Sentimental Business Cycles

Andresa Lagerborg, Evi Pappa, Morten O. Ravn
IMF, UC3M, UCL, CEPR and CfM

Delhi, December 2018
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)
  - 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).
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?”
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?”

2. **BUS12**: “Now turning to business conditions in the country as a whole–do you think that during the next 12 months we’ll have good times financially, or bad times, or what?”

Responses tend to be bimodal (either 1 or 5). ICE computed as 100 + “% positive respondents” - “% negative respondents” (normalized to 1966 base).
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?”

2. **BUS12**: “Now turning to business conditions in the country as a whole—do you think that during the next 12 months we’ll have good times financially, or bad times, or what?”

3. **BUS5**: “..which would you say is more likely—that in the country as a whole we’ll have continuous good times during the 5 years or so, or that we will have periods of widespread unemployment or depression, or what?”

Responses tend to be bimodal (either 1 or 5). ICE computed as 100 + “% positive respondents” - “% negative respondents” (normalized to 1966 base).
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?”

2. **BUS12**: “Now turning to business conditions in the country as a whole—do you think that during the next 12 months we’ll have good times financially, or bad times, or what?”

3. **BUS5**: “..which would you say is more likely—that in the country as a whole we’ll have continuous good times during the 5 years or so, or that we will have periods of widespread unemployment or depression, or what?”

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

2. **BUS12**: “Now turning to business conditions in the country as a whole–do you think that during the next 12 months we’ll have good times financially, or bad times, or what?”

3. **BUS5**: “..which would you say is more likely–that in the country as a whole we’ll have continuous good times during the 5 years or so, or that we will have periods of widespread unemployment or depression, or what?”

- Responses tend to be bimodal (either 1 or 5).
- **ICE** computed as $100 + \frac{\% \text{ positive respondents}}{\% \text{ negative respondents}}$ (normalized to 1966 base).
Empirics

Michigan Confidence Indices

-6 -4 -2 0 2

Confidence (Baseline ICE)  Confidence (current ICC)  Confidence (overall ICS)

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

Does Consumer Confidence indices contain valuable information?

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

Does Consumer Confidence indices contain valuable information?

- **Matsusaka and Sbordone** (1995): ICS Granger causes GDP.
- **Carroll, Fuhrer and Wilcox** (1994): ICS has predictive power for consumption growth on top of the information incorporated in income and other control variables.

Problem: Predictive power / Granger causality may simply be due to confidence data reflecting news about future fundamentals and not necessarily due to sentiments.
Does Consumer Confidence indices contain valuable information?

- **Matsusaka and Sbordone** (1995): ICS Granger causes GDP.
- **Carroll, Fuhrer and Wilcox** (1994): ICS has predictive power for consumption growth on top of the information incorporated in income and other control variables.
- **Ludvigson** (2004): ICE has predictive power for aggregate consumption growth (but not robust to allowing for control variables such as the consumption-wealth ratio).
Does Consumer Confidence indices contain valuable information?

- **Matsusaka and Sbordone** (1995): ICS Granger causes GDP.
- **Carroll, Fuhrer and Wilcox** (1994): ICS has predictive power for consumption growth on top of the information incorporated in income and other control variables.
- **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:

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

- How can one isolate the expectational/non-fundamental component?
Confidence and Sentiments: Think of consumer confidence as:

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

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

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

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

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

Barsky and Sims: Estimate VAR:
**Empirics**

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

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

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

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

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

- Look at response to *innovation* to \( CI_t \).
Empirics

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

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

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

\[
X_t = \begin{bmatrix} \text{CI}_t \\ C_t \\ Y_t \end{bmatrix}
X_t = A(L) X_{t-1} + u_t
\]

- Look at response to *innovation* to \( \text{CI}_t \).
- Do not claim causality
Empirics: Barsky and Sims

Con...dence innovation predicts future income and consumption growth.
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.

- 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.
Empirics: Barsky and Sims

Barsky and Sims: Construct NK model with imperfect information.

- TFP follows:

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

- \( \varepsilon_{a,t} \): Technology shocks.
- \( \varepsilon_{g,t} \): News shocks.
Empirics: Barsky and Sims

Barsky and Sims: Construct NK model with imperfect information.

