transformation

- Use Montiel Olea, Stock and Watson (2017) parametric bootstrap with Newey-West HAC-robust covariance matrix
Significant drop in ICE for approximately 2 years.

Relevance √
Slightly more precisely estimated for full sample

Relevance √
Placebo: Random Reshuffling of Shootings

IV with random reshuffling of mass fatalities
**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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- **Normalization**: 1 percent drop in consumer confidence.
- **Augment with other variables.**
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

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More Results

**Dynamic Causal Effects**: Robustness and impact on other variables:

- Robust to using news coverage.

**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.
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- Robust to using news coverage.
- Robust to 12 lags instead of 18.

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More Results

**Dynamic Causal Effects:** Robustness and impact on other variables:

- Robust to using news coverage.
- Robust to 12 lags instead of 18.
- Robust over time.

**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.
More Results

**Dynamic Causal Effects**: Robustness and impact on other variables:

- Robust to using news coverage.
- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to not detrending fatalities.

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Consumption

Consumption - Nondurables

Consumption - Durables
EPU and Stock Market Returns

Economic Policy Uncertainty

Excess returns

Andresa Lagerborg, Evi Pappa, Morten O. Ravn
IMF, EUI, UCL, CEPR and CfM

ECB, Money Macro Workshop, 21st of March 2019
## Contribution to Business Cycles:

<table>
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- 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:

(filtering)

Noise shock(−) \rightarrow \text{Confused with } A^P \downarrow
Theory: The main mechanism

Countercyclical Endogenous Risk:

\[
\begin{align*}
\text{Noise shock} & \quad \rightarrow \quad \text{Confused with } A^p \downarrow \\
& \quad \downarrow \\
& \quad \text{goods demand} \downarrow
\end{align*}
\]
Theory: The main mechanism

Countercyclical Endogenous Risk:

(filtering)
Noise shock\((-)\) \rightarrow \text{Confused with } A^P \downarrow
\downarrow \text{goods demand} \downarrow
\downarrow (NK) \text{Firms labor demand} \downarrow
Theory: The main mechanism

Countercyclical Endogenous Risk:

- Noise shock (-) → Confused with $A^P$ ↓
- goods demand ↓
- (NK) Firms labor demand ↓
- (SAM) u ↑, real wages ↓
Theory: The main mechanism

Countercyclical Endogenous Risk:

Noise shock $(-)$ \[\rightarrow\] Confused with $A^p \downarrow$

\[\downarrow\]

goods demand $\downarrow$

**Households**

(precautionary saving $\uparrow$)

$\leftarrow (HA)$ $\rightarrow$ (NK)

$\leftarrow (HA)$ $\rightarrow$ (SAM)

**Firms**

labor demand $\downarrow$

$u \uparrow$, real wages $\downarrow$
Households - Preferences

**Composition:** Continuum of single-member households.

**Preferences:**

\[
V_{it} = \max \hat{E}_t \sum_{s=t}^{\infty} \beta^{s-t} \left( \frac{c_{i,s}^{1-\mu} - 1}{1 - \mu} - \zeta n_{i,s} \right),
\]

**Consumption:**

\[
c_{i,s} = \left( \int (c_{i,s}^{1-1/\gamma}) dj \right)^{1/(1-1/\gamma)}
\]

**Employment Status and Earnings:**

\[
n_{i,s} = \begin{cases} 
0 & \text{if not employed at date } s, \text{ home production } \\
1 & \text{if employed at date } s, \text{ earns wage } w_{i,s}
\end{cases}
\]
Technology:

\[ y_{j,s} = \exp (A_s) (z_{js}k_{js})^{\tau} n_{j,s}^{1-\tau} \]

Employment Dynamics:

\[ n_{j,s} = (1 - \omega)n_{j,s-1} + h_{j,s} \]

Hiring:

\[ h_{j,s} = q_s v_{j,s} \]

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

Capital accumulation:

\[ k_{j,s+1} = (1 - \delta (z_{j,s}))k_{j,s} + i_{j,s} \]
Matching technology

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

**Matching function:**

\[ M_s = \bar{m} u_s^\alpha v_s^{1-\alpha}, \]
\[ v_s = \int_j v_{j,s} dj \]

