

Sentiment Booms Go Wrong

Marco Brianti

Vito Cormun

March 2019

Dissertation Workshop, Boston College

Two long Traditions in Macroeconomics

- ① **Changes in expectation** as an important driver of economic fluctuations
 - Incentives to anticipate potential economic developments
 - ⇒ Pigou (1927); Keynes (1936)
 - ⇒ Beaudry and Portier (2004, 2006)

- ② **Endogenous cycle**: expansions lead recessions
 - Economic fluctuations are driven by **internal forces** which favor recurrent periods of boom and bust.
 - ⇒ von Mises (1940); Beaudry, Galizia, and Portier (2018, 2019)
 - ⇒ Minsky (1977); Bordalo, Gennaioli, Shleifer (2018)

This paper

- ① We empirically estimate **sentiment shocks** and evaluate their effects on aggregate U.S. variables
 - We define sentiment shocks as **changes in expectations** uncorrelated with fundamentals
 - Sentiment shocks trigger **boom-and-bust dynamics** on most macroeconomic variables
 - Sentiments explain up to **40% of output**

- ② We write a **general equilibrium model** that rationalizes our empirical findings
 -
 -

Contributions

- ① We use Instrumental Variable Local Projection (**IV-LP**) to estimate sentiments shocks
 - Previous literature estimates DSGE models or employ SVAR
 - ⇒ Milani, 2011; Levchenko and Pandalai-Nayar, 2018
- ② Uncover **new dynamics** in response to sentiment shocks
 - **Informative** for the literature on sentiments
 - ⇒ Angeletos and La'O, 2013; Angeletos et al. (2018)
- ③ New supportive evidence for the literature on **credit cycles**
 - We proposed **structural evidence** in favor of credit booms with negative macroeconomic consequences
 - ⇒ Lopez-Salido, Stein, and Zakrajsek (2017)
- ④ (Ideally) Theory that displays **boom-and-bust** dynamics conditional on a specific type of shock
 - Hard to get shock specific boom and busts
 - ⇒ Beaudry, Galizia, and Portier (2019)

1. **Empirical Strategy**
2. Empirical Results
3. Test
4. Model
5. Conclusions

A 2-step procedure:

- ① Build an **instrument** Z_t correlated with changes in expectations and orthogonal to fundamentals.
- ② Estimate **dynamic responses** of macroeconomic variables using IV-LP.

Data Treatment on Expectations

Quarterly data from 1982 to 2018 of forecasts on macroeconomic variables, X_t^s , made by **Survey of Professional Forecasters**

Define,

- $E_t^i(X_{t+k}^s)$ as the expectation on X_{t+k}^s given the information set at time t released by professional forecaster i
- $E_t(X_{t+k}^s)$ as the sample mean across i of $E_t^i(X_{t+k}^s)$
- $E_t(\hat{x}_{t+k}^s) = E_t(X_{t+k}^s)/E_t(X_t^s) - 1$ as the expectation of the growth rate of X^s from t to $t + k$ given information set t
- $R_{t,k}^s = E_t(\hat{x}_{t+k}^s) - E_{t-1}(\hat{x}_{t+k}^s)$ as the revision on expectations from $t - 1$ to t of the growth rate of X^s from t to $t + k$
- R_t^k is the first principal component of $R_{t,k}^s$

IV-LP Estimator

Dynamic response of endogenous variable Y_{t+h} to R_t is

$$Y_{t+h} = \Theta_h^Y R_t + u_{h,t+h}^Y \quad (1)$$

Because R_t is endogenous, OLS estimation of 1 is not valid. Eq. 1 can be estimated by IV if Z_t satisfies the following conditions

- ❶ $E(\varepsilon_{1,t} Z_t) = \alpha \neq 0$ (relevance)
- ❷ $E(\varepsilon_{2:N,t} Z_t) = 0$ (contemporaneous exogeneity)
- ❸ $E(\varepsilon_{1:N,t+j} Z_t) = 0$ for $j \neq 0$ (lead-lag exogeneity)

Given the validity of previous conditions, a consistent estimator for Θ_h^Y is defined as

$$\hat{\Theta}_h^Y = \frac{\sum_{t=0}^{T-h} Y_{t+h} Z_t}{\sum_{t=0}^{T-h} R_t Z_t}$$

Instrument Z_t

We estimate instrument Z_t as the unpredictable component of R_t orthogonal to fundamentals,

$$R_t = c + B(L)\Delta TFP_t + \delta W_t + Z_t$$

where,

- ΔTFP is the first difference of utilization-adjusted TFP
- W_t represents a series of controls
 - Lagged principal components
 - Other structural shocks