- TFP follows:

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

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

- \( \epsilon_{a,t} \): Technology shocks.
- \( \epsilon_{g,t} \): News shocks.

Agents observe:

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

- \( \epsilon_{s,t} \): Sentiments/animal spirits (pure expectational shocks).
Empirics: Barsky and Sims

Barsky and Sims: Construct NK model with imperfect information.

- **TFP follows:**

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

- **\( \varepsilon_{a,t} \): 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:**

  \[
  \text{CI}_t = \zeta_1 (a_t - a_{t-1} - g_{t|t-1}) + \zeta_2 (g_{t|t} - \rho_a g_{t|t-1}) + \zeta_2 \varepsilon_{c, t}
  \]
Confidence innovations are news shocks, animal spirits don’t matter.
Empirical Approach

Our **approach**: Dynamic causal analysis:

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

- Rather than indirectly inferring on impact of sentiments, propose instrument and estimate causal impact.
Our approach: Dynamic causal analysis:

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

- Rather than indirectly inferring on impact of sentiments, propose instrument and estimate causal impact.
- We adopt **Proxy SVAR** estimator (Mertens & Ravn, AER, 2013).
Empirical Approach

Our **approach**: Dynamic causal analysis:

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

- Rather than indirectly inferring on impact of sentiments, propose instrument and estimate causal impact.
- We adopt **Proxy SVAR** estimator (Mertens & Ravn, AER, 2013).
- The idea is to identify structural shocks using external instruments.
Empirical Approach

Our approach: Dynamic causal analysis:

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

- Rather than indirectly inferring on impact of sentiments, propose instrument and estimate causal impact.
- We adopt **Proxy SVAR** estimator (Mertens & Ravn, AER, 2013).
- The idea is to identify structural shocks using external instruments.
- Can be estimated with 2SLS or 3SLS.
Empirical Approach

Assume that the dynamics of observables is:

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

\[ u_t = B \epsilon_t \]

- Structural shocks not observed.
Empirical Approach

Assume that the dynamics of observables is:

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

\[ u_t = B \varepsilon_t \]

- Structural shocks not observed.
- We want to identify the relevant column of \( B \).
Empirical Approach

Assume that the dynamics of observables is:

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

\[ u_t = B\varepsilon_t \]

- Structural shocks not observed.
- We want to identify the relevant column of \( B \).
- Order CI (wlog) first
Identification

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

External instruments: $s_{t}$ - a proxy, such that:

\[ E(s_t \epsilon_{CI}, t) = \phi_s = 0 \text{ (relevance)} \]

\[ E(s_t \epsilon_{CI}, t) = 0 \text{ (exogeneity)} \]

$s_{t}$ identifies $\epsilon_{1,t}$ and $B_{CI}$ column. From this can compute identified impulse responses etc.

Implements IV with external instrument in a VAR. Proxy only needs to be correlated with true shock but not necessarily identically equal to it. Allows for measurement errors and one can correct for scaling issues.
Empirical Approach

Identification

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

\[
\begin{align*}
\mathbb{E}(s_t \epsilon_{CI,t}) &= \varphi \neq 0 \quad \text{(relevance)} \\
\mathbb{E}(s_t \epsilon_{\neq CI,t}) &= 0 \quad \text{(exogeneity)}
\end{align*}
\]
Empirical Approach

**Identification**

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

\[
\begin{align*}
\mathbb{E}(s_t \varepsilon_{CI,t}) &= \varphi \neq 0 \quad \text{(relevance)} \\
\mathbb{E}(s_t \varepsilon_{\neq CI,t}) &= 0 \quad \text{(exogeneity)}
\end{align*}
\]

⇒ \( s_t \) identifies \( \varepsilon_{1t} \) and \( B_{CI} \) column.
**Empirical Approach**

**Identification**

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

\[
\begin{align*}
\mathbb{E} (s_t \varepsilon_{CI,t}) &= \varphi \neq 0 \quad \text{(relevance)} \\
\mathbb{E} (s_t \varepsilon_{\neq CI,t}) &= 0 \quad \text{(exogeneity)}
\end{align*}
\]

\( s_t \) identifies \( \varepsilon_{1t} \) and \( B_{CI} \) column.
- From this can compute identified impulse responses etc.
Empirical Approach

Identification

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

\[
\begin{align*}
\mathbb{E} (s_t \varepsilon_{CI,t}) &= \varphi \neq 0 \quad \text{(relevance)} \\
\mathbb{E} (s_t \varepsilon_{\neq CI,t}) &= 0 \quad \text{(exogeneity)}
\end{align*}
\]

\( s_t \) identifies \( \varepsilon_{1t} \) and \( \mathbf{B}_{CI} \) column.