**Matching rates:** Let \( \theta_s = v_s / u_s \) denote labor market tightness:

**job finding rate:** \( \eta_s = \frac{M_s}{u_s} = \bar{m} \theta_s^{1-\alpha} \)

**vacancy filling rate:** \( q_s = \frac{M_s}{v_s} = \bar{m}^{1/(1-\alpha)} \eta_s^{-\alpha} / (1-\alpha) \)
**Price Setting:** Monopolistically competition firms, price adjustment costs:

$$\max \mathbb{E}_t \sum_{s=t}^{\infty} \Lambda_{j,t,s} \left[ \frac{P_{j,s}}{P_s} y_{j,s} - w_s n_{j,s} - \kappa v_{j,s} - i_{j,s} - \frac{\phi}{2} \left( \frac{P_{j,s} - P_{j,s-1}}{P_{j,s-1}} \right)^2 y_s \right]$$

subject to:

$$y_{j,s} = \exp \left( A_s \right) \left( z_{j,s} k_{j,s} \right)^\tau n_{j,s}^{1-\tau}$$

$$n_{j,s} = (1 - \omega) n_{j,s-1} + h_{j,s}$$

$$k_{j,s+1} = (1 - \delta (z_{j,s})) k_{j,s} + i_{j,s}$$

$$y_{j,s} = \left( \frac{P_{j,s}}{P_s} \right)^{-\gamma} y_s$$

- $\Lambda_{j,t,s}$: firm owners' intertemporal discount factor.
Wages, Interest Rates, Asset Markets

**Wages:** Wage function:

\[ w_s = \bar{w} \left( \frac{n_s}{\bar{n}} \right)^x \]

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

**Monetary Policy:** Interest Rate Rule:

\[ R_s = R_s^{\delta_R} \left( \bar{R} \left( \frac{\Pi_s}{\bar{\Pi}} \right)^{\delta_{\pi}} \right)^{1-\delta_R} \exp \left( e_s^R \right) \]

**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:**

\[
\begin{align*}
    c_{r,s}^{-\mu} & \geq \beta \hat{E}_s \frac{R_s}{\Pi_{s+1}} c_{r,s+1}^{-\mu}, \\
    c_{u,s}^{-\mu} & \geq \beta \hat{E}_s \frac{R_s}{\Pi_{s+1}} \left( (1 - \eta_{s+1}) c_{u,s+1}^{-\mu} + \eta_{s+1} c_{e,s+1}^{-\mu} \right), \\
    c_{e,s}^{-\mu} & \geq \beta \hat{E}_s \frac{R_s}{\Pi_{s+1}} \left( \omega (1 - \eta_{s+1}) c_{u,s+1}^{-\mu} + (1 - \omega (1 - \eta_{s+1})) c_{e,s+1}^{-\mu} \right),
\end{align*}
\]

- 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:

\[
A_s = A_s^P + \varepsilon_s^T, \quad \varepsilon_s^T \sim \text{nid} \left(0, \sigma_T^2\right)
\]

\[
A_s^P = \rho_A A_{s-1}^P + \varepsilon_s^P, \quad \varepsilon_s^P \sim \text{nid} \left(0, \sigma_P^2\right)
\]

**Information**: Imperfect common information.

- \(A_s \in I_s\) but \(A_s^P, \varepsilon_s \not\in I_s\).

**Monetary Policy**:

\[
e_s^R = \varphi \varepsilon_s^S + \varepsilon_s^R, \quad \varepsilon_s^R \sim \text{nid} \left(0, \sigma_R^2\right)
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A_s = A^p_s + \varepsilon^T_s, \quad \varepsilon^T_s \sim \text{nid} \left(0, \sigma^2_T\right)
\]
\[
A^p_s = \rho A^p_{s-1} + \varepsilon^p_s, \quad \varepsilon^p_s \sim \text{nid} \left(0, \sigma^2_P\right)
\]

**Information**: Imperfect common information.

- \(A_s \in I_s\) but \(A^p_s, \varepsilon^T_s \notin I_s\).
- Agents receive a signal on \(A^p_s\):

\[
\Psi_s = A^p_s + \varepsilon^S_s, \quad \varepsilon^S_s \sim \text{nid} \left(0, \sigma^2_S\right)
\]

**Monetary Policy**:

\[
e^R_s = \phi \varepsilon^S_s + \varepsilon^R_s, \quad \varepsilon^R_s \sim \text{nid} \left(0, \sigma^2_R\right)
\]
Shocks and Information

**Technology**: Sum of persistent and transitory component:

\[
A_s = A_s^P + \varepsilon_s^T, \quad \varepsilon_s^T \sim \text{nid} \left(0, \sigma_T^2 \right)
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- \(\varepsilon_s^S\): sentiment / expectational shock.

