

# Identifying Monetary Policy Shocks: A Natural Language Approach

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# Paper Overview

- **Research Question:** Is NLP+ML helpful in identifying monetary policy shocks?
  - ▶ Monetary policymaking rule:  $s_t = f(\Omega_t) + \epsilon_t$
  - ▶ Romer and Romer (2004):  $\Delta i_t = \alpha + \beta i_{t-1} + \gamma X_t + \epsilon_t^{RR}$ 
    - ★ Information set  $\Omega_t$ : numerical forecasts ( $X_t$ )
    - ★ Linear regression

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  - ▶ This paper:  $\Delta i_t = \alpha + \beta i_{t-1} + \Gamma(\tilde{X}_t, Z_t) + \epsilon_t^*$ 
    - ★ Information set  $\Omega_t$ : numerical forecasts and **verbal information (sentiment)** ← **NLP**
    - ★ **Nonlinearities** ← **ML**

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  - ▶ ✓ Greenbook+Tealbook: staff analysis and outlook, Redbook+Beigebook: economic conditions by district ← information set at the onset of the FOMC meeting
  - ▶ × FOMC meeting minutes and transcripts ← decision process rather than information set

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- **Method**
  - ▶ FOMC documents → Economic Concepts → Sentiment Indicators → Model Estimation
  - ▶ Ridge/LASSO regression

# Paper Overview

## Main findings

- Description of the new shock measurement
  - ▶ Better capture the systematic component of monetary policy  $R^2$  0.50  $\rightarrow$  0.76
  - ▶ Main drivers: sentiment about broad real activity and international economic development, numerical forecasts of real activity
- Effects of the new shock measurement
  - ▶ BVAR analysis: consistent with theoretical consensus

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## A lot to like

- Important and innovative: NLP+ML  $\rightarrow$  “pure” monetary policy shocks
- Enormous data work
- Results already very rich and robust

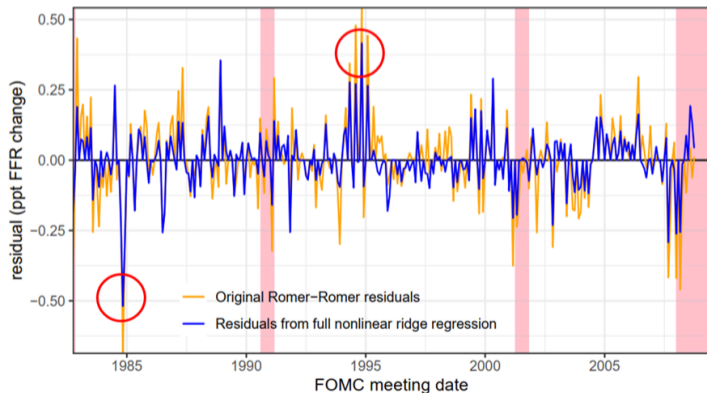
## When the shock is large

- Nov 1984, FOMC participants' views about the economy differ from that of the Fed staffs'
- Nov 1994, "behind the curve", "ahead of general expectation"

⇒ Uncertainty

⇒ Non "pure" shocks: information effect, forward guidance, large-scale asset purchase

Figure 4: ESTIMATED MONETARY POLICY SHOCKS



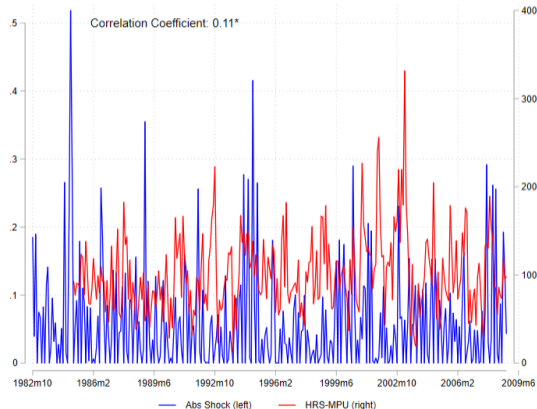
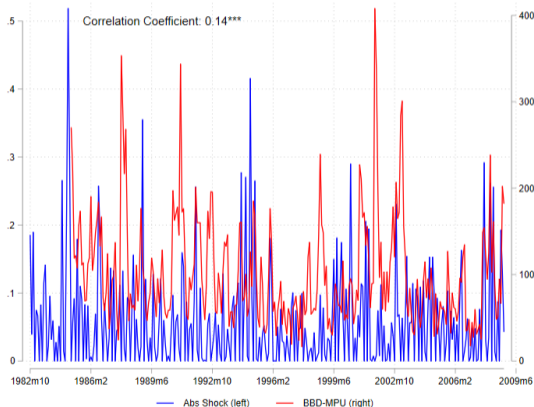


## Comment 1: Uncertainty

- The unsystematic surprises could be larger when **uncertainty** is higher
- Baker-Bloom-Davis and Husted-Rogers-Sun monetary policy uncertainty index

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## Comment 1: Uncertainty

- Significant correlation coefficients between larger surprises and uncertainty

### Suggestion

- Second moment of sentiment
- NLP for uncertainty and account for it in the model
- Compare the increase in  $R^2$  in periods with low and high uncertainty

## Comment 2: Non “pure” shocks

### ① Information effect

- ▶ Fed:  $s_t = f(\Omega_t^m, \Omega_t^f) + \epsilon_t$ , say  $f(\Omega_t^m) + g(\Omega_t^f) + \epsilon_t$
- ▶ The method in this paper can produce a cleaner measure of  $\epsilon_t$
- ▶ But market reacts to  $g(\Omega_t^f) + \epsilon_t$ , information effect matters in the full responses

### Suggestion

- Can construct  $\Omega_t^m$  and separate information effect and “pure” shock
  - ▶ Among the variables in numerical forecasts, use market consensus
  - ▶ Difference between Fed staff forecasts and market consensus
- Further, can even measure market sentiment and find the difference with Fed sentiment
- Show time series of this measurement and HF measurement

## Comment 2: Non “pure” shocks

### ② Forward guidance

- ▶ “ahead of general expectation”, guide future course of FFR
- ▶ Fed:  $s_t = f(\Omega_t^m) + g(\Omega_t^f) + \Gamma^{FG} + \epsilon_t$
- ▶ Market reacts to  $g(\Omega_t^f) + \Gamma^{FG} + \epsilon_t$

### Suggestion

- Can identify forward guidance from the FOMC meeting minutes based on textual analysis
- Show the IRF separately to “pure” shock, information effect, and forward guidance

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### ③ Large-scale asset purchase

- ▶ Less concern in the pre-2008M10 sample
- ▶ But matters in the BVAR covering through 2016

### Suggestion

- Show results limiting the BVAR analysis to the same pre-2008M10 sample
- Show results using the new measurement but the same periods as Romer and Romer (2004)

## Conclusion

- A very nice application of NLP+ML on monetary policy shock identification!
- Important for evaluating and guiding policymaking
- Tons of possibilities
- Good luck with the paper!