- From this can compute identified impulse responses etc.
- Implements IV with external instrument in a VAR
Identification

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

\[
\begin{align*}
\mathbb{E}(s_t \epsilon_{CI,t}) &= \varphi \neq 0 \quad \text{(relevance)} \\
\mathbb{E}(s_t \epsilon_{\neq CI,t}) &= 0 \quad \text{(exogeneity)}
\end{align*}
\]

\( s_t \) identifies \( \epsilon_{1t} \) and \( B_{CI} \) column.

- From this can compute identified impulse responses etc.
- Implements IV with external instrument in a VAR
- Proxy only needs to be *correlated* with true shock but not necessarily identically equal to it
Empirical Approach

Identification

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

\[
\begin{align*}
\mathbb{E} (s_t \varepsilon_{CI, t}) &= \varphi \neq 0 \quad \text{(relevance)} \\
\mathbb{E} (s_t \varepsilon_{\neq CI, t}) &= 0 \quad \text{(exogeneity)}
\end{align*}
\]

\[\Rightarrow s_t \text{ identifies } \varepsilon_{1t} \text{ and } B_{CI} \text{ column.}\]

- From this can compute identified impulse responses etc.
- Implements IV with external instrument in a VAR
- Proxy only needs to be *correlated* with true shock but not necessarily identically equal to it
- Allows for measurement errors and one can correct for scaling issues
**Instrument**: Fatalities in mass shootings in the US.

- **mass shootings** = shootings with 4 fatalities or more (perpetrator excluded), carried out by lone shooter in a public space.
**Instrument**: Fatalities in mass shootings in the US.

- **mass shootings** = shootings with 4 fatalities or more (perpetrator excluded), carried out by lone shooter in a public space.
- **Source**: MotherJones 1982-2017, extended with Wikipedia data to 1960 - 90 separate events, 15 had more than 10 fatalities.
**Instrument:** Fatalities in mass shootings in the US.

- **mass shootings** = shootings with 4 fatalities or more (perpetrator excluded), carried out by lone shooter in a public space.
- **Source:** MotherJones 1982-2017, extended with Wikipedia data to 1960 - 90 separate events, 15 had more than 10 fatalities.
- **Alternative source:** Duwe (2007), 1960-2017 - more incidents but more serious ones are identical.
**Instrument:** Fatalities in mass shootings in the US.

- **mass shootings** = shootings with 4 fatalities or more (perpetrator excluded), carried out by lone shooter in a public space.

- **Source:** MotherJones 1982-2017, extended with Wikipedia data to 1960 - 90 separate events, 15 had more than 10 fatalities.

- **Alternative source:** Duwe (2007), 1960-2017 - more incidents but more serious ones are identical.

- Mass shootings are unpredictable over time.
**Instrument**: Fatalities in mass shootings in the US.

- **mass shootings** = shootings with 4 fatalities or more (perpetrator excluded), carried out by lone shooter in a public space.
- **Source**: MotherJones 1982-2017, extended with Wikipedia data to 1960 - 90 separate events, 15 had more than 10 fatalities.
- **Alternative source**: Duwe (2007), 1960-2017 - more incidents but more serious ones are identical.
- Mass shootings are unpredictable over time.
- Each event unlikely to bear much in terms of direct costs.
# Mass Shootings with 10 or More Fatalities