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**Monetary Policy**:

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- Sentiments impact **directly** and **indirectly** on monetary policy.
The Endogenous Risk Channel

Endogenous earnings risk: log-linearized Euler equation:

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

1. Discounting: \( \hat{c}_{e,s+1} \) enters with coefficient \( \beta \hat{R} < 1 \).
Endogenous earnings risk: log-linearized Euler equation:

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1. **Discounting:** \(\hat{c}_{e,s+1}\) enters with coefficient \(\beta \bar{R} < 1\).

2. **Incomplete markets wedge:**

\[\Theta^F \equiv \omega \eta \left( (\vartheta / w)^{-\mu} - 1 \right) - \chi \mu \omega (1 - \eta)\]

- **unemployment risk**
- **wage risk**
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unemployment risk wage risk

- **procyclical** if \( \Theta^F < 0 \) : **Stabilization**
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- **countercyclical** if \( \Theta^F > 0 \): **Amplification/Propagation**
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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

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

Can also generate inflationary impact of technology shocks.

Procyclical risk: Stabilization

\[ \text{recession} \Rightarrow \text{lower real wage} \Rightarrow \text{less precautionary savings demand} \Rightarrow \text{demand expands at the current real interest rate} \Rightarrow \text{stabilization.} \]

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

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

Can also generate inflationary impact of technology shocks.

Procyclical risk: Stabilization

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Hence, key to the endogenous risk channel is whether unemployment risk or wage risk matters most.
The Endogenous Risk Channel

- **Countercyclical risk:** *Amplification*
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- **Procyclical risk:** Stabilization

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

**Estimation**: Divide parameters into two sets:

- $\Theta_1$: Calibrated.

$\Theta_2$: Estimated by a simulation estimator:

$$\hat{\Theta}_2 = \arg\min_{\Theta_2} \left( (\hat{\Lambda}_d^T - \Lambda_m^T(\Theta_2 | \Theta_1))' \Sigma^{-1} d (\hat{\Lambda}_d^T - \Lambda_m^T(\Theta_2 | \Theta_1)) \right)$$

$\hat{\Lambda}_d^T$: Moments that are matched:

$$\hat{\Lambda}_d^T = [F_{\text{stat}}, \sigma_2^2, \text{Solow}, \text{IRF}_n, \text{IRF}_n^1]$$

$\Lambda_m^T(\Theta_2 | \Theta_1)$: Model equivalents of $\hat{\Lambda}_d^T$ obtained by simulation.

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$$
\hat{\Theta}_2 = \arg\min_{\Theta_2} \left[ \left( \hat{\Lambda}_d^T - \Lambda_m^T (\Theta_2 | \Theta_1) \right) \right. \\
\times \left. \left( \Sigma_d^{-1} (\hat{\Lambda}_d^T - \Lambda_m^T (\Theta_2 | \Theta_1)) \right) \right]
$$
Estimation of Model

**Estimation**: Divide parameters into two sets:

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$$
\hat{\Theta}_2 = \arg \min_{\Theta_2} \left[ \left( \hat{\Lambda}_T^d - \Lambda_T^m (\Theta_2|\Theta_1) \right) \right] \Sigma_d^{-1} \left( \hat{\Lambda}_T^d - \Lambda_T^m (\Theta_2|\Theta_1) \right)
$$

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

$$
\hat{\Lambda}_T^d = \left[ F - \text{stat}, \sigma_{\text{Solow}}^2, \text{IRF}_{nfore} \right]
$$

$$
\text{IRF}_{nfore} = \left[ \text{identified impulse resp. to sentiments} \right]_{1}^{nfore}
$$
**Estimation of Model**