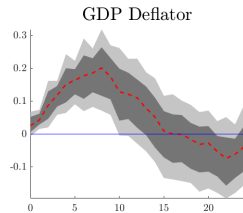
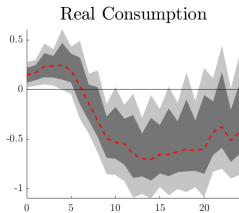
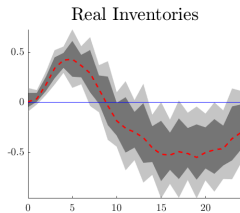
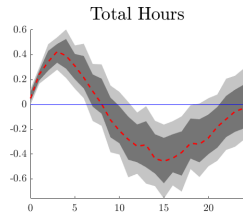
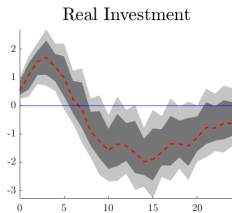
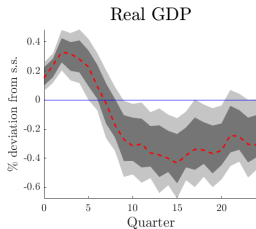
Importantly, R-Squared are relatively small (30%-50%)

⇒ A large part of SPF expectations is unrelated to fundamentals

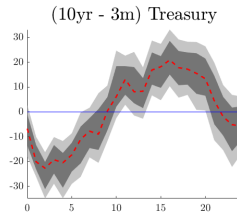
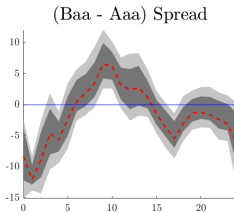
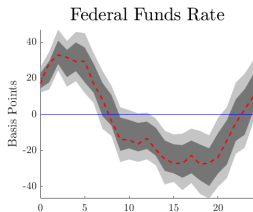
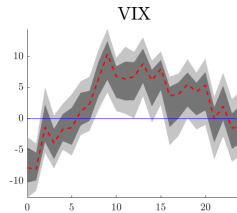
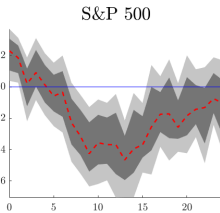
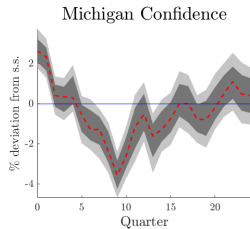
⇒ Z_t is a relevant instrument

1. Empirical Strategy
2. **Empirical Results**
3. Test
4. Model
5. Conclusions

Impulse Responses (I)



Impulse Responses (I)



Variance Decomposition

	<i>Impact</i>	<i>1 Year</i>	<i>2 Years</i>	<i>5 Years</i>
Real GDP	9.38%	19.81%	16.50%	37.72%
Real Investment	4.95%	19.69%	15.06%	35.96%
Total Hours	1.50%	23.38%	14.87%	25.21%
Real Consumption	4.51%	6.70%	5.50%	32.21%

Takeaways

- Sentiment shocks generate cycles of 6 to 7 years in both real and financial variables.
- Sentiments account for the bulk of fluctuations at Business Cycle frequency.
- Technology? Financial variables?

Robustness Checks

- Detrending techniques: first difference, linear, quadratic, Hodrick-Prescott and Band-pass.
- Bivariate VAR(10).
- Choice of lags and controls such as news shocks.
- Use data from Michigan Consumer Survey as a measure of expectations.

Roadmap

1. Empirical Strategy
2. Empirical Results
3. **Test**
4. Model
5. Conclusions

Roadmap

1. Empirical Strategy
2. Empirical Results
3. Test
4. **Model**
5. Conclusions

Roadmap

1. Empirical Strategy
2. Empirical Results
3. Test
4. Model
5. **Conclusions**

Conclusions

Roadmap

1. Empirical Strategy
2. Empirical Results
3. Test
4. Model
5. Conclusions
6. **Appendix**

Technical Details on Empirical Strategy

- Forecast horizon k from SPF data is either 2 or 3
- Forecasted variables X^s are real GDP, nominal GDP, real consumption, real investment, and industrial production
- If Y_t is non-stationary,
 - Detrend Y_t with low-frequency filters
 - Take the first difference of Y_t and $\Gamma_h^Y = \sum_{i=0}^h \Theta_h^Y$ is the response of Y_{t+h}
- Bootstrap method is from Kilian and Kim (2011)

Bootstrapping Technique

- 1 Consider tuple $\Lambda_{h,t}^Y = \{Y_{t+h} \ R_t \ W_t \ u_{h-1,t+h}^Y\}$
- 2 Create $\Lambda_{h,t,1}^Y$ of the same length of T of $\Lambda_{h,t}^Y$ where $\Lambda_{h,t,1}^Y$ is formed by randomly extracted blocks of length l from $\Lambda_{h,t}^Y$
- 3 Estimate $\Theta_{h,1}^Y$ from $\Lambda_{h,t,1}^Y$ using IV-LP estimator
- 4 Redo first 3 steps $B = 2000$ times and get $\Theta_{h,b}^Y$ where $b = 1, \dots, B$
- 5 Select confidence bands of $\Theta_{h,b}^Y$ across b for all h

Impulse Responses to a Surprise Productivity Shocks