<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>GMAC massacre</td>
<td>Jacksonville, Fla</td>
<td>Jun 1990</td>
<td>10</td>
<td>4</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>
<td>Red Lake massacre</td>
<td>Red Lake, Minn</td>
<td>Mar 2005</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Virginia Tech massacre</td>
<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>
<td>Fort Hood, TX</td>
<td>Nov 2009</td>
<td>13</td>
<td>30</td>
</tr>
<tr>
<td>Aurora Theatre shooting</td>
<td>Aurora, Col</td>
<td>Jul 2012</td>
<td>12</td>
<td>70</td>
</tr>
<tr>
<td>Sandy Hook massacre</td>
<td>Newtown, Conn</td>
<td>Dec 2012</td>
<td>28</td>
<td>2</td>
</tr>
<tr>
<td>San Bernadino mass shooting</td>
<td>San Bernadino, Cal</td>
<td>Dec 2015</td>
<td>14</td>
<td>21</td>
</tr>
<tr>
<td>Orlando Nightclub massacre</td>
<td>Orlando, Fla</td>
<td>Jun 2016</td>
<td>49</td>
<td>53</td>
</tr>
</tbody>
</table>
Fatalities in Mass Shootings

Mass Shooting Fatalities

Source: Mother Jones

Number of fatalities

Year
Mechanism: Shooting -> News -> Confidence

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

(source: Schildkraut, Elsass and Meredith, 2017)

- In addition to electronic news coverage.
Substantial similar evidence on news coverage:

- Lexis Nexis: 182 articles on Fort Hood massacre (TX, 2009), 156 on Newtown school shooting (Conn., 2012).

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.
Substantial similar evidence on news coverage:

- Lexis Nexis: 182 articles on Fort Hood massacre (TX, 2009), 156 on Newtown school shooting (Conn., 2012).
- Lankford (2018): Mass killers (7 biggest shootings since 2012) received more news coverage than top sports stars and celebrities.
Substantial similar evidence on news coverage:

- Lexis Nexis: 182 articles on Fort Hood massacre (TX, 2009), 156 on Newtown school shooting (Conn., 2012).
- Lankford (2018): Mass killers (7 biggest shootings since 2012) received more news coverage than top sports stars and celebrities.

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

Substantial similar evidence on news coverage:

- Lexis Nexis: 182 articles on Fort Hood massacre (TX, 2009), 156 on Newtown school shooting (Conn., 2012).
- Lankford (2018): Mass killers (7 biggest shootings since 2012) received more news coverage than top sports stars and celebrities.
Substantial similar evidence on news coverage:

- Lexis Nexis: 182 articles on Fort Hood massacre (TX, 2009), 156 on Newtown school shooting (Conn., 2012).
- Lankford (2018): Mass killers (7 biggest shootings since 2012) received more news coverage than top sports stars and celebrities.

**Conclusion:** Many (most) Americans would be aware of mass shooting events.
Substantial similar evidence on news coverage:

- Lexis Nexis: 182 articles on Fort Hood massacre (TX, 2009), 156 on Newtown school shooting (Conn., 2012).
- Lankford (2018): Mass killers (7 biggest shootings since 2012) received more news coverage than top sports stars and celebrities.

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

Estimation

**Implementation**: US time series data:

- Monthly data.

\[ X_t = \beta_0 + \beta_1 c_t + \beta_2 y_t + \beta_3 u_t + \beta_4 p_t + \beta_5 r_t + \epsilon_t \]

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

Instrument: Detrended fatalities.

LaPaRa (U(C,L))

Sentiments

Delhi, December 2018
Implementation: US time series data:

- Monthly data.
**Implementation**: US time series data:

- Monthly data.
- Estimate VAR with 18 lags.
Estimation

Implementation: US time series data:

- Monthly data.
- Estimate VAR with 18 lags.
- Benchmark VAR:

  \[ X_t = \begin{pmatrix} 
  C_{t} & (\text{log consumer confidence}) \\
  Y_{t} & (\text{log industrial production}) \\
  U_{t} & (\text{unemployment rate}) \\
  P_{t} & (\text{log CPI}) \\
  R_{t} & (\text{Federal funds rate}) 
  \end{pmatrix} \]

  Detrend all apart from \( R_t \) with 4th order time polynomial. Instrument: Detrended fatalities.
**Implementation**: US time series data:

- Monthly data.
- Estimate VAR with 18 lags.
- Benchmark VAR:

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

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

**Implementation**: US time series data:

- Monthly data.
- Estimate VAR with 18 lags.
- Benchmark VAR:

  \[ X_t = \begin{pmatrix}
  C_{t} & \text{(log consumer confidence)} \\
  Y_{t} & \text{(log industrial production)} \\
  U_{t} & \text{(unemployment rate)} \\
  P_{t} & \text{(log CPI)} \\
  R_{t} & \text{(Federal funds rate)}
  \end{pmatrix} \]

