# Animal Spirits, Fundamental Factors and Business Cycle Fluctuations

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# Disclaimer

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**What drives business cycles?**

Fundamental factors - technology

Animal spirits - optimism and pessimism

**Main goal:**

- Use Structural Vector auto-regression to explore the role of technology and “animal spirits”.

- Theoretical background: models where consumers cannot perfectly observe technology and face a signal extraction problem.
- Animal spirits are modeled as noise shocks - consumers are rational, but they do mistakes ("animal spirits") as they cannot observe technology.
- Fundamental shocks are supply (or technology) shocks - in the long-run, economic growth depends only on technology $\rightarrow$ "animal spirits" can have only transitory effects.

# Contribution

- Blanchard et al. (2013) show the effects of fundamental and noise shocks cannot be explored with a SVAR model.
- Intuition:
  - VARs use information only up to the current period.
  - Whenever we could identify shocks with a VAR, so can consumers.
  - In that case, there is no signal extraction problem
- We show that VARs can still be used:
  - **Future observations**: We explore the fact that consumer can observe only present and past data, while econometricians can observe ‘future’ data.
  - **Revised data**: Consumer observes only real-time data, while econometricians have access to revised data.

# The structure

The structure of presentation:

1. **The model**
2. From the model to a SVAR
3. Empirical evidence on US data
4. Robustness checks
5. Conclusions

# The model

- Slightly modified model from Blanchard et al. (2013).
- The crucial equation is:

$$c_t = \lim_{t \to \infty} E_t[a_{t+j} | \mathcal{I}_t] \tag{1}$$

$\rightarrow$ consumption depends on expectations about long-run productivity.

- Can be seen as a permanent income hypothesis.
- Other variables, like output and utilization, are a linear function of consumption.
- The structure of model not crucial, can be extended to large scale DSGE model.

# The model - Information structure

- The relevant state in example economy is technology:

$$a_t = (1+\rho)a_{t-1} - \rho a_{t-2} + \epsilon_t \tag{2}$$

  where $a_t$ is technology with stochastic trend and $\epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2)$ is a **supply or technology (permanent) shock**.

- The agent observes only noisy signal of technology, $s_t$:

$$s_t = a_t + \upsilon_t \tag{3}$$

  where $\upsilon_t \sim \mathcal{N}(0, \sigma_\upsilon^2)$ is an **"animal spirits" (Noise) shock**.

- Using Kalman filter, consumer forms expectations about the level of technology by observing the signal.

# The model - solution

- The solution gives consumption as a function of consumer's expectations about technology:

$$c_t = \frac{1}{1-\rho}\left(a_{t|t} - \rho a_{t-1|t}\right) \tag{4}$$

- Other variables are linear function of consumption and technology.
- Output:

$$y_t = c_t \tag{5}$$

- Utilization:

$$u_t = a_t - y_t \tag{6}$$

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# Singularity of VAR models

- Consider running a VAR with consumption and signal to obtain the structural shocks.
- Consumption is a linear function of expectations about current and past state:

$$c_t = f\left(E_t[a_t|\mathcal{I}_t]\right) \tag{7}$$

- Expectations about current and past state are a linear function of current and past observables:

$$E_t[a_t|\mathcal{I}_t] = g(s_t, s_{t-1}, ...) \tag{8}$$

- This implies consumption is a linear function of current and past signals:

$$c_t = f(g(s_t, s_{t-1}, ...)) \tag{9}$$

- Remember $s_t = (1+\rho)a_{t-1} - \rho a_{t-2} + \epsilon_t + \upsilon_t$. It follows:

$$\frac{\partial s_t}{\partial \epsilon_t} = \frac{\partial s_t}{\partial \upsilon_t} \tag{10}$$

# Singularity of VAR models

- Consumption is a linear function of signal, which implies:

$$\frac{\partial c_t}{\partial \epsilon_t} = \frac{\partial c_t}{\partial \upsilon_t} \tag{11}$$

- On impact, an agent responds equally to a supply ($\epsilon_t$) and to a noise shock ($\upsilon_t$) - as only the increase in signal can be observed.
- Running a VAR with consumption and signal results in a singular system.
- It also implies other measures do not help to identify the shocks:

$$\frac{\partial x_t}{\partial \epsilon_t} = \frac{\partial x_t}{\partial \upsilon_t} \Big| \; |\epsilon_t| = |\upsilon_t| \tag{12}$$

  where $x_t$ could be, for example, stock prices, consumer sentiment, growth forecasts...
- Intuition: In the opposite case agent would run a VAR and we do not have a signal extraction problem anymore.

