Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?

Sydney C. Ludvigson, Sai Ma, Serena Ng

New York University, New York University and Columbia University

Motivation

- **Uncertainty** rises sharply in **recessions**.
- But is uncertainty an exogenous *source* of business cycles or an endogenous *response* to them?
- And does the **type of uncertainty** matter?
- No theoretical consensus on these questions.
- **Econometric challenges**: "effects"of uncertainty shocks based on recursive schemes in VARs.

Motivation

- **Uncertainty** rises sharply in **recessions**.
- But is uncertainty an exogenous *source* of business cycles or an endogenous *response* to them?
- And does the **type of uncertainty** matter?
- No theoretical consensus on these questions.
- **Econometric challenges**: "effects"of uncertainty shocks based on recursive schemes in VARs.
    - Ordering of uncertainty variables in VAR differs study to study.

Motivation

- **Uncertainty** rises sharply in **recessions**.
- But is uncertainty an exogenous *source* of business cycles or an endogenous *response* to them?
- And does the **type of uncertainty** matter?
- No theoretical consensus on these questions.
- **Econometric challenges**: "effects"of uncertainty shocks based on recursive schemes in VARs.
  - Ordering of uncertainty variables in VAR differs study to study.
  - Any presumed ordering hard to defend on theoretical grounds.

Motivation

- **Uncertainty** rises sharply in **recessions**.
- But is uncertainty an exogenous *source* of business cycles or an endogenous *response* to them?
- And does the **type of uncertainty** matter?
- No theoretical consensus on these questions.
- **Econometric challenges**: “effects”of uncertainty shocks based on recursive schemes in VARs.
  - Ordering of uncertainty variables in VAR differs study to study.
  - Any presumed ordering hard to defend on theoretical grounds.
  - Recursive structures rule out contemporaneous feedback.

Econometric Strategy

- Address questions using small-scale structural VAR.

Econometric Strategy

- Address questions using small-scale structural VAR.
  1. Distinguish *macro* from *financial* uncertainty.
     - Baseline VAR: index macro uncertainty, $\mathbf{U_{Mt}}$, measure real activity, $\mathbf{Y_t}$, index financial uncertainty $\mathbf{U_{Ft}}$.

Econometric Strategy

- Address questions using small-scale structural VAR.
  1. Distinguish *macro* from *financial* uncertainty.
     - Baseline VAR: index macro uncertainty, $\mathbf{U_{Mt}}$, measure real activity, $\mathbf{Y_t}$, index financial uncertainty $\mathbf{U_{Ft}}$.
  2. Identification relies on **external instruments** rather than ordering or timing assumptions.

Econometric Strategy

- Address questions using small-scale structural VAR.
  1. Distinguish *macro* from *financial* uncertainty.
     - Baseline VAR: index macro uncertainty, $\mathbf{U_{Mt}}$, measure real activity, $\mathbf{Y_t}$, index financial uncertainty $\mathbf{U_{Ft}}$.
  2. Identification relies on **external instruments** rather than ordering or timing assumptions.
     - Z_{1t} correlated with U_{Mt} and U_{Ft}, uncorrelated with Y_t (shocks).
     - Z_{2t} correlated with U_{Ft}, uncorrelated with U_{Mt} and Y_t (shocks).

Econometric Strategy

- Address questions using small-scale structural VAR.
  1. Distinguish *macro* from *financial* uncertainty.
     - Baseline VAR: index macro uncertainty, $\mathbf{U_{Mt}}$, measure real activity, $\mathbf{Y_t}$, index financial uncertainty $\mathbf{U_{Ft}}$.
  2. Identification relies on **external instruments** rather than ordering or timing assumptions.
     - Z_{1t} correlated with U_{Mt} and U_{Ft}, uncorrelated with Y_t (shocks).
     - Z_{2t} correlated with U_{Ft}, uncorrelated with U_{Mt} and Y_t (shocks).
- Such instruments have no empirical counterparts. Propose a novel approach: *iterative projection IV* (IPIV).
  - *Construct* Z_{1t} and Z_{2t} from observables using projections.

Econometric Framework

- Let $\mathbf{X}_t$ be a $K \times 1$ vector.
- Consider p-th order structural vector autoregressive (SVAR)

$$\mathbf{X}_t = \mathbf{k} + \mathbb{A}_1 \mathbf{X}_{t-1} + \mathbb{A}_2 \mathbf{X}_{t-2} + \cdots + \mathbb{A}_p \mathbf{X}_{t-p} + \mathbf{H}\boldsymbol{\Sigma}\mathbf{e}_t. \quad (1)$$

$$\mathbf{e}_t \sim (0, \mathbf{I_K}), \qquad \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_{11} & 0 & \cdot & 0 \\ 0 & \sigma_{22} & 0 & 0 \\ 0 & \cdot & \cdot & 0 \\ 0 & 0 & \cdot & \sigma_{KK} \end{pmatrix}.$$

The structural shocks $\mathbf{e}_t$ are serially and mutually uncorrelated.

- Unit effect normalization & restrict admissible parameter space:

$$diag\,(\mathbf{H}) = 1 \qquad \sigma_{jj} \geq 0 \quad \forall j$$

Econometric Framework

- The reduced form representation of $\mathbf{X}_t$ is a p-th order VAR with $MA(\infty)$ representation

$$\begin{aligned} \mathbf{X}_t &= \boldsymbol{\mu} + \boldsymbol{\Psi}(L)\boldsymbol{\eta}_t \\ \boldsymbol{\eta}_t &\sim (0, \boldsymbol{\Omega}), \quad \boldsymbol{\Omega} = E\left(\boldsymbol{\eta}_t \boldsymbol{\eta}_t'\right). \end{aligned}$$

- The structural shocks $\mathbf{e}_t$ are related to the reduced form innovations by an invertible $K \times K$ matrix $\mathbf{H}$:

$$\boldsymbol{\eta}_t = \mathbf{H}\boldsymbol{\Sigma}\mathbf{e}_t \equiv \mathbf{B}\mathbf{e}_t$$

- Here $K = 3$ and $\mathbf{X}_t = (U_{Mt}, Y_t, U_{Ft})'$, $\mathbf{e}_t = (e_{Mt}, e_{Yt}, e_{Ft})'$
- Want to identify $\mathbf{e}_t = \mathbf{B}^{-1}\boldsymbol{\eta}_t$, nine unknown elements in $\mathbf{B} \rightarrow$
- Need nine restrictions for identification.

Identification

- Covariance structure $\boldsymbol{\eta}_t$ provides $K(K+1)/2 = 6$ restrictions:

$$\text{vech}(\boldsymbol{\Omega}) = \text{vech}(\mathbf{BB}')$$

- Need 3 more for identification

- Suppose we have measures of Y_t, U_{Mt}, U_{Ft}, and two generic instruments, $Z_t = (Z_{1t}, Z_{2t})'$.

  Assumption A: Let Z_{1t} and Z_{2t} be two IVs such that

$$\begin{array}{lllllll} (A.i) & \mathbb{E}[Z_{1t}e_{Mt}] & = \phi_{1M}, & \mathbb{E}[Z_{1t}e_{Yt}] & = 0, & \mathbb{E}[Z_{1t}e_{Ft}] & = \phi_{1F} \\ (A.ii) & \mathbb{E}[Z_{2t}e_{Mt}] & = 0, & \mathbb{E}[Z_{2t}e_{Yt}] & = 0, & \mathbb{E}[Z_{2t}e_{Ft}] & = \phi_{2F} \end{array}$$

- **Instrument Exogeneity**: $\mathbb{E}[Z_{1t}e_{Yt}] = \mathbb{E}[Z_{2t}e_{Yt}] = \mathbb{E}[Z_{2t}e_{Mt}] = 0$

- **Instrument Relevance**: $\phi_{1M}, \phi_{1F}, \phi_{2F} \neq 0$

Identification

- Let $\mathbf{m}_{1t}(\boldsymbol{\eta}_t, Z_t) = (\text{vech}(\boldsymbol{\eta}_t \boldsymbol{\eta}_t'), \text{vec}\,(Z_t \otimes \boldsymbol{\eta}_t))'$ and $\boldsymbol{\beta}_1 = \text{vec}(\boldsymbol{B})$.
- At the true value of $\boldsymbol{\beta}_1$, denoted $\boldsymbol{\beta}_1^0$, the model satisfies

$$0 = \mathbb{E}[\mathbf{g}_1(\mathbf{m}_{1t}(\boldsymbol{\eta}_t, Z_t); \boldsymbol{\beta}_1^0)]$$

- Nonlinear system with nine equations in nine unknowns.

Identification

Proposition

Under Assumption A with $\phi_{1M} \neq 0, \phi_{1F} \neq 0, \phi_{2F} \neq 0$, $diag(\mathbf{H}) = 1$, and $\sigma_{jj} > 0 \; \forall j$, $\boldsymbol{\beta}_1$ is identified.

In words, identification is achieved by

1. Use movements in U_{Mt} and U_{Ft} correlated with Z_{1t} to **identify U_{Mt} and U_{Ft} shocks, disentangle them from real activity shocks**
2. Use movements in U_{Ft} correlated with Z_{2t} to **identify U_{Ft} shocks and disentangle them from U_{Mt} shocks**
3. Use movements in Y_t uncorrelated with *both* Z_{1t}, Z_{2t} to **identify Y shocks, disentangle them from U_{Mt} and U_{Ft} shocks**

Construction of Instruments

- How to obtain valid instruments Z? **Exploit external variables**.

Construction of Instruments

- How to obtain valid instruments Z? **Exploit external variables**.
- **Maintained hypothesis**: Both U_M, U_F shocks reflected in stock returns $\mathbf{S}_t = (S_{1t}, S_{2t})'$. But $\mathbf{S}_t$ partly *endogenous*, corr with Y_t.
- Assume $\mathbf{S}_t$ driven by $\mathbf{e}_t = (e_{Yt}, e_{Mt}$ and $e_{Ft})'$ and idiosyncratic shocks collected into $\mathbf{e}_{St}$ orthogonal to $\mathbf{e}_t$.
- Shocks $\mathbf{e}_{St}$ presumed not to affect $\mathbf{X}_t$. Represent $\mathbf{S}_{jt}$, $j = 1, 2$ as

$$\delta_S(L)S_{jt} = \delta_{j0} + \delta_{jY}Y_t + \delta_{jM}U_{Mt} + \delta_{jF}U_{Ft} + \delta_{jX}(L)'\mathbf{X}_{t-1} + e_{Sjt} \quad (2)$$

- Equation (2) motivates two orthogonal decompositions:

$$\begin{aligned} d_{1S}(L)S_{1t} &= d_{10} + d_{1Y}e_{Yt} + Z_{1t} \\ d_{2S}(L)S_{2t} &= d_{20} + d_{2Y}e_{Yt} + d_{2M}e_{Mt} + Z_{2t}, \end{aligned}$$

Construction of Instruments

- How to obtain valid instruments Z? **Exploit external variables**.
- **Maintained hypothesis**: Both U_M, U_F shocks reflected in stock returns $\mathbf{S}_t = (S_{1t}, S_{2t})'$. But $\mathbf{S}_t$ partly *endogenous*, corr with Y_t.
- Assume $\mathbf{S}_t$ driven by $\mathbf{e}_t = (e_{Yt}, e_{Mt}$ and $e_{Ft})'$ and idiosyncratic shocks collected into $\mathbf{e}_{St}$ orthogonal to $\mathbf{e}_t$.
- Shocks $\mathbf{e}_{St}$ presumed not to affect $\mathbf{X}_t$. Represent $\mathbf{S}_{jt}$, $j = 1, 2$ as

$$\delta_S(L)S_{jt} = \delta_{j0} + \delta_{jY}Y_t + \delta_{jM}U_{Mt} + \delta_{jF}U_{Ft} + \delta_{jX}(L)'\mathbf{X}_{t-1} + e_{Sjt} \quad (2)$$

- Equation (2) motivates two orthogonal decompositions:

$$\begin{aligned} d_{1S}(L)S_{1t} &= d_{10} + d_{1Y}e_{Yt} + Z_{1t} \\ d_{2S}(L)S_{2t} &= d_{20} + d_{2Y}e_{Yt} + d_{2M}e_{Mt} + Z_{2t}, \end{aligned}$$

- **Problem:** projections are infeasible b/c e_{Yt}, e_{Mt} are unobserved.
- **Solution**: *generate* Z_{1t} and Z_2 using iterative approach to jointly solve for e_t and Z_t that satisfy restrictions for instrument **exogeneity & relevance**.