**Estimation**: Divide parameters into two sets:

- $\Theta_1$: Calibrated.
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- $\hat{\Lambda}_{dT}$: Moments that are matched:

$$\hat{\Lambda}_{dT} = [F - \text{stat}, \sigma^2_{\text{Solow}}, \text{IRF}_{nfore}]$$

$$\text{IRF}_{nfore} = [\text{identified impulse resp. to sentiments}]_{1}^{nfore}$$

- $\Lambda_{mT}^m (\Theta_2|\Theta_1)$: Model equivalents of $\hat{\Lambda}_{dT}$ obtained by simulation.
Simulation estimator

1. Simulate model to generate:

\[ X_{t}^{theory} = \begin{pmatrix} Cl_{t} \quad (\text{log consumer confidence}) \\ Y_{t} \quad (\text{log industrial production}) \\ U_{t} \quad (\text{unemployment rate}) \\ P_{t} \quad (\text{log CPI}) \\ R_{t} \quad (\text{Federal funds rate}) \end{pmatrix} \]
Simulation estimator

1. Simulate model to generate:

\[ \boldsymbol{X}_t^{\text{theory}} = \begin{pmatrix}
C_l_t \\ Y_t \\ U_t \\ P_t \\ R_t
\end{pmatrix}
\]

- \( C_l_t \) (log consumer confidence)
- \( Y_t \) (log industrial production)
- \( U_t \) (unemployment rate)
- \( P_t \) (log CPI)
- \( R_t \) (Federal funds rate)

2. Add measurement error to \( \tilde{\boldsymbol{X}}_t^{\text{theory}} = \boldsymbol{X}_t^{\text{theory}} + m_{1,t} \), detrend.
Simulation estimator

1. Simulate model to generate:

   \[ \tilde{X}_t^{\text{theory}} = \begin{pmatrix} C_l_t \ (\text{log consumer confidence}) \\ Y_t \ (\text{log industrial production}) \\ U_t \ (\text{unemployment rate}) \\ P_t \ (\text{log CPI}) \\ R_t \ (\text{Federal funds rate}) \end{pmatrix} \]