- Detrend all apart from \( R_t \) with 4th order time polynomial.
- Instrument: Detrended fatalities.
### F tests for Alternative Confidence Indices

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Mass fatalities coefficient</th>
<th>IV exclusion F-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MotherJones Fatalities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICE</td>
<td>-1.73***</td>
<td>10.83</td>
</tr>
<tr>
<td>ICS</td>
<td>-1.07***</td>
<td>7.35</td>
</tr>
<tr>
<td>BUS5</td>
<td>-1.40***</td>
<td>3.35</td>
</tr>
<tr>
<td>BUS12</td>
<td>-0.86**</td>
<td>4.35</td>
</tr>
<tr>
<td>PEXP</td>
<td>-0.27**</td>
<td>4.25</td>
</tr>
</tbody>
</table>
• Significant drop in ICE for approximately 2 years.
• **Relevance ✓**
Placebo: Random Reshuffling of Shootings

IV with random reshuffling of mass fatalities

Confidence

Industrial production

Unemployment rate

CPI

FFR
**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.
**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.
- Look at benchmark VAR.
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.
- Look at benchmark VAR.
- Augment with other variables.
**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.
- Look at benchmark VAR.
- Augment with other variables.
- Compare with Choleski factorization results (Barsky and Sims).
**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.
- Look at benchmark VAR.
- Augment with other variables.
- Compare with Choleski factorization results (Barsky and Sims).
- Look at relationship to other shocks.
Benchmark VAR

Confidence

Industrial production

Unemployment rate

CPI

FFR

LaPaRa (U(C,L))

Sentiments

Delhi, December 2018
Dynamic Causal Effects: Results indicate:

- Long-lived slump in output.
**Dynamic Causal Effects**: Results indicate:

- Long-lived slump in output.
- Persistent increase in unemployment.
**Dynamic Causal Effects**: Results indicate:

- Long-lived slump in output.
- Persistent increase in unemployment.
- Rise in price level.
Dynamic Causal Effects: Results indicate:

- Long-lived slump in output.
- Persistent increase in unemployment.
- Rise in price level.
- Drop in nominal interest rates.
Dynamic Causal Effects: Results indicate:

- Long-lived slump in output.
- Persistent increase in unemployment.
- Rise in price level.
- Drop in nominal interest rates.
- Increase in price level and drop in interest rates: Suggests monetary policy shock accompanying the drop in sentiments.
**Dynamic Causal Effects**: Results indicate:

- Long-lived slump in output.
- Persistent increase in unemployment.
- Rise in price level.
- Drop in nominal interest rates.
- 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

![Negative Confidence Shock IRF](image)

(NIV: Mass shootings)

- Gertler Karadi (1M) Cumulative MP Shock
- 2 std. errors band
- 1 std. errors band

Horizons (months)

0 10 20 30 40

Delhi, December 2018

LaPaRa (U(C,L))

Sentiments
More Results

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

- Robust to 12 lags instead of 18.

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

- Robust to 12 lags instead of 18.
- Robust over time.

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

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.

**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.
More Results

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

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.
- Robust to individual big shootings.

**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.
More Results

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

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.
- Robust to individual big shootings.

**Other variables**:

- Drop in consumption.
More Results

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

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.
- Robust to individual big shootings.

**Other variables**:

- Drop in consumption.
- Labor market variables: Hours worked down, tightness down.
More Results

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

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.
- Robust to individual big shootings.

**Other variables**:

- Drop in consumption.
- Labor market variables: Hours worked down, tightness down.
- Capacity utilization drops.
More Results

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

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.
- Robust to individual big shootings.

**Other variables**:

- Drop in consumption.
- Labor market variables: Hours worked down, tightness down.
- Capacity utilization drops.
- Nominal exchange rate depreciates.
Dynamic Causal Effects: Robustness and impact on other variables:

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.
- Robust to individual big shootings.

Other variables:

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

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

- Robust to 12 lags instead of 18.
- Robust over time.
- Robust to detrending fatalities.
- Robust to individual big shootings.