Iterative Projection IV (IPIV)

$$d_{1S}(L)S_{1t} = d_{10} + d_{1Y}e_{Yt} + Z_{1t} \qquad (*)$$
$$d_{2S}(L)S_{2t} = d_{20} + d_{2Y}e_{Yt} + d_{2M}e_{Mt} + Z_{2t}, \qquad (**)$$

Let $T \times 1$ $\mathbf{e_M}^{(0)k}$, $\mathbf{e_Y}^{(0)k}$ be the k^{th} initial guess in a compact set $\mathcal{K}$. Initialize $j = 0$.

i Replace $\mathbf{e_M}$ and $\mathbf{e_Y}$ in $(*)$ and $(**)$ by $\mathbf{e_M}^{(j)k}$ and $\mathbf{e_Y}^{(j)k}$. Obtain $\mathbf{Z}_1^{(j)k}$ and $\mathbf{Z}_2^{(j)k}$.

ii Use $\mathbf{Z}_1^{(j)k}, \mathbf{Z}_2^{(j)k}$ to solve $0 = \mathbb{E}[\mathbf{g}_1(\mathbf{m}_{1t}(\boldsymbol{\eta}_t, Z_t); \boldsymbol{\beta}_1^0)]$ for $\boldsymbol{\beta}_1$. Form $\mathbf{B}^{(j)k}$ from $\boldsymbol{\beta}_1^{(j)k}$.

iii Update shocks $\mathbf{e}^{(j+1)k} = (\mathbf{e_M}^{(j+1)k}, \mathbf{e_Y}^{(j+1)k}, \mathbf{e_F}^{(j+1)k}) = \left(\mathbf{B}^{(j)k}\right)^{-1} \hat{\boldsymbol{\eta}}$.

iv If $\|\mathbf{e_M}^{(j+1)k} - \mathbf{e_M}^{(j)k}\| \leq$ tol and $\|\mathbf{e_Y}^{(j+1)k} - \mathbf{e_Y}^{(j)k}\| <$ tol, stop and let $\mathbf{e}^k = \mathbf{e}^{(j)k}, \boldsymbol{\beta}_1^k = \boldsymbol{\beta}_1^{(j)k}$. Else, set $j = j + 1$ and return to (i).

v-a **Economic constraints**: large shock episodes

v-b **Econometric constraints**: Store $\hat{c}_1 = corr(Z_{1t}(\boldsymbol{\beta}_1^k), e_{Mt}^k)$, $\hat{c}_2 = corr(Z_{1t}(\boldsymbol{\beta}_1^k), e_{Ft}^k)$, $\hat{c}_3 = corr(Z_{2t}(\boldsymbol{\beta}_1^k), e_{Ft}^k)$, $C(\boldsymbol{\beta}_1^k) = \frac{1}{3}(|\hat{c}_1| + |\hat{c}_2| + |\hat{c}_3|)$. Keep $\boldsymbol{\beta}_1^k$ that satisfy (a) $C(\boldsymbol{\beta}_1^k) \geq \bar{C}$, (b), each $|\hat{c}_i| \geq \bar{c}$, and (c) $\det(B^{(j)k}) \geq \underline{b}$.

Iterative Projection IV (IPIV)

1. **Instrument exogeneity:** holds by construction.
2. **If estimation unconstrained:** diverse multiplicity of solutions, esp. if starting values are poor $\Rightarrow$ add restrictions to narrow set:
3. **Additional restrictions** for instrument relevance:
   - Minimum thresholds for individual and collective instrument strength and $\det(\mathbf{B}) > 0$ (step (v-b)).
4. **Further winnow solutions using prior economic reasoning:** Study estimated shocks in detail check that signs and magnitudes are sensible:
   - 1987 crash & 2007-09 fin. crisis identified as big positive U_{Ft} shocks
   - Great Recession not identified with big *positive* Y shock.
5. **Left: handful of credible solutions** (≈ 6) all very close and tell same economic story. Results shown for one solution (base case).

Measuring Uncertainty: Jurado, Ludvigson, Ng (JLN)

- Methodology: DI forecasting plus stochastic volatility model hundreds economic time-series
- **One month-ahead uncertainty indexes:**
- **Macro uncertainty** U_{Mt} aggregates uncertainty estimates of 134 macro indicators
  - Real activity, price, financial
- **Financial uncertainty** U_{Ft} aggregates uncertainty estimates of 147 financial indicators
  - Stock, bond returns and risk factors
- **Real activity uncertainty** U_{Rt} aggregates uncertainty estimates of 73 real activity variables

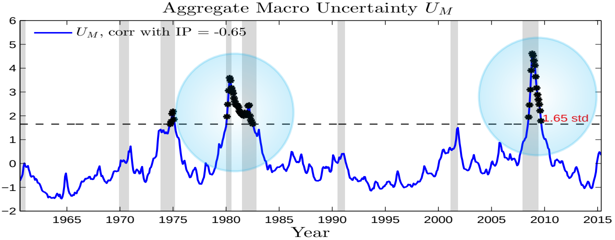
Measuring Stock Market Returns and Real Activity

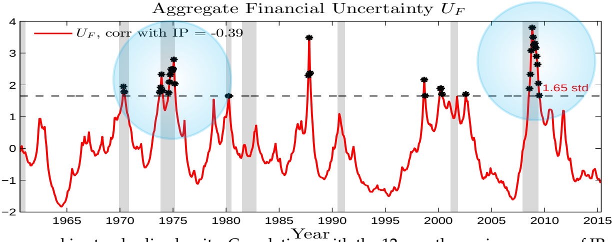
- Set $S_{2t} = r_{S\&Pt}$ to generate Z_{2t}
- Set $S_{1t} = r_{pt} \equiv \alpha_p r_{CRSPt} + (1 - \alpha_p) r_{smallt}$ to generate Z_{1t}
- **Real activity** $Y_t =$
  1. log of **industrial production** ip_t
  2. log of total non-farm **employment** emp_t
  3. **Real activity factor**: Q_{1t} (cumulative sum of first common factor estimated from large macro dataset).
- **Estimation**: all parameters by GMM.
- **Data**: monthly.

Results

Time Series of Uncertainty Measures

- Both exhibit large spikes in deep recessions.

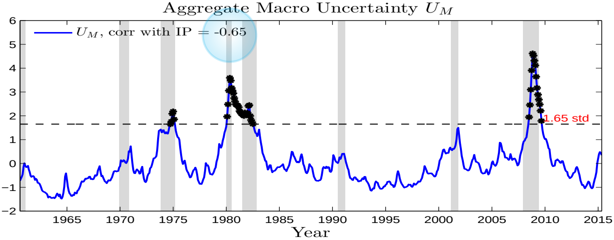


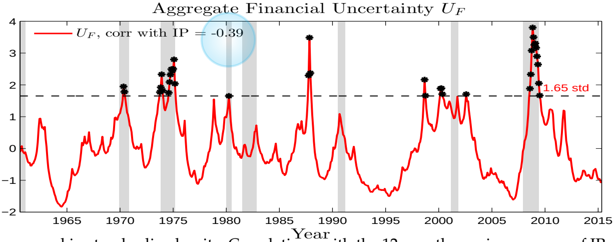


Note: U_M, U_F are expressed in standardized units. Correlations with the 12-month moving average of IP growth are reported. The black dots represent months when uncertainty is 1.65 standard deviations above its unconditional mean. The shaded areas correspond to the NBER recession dates. The sample spans the period 1960:07 to 2015:04.

Time Series of Uncertainty Measures

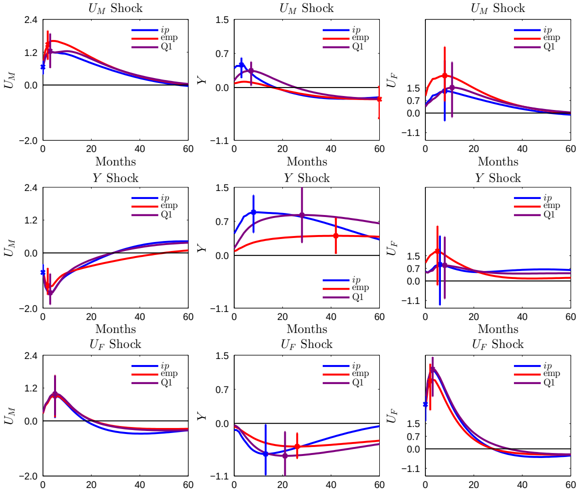
- U_{Ft} less countercyclical than U_{Mt}; **corr**$(U_{Mt}, U_{Ft}) = 0.58$.





Note: U_M, U_F are expressed in standardized units. Correlations with the 12-month moving average of IP growth are reported. The black dots represent months when uncertainty is 1.65 standard deviations above its unconditional mean. The shaded areas correspond to the NBER recession dates. The sample spans the period 1960:07 to 2015:04.