# Singularity of VAR models

- To identify shocks we have to use superior information set than that available to consumer.
- The solution is to use the forecast error about the state:

$$\eta_t = E_t[a_t|\mathcal{I}_t] - a_t \tag{13}$$

- Technology responds differently to the two shocks:

$$\epsilon_t = \frac{\partial a_t}{\partial \epsilon_t} \neq \frac{\partial a_t}{\partial \upsilon_t} = 0 \tag{14}$$

- As forecast error is a linear function of technology and signal:

$$\eta_t = k(\upsilon_t, \upsilon_{t-1}, ..., \epsilon_t, \epsilon_{t-1}, ...) \tag{15}$$

$$\frac{\partial \eta_t}{\partial \epsilon_t} \neq \frac{\partial \eta_t}{\partial \upsilon_t} \tag{16}$$

- Running a VAR with consumption and the forecast error allows us to identify the supply shock, $\epsilon_t$, and the noise shock, $\upsilon_t$.

# Consumers vs. Econometricians

- We do not observe $a_t$ and therefore $\eta_t$.
- Can we approximate the forecast error by using superior information than the agent, $\mathcal{I}_t^e$?

$$\eta_t = E_t[a_t|\mathcal{I}_t] - a_t \quad \rightarrow \quad \hat{\eta}_t = E_t[a_t|\mathcal{I}_t] - E_t[a_t|\mathcal{I}_t^e] \qquad (17)$$

where $\mathcal{I}_t^e$ is the econometrician's information set.

- 2 ways to achieve $var(E_t[a_t|\mathcal{I}_t^e] - a_t) < var(E_t[a_t|\mathcal{I}_t] - a_t)$:
  1. Use of more accurate signals: $var[\upsilon_t|\mathcal{I}_t^e] < var[\upsilon_t|\mathcal{I}_t]$
  2. Use of future observations: $\mathcal{I}_t \subset \mathcal{I}_t^e$

# Consumers vs. Econometricians

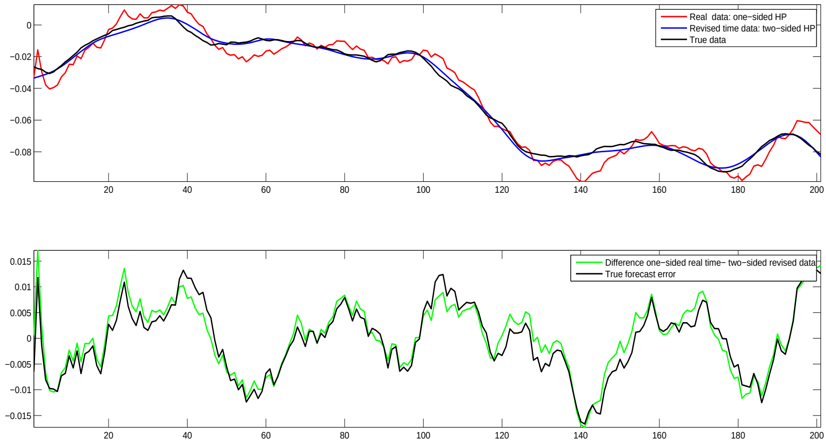
We show on simulated data that:

- More accurate signals help to estimate the forecast error: As the signal becomes less noisy, the correlation between the estimated and the true forecast errors increase
- Increasing the number of leads help to estimate the forecast error: With four leads the estimated forecast errors moves closer to the actual forecast error.

| | **Kalman Filter** | **Kalman Smoother** |
|---|---|---|
| **RT data** | Consumers' expectation | $\hat{\kappa}_t$ |
| **Revisions** | $\hat{\lambda}_t$ | Econometrician's estimate ($\hat{\eta}_t$ ) |