**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

Nondurables consumption

percent

months

LaPaRa (U(C,L))  Sentiments  Delhi, December 2018 32 / 64
Controlling for Stock Prices

LaPaRa (U(C,L))

 Delhi, December 2018
### Contribution to Business Cycles:

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

- 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:

Noise shock (-) → Confused with $A^P$ ↓

(filtering)
**Theory: The main mechanism**

**Countercyclical Endogenous Risk:**

\[
\text{Noise shock}(-) \quad \rightarrow \quad \text{Confused with } A^P \downarrow \\
\downarrow \\
\text{goods demand} \downarrow
\]
Theory: The main mechanism

**Countercyclical Endogenous Risk:**

( filtering )

Noise shock( - ) → Confused with $A^P \downarrow$

↓

goods demand ↓

$\downarrow$ (NK) Firms

labor demand ↓
Theory: The main mechanism

Countercyclical Endogenous Risk:

Noise shock\((-)\) → Confused with $A^P$ ↓

\[ \text{goods demand ↓} \]

\[ \text{(NK)} \]

\[ \text{Firms} \]

\[ \text{labor demand ↓} \]

\[ \text{(SAM)} \]

$u \uparrow$, real wages ↓
Theory: The main mechanism

Countercyclical Endogenous Risk:

Noise shock\((-\)\) → Confused with \(A^P\) ↓

Households (HA) ↑

precautionary saving ↑

(NA) ↩

u ↑, real wages ↓

Firms (NK) ↓

labor demand ↓

(SAM) ↩

goods demand ↓

(filtering)
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:

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

Employment Status and Earnings:

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

\[
M_s = m u_s^\alpha v_s^{1-\alpha},
\]

\[
v_s = \int_j v_{j,s} dj
\]

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

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

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

subject to:

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

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

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

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

- $\Lambda_{j,t,s}$: firm owners’ intertemporal discount factor.
Wages: Wage function:

\[ w_s = \bar{w} \left( \frac{\eta_s}{\bar{\eta}} \right)^\chi \]

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

Monetary Policy: Interest Rate Rule:

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

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
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:

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

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

**Information**: Imperfect common information.

- \(A_s \in I_s\) but \(A_s^P, \varepsilon_s^T \notin I_s\).

**Monetary Policy**:

\[
e_s^R = \phi \varepsilon_s^S + \varepsilon_s^R, \quad \varepsilon_s^R \sim \text{nid}(0, \sigma_R^2)
\]
**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 \(A_s^P, \varepsilon_s^T \notin I_s\).
- Agents receive a signal on \(A_s^P\):

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

**Monetary Policy:**

\[
e_s^R = \varphi \varepsilon_s^S + \varepsilon_s^R, \quad \varepsilon_s^R \sim \text{nid} \left(0, \sigma_R^2 \right)
\]
**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 \(A_s^p, \varepsilon_s^T \notin I_s\).
- Agents receive a signal on \(A_s^p\):

\[
\Psi_s = A_s^p + \varepsilon_s^S, \quad \varepsilon_s^S \sim \text{nid} \left(0, \sigma_S^2\right)
\]

- \(\varepsilon_s^S\): sentiment / expectational shock.

**Monetary Policy**:

\[
e_s^R = \varphi \varepsilon_s^S + \varepsilon_s^R, \quad \varepsilon_s^R \sim \text{nid} \left(0, \sigma_R^2\right)
\]
Shocks and Information

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

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

**Information**: Imperfect common information.

- \(A_s \in I_s\) but \(A_s^P, \varepsilon_s^T \notin I_s\).
- Agents receive a signal on \(A_s^P\):
  \[
  \Psi_s = A_s^P + \varepsilon_s^S, \quad \varepsilon_s^S \sim \text{nid} (0, \sigma_S^2)
  \]
- \(\varepsilon_s^S\): sentiment / expectational shock.