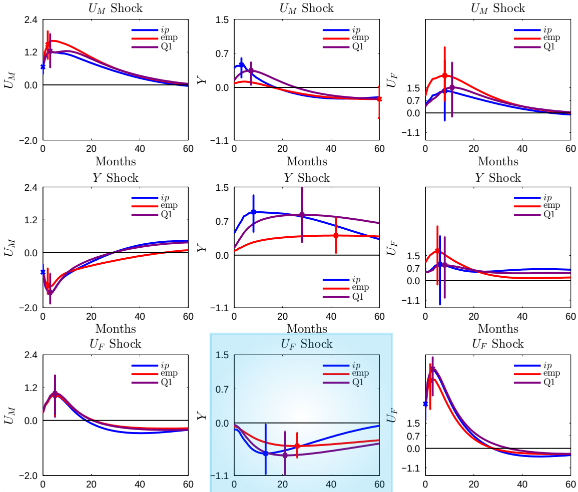
IRF for SVAR $(U_M, Y, U_F)'$



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to positive one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

IRF for SVAR $(U_M, Y, U_F)'$

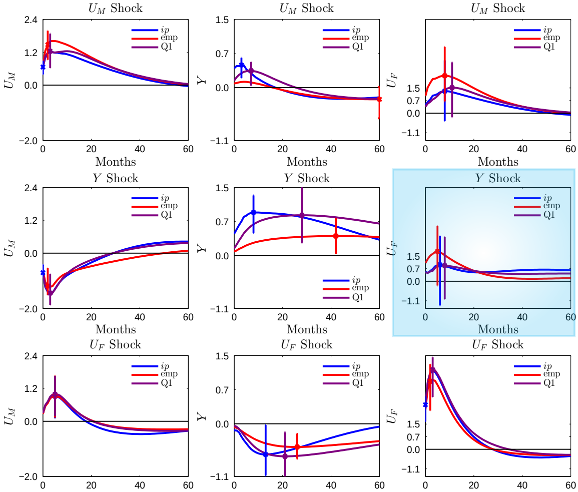
- Positive U_F shocks $\Rightarrow$ sharp, persistent decline in real activity



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to positive one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

IRF for SVAR $(U_M, Y, U_F)'$

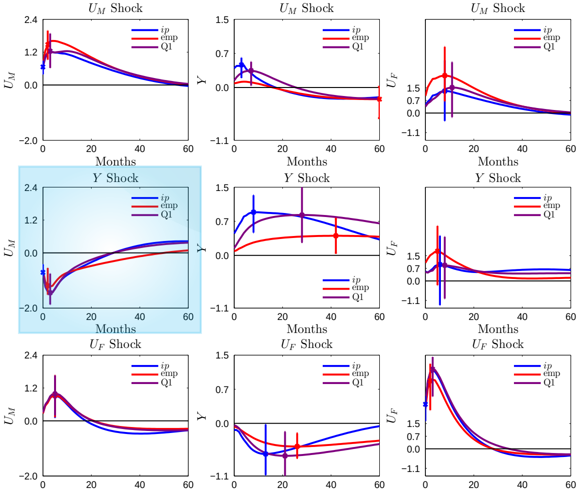
- Little evidence that Y shocks affect U_F



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to positive one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

IRF for SVAR $(U_M, Y, U_F)'$

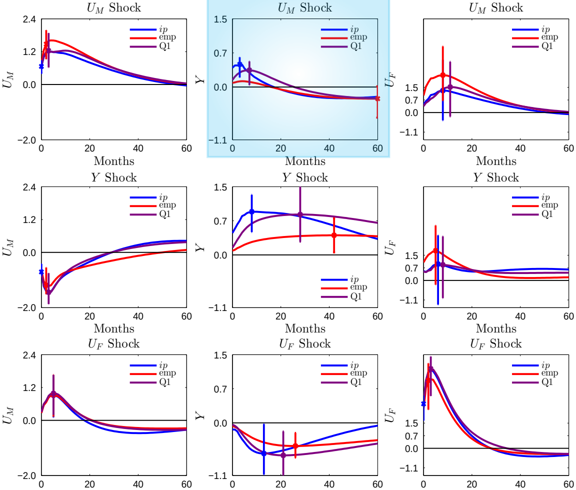
- *Macro* uncertainty falls sharply in response to *positive* Y shocks



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to positive one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

IRF for SVAR $(U_M, Y, U_F)'$

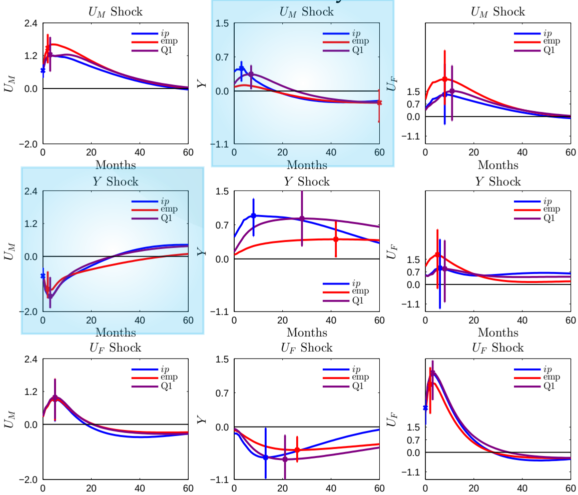
- No evidence that positive U_M shocks lead to declines in real activity; indeed the opposite.



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to positive one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

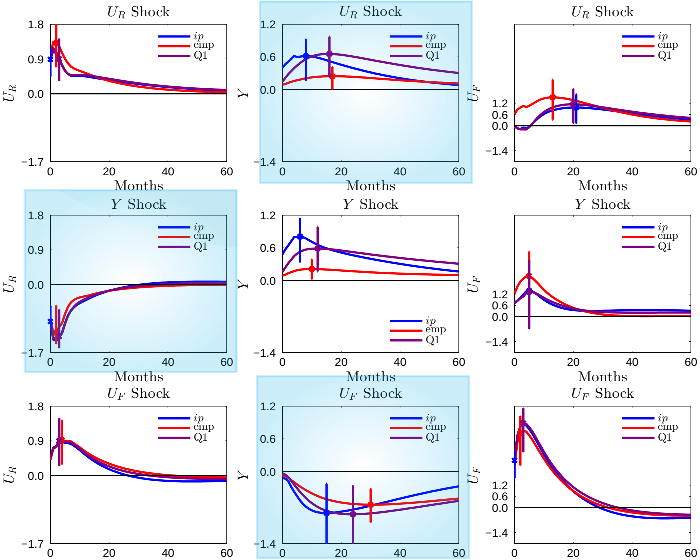
IRF for SVAR $(U_M, Y, U_F)'$

- Higher macro uncertainty in recessions entirely an **endogenous response** to lower economic activity.



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to positive one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

IRF for SVAR $(U_R, Y, U_F)'$



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

Overidentifying Exclusion Restrictions

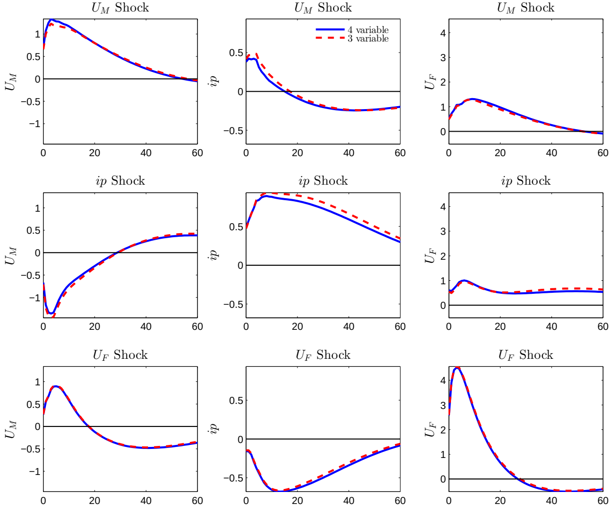
- S_t assumed external to VAR. This is tantamount to imposing an exclusion restriction on larger VAR that includes S_t.
- Let $\mathbf{X}_t = (U_{Mt}, Y_t, U_{Ft})'$ and S_t stock returns. VAR(1) with S_t:

$$\underbrace{\begin{pmatrix} \underset{3\times 3}{\mathbf{A}_{XX,0}} & \underset{3\times 2}{\mathbf{A}_{XS,0}} \\ \underset{2\times 3}{\mathbf{A}_{SX,0}} & \underset{2\times 2}{A_{SS,0}} \end{pmatrix}}_{\mathbf{A}_0 \equiv \mathbf{H}^{-1}} \begin{pmatrix} \mathbf{X}_t \\ S_t \end{pmatrix} = \begin{pmatrix} \mathbf{A}_{XX,1} & \mathbf{A}_{XS,1} \\ \mathbf{A}_{SX,1} & A_{SS,1} \end{pmatrix} \begin{pmatrix} \mathbf{X}_{t-1} \\ S_{t-1} \end{pmatrix} + \begin{pmatrix} \mathbf{\Sigma}_X & 0 \\ 0 & \Sigma_S \end{pmatrix} \begin{pmatrix} \mathbf{e}_{Xt} \\ \mathbf{e}_{St} \end{pmatrix}$$

- Maintained assumption baseline case: $\mathbf{A}_{XS,0} = \mathbf{A}_{XS,1} = \mathbf{0}$.
- Paper: in 4 variable VAR, still need $\mathbf{A}_{XS,0} = \mathbf{0}$ for identification. But don't need $\mathbf{A}_{XS,1} = 0$.
- Evaluate validity of OID restrictions by comparing IRF for 3 variable $\mathbf{X}_t$ with 4 variable $(\mathbf{X}_t', S_t)'$ where $\mathbf{A}_{XS,1}$ left unconstrained.

Evaluating OID Restrictions: Compare IRFs

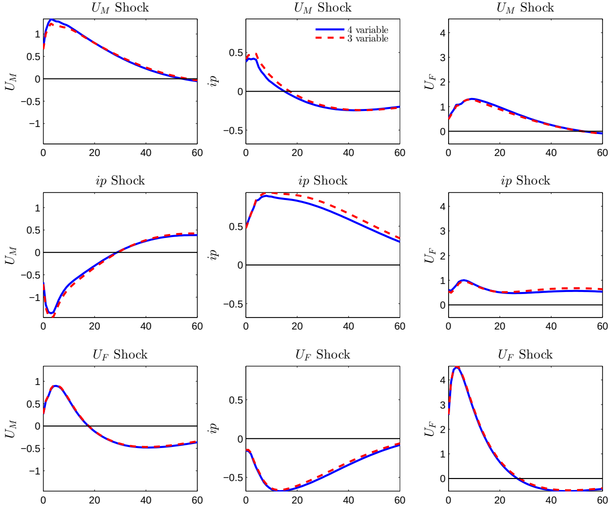
- IRFs from 3 variable $\mathbf{X}_t$ v.s. 4 variable $(\mathbf{X}_t', S_t)'$ with free $\mathbf{A}_{XS,j} \forall j \geq 1$.



Note: S_t is the CRSP value weighted average returns. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

Evaluating OID Restrictions: Compare IRFs

- Data appear consistent with assumption stock returns can be excluded.



Note: S_t is the CRSP value weighted average returns. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

Test of Recursive Restrictions

- Our SVAR model nests any recursive structure.
- Chi-square test H_0 : recursive structure is supported by the data.
  - Strongly reject lower triangular structure for *any* possible ordering.
- Inspection of $\hat{\mathbf{A}}_0$ reveals non-zero contemporaneous correlations $\rho(U_M, Y)$, $\rho(U_F, Y)$, inconsistent with any recursive ordering.

$$\hat{\mathbf{A}}_0 = \begin{pmatrix} \mathbf{0.5130} & \mathbf{0.7815} & -\mathbf{0.0106} \\ [0.0205] & [0.0324] & [0.0034] \\ -\mathbf{0.3251} & \mathbf{0.4441} & \mathbf{0.0590} \\ [0.0135] & [0.0184] & [0.0024] \\ -0.0046 & -\mathbf{1.0969} & \mathbf{0.9394} \\ [0.1625] & [0.2666] & [0.0258] \end{pmatrix}$$

Conclusion. Uncertainty Rises in Recessions. Why?

- Is **uncertainty a cause or effect** of business cycle fluctuations? And does the type of uncertainty matter? Empirical question.

Conclusion. Uncertainty Rises in Recessions. Why?

- Is **uncertainty a cause or effect** of business cycle fluctuations? And does the type of uncertainty matter? Empirical question.
- Establish structural, dynamic, causal effects using novel approach: **Iterative Projection IV (IPIV)**
  - Combines information in **external variables** with **projections** to *construct* valid instruments to identify structural shocks.

Conclusion. Uncertainty Rises in Recessions. Why?