# Estimate of forecast error

Figure: A final estimate of forecast error - $\hat{\eta}_t$ (simulated data)




$$corr(\hat{\eta}_t, \eta_t) = 0.93$$

# Approximation with a VAR model

- Using future observations and more precise signals (due to revisions), we can construct estimate of forecast error, $\hat{\eta}_t$.
- We know:
  1. Supply shock: $\eta_t < 0 \rightarrow \hat{\eta}_t < 0$.
  2. Noise shock: $\eta_t > 0 \rightarrow \hat{\eta}_t > 0$.
- We can run a VAR with consumption and $\hat{\eta}_t$ and use sign restrictions to identify supply and noise shocks:

| | Supply shock | Noise shock |
|---|---|---|
| Consumption | + | + |
| Forecast error ($\hat{\eta}_t$) | - | + |

- In the following example, we use 50 percent less noisy signal and four leads of signal to approximate $\hat{\eta}_t$ .

# Impulse responses - simulated data

Figure: Estimated IRF to supply (above) and noise (below) shocks by using estimated forecast errors

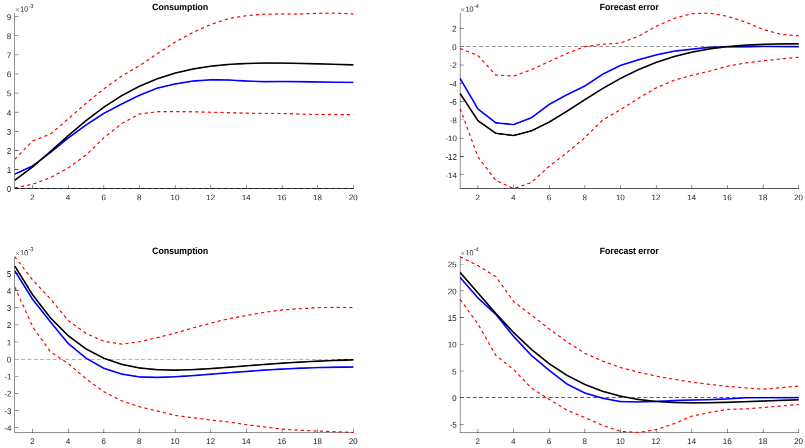
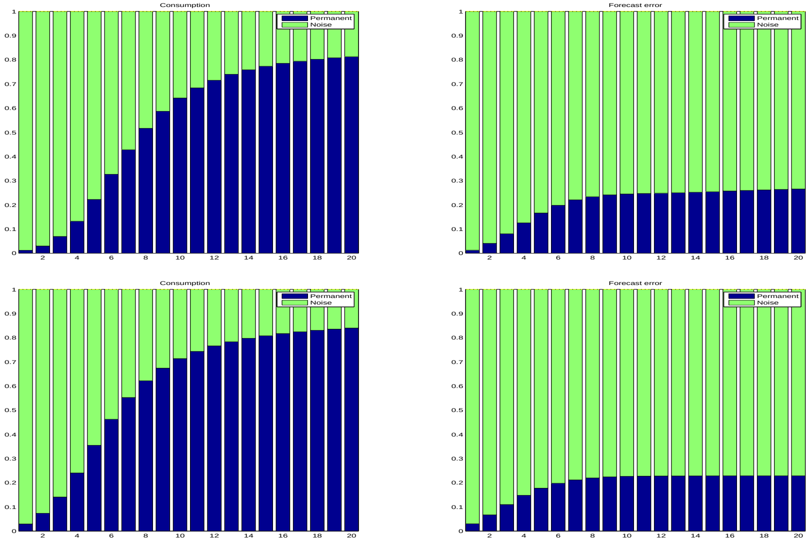


Figure: Estimated FEVD (above) and theoretical FEVD (below)



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# Constructing forecast errors

- Forecast errors constructed by taking the difference between a real-time estimate of potential GDP and the actual/official estimate provided by the CBO.
- To compute our estimate of real-time potential GDP, we use the real-time estimate and projections of the output gap available in the Greenbook and add it to the real-time level of GDP.
- Due to data publication lags, we construct the measure of real GDP in period $t$ by using GDP forecasts for period $t$ from the Survey of Professional Forecasters.