2. Add measurement error to \( \tilde{X}_t^{\text{theory}} = X_t^{\text{theory}} + m_{1,t}, \text{detrend.} \)

3. Use \( \varepsilon_t^S + m_{2,t} \) as proxy for sentiment shock.
Simulation estimator

1. Simulate model to generate:

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

2. Add measurement error to \( \tilde{X}^\text{theory}_t = X^\text{theory}_t + m_{1,t}, \text{detrend.} \)

3. Use \( \varepsilon^S_t + m_{2,t} \) as proxy for sentiment shock.

4. Estimate Proxy SVAR on theory data and obtain \( \Lambda_{T}^{m_i} (\Theta_2|\Theta_1) \).
Simulation estimator

1. Simulate model to generate:

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

2. Add measurement error to $\tilde{X}^\text{theory}_t = X^\text{theory}_t + m_{1,t}$, detrend.

3. Use $\varepsilon^S_t + m_{2,t}$ as proxy for sentiment shock.

4. Estimate Proxy SVAR on theory data and obtain $\Lambda^m_T (\Theta_2 | \Theta_1)_i$.

5. Repeat $N$ times and average:

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

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Sentimental Business Cycles
ECB, Money Macro Workshop, 21st of March
### Calibrated parameters (monthly)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\bar{u})</td>
<td>st.st. unemployment rate</td>
<td>6 percent</td>
</tr>
<tr>
<td>(\bar{\eta})</td>
<td>st.st. job finding rate</td>
<td>34 percent</td>
</tr>
<tr>
<td>((\kappa/q) / (3w))</td>
<td>st.st. hiring cost</td>
<td>4.5 percent</td>
</tr>
<tr>
<td>(\bar{R}/\bar{\Pi})</td>
<td>st.st. gross real rate</td>
<td>1.04^{1/12}</td>
</tr>
<tr>
<td>(\bar{\Pi})</td>
<td>st.st. gross inflation rate</td>
<td>1</td>
</tr>
<tr>
<td>(\delta_R)</td>
<td>interest rate smoothing</td>
<td>0.25</td>
</tr>
<tr>
<td>(\sigma_m)</td>
<td>st. dev., monetary pol. shock</td>
<td>0.1 percent</td>
</tr>
<tr>
<td>(\gamma)</td>
<td>elasticity of substitution</td>
<td>8</td>
</tr>
<tr>
<td>(\mu)</td>
<td>CRRA parameter</td>
<td>2</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>matching function parameter</td>
<td>0.5</td>
</tr>
<tr>
<td>(\tau)</td>
<td>output elasticity to capital</td>
<td>0.35</td>
</tr>
<tr>
<td>(\zeta_{\delta,z})</td>
<td>elast. of depr. rate to cap.ut.</td>
<td>1</td>
</tr>
<tr>
<td>(\delta)</td>
<td>depreciation rate (annually)</td>
<td>7.1 percent</td>
</tr>
<tr>
<td>((c_e - c_u) / c_e)</td>
<td>st.st. cons. drop upon unempl.</td>
<td>12 percent</td>
</tr>
</tbody>
</table>
## Estimated Parameters - Preliminary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
<td>price adj. cost</td>
<td>401</td>
</tr>
<tr>
<td>$\chi$</td>
<td>real wage elasticity</td>
<td>0.04</td>
</tr>
<tr>
<td>$\rho_A$</td>
<td>persistence of TFP shocks</td>
<td>0.99</td>
</tr>
<tr>
<td>$\delta_{\Pi}$</td>
<td>interest rate resp. to infl.</td>
<td>1.32</td>
</tr>
<tr>
<td>$\psi$</td>
<td>impact of noise on mon.pol.</td>
<td>0.004</td>
</tr>
<tr>
<td>$\beta$</td>
<td>implied disc. factor (annually)</td>
<td>0.870</td>
</tr>
<tr>
<td>$\Theta^F$</td>
<td>implied risk wedge</td>
<td>0.0026 &gt; 0</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>average price contract length</td>
<td>7.82 months</td>
</tr>
</tbody>
</table>
## Estimated Parameters - Preliminary

<table>
<thead>
<tr>
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<th>Meaning</th>
<th>Estimate</th>
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</thead>
<tbody>
<tr>
<td>$\sigma_T$</td>
<td>std., transitory TFP shock</td>
<td>0.50 percent</td>
</tr>
<tr>
<td>$\sigma_P$</td>
<td>std., innov. to perst. TFP</td>
<td>0.05 percent</td>
</tr>
<tr>
<td>$\sigma_S$</td>
<td>std., sentiment shock</td>
<td>0.19 percent</td>
</tr>
<tr>
<td>$\rho_{CI}$</td>
<td>confidence persistence</td>
<td>0.960</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>confidence parameter</td>
<td>1.019</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>confidence parameter</td>
<td>7.968</td>
</tr>
<tr>
<td>$\sigma_{CI}$</td>
<td>measurement error, confidence</td>
<td>0.15 percent</td>
</tr>
<tr>
<td>$\sigma_{m_2}$</td>
<td>measurement error, proxy</td>
<td>1.6 percent</td>
</tr>
</tbody>
</table>
## Contribution to Business Cycles: Forecast error variance decomposition

<table>
<thead>
<tr>
<th>Horizon</th>
<th>ICE</th>
<th>IP</th>
<th>U</th>
<th>CPI</th>
<th>FFR</th>
<th>TIGHT</th>
<th>V</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>30</td>
<td>0.7</td>
<td>19</td>
<td>34</td>
<td>0.3</td>
<td>18</td>
<td>18</td>
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<tr>
<td>3</td>
<td>18</td>
<td>1.3</td>
<td>16</td>
<td>28</td>
<td>0.6</td>
<td>9.3</td>
<td>8.2</td>
</tr>
<tr>
<td>6</td>
<td>10</td>
<td>8.4</td>
<td>12</td>
<td>19</td>
<td>0.8</td>
<td>2.7</td>
<td>2.9</td>
</tr>
<tr>
<td>12</td>
<td>2.5</td>
<td>0.7</td>
<td>4.2</td>
<td>5.7</td>
<td>1.1</td>
<td>0.7</td>
<td>1.0</td>
</tr>
<tr>
<td>24</td>
<td>0.7</td>
<td>0.2</td>
<td>0.8</td>
<td>1.2</td>
<td>0.7</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>48</td>
<td>0.2</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>
Summary

Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks

Identification: Shock to confidence proxied by fatalities in mass shootings

Confidence matters for labor market

Interaction with monetary policy

Proposed HANK&SAM model with imperfect information to account for this

Find countercyclical risk wedge to be important
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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?”