- Is **uncertainty a cause or effect** of business cycle fluctuations? And does the type of uncertainty matter? Empirical question.
- Establish structural, dynamic, causal effects using novel approach: **Iterative Projection IV (IPIV)**
  - Combines information in **external variables** with **projections** to *construct* valid instruments to identify structural shocks.
- Distinguish **macro** from **financial** uncertainty in SVAR $(U_M, Y, U_F)'$.

Conclusion. Uncertainty Rises in Recessions. Why?

- Is **uncertainty a cause or effect** of business cycle fluctuations? And does the type of uncertainty matter? Empirical question.
- Establish structural, dynamic, causal effects using novel approach: **Iterative Projection IV (IPIV)**
  - Combines information in **external variables** with **projections** to *construct* valid instruments to identify structural shocks.
- Distinguish **macro** from **financial** uncertainty in SVAR $(U_M, Y, U_F)'$.
- **Maintained theoretical hypothesis**: variables e.g., stock returns, while endogenous, contain *components* satisfy population exogeneity restrictions and can serve as valid instruments.

Conclusion. Uncertainty Rises in Recessions. Why?

- Is **uncertainty a cause or effect** of business cycle fluctuations? And does the type of uncertainty matter? Empirical question.
- Establish structural, dynamic, causal effects using novel approach: **Iterative Projection IV (IPIV)**
  - Combines information in **external variables** with **projections** to *construct* valid instruments to identify structural shocks.
- Distinguish **macro** from **financial** uncertainty in SVAR $(U_M, Y, U_F)'$.
- **Maintained theoretical hypothesis**: variables e.g., stock returns, while endogenous, contain *components* satisfy population exogeneity restrictions and can serve as valid instruments.
  - Our IPIV is a **way to isolate** those components.

Conclusion. Uncertainty Rises in Recessions. Why?

- Is **uncertainty a cause or effect** of business cycle fluctuations? And does the type of uncertainty matter? Empirical question.
- Establish structural, dynamic, causal effects using novel approach: **Iterative Projection IV (IPIV)**
  - Combines information in **external variables** with **projections** to *construct* valid instruments to identify structural shocks.
- Distinguish **macro** from **financial** uncertainty in SVAR $(U_M, Y, U_F)'$.
- **Maintained theoretical hypothesis**: variables e.g., stock returns, while endogenous, contain *components* satisfy population exogeneity restrictions and can serve as valid instruments.
- We find: sharply higher **real economic uncertainty** in recessions an endogenous response...

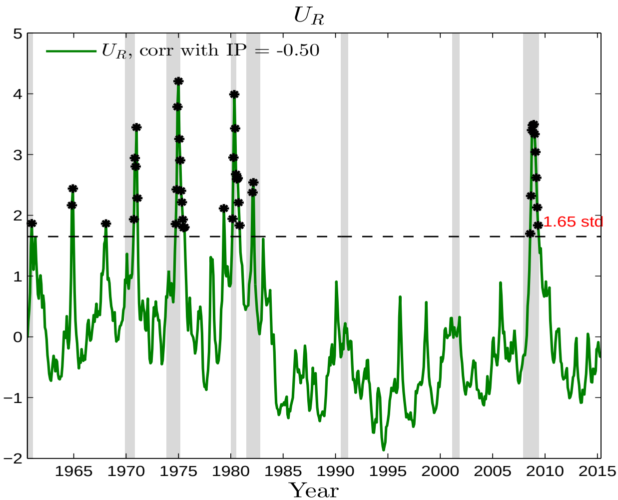
Conclusion. Uncertainty Rises in Recessions. Why?

- Is **uncertainty a cause or effect** of business cycle fluctuations? And does the type of uncertainty matter? Empirical question.
- Establish structural, dynamic, causal effects using novel approach: **Iterative Projection IV (IPIV)**
  - Combines information in **external variables** with **projections** to *construct* valid instruments to identify structural shocks.
- Distinguish **macro** from **financial** uncertainty in SVAR $(U_M, Y, U_F)'$.
- **Maintained theoretical hypothesis**: variables e.g., stock returns, while endogenous, contain *components* satisfy population exogeneity restrictions and can serve as valid instruments.
- We find: sharply higher **real economic uncertainty** in recessions an endogenous response...
- ...Uncertainty in **financial markets** a likely source of business cycles.

Appendix

Real Activity Uncertainty U_R

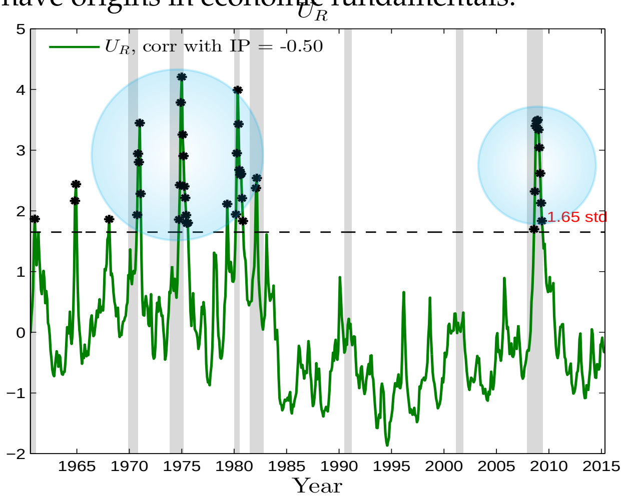
- Sub-index of U_M corresponding to real activity variables.



Note: U_R is expressed in standardized units. Correlations with the 12-month moving average of IP growth are reported. The shaded areas correspond to the NBER recession dates. The monthly data span the period 1960:07 to 2015:04.

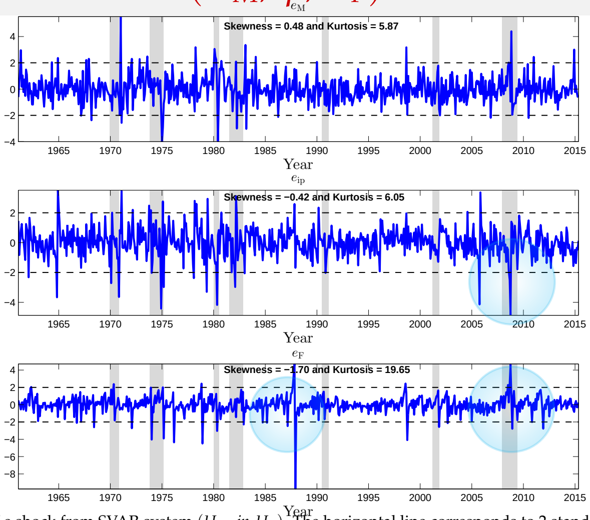
Real Activity Uncertainty U_R

- Special relevance to uncertainty literature, where uncertainty shocks have origins in economic fundamentals.



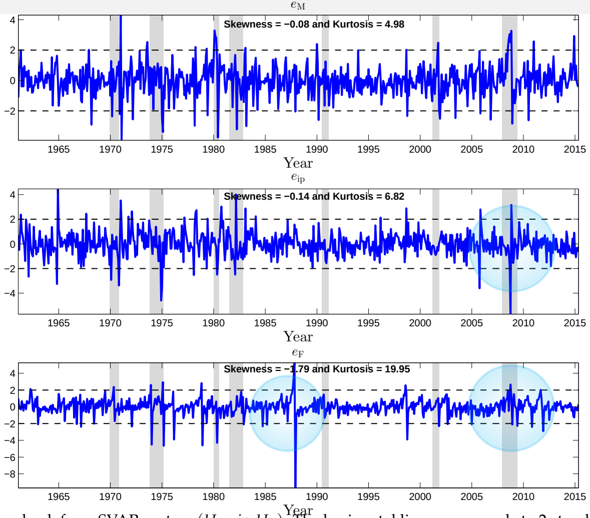
Note: U_R is expressed in standardized units. Correlations with the 12-month moving average of IP growth are reported. The shaded areas correspond to the NBER recession dates. The monthly data span the period 1960:07 to 2015:04.

e shock Time series $(U_M, ip, U_F)'$



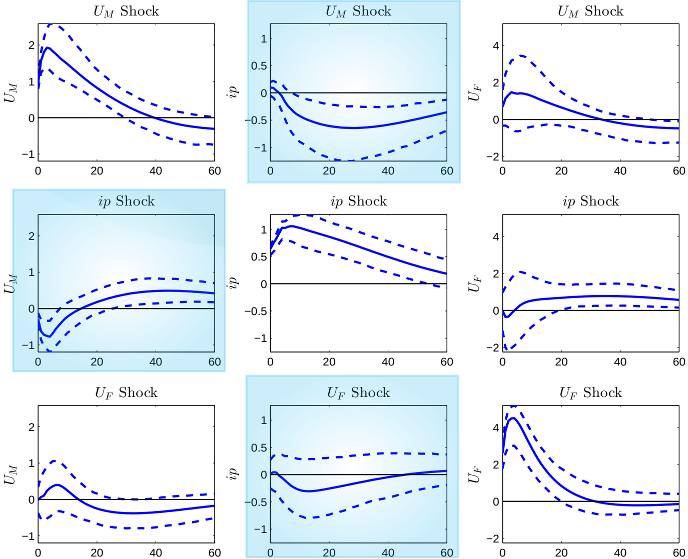
Note: Time series of e shock from SVAR system (U_M, ip, U_F). The horizontal line corresponds to 2 standard deviations above/below the unconditional mean of each series. The shocks $e = B^{-1}\eta_t$ are reported, where η_t is the residual from VAR(6) of (U_M, ip, U_F) and $B = A^{-1}\Sigma$. The shaded areas correspond to the NBER recession dates. The sample spans the period 1960:07 to 2015:04.

e solution fails economics constraint



Note: Time series of e shock from SVAR system (U_M, ip, U_F). The horizontal line corresponds to 2 standard deviations above/below the unconditional mean of each series. The shocks $e = B^{-1}\eta_t$ are reported, where η_t is the residual from VAR(6) of (U_M, ip, U_F) and $B = A^{-1}\Sigma$. The shaded areas correspond to the NBER recession dates. The sample spans the period 1960:07 to 2015:04.