# Empirical Application with US data - Identification

- The identification is achieved by sign restrictions.
- From theory we know:
  - Forecast error positive for positive noise shocks - consumers are too optimistic.
  - Forecast error negative for positive supply shocks - consumers are too pessimistic.
- Other variables respond similar to both shocks.

| | Forecast error | Consumption |
|---|---|---|
| Supply shock | - | + |
| Noise shock | + | + |

- Restrictions are imposed for one year.
- Slight modification do not considerably affect the results.

Figure: IRFs to noise shock

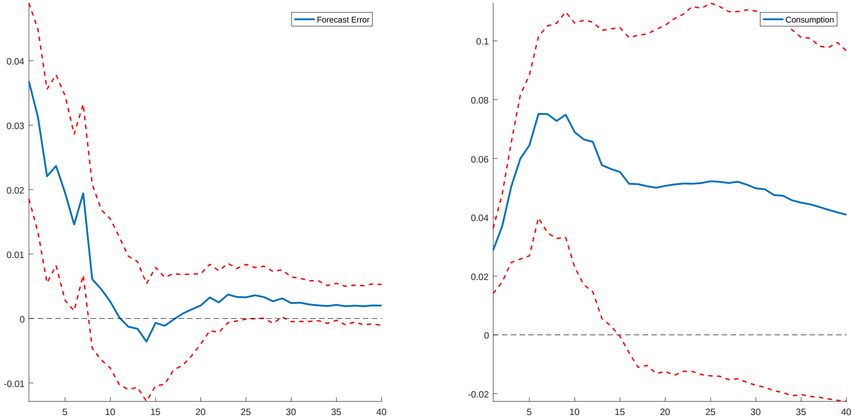
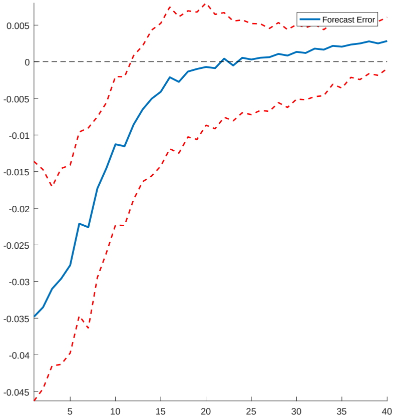
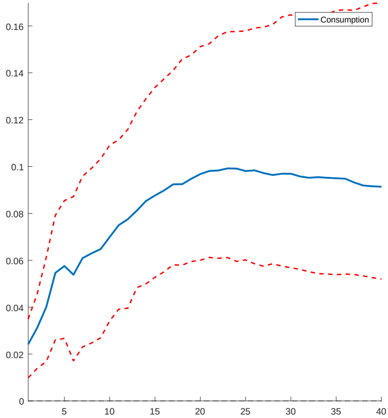


Figure: IRFs to supply shock



# Large-sale VAR

- In a large system, we use the following variables:

1. Estimated Forecast Errors
2. GDP (Y)
3. Private Consumption (C)
4. Stock prices (S&P500)
5. Fed funds rate (IR)
6. CPI Inflation (INF)
7. Consumer Sentiment (SENT)

- The estimation period is Q3 1977 - Q4 2011; at both ends we drop 4 observations.
- The system is estimated with classical methods (bootstrap) in differences with three lags.
- The results are robust to changes from differences to levels and using different number of lags.

# Empirical Application with US data - Identification

- The identification assumption to separate noise and supply shocks is similar to the small-scale VAR.
- A larger VAR allows us to distinguish, among the transitory shocks, those that are related with animal spirits from those that are related to more standard shocks, in particular aggregate demand shocks.
- We use sign restrictions to separate supply and noise shocks from standard demand shocks with additional restrictions on inflation and interest rates.

| | FE | Y | C | SP | IR | INF | SENT |
|---|---|---|---|---|---|---|---|
| Supply shock | - | + | + | + | - | - | + |
| Noise shock | + | + | + | + | - | - | + |
| Demand shock | + | + | + | + | + | + | + |

- Restrictions are imposed for one year.
- Slight modification do not considerably affect the results.