**Monetary Policy**:

\[
e_s^R = \varphi \varepsilon_s^S + \varepsilon_s^R, \quad \varepsilon_s^R \sim \text{nid} (0, \sigma_R^2)
\]

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

**Endogenous earnings risk**: log-linearized Euler equation:

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

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

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

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

2. **Incomplete markets wedge**:

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

- unemployment risk
- wage risk
The Endogenous Risk Channel

**Endogenous earnings risk**: log-linearized Euler equation:

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

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

2. **Incomplete markets wedge**:

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

- **procyclical** if \(\Theta^F < 0\): Stabilization

**unemployment risk**

**wage risk**
The Endogenous Risk Channel

**Endogenous earnings risk**: log-linearized Euler equation:

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

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

2. **Incomplete markets wedge**:

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

- **procyclical** if \(\Theta^F < 0\): Stabilization
- **countercyclical** if \(\Theta^F > 0\): Amplification/Propagation
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 \(\beta \hat{R} < 1\).
2. **Incomplete markets wedge:**

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

- **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

  - Recession: Lower job finding rate, higher precautionary savings 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

  - Recession: Lower real wage, less precautionary savings, demand expands at the current real interest rate, stabilization.

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

- **Countercyclical risk**: Amplification
  - 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.

Can also generate inflationary impact of technology shocks.

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

- **Countercyclical risk:** *Amplification*
  - 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.
  - Can also generate inflationary impact of technology shocks.
The Endogenous Risk Channel

- Countercyclical risk: **Amplification**
  - 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.
  - Can also generate inflationary impact of technology shocks.

- Procyclical risk: **Stabilization**
The Endogenous Risk Channel

- **Countercyclical risk**: Amplification
  - 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.
  - Can also generate inflationary impact of technology shocks.

- **Procyclical risk**: Stabilization
  - recession $\Rightarrow$ lower real wage $\Rightarrow$ less precautionary savings demand $\Rightarrow$ demand expands at the current real interest rate $\Rightarrow$ stabilization.
The Endogenous Risk Channel

- **Countercyclical risk**: **Amplification**
  - 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.
  - Can also generate inflationary impact of technology shocks.

- **Procylical 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.
Estimation of Model

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

- $\Theta_1$: Calibrated.

\[ b_{\Theta_2} = \arg \min_{\Theta_2} b \Lambda d_T \Lambda_m T (\Theta_2 j \Theta_1) 0 \Sigma_1 d b \Lambda d_T \Lambda_m T (\Theta_2 j \Theta_1) \]

- Moments that are matched:

\[ b \Lambda d_T = F_{\text{stat}}, \sigma^2, \text{Solow}, \text{IRF nfore} \]

IRF nfore = [identified impulse resp. to sentiments nfore]

$\Lambda m_T (\Theta_2 j \Theta_1)$: Model equivalents of $b \Lambda d_T$ obtained by simulation.
Estimation of Model

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

- $\Theta_1$: Calibrated.
- $\Theta_2$: Estimated by a simulation estimator:

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

- Moments that are matched:
  $$\hat{\Lambda}_T^d: \text{Moments that are matched:}$$
  $$\hat{\Lambda}_T^d = F_{\text{stat}}, \sigma^2_{\text{Solow}}, IRF_{n\text{fore}}$$
  $$IRF_{n\text{fore}} = \text{identified impulse resp. to sentiments}$$

- Model equivalents of $\hat{\Lambda}_T^d$ obtained by simulation.
**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:

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

$$
\text{IRF}^{nfore} = \left[ \text{identified impulse resp. to sentiments} \right]^{nfore}_1
$$
Estimation of Model

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

- $\Theta_1$: Calibrated.
- $\Theta_2$: Estimated by a simulation estimator:

$$\hat{\Theta}_2 = \arg \min_{\Theta_2} \left[ \left( \hat{\Lambda}^d_T - \Lambda^m_T (\Theta_2|\Theta_1) \right)' \Sigma^{-1}_d \left( \hat{\Lambda}^d_T - \Lambda^m_T (\Theta_2|\Theta_1) \right) \right]$$

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

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

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

- $\Lambda^m_T (\Theta_2|\Theta_1)$: Model equivalents of $\hat{\Lambda}^d_T$ obtained by simulation.
1) Simulate model to generate:

\[ \mathbf{X}_{t}^{\text{theory}} = \begin{pmatrix} C_{t} & (\text{log consumer confidence}) \\ Y_{t} & (\text{log industrial production}) \\ U_{t} & (\text{unemployment rate}) \\ P_{t} & (\text{log CPI}) \\ R_{t} & (\text{Federal funds rate}) \end{pmatrix} \]
Simulation estimator

1. Simulate model to generate:

\[ \mathbf{X}_t^{\text{theory}} = \begin{pmatrix} \text{Cl}_t \ (\text{log consumer confidence}) \\
\text{Y}_t \ (\text{log industrial production}) \\
\text{U}_t \ (\text{unemployment rate}) \\
\text{P}_t \ (\text{log CPI}) \\
\text{R}_t \ (\text{Federal funds rate}) \end{pmatrix} \]

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

1. Simulate model to generate:

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

- \( C_l_t \) (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 \( \tilde{X}^\text{theory}_t = X^\text{theory}_t + m_{1,t} \), detrend.