IRF that fails economics constraint



Note: Bootstrapped 90 percent error bands appear as vertical lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

Variance Decomposition $(U_M, Y, U_F)'$

	SVAR $(U_M, ip, U_F)'$			SVAR $(U_M, emp, U_F)'$			SVAR $(U_M, Q_1, U_F)'$		
	Fraction variation in U_M			Fraction variation in U_M			Fraction variation in U_M		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.371	0.527	0.102	0.531	0.376	0.093	0.390	0.497	0.113
12	0.419	0.409	0.172	0.601	0.249	0.150	0.434	0.371	0.195
∞	0.420	0.368	0.212	0.619	0.220	0.161	0.478	0.322	0.200
$s_{\max}$	0.511	0.528	0.215	0.664	0.384	0.161	0.572	0.498	0.203
	[0.25, 0.79]	[0.22, 0.71]	[0.05, 0.57]	[0.34, 0.87]	[0.15, 0.59]	[0.06, 0.46]	[0.30, 0.79]	[0.21, 0.70]	[0.06, 0.53]
	Fraction variation in ip			Fraction variation in emp			Fraction variation in Q_1		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.401	0.556	0.043	0.352	0.402	0.246	0.456	0.508	0.036
12	0.121	0.659	0.220	0.075	0.406	0.519	0.169	0.563	0.269
∞	0.082	0.691	0.227	0.124	0.424	0.453	0.063	0.621	0.317
$s_{\max}$	0.415	0.696	0.272	0.373	0.424	0.587	0.468	0.621	0.358
	[0.19, 0.61]	[0.34, 0.94]	[0.04, 0.73]	[0.21, 0.63]	[0.16, 0.85]	[0.16, 0.92]	[0.24, 0.62]	[0.33, 0.95]	[0.07, 0.81]
	Fraction variation in U_F			Fraction variation in U_F			Fraction variation in U_F		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.029	0.023	0.948	0.140	0.119	0.743	0.019	0.022	0.959
12	0.080	0.041	0.878	0.243	0.133	0.624	0.082	0.039	0.879
∞	0.121	0.131	0.748	0.332	0.138	0.530	0.156	0.098	0.746
$s_{\max}$	0.128	0.131	0.950	0.339	0.152	0.744	0.163	0.098	0.961
	[0.03, 0.47]	[0.05, 0.52]	[0.53, 0.99]	[0.08, 0.64]	[0.03, 0.58]	[0.33, 0.95]	[0.03, 0.53]	[0.03, 0.48]	[0.60, 0.99]

Note: Each panel shows the fraction of s-step-ahead forecast-error variance of the variable given in the panel title that is explained by the shock named in the column heading. The row denoted "$s = s_{max}$"reports the maximum fraction (across all VAR forecast horizons m) of forecast error variance explained by the shock listed in the column heading. The numbers in parentheses represent the 5th and 95th percentiles of these statistics from bootstrapped samples. The data are monthly and span the period 1960:07 to 2015:04.

Variance Decomposition $(U_M, Y, U_F)'$

- Variation in U_F driven by *its own* shocks.

	SVAR $(U_M, ip, U_F)'$			SVAR $(U_M, emp, U_F)'$			SVAR $(U_M, Q_1, U_F)'$		
	Fraction variation in U_M			Fraction variation in U_M			Fraction variation in U_M		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.371	0.527	0.102	0.531	0.376	0.093	0.390	0.497	0.113
12	0.419	0.409	0.172	0.601	0.249	0.150	0.434	0.371	0.195
∞	0.420	0.368	0.212	0.619	0.220	0.161	0.478	0.322	0.200
$s_{\max}$	0.511	0.528	0.215	0.664	0.384	0.161	0.572	0.498	0.203
	[0.25, 0.79]	[0.22, 0.71]	[0.05, 0.57]	[0.34, 0.87]	[0.15, 0.59]	[0.06, 0.46]	[0.30, 0.79]	[0.21, 0.70]	[0.06, 0.53]
	Fraction variation in ip			Fraction variation in emp			Fraction variation in Q_1		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.401	0.556	0.043	0.352	0.402	0.246	0.456	0.508	0.036
12	0.121	0.659	0.220	0.075	0.406	0.519	0.169	0.563	0.269
∞	0.082	0.691	0.227	0.124	0.424	0.453	0.063	0.621	0.317
$s_{\max}$	0.415	0.696	0.272	0.373	0.424	0.587	0.468	0.621	0.358
	[0.19, 0.61]	[0.34, 0.94]	[0.04, 0.73]	[0.21, 0.63]	[0.16, 0.85]	[0.16, 0.92]	[0.24, 0.62]	[0.33, 0.95]	[0.07, 0.81]
	Fraction variation in U_F			Fraction variation in U_F			Fraction variation in U_F		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.029	0.023	0.948	0.140	0.119	0.743	0.019	0.022	0.959
12	0.080	0.041	0.878	0.243	0.133	0.624	0.082	0.039	0.879
∞	0.121	0.131	0.748	0.332	0.138	0.530	0.156	0.098	0.746
$s_{\max}$	0.128	0.131	0.950	0.339	0.152	0.744	0.163	0.098	0.961
	[0.03, 0.47]	[0.05, 0.52]	[0.53, 0.99]	[0.08, 0.64]	[0.03, 0.58]	[0.33, 0.95]	[0.03, 0.53]	[0.03, 0.48]	[0.60, 0.99]

Note: Each panel shows the fraction of s-step-ahead forecast-error variance of the variable given in the panel title that is explained by the shock named in the column heading. The row denoted "$s = s_{max}$ "reports the maximum fraction (across all VAR forecast horizons m) of forecast error variance explained by the shock listed in the column heading. The numbers in parentheses represent the 5th and 95th percentiles of these statistics from bootstrapped samples. The data are monthly and span the period 1960:07 to 2015:04.

Variance Decomposition $(U_M, Y, U_F)'$

- Large fractions of variance in *emp* driven by U_F shocks.

	SVAR $(U_M, ip, U_F)'$			SVAR $(U_M, emp, U_F)'$			SVAR $(U_M, Q_1, U_F)'$		
	Fraction variation in U_M			Fraction variation in U_M			Fraction variation in U_M		
s	U_M Shock	*ip* Shock	U_F Shock	U_M Shock	*emp* Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.371	0.527	0.102	0.531	0.376	0.093	0.390	0.497	0.113
12	0.419	0.409	0.172	0.601	0.249	0.150	0.434	0.371	0.195
∞	0.420	0.368	0.212	0.619	0.220	0.161	0.478	0.322	0.200
$s_{\max}$	0.511	0.528	0.215	0.664	0.384	0.161	0.572	0.498	0.203
	[0.25, 0.79]	[0.22, 0.71]	[0.05, 0.57]	[0.34, 0.87]	[0.15, 0.59]	[0.06, 0.46]	[0.30, 0.79]	[0.21, 0.70]	[0.06, 0.53]
	Fraction variation in *ip*			Fraction variation in *emp*			Fraction variation in Q_1		
s	U_M Shock	*ip* Shock	U_F Shock	U_M Shock	*emp* Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.401	0.556	0.043	0.352	0.402	0.246	0.456	0.508	0.036
12	0.121	0.659	0.220	0.075	0.406	0.519	0.169	0.563	0.269
∞	0.082	0.691	0.227	0.124	0.424	0.453	0.063	0.621	0.317
$s_{\max}$	0.415	0.696	0.272	0.373	0.424	0.587	0.468	0.621	0.358
	[0.19, 0.61]	[0.34, 0.94]	[0.04, 0.73]	[0.21, 0.63]	[0.16, 0.85]	[0.16, 0.92]	[0.24, 0.62]	[0.33, 0.95]	[0.07, 0.81]
	Fraction variation in U_F			Fraction variation in U_F			Fraction variation in U_F		
s	U_M Shock	*ip* Shock	U_F Shock	U_M Shock	*emp* Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.029	0.023	0.948	0.140	0.119	0.743	0.019	0.022	0.959
12	0.080	0.041	0.878	0.243	0.133	0.624	0.082	0.039	0.879
∞	0.121	0.131	0.748	0.332	0.138	0.530	0.156	0.098	0.746
$s_{\max}$	0.128	0.131	0.950	0.339	0.152	0.744	0.163	0.098	0.961
	[0.03, 0.47]	[0.05, 0.52]	[0.53, 0.99]	[0.08, 0.64]	[0.03, 0.58]	[0.33, 0.95]	[0.03, 0.53]	[0.03, 0.48]	[0.60, 0.99]

Note: Each panel shows the fraction of s-step-ahead forecast-error variance of the variable given in the panel title that is explained by the shock named in the column heading. The row denoted "$s = s_{max}$" reports the maximum fraction (across all VAR forecast horizons m) of forecast error variance explained by the shock listed in the column heading. The numbers in parentheses represent the 5th and 95th percentiles of these statistics from bootstrapped samples. The data are monthly and span the period 1960:07 to 2015:04.

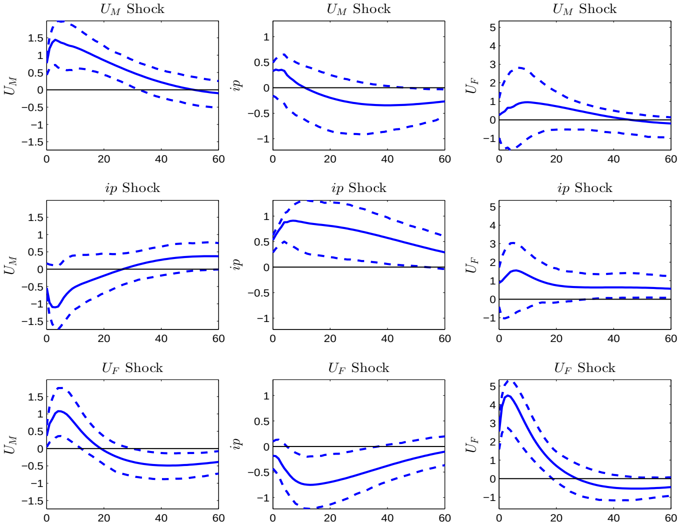
Variance Decomposition $(U_M, Y, U_F)'$

- Sizable amount variation in U_M driven by Y shocks.

	SVAR $(U_M, ip, U_F)'$			SVAR $(U_M, emp, U_F)'$			SVAR $(U_M, Q_1, U_F)'$		
	Fraction variation in U_M			Fraction variation in U_M			Fraction variation in U_M		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.371	0.527	0.102	0.531	0.376	0.093	0.390	0.497	0.113
12	0.419	0.409	0.172	0.601	0.249	0.150	0.434	0.371	0.195
∞	0.420	0.368	0.212	0.619	0.220	0.161	0.478	0.322	0.200
$s_{\max}$	0.511	0.528	0.215	0.664	0.384	0.161	0.572	0.498	0.203
	[0.25, 0.79]	[0.22, 0.71]	[0.05, 0.57]	[0.34, 0.87]	[0.15, 0.59]	[0.06, 0.46]	[0.30, 0.79]	[0.21, 0.70]	[0.06, 0.53]
	Fraction variation in ip			Fraction variation in emp			Fraction variation in Q_1		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.401	0.556	0.043	0.352	0.402	0.246	0.456	0.508	0.036
12	0.121	0.659	0.220	0.075	0.406	0.519	0.169	0.563	0.269
∞	0.082	0.691	0.227	0.124	0.424	0.453	0.063	0.621	0.317
$s_{\max}$	0.415	0.696	0.272	0.373	0.424	0.587	0.468	0.621	0.358
	[0.19, 0.61]	[0.34, 0.94]	[0.04, 0.73]	[0.21, 0.63]	[0.16, 0.85]	[0.16, 0.92]	[0.24, 0.62]	[0.33, 0.95]	[0.07, 0.81]
	Fraction variation in U_F			Fraction variation in U_F			Fraction variation in U_F		
s	U_M Shock	ip Shock	U_F Shock	U_M Shock	emp Shock	U_F Shock	U_M Shock	Q_1 Shock	U_F Shock
1	0.029	0.023	0.948	0.140	0.119	0.743	0.019	0.022	0.959
12	0.080	0.041	0.878	0.243	0.133	0.624	0.082	0.039	0.879
∞	0.121	0.131	0.748	0.332	0.138	0.530	0.156	0.098	0.746
$s_{\max}$	0.128	0.131	0.950	0.339	0.152	0.744	0.163	0.098	0.961
	[0.03, 0.47]	[0.05, 0.52]	[0.53, 0.99]	[0.08, 0.64]	[0.03, 0.58]	[0.33, 0.95]	[0.03, 0.53]	[0.03, 0.48]	[0.60, 0.99]

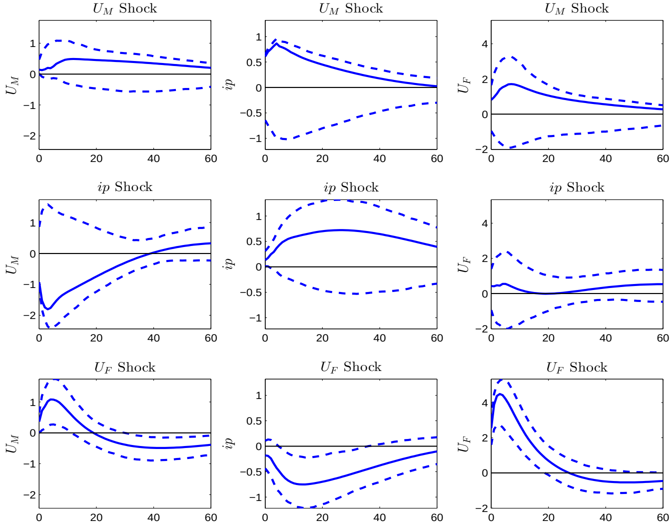
Note: Each panel shows the fraction of s-step-ahead forecast-error variance of the variable given in the panel title that is explained by the shock named in the column heading. The row denoted "$s = s_{max}$" reports the maximum fraction (across all VAR forecast horizons m) of forecast error variance explained by the shock listed in the column heading. The numbers in parentheses represent the 5th and 95th percentiles of these statistics from bootstrapped samples. The data are monthly and span the period 1960:07 to 2015:04.