# US data - IRFs to noise shock

Figure: IRFs to noise shock

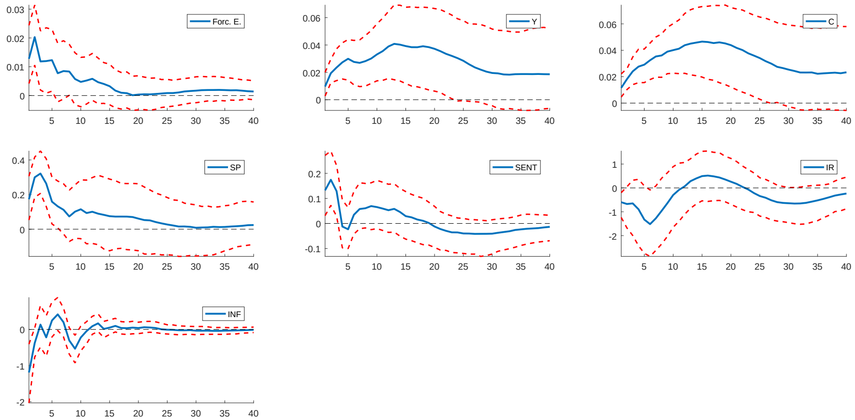
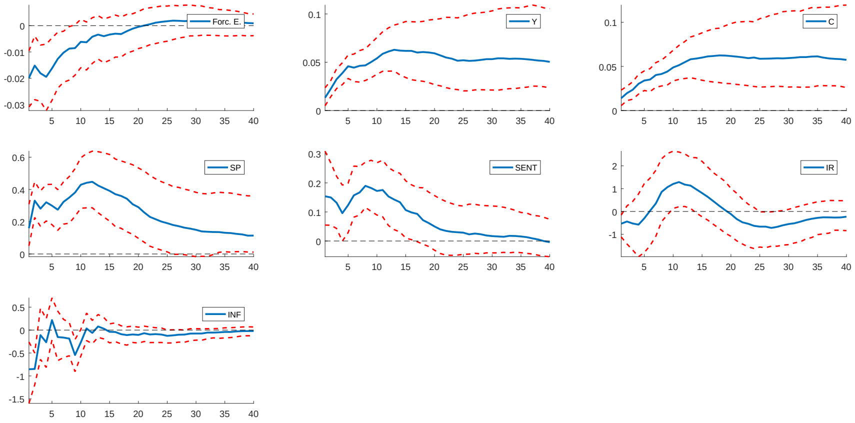
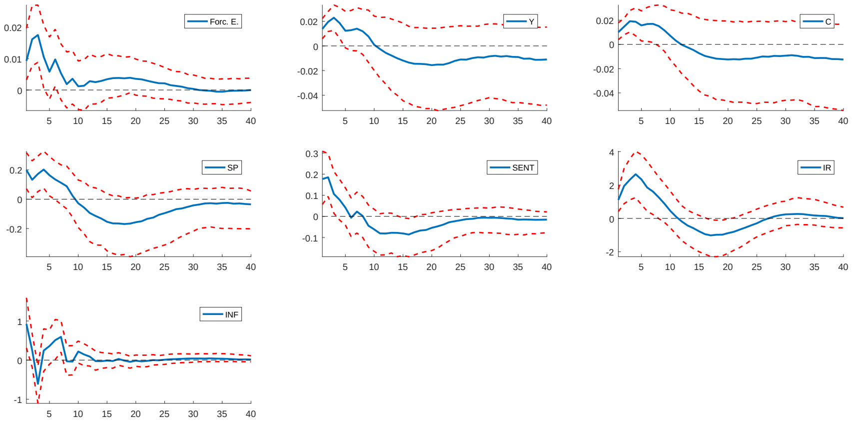