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

1. Simulate model to generate:

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

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

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

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

1. Simulate model to generate:

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

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

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

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

5. Repeat \( N \) times and average:

\[ \Lambda^n_T (\Theta_2 | \Theta_1) = \frac{1}{N} \sum_{i=1}^{N} \Lambda^n_T (\Theta_2 | \Theta_1)_i \]
## 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>$(\kappa / \bar{q}) / (3\bar{w})$</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>282.9</td>
</tr>
<tr>
<td>$\chi$</td>
<td>real wage elasticity</td>
<td>0.016</td>
</tr>
<tr>
<td>$\rho_A$</td>
<td>persistence of TFP shocks</td>
<td>0.987</td>
</tr>
<tr>
<td>$\delta_{\Pi}$</td>
<td>interest rate resp. to infl.</td>
<td>2.09</td>
</tr>
<tr>
<td>$\psi$</td>
<td>impact of noise on mon.pol.</td>
<td>0.145</td>
</tr>
<tr>
<td>$\beta$</td>
<td>implied disc. factor (annually)</td>
<td>0.892</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>6.62 months</td>
</tr>
</tbody>
</table>
## Estimated Parameters - Preliminary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
<th>Estimate</th>
</tr>
</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>$\sigma_{m2}$</td>
<td>measurement error, proxy</td>
<td>1.6 percent</td>
</tr>
</tbody>
</table>
Matched VAR IRFs - Preliminary
Incomplete Markets: Response to sentiments

- Job finding rate
- Unemployment

Inflation
Nominal Interest Rate
Real Interest Rate

Output
Consumption

Capacity utilization
The Role of Countercyclical Risk - Preliminary
**Contribution to Business Cycles:** Forecast error variance decomposition

<table>
<thead>
<tr>
<th>Horizon</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C</td>
</tr>
<tr>
<td>1</td>
<td>1.5</td>
</tr>
<tr>
<td>3</td>
<td>4.1</td>
</tr>
<tr>
<td>6</td>
<td>6.7</td>
</tr>
<tr>
<td>12</td>
<td>9.7</td>
</tr>
<tr>
<td>24</td>
<td>5.0</td>
</tr>
<tr>
<td>1</td>
<td>13.3</td>
</tr>
<tr>
<td>3</td>
<td>18.5</td>
</tr>
<tr>
<td>6</td>
<td>22.1</td>
</tr>
<tr>
<td>12</td>
<td>22.3</td>
</tr>
<tr>
<td>24</td>
<td>9.8</td>
</tr>
</tbody>
</table>

No Monetary Response ($\psi = 0$)
Summary

Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks
Summary

Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks
- Identification: Shock to confidence proxied by fatalities in mass shootings
Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks
- Identification: Shock to confidence proxied by fatalities in mass shootings
- Find large and persistent effects of confidence shocks - account for up to 20 percent of variance of unemployment
Summary

Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks
- Identification: Shock to confidence proxied by fatalities in mass shootings
- Find large and persistent effects of confidence shocks - account for up to 20 percent of variance of unemployment
- Interaction with monetary policy
Summary

Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks
- Identification: Shock to confidence proxied by fatalities in mass shootings
- Find large and persistent effects of confidence shocks - account for up to 20 percent of variance of unemployment
- Interaction with monetary policy
- Proposed HANK&SAM model with imperfect information to account for this
Key contributions:

- Proposed dynamic causal estimation of consumer sentiment shocks
- Identification: Shock to confidence proxied by fatalities in mass shootings
- Find large and persistent effects of confidence shocks - account for up to 20 percent of variance of unemployment
- Interaction with monetary policy
- Proposed HANK&SAM model with imperfect information to account for this
- Find countercyclical risk wedge to be important