IRF for SVAR $(U_M, ip, U_F)'$ using *Baa*



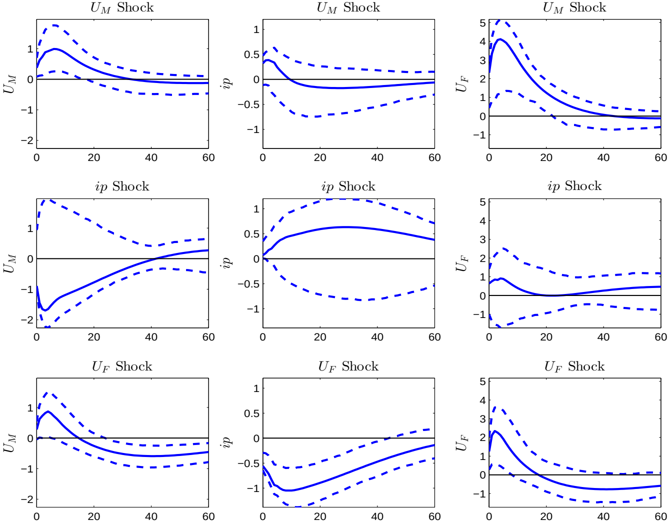
Note: Z_1 is created by using *Baa* and Z_2 is generated by using CRSP excess returns. The correlation $\rho(Z_{1t}, \hat{e}_{Mt}) = 0.1988$, $\rho(Z_{1t}, \hat{e}_{Ft}) = 0.1219$, $\rho(Z_{2t}, \hat{e}_{Ft}) = -0.1617$ and $\rho(Z_{1t}, Z_{2t}) = -0.20$. The sample is from 1960:07 to 2015:04.

IRF for SVAR $(U_M, ip, U_F)'$ using *noi* for Z_1



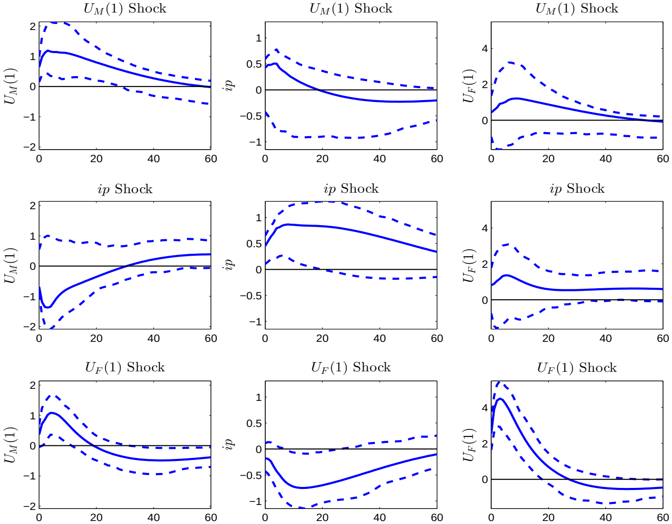
Note: Z_1 is created by using *noi* and Z_2 is generated by using CRSP excess returns. The correlation $\rho(Z_{1t}, \hat{e}_{Mt}) = 0.1799$, $\rho(Z_{1t}, \hat{e}_{Ft}) = -0.0301$, $\rho(Z_{2t}, \hat{e}_{Ft}) = -0.1617$ and $\rho(Z_{1t}, Z_{2t}) = 0.1612$. One lag of *noi* is included. The sample is from 1960:07 to 2015:04.

IRF for SVAR $(U_M, ip, U_F)'$ using *noi* for Z_2



Note: Z_1 is generated by using CRSP excess returns and Z_2 is created by using *noi*. The correlation $\rho(Z_{1t}, \hat{e}_{Mt}) = -0.1679$, $\rho(Z_{1t}, \hat{e}_{Ft}) = -0.0702$, $\rho(Z_{2t}, \hat{e}_{Ft}) = -0.1536$ and $\rho(Z_{1t}, Z_{2t}) = 0.1503$. One lag of *noi* is included. The sample is from 1960:07 to 2015:04.

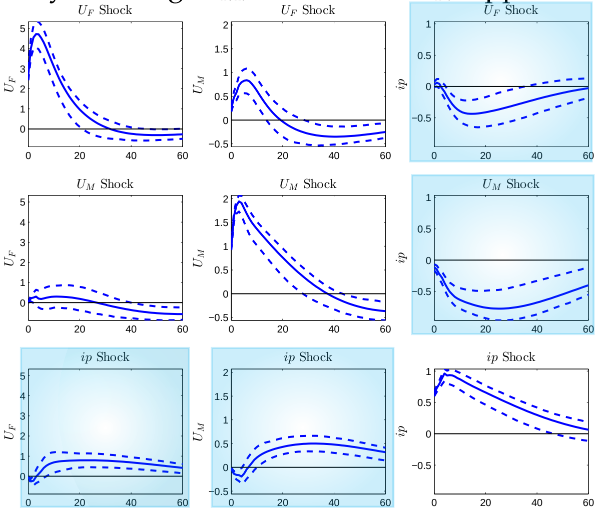
IRF for SVAR $(U_M, ip, U_F)'$ using r^{small} Index for Z_1



Note: Z_1 is created by using r^{small} index and Z_2 is generated by using CRSP excess return. The correlation $\rho(Z_{1t}, \hat{e}_{Mt}) = -0.0667$, $\rho(Z_{1t}, \hat{e}_{Ft}) = -0.1840$, $\rho(Z_{2t}, \hat{e}_{Ft}) = -0.1617$ and $\rho(Z_{1t}, Z_{2t}) = 0.7868$. One lag of r^{small} is included. The sample is from 1960:07 to 2015:04.

Recursive Identification with Order $(U_F, U_M, ip)'$

- Under any ordering, U_{Mt} shocks, like U_{Ft}, appear to decrease Y_t.



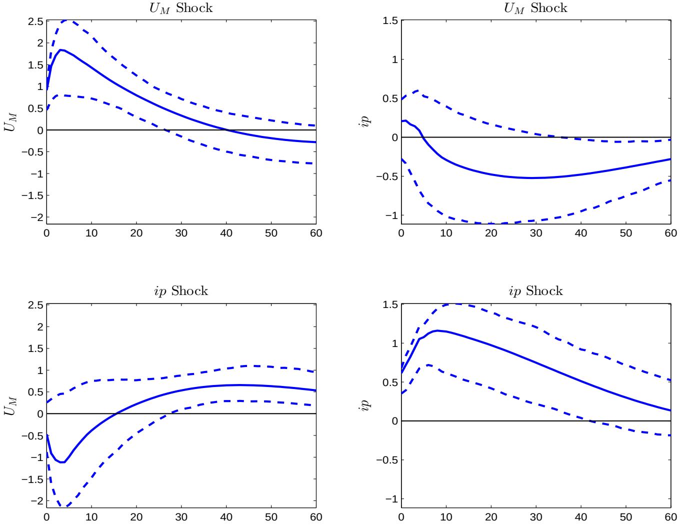
Note: Bootstrapped 90 percent error bands appear as dashed lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

Recursive Identification with Order $(U_F, U_M, ip)'$

- Inspection of $\hat{\mathbf{A}}_0$ reveals non-zero contemporaneous correlations $\rho(U_M, Y), \rho(U_F, Y)$, inconsistent with any recursive ordering.

$$\hat{\mathbf{A}}_0 = \begin{pmatrix} 1 & \mathbf{1.5233} & -0.0206 \\ & [0.2110] & [0.0583] \\ -\mathbf{0.7321} & 1 & 0.1328 \\ [0.1563] & & [0.0702] \\ -0.0049 & -\mathbf{1.1676} & 1 \\ [0.6933] & [0.5902] & \end{pmatrix}$$

IRF for SVAR $(U_M, ip)'$



Note: Bootstrapped 90 percent error bands appear as dashed lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. Z_1 is generated by using CRSP excess returns. The sample is from 1960:07 to 2015:04.

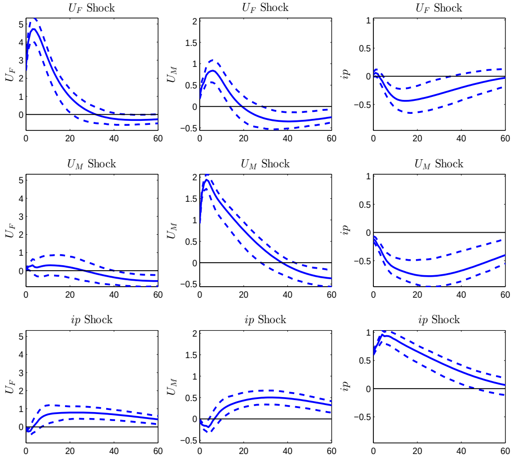
Variance Decomposition for $(U_R, Y, U_F)'$