Figure: IRFs to supply shock



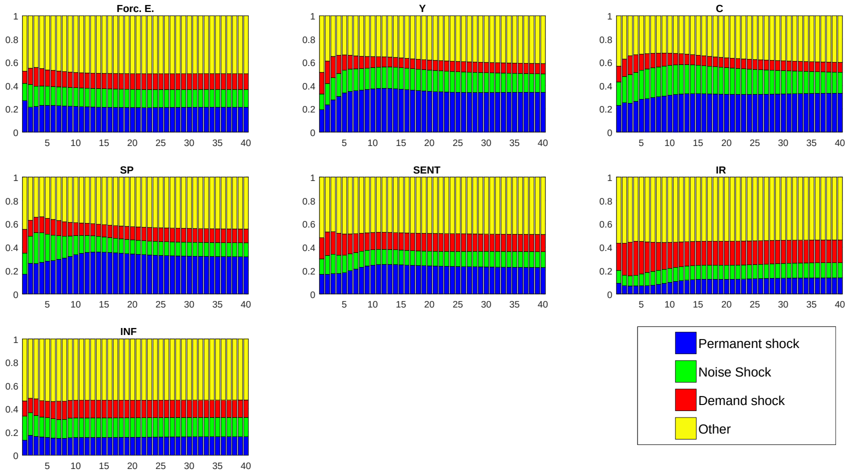
# US data - IRFs to demand shock

Figure: IRFs to demand shock



# US data - FEVD

Figure: FEVD



# Conclusions

- Supply and noise shocks cannot be identified in standard structural VAR models owing to invertibility issues.
- However, by considering that the econometrician can potentially have a richer and more accurate information set, a standard SVAR model can recover both supply and noise shocks.
- We have shown that:
  - noise shocks explain a significant share of business cycle fluctuations in the short term, while supply shocks explain output variations mainly in the long term;
  - consumption is even more affected by noise shocks than output at business cycle frequencies;
  - interest rates do not seem to be strongly affected by noise shocks, as central banks may be more immune to animal spirits.

**Thanks for your attention**

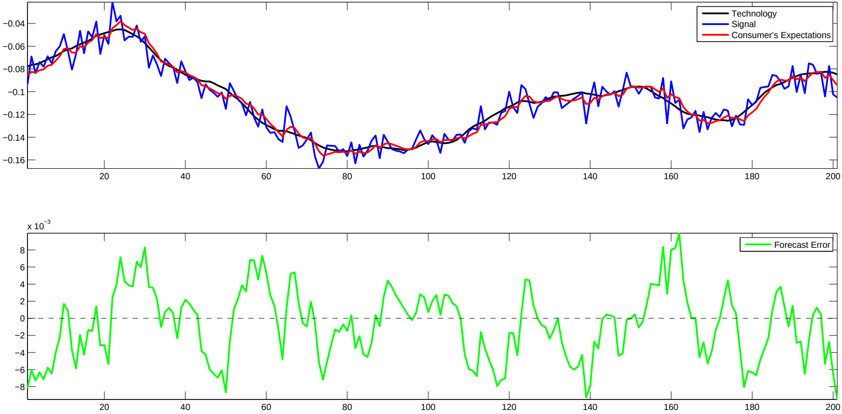



Figure: Simulated technology, signal and consumer's expectations (upper panel) and forecast error (lower panel)

Figure: IRF of consumption to a supply and noise shocks

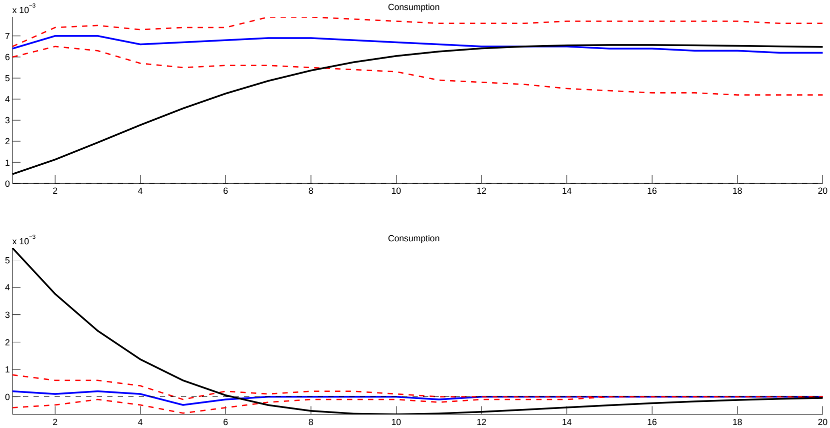


Figure: IRFs to supply shock