Responses tend to be bimodal (either 1 or 5).

ICE = 100 + “% positive respondents” - “% negative respondents” (normalized to 1966 base).
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Confidence and Sentiments: Think of consumer confidence as:

\[ CI = F(\text{fundamentals, news, noise, sentiments}) \]

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

**Confidence and Sentiments:** Think of consumer confidence as:

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- How can one isolate the expectational/non-fundamental component?
- **Barsky and Sims:** Estimate VAR:

$$X_t = \begin{bmatrix} \text{CI}_t \\ C_t \\ Y_t \end{bmatrix}$$

$$X_t = A(L)X_{t-1} + u_t$$
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- **Barsky and Sims**: Estimate VAR:

\[
\begin{bmatrix}
\text{CI}_t \\
\text{C}_t \\
\text{Y}_t
\end{bmatrix}
= A(L) \begin{bmatrix}
\text{CI}_{t-1} \\
\text{C}_{t-1} \\
\text{Y}_{t-1}
\end{bmatrix} + u_t
\]

- Look at response to *innovation* to \(\text{CI}_t\).
Confidence and Sentiments: Think of consumer confidence as:

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- How can one isolate the expectational/non-fundamental component?
- Barsky and Sims: Estimate VAR:

\[
X_t = \begin{bmatrix} CI_t \\ C_t \\ Y_t \end{bmatrix} \\
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\]

- Look at response to innovation to \( CI_t \).
- Do not claim causality
Confidence innovation predicts future income and consumption growth.
Empirics: Barsky and Sims

Barsky and Sims: Construct NK model with imperfect information.

- TFP follows:

\[ a_t = a_{t-1} + g_{t-1} + \varepsilon_{a,t} \]
\[ g_t = (1 - \rho_a) g^* + \rho a g_{t-1} + \varepsilon_{g,t} \]
Barsky and Sims: Construct NK model with imperfect information.

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- \( \varepsilon_{a,t} \): Technology shocks.
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- TFP follows:

\[
\begin{align*}
a_t &= a_{t-1} + g_{t-1} + \varepsilon_{a,t} \\
g_t &= (1 - \rho_a) g^* + \rho_ag_{t-1} + \varepsilon_{g,t}
\end{align*}
\]

- \(\varepsilon_{a,t}\): Technology shocks.
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- TFP follows:
  \[ a_t = a_{t-1} + g_{t-1} + \varepsilon_{a,t} \]
  \[ g_t = (1 - \rho_a) g^* + \rho_a g_{t-1} + \varepsilon_{g,t} \]

- \( \varepsilon_{a,t} \): **Technology shocks**.
- \( \varepsilon_{g,t} \): **News shocks**.
- Agents observe:
  \[ s_t = g_t + \varepsilon_{s,t} \]
Empirics: Barsky and Sims

Barsky and Sims: Construct NK model with imperfect information.

- TFP follows:

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- \( \varepsilon_{a,t} \): Technology shocks.
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Agents observe:

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- \( \varepsilon_{s,t} \): Sentiments/animal spirits (pure expectational shocks).
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- \( \varepsilon_{a,t} \): Technology shocks.
- \( \varepsilon_{g,t} \): News shocks.
- Agents observe:

\[ s_t = g_t + \varepsilon_{s,t} \]

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

\[ \text{CI}_t = \zeta_1 \left( a_t - a_{t-1} - g_t|_{t-1} \right) + \zeta_2 \left( g_t|_t - \rho a g_{t|t-1} \right) + \zeta_2 \varepsilon_{c,t} \]
Alternative IV

Confidence (ICE)

Industrial production

Unemployment rate

CPI

Federal Funds Rate

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IMF, EUI, UCL, CEPR and CfM

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Other stock market variables
No detrending of mass fatalities

Confidence (ICE)

Industrial production

Unemployment rate

CPI

Federal Funds Rate
Before the Great Recession

Andresa Lagerborg, Evi Pappa, Morten O. Ravn

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Whole Sample

Confidence (ICE)

Industrial production

Unemployment rate

CPI

Federal Funds Rate

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Whole Sample Alternative IV with TV coverage

Confidence (ICE)

Industrial production

Unemployment rate

CPI

Federal Funds Rate

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