	SVAR $(U_R, ip, U_F)'$			SVAR $(U_R, emp, U_F)'$			SVAR $(U_R, Q_1, U_F)'$		
	Fraction variation in U_R			Fraction variation in U_R			Fraction variation in U_R		
s	U_R Shock	ip Shock	U_F Shock	U_R Shock	emp Shock	U_F Shock	U_R Shock	Q_1 Shock	U_F Shock
$s=1$	0.359	0.513	0.128	0.483	0.405	0.112	0.391	0.482	0.127
$s=12$	0.253	0.463	0.285	0.409	0.292	0.299	0.263	0.440	0.297
$s=\infty$	0.302	0.407	0.291	0.419	0.263	0.318	0.327	0.379	0.294
$s=s_{\max}$	0.302	0.407	0.291	0.519	0.405	0.318	0.437	0.515	0.305
	[0.16, 0.72]	[0.18, 0.80]	[0.07, 0.63]	[0.23, 0.80]	[0.13, 0.69]	[0.07, 0.62]	[0.19, 0.70]	[0.22, 0.75]	[0.06, 0.62]
	Fraction variation in ip			Fraction variation in emp			Fraction variation in Q_1		
s	U_R Shock	ip Shock	U_F Shock	U_R Shock	emp Shock	U_F Shock	U_R Shock	Q_1 Shock	U_F Shock
$s=1$	0.391	0.577	0.032	0.378	0.392	0.230	0.439	0.532	0.029
$s=12$	0.295	0.456	0.249	0.220	0.217	0.563	0.362	0.371	0.267
$s=\infty$	0.211	0.326	0.463	0.092	0.064	0.845	0.265	0.233	0.502
$s=s_{\max}$	0.397	0.580	0.463	0.392	0.395	0.845	0.442	0.534	0.502
	[0.10, 0.73]	[0.22, 0.89]	[0.08, 0.84]	[0.13, 0.68]	[0.14, 0.74]	[0.32, 0.96]	[0.19, 0.72]	[0.27, 0.81]	[0.09, 0.87]
	Fraction variation in U_F			Fraction variation in U_F			Fraction variation in U_F		
s	U_R Shock	ip Shock	U_F Shock	U_R Shock	emp Shock	U_F Shock	U_R Shock	Q_1 Shock	U_F Shock
$s=1$	0.010	0.059	0.941	0.050	0.182	0.768	0.001	0.055	0.944
$s=12$	0.011	0.083	0.906	0.094	0.200	0.707	0.015	0.079	0.906
$s=\infty$	0.117	0.093	0.790	0.214	0.167	0.619	0.150	0.082	0.768
$s=s_{\max}$	0.117	0.093	0.943	0.217	0.216	0.774	0.150	0.082	0.947
	[0.04, 0.35]	[0.03, 0.52]	[0.56, 0.99]	[0.06, 0.49]	[0.04, 0.64]	[0.37, 0.97]	[0.04, 0.39]	[0.02, 0.53]	[0.59, 0.99]

Note: Each panel shows the fraction of s-step-ahead forecast-error variance of the variable given in the panel title that is explained by the shock named in the column heading. The row denoted "$s = s_{max}$ "reports the maximum fraction (across all VAR forecast horizons m) of forecast error variance explained by the shock listed in the column heading. The numbers in parentheses represent the 5th and 95th percentiles of these statistics from bootstrapped samples. The data are monthly and span the period 1960:07 to 2015:04.

Recursive IRF $(U_F, U_M, ip)'$

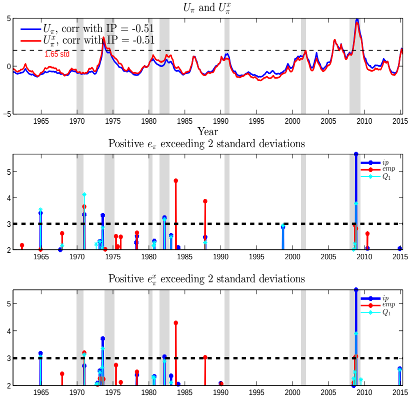
- Recursive IRF $(U_F, U_M, ip)'$



Note: Bootstrapped 90 percent error bands appear as dashed lines. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

Time Series of Price Uncertainty

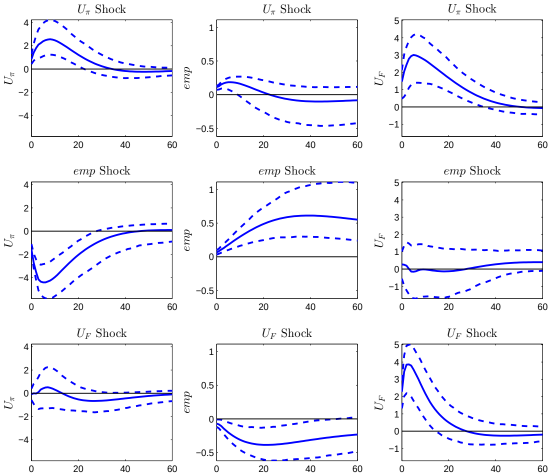
- Time Series of Price Uncertainty.



Note: The upper panel plots U_π and U_π^x where the latter excludes uncertainties for 5 volatile sub-series defined in the text, expressed in standardized units. The middle and lower panel exhibit shocks that are at least 2 standard deviations above the unconditional mean for U_π and U_π^x. The shaded areas correspond to the NBER recession dates. The data are monthly and span the period 1960:07 to 2015:04.

SVAR IRF $(U_\pi, emp, U_F)'$

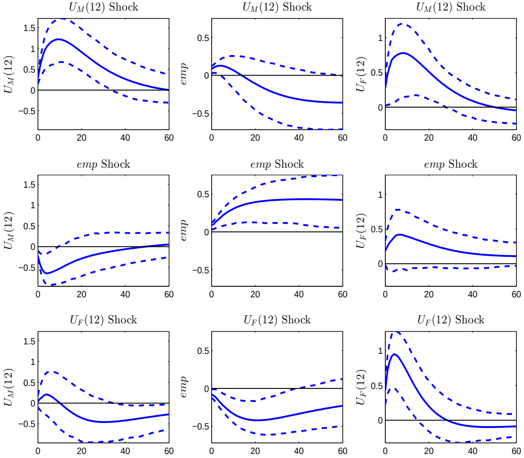
- SVAR IRF $(U_\pi, emp, U_F)'$



Note: Bootstrapped 90 percent error bands appear as dashed lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

SVAR IRF $(U_M(12), emp, U_F(12))'$

- SVAR IRF $(U_M(12), emp, U_F(12))'$



Note: Bootstrapped 90 percent error bands appear as dashed lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. The sample spans the period 1960:07 to 2015:04.

Test of Recursive Restrictions, Real Uncertainty

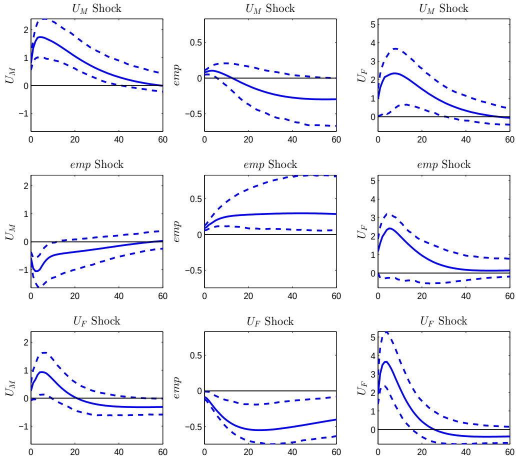
- Test of Recursive Restrictions, Real Uncertainty

Ordering:	$(U_R, ip, U_F)'$	$(U_R\,(12)\,, ip, U_F\,(12))'$
H_0: $B_{RY} = B_{RF} = B_{YF} = 0$	**133.69**	**303.24**
	[71.23]	[77.88]
H_0: $B_{YR} = B_{YF} = B_{RF} = 0$	**29.11**	**167.57**
	[35.83]	[52.54]
H_0: $B_{RY} = B_{RF} = B_{FY} = 0$	**130.41**	**306.34**
	[77.34]	[72.79]
$\chi^2_{5\%}\,(3)$	7.81	7.81
	$(U_R, emp, U_F)'$	$(U_R\,(12)\,, emp, U_F\,(12))'$
H_0: $B_{RY} = B_{RF} = B_{YF} = 0$	**178.68**	**327.91**
	[62.11]	[76.35]
H_0: $B_{YR} = B_{YF} = B_{RF} = 0$	**85.58**	**244.85**
	[46.43]	[67.50]
H_0: $B_{RY} = B_{RF} = B_{FY} = 0$	**154.76**	**310.66**
	[76.22]	[78.04]
$\chi^2_{5\%}\,(3)$	7.81	7.81

Note: The table reports the Wald test statistic for testing the null hypothesis given in the column . The bold indicates that Wald test rejects the null at 95 percent level according to $\chi^2(3)$ distribution. The SVAR system is solved using GMM and delta method is used for computing the standard error. Estimates of **B** are based on the SVAR identified with external instruments described in the text. The mean of bootstrap Wald statistics is reported in parenthesis. The sample size spans 1960:07 to 2015:04.

SVAR IRF $(U_M(1), emp, U_F(1))'$ with 1987 Dummies

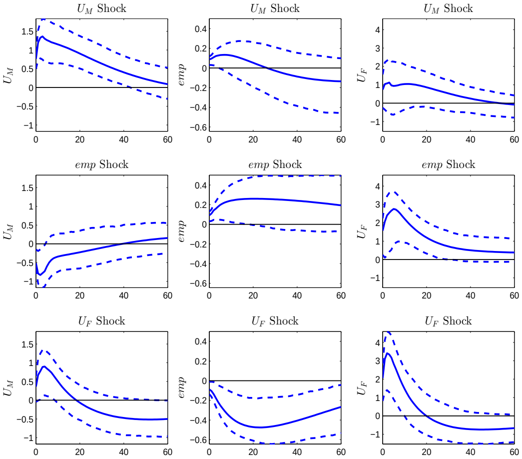
- SVAR IRF $(U_M(1), emp, U_F(1))'$ using 1987 Crash Dummies



Note: The red line exhibits the 90 percent robust confidence set defined in the appendix. The sample spans the period 1962:07 to 2015:04.

Pre-2008 SVAR IRF $(U_M(1), emp, U_F(1))'$

- Pre-2008 SVAR IRF $(U_M(1), emp, U_F(1))'$



Note: The red line exhibits the 90 percent robust confidence set defined in the appendix. The sample spans the period 1962:07 to 2015:04.

Monte Carlo Procedure

1. For each MC replication $i = 1, ..., I$, draw $T \times 1$ vectors $\mathbf{e}_F^{(i)}, \mathbf{e}_Y^{(i)}, \mathbf{e}_M^{(i)}$ independently from $N(0,1)$.
2. Generate true data for $\left(U_M^{(i)}, Y^{(i)}, U_F^{(i)}\right)$ from the trivariate VAR
$$\underbrace{\begin{pmatrix} A_{MM}(0) & A_{MY}(0) & A_{MF}(0) \\ A_{YM}(0) & A_{YY}(0) & A_{YF}(0) \\ A_{FM}(0) & A_{FY}(0) & A_{FF}(0) \end{pmatrix}}_{\mathbf{A}_0} \begin{pmatrix} U_{Mt}^{(i)} \\ Y_t^{(i)} \\ U_{Ft}^{(i)} \end{pmatrix} = \underbrace{\begin{pmatrix} A_{MM}(1) & A_{MY}(1) & A_{MF}(1) \\ A_{YM}(1) & A_{YY}(1) & A_{YF}(1) \\ A_{FM}(1) & A_{FY}(1) & A_{FF}(1) \end{pmatrix}}_{\mathbf{A}_1} \begin{pmatrix} U_{Mt-1}^{(i)} \\ Y_{t-1}^{(i)} \\ U_{Ft-1}^{(i)} \end{pmatrix} + \begin{pmatrix} e_{Mt}^{(i)} \\ e_{Yt}^{(i)} \\ e_{Ft}^{(i)} \end{pmatrix}$$
3. Generate data for S_{1t} and S_{2t} by drawing $T \times 1$ vectors $e_{S1t}^{(i)}, e_{S2t}^{(i)}$ independently from $N(0,1)$ distributions, where
$$S_{1t}^{(i)} = d_{10} + d_{11} S1_{t-1}^{(i)} + d_{12} e_{Mt}^{(i)} + d_{13} e_{Yt}^{(i)} + d_{14} e_{Ft}^{(i)} + d_{15} e_{S1t}^{(i)} + d_{16} e_{S2t}^{(i)}$$
$$S_{2t}^{(i)} = d_{20} + d_{21} S_{2t-1}^{(i)} + d_{22} e_{Mt}^{(i)} + d_{23} e_{Yt}^{(i)} + d_{24} e_{Ft}^{(i)} + d_{25} e_{S1t}^{(i)}$$
4. Initialize $j = 0$ and $\left(\hat{\mathbf{e}}_Y^{(i),[0]}, \hat{\mathbf{e}}_M^{(i),[0]}\right)' = \left(Y^{(i)}, U_M^{(i)}\right)'$.
   - 4.1 Given $\left(\hat{\mathbf{e}}_Y^{(i),[j]}, \hat{\mathbf{e}}_M^{(i),[j]}\right)$, calculate the $\mathbf{Z}$ by running the following regressions.
   $$S_{1t}^{(i)} = \beta_1' x_{1t}^{(i),[j]} + Z_{1t}^{(i),[j]} \text{ and } S_{2t}^{(i)} = \beta_2' x_{2t}^{(i),[j]} + Z_{2t}^{(i),[j]}$$
   where $x_{1t}^{(i)} = (1, S1_{t-1}^{(i)}, e_Y^{(i),[j]})'$ and $x_{2t}^{(i)} = (1, S_{2t-1}^{(i)}, e_Y^{(i),[j]}, e_M^{(i),[j]})'$,
   - 4.2 Use $Z_1^{(i),[j]}$ and $Z_2^{(i),[j]}$ and estimates $\text{vech}\left(\hat{\boldsymbol{\eta}}_t^{(i)} \hat{\boldsymbol{\eta}}_t^{(i)\prime}\right)$ and $\text{vec}\left(Z_t^{(i),[j]} \otimes \hat{\boldsymbol{\eta}}_t^{(i)}\right)$ to impose Assumption A of the paper and solve for $\mathbf{B}$. We obtain $\hat{e}_Y^{(i),[j+1]}, \hat{e}_M^{(i),[j+1]}, \hat{e}_F^{(i),[j+1]}$ from $\hat{\mathbf{e}}^{(i),[j+1]} = \left(\mathbf{B}^{(i),[j]}\right)^{-1} \hat{\boldsymbol{\eta}}_t^{(i)}$
   - 4.3 If $\left\| \hat{\mathbf{e}}^{(i),[j+1]} - \hat{\mathbf{e}}^{(i),[j]} \right\| < \epsilon$ (where ϵ is an arbitrarily small number), then set $\hat{\mathbf{e}}^{(i)} = \hat{\mathbf{e}}^{(i),[j]}$ and $\mathbf{Z}^{(i)} = \mathbf{Z}^{(i),[j]}$. Otherwise, set $j = j + 1$ and return to step 4.1.
5. Store $\hat{c}_1 = corr(\mathbf{Z_{1t}}^{(i)}, \hat{\mathbf{e}}_{\mathbf{Mt}}^{(i)})$, $\hat{c}_2 = corr(\mathbf{Z_{1t}}^{(i)}, \hat{\mathbf{e}}_{\mathbf{Ft}}^{(i)})$, $\hat{c}_3 = corr(\mathbf{Z_{2t}}^{(i)}, \hat{\mathbf{e}}_{\mathbf{Ft}}^{(i)})$, $C(\boldsymbol{\beta}_1) = \frac{1}{3}(|\hat{c}_1| + |\hat{c}_2| + |\hat{c}_3|)$. Keep replication i that satisfies (a) $C(\boldsymbol{\beta}_1) \geq \bar{C}$, (b), each $\hat{c}_i \geq \bar{c}$, and (c) $\det(B^{(j)}) \geq \bar{b}$.

Iterative Monte Carlo

$$Y_t = A_1 Y_{t-1} + H\Sigma e_t, B \equiv H\Sigma$$

True			Estimated		
B	$=$	$\begin{pmatrix} 0.660 & -0.710 & 0.270 \\ 0.420 & 0.470 & -0.140 \\ 0.490 & 0.500 & 2.600 \end{pmatrix}_{\times 10^{-2}}$	$\hat{B}$	$=$	$\begin{pmatrix} 0.646 & -0.710 & 0.288 \\ 0.424 & 0.470 & -0.117 \\ 0.379 & 0.471 & 2.611 \end{pmatrix}_{\times 10^{-2}}$
A_1	$=$	$\begin{pmatrix} 0.996 & 0.027 & 0.010 \\ -0.023 & 0.983 & -0.002 \\ -0.045 & 0.040 & 0.978 \end{pmatrix}$	$\hat{A}_1$	$=$	$\begin{pmatrix} 0.996 & 0.029 & 0.010 \\ -0.023 & 0.983 & -0.002 \\ -0.046 & 0.041 & 0.978 \end{pmatrix}$
$\text{diag}(\boldsymbol{\Sigma})$	$=$	$[0.660, 0.470, 2.600]_{\times 10^{-2}}$	$\text{diag}(\hat{\boldsymbol{\Sigma}})$	$=$	$[0.646, 0.470, 2.611]_{\times 10^{-2}}$
$\text{RMSE}(\hat{B})$	$=$	$\begin{pmatrix} 0.023 & 0.022 & 0.034 \\ 0.012 & 0.007 & 0.030 \\ 0.138 & 0.094 & 0.023 \end{pmatrix}_{\times 10^{-2}}$	$\text{RMSE}(\hat{A}_1)$	$=$	$\begin{pmatrix} 0.001 & 0.001 & 0.001 \\ 0.000 & 0.001 & 0.000 \\ 0.002 & 0.003 & 0.002 \end{pmatrix}$
$\text{corr}(Z_{1t}, e_t)$	$=$	$[-0.077, 0.000, -0.118]$	$\text{corr}(Z_{1t}(\hat{\beta}), e_t)$	$=$	$[-0.073, 0.000, -0.119]$
			$\text{corr}(Z_{1t}(\hat{\beta}), \hat{e}_t)$		$[-0.073, 0.000, -0.124]$
$\text{corr}(Z_{2t}, e_t)$	$=$	$[0.000, 0.000, -0.166]$	$\text{corr}(Z_{2t}(\hat{\beta}), e_t)$	$=$	$[-0.002, 0.002, -0.165]$
			$\text{corr}(Z_{2t}(\hat{\beta}), \hat{e}_t)$	$=$	$[0.000, 0.000, -0.169]$
$\text{corr}(e_t, \hat{e}_t)$	$=$	$[0.995, 0.996, 0.995]$			

Reported are the average of estimates over 5000 replications. IPIV initial guess: $\left(\mathbf{e}_1^{[i](0)}, \mathbf{e}_2^{[i](0)}\right)' = \left(\mathbf{X}_1^{[i]}, \mathbf{X}_2^{[i]}\right)'$. The sample size $T = 500$.

Returns Uncertainty with and without Jumps

- Returns with and without Jumps

	Model without Jump	Model with Jump
	$r_t^{NJ} \sim N(\kappa_1, \kappa_2)$	$r_t^J = w_t + z_t$ $w_t \sim N(\mu, \sigma^2)$ $z_t \vert j \sim N(j\theta, j\delta^2)$ $j \sim Poission(\omega)$ $E\left(r_t^J\right) = \kappa_1 = \mu + \omega\theta$ $Var\left(r_t^J\right) = \kappa_2 = \sigma^2 + \omega(\theta^2 + \delta^2)$
$E(\mathcal{U}_t^r)$	0.0335	0.0337
$\sqrt{Var(\mathcal{U}_t^r)}$	6.62×10^{-5}	2.39×10^{-4}
Skewness	1.3831	1.7809
Kurtosis	6.6707	8.4183
Number $>$ 3 std	263	335

Note: The table reports the mean, standard deviation, skewness and kurtosis of the uncertainty measure of returns with and without jumps. The model is specified in each column and both model has the same unconditional mean κ_1 and variance κ_2. We calibrate the mean (μ), volatility (σ), jump intensity (ω), mean jump size (θ) and volatility of jumps (δ) according to the true distribution of the aggregate stock returns as in Table 2 in Backus, Chernov and Martin (2011). Last row reports the number of samples that exceed 3 standard deviation above its mean. The monte carlo sample size is 20,000.

Measuring Uncertainty: Jurado, Ludvigson, Ng (JLN)

- Methodology: DI forecasting plus stochastic volatility model
- Let $y_{jt}^C \in Y_t^C = (y_{1t}^C, \ldots, y_{N_C t}^C)'$ be a variable in category C. JLN estimate its *h-period ahead* uncertainty, $\mathcal{U}_{jt}^C(h)$, defined

$$\mathcal{U}_{jt}^C(h) \equiv \sqrt{\mathbb{E}\left[(y_{jt+h}^C - \mathbb{E}[y_{jt+h}^C | I_t])^2 | I_t\right]}$$

- Aggregate uncertainty in category C:

$$U_{Ct}(h) \equiv \text{plim}_{N_C \to \infty} \sum_{j=1}^{N_C} \frac{1}{N_C} \mathcal{U}_{jt}^C(h) \equiv \mathbb{E}_C[\mathcal{U}_{jt}^C(h)].$$

- Focus on $h = 1$ month-ahead uncertainty in three categories:

Category (C)	Y_t^C	N_C
(M): Macro	all variables in χ^M (JLN)	134
(F): Financial	all variables in χ^F (new)	147
(R): Real activity	real activity variables in χ^M (new)	73

Econometric Model

- For each $y_{jt}, j = 1, \ldots, N_y$, we specify:

$$y_{j,t+1} = \underbrace{E[y_{jt+1}|I_t]}_{\text{forecastable}} + \underbrace{v^y_{j,t+1}}_{\text{unforecastable}}$$

$$v^y_{j,t+1} = \underbrace{\sigma^y_{j,t+1}}_{\text{stochastic vol}} \varepsilon^y_{j,t+1}$$

$$\log[(\sigma^y_{j,t+1})^2] = \alpha^y_j + \beta^y_j \log(\sigma^y_{jt})^2 + \tau^y_j \eta_{j,t+1},$$

where $\varepsilon_{j,t+1}$ and $\eta_{j,t+1}$ are iid $N(0,1)$ random variables.

Econometric Model

- For each $y_{jt}, j = 1, \ldots, N_y$, we specify:

$$y_{j,t+1} = \underbrace{E[y_{jt+1}|I_t]}_{\text{forecastable}} + \underbrace{v^y_{j,t+1}}_{\text{unforecastable}}$$

$$v^y_{j,t+1} = \underbrace{\sigma^y_{j,t+1}}_{\text{stochastic vol}} \varepsilon^y_{j,t+1}$$

$$\log[(\sigma^y_{j,t+1})^2] = \alpha^y_j + \beta^y_j \log(\sigma^y_{jt})^2 + \tau^y_j \eta_{j,t+1},$$

  where $\varepsilon_{j,t+1}$ and $\eta_{j,t+1}$ are iid $N(0,1)$ random variables.
- Estimation:
  (1) $\hat{E}[y_{jt+1}|I_t]$ using diffusion index forecasts.
  (2) $\log(\widehat{\sigma}^y_{jt})^2$ stochastic volatility estimates, improved version of Kim, Shephard, and Chib (1998, RES) algorithm.

Stochastic Volatility Estimates

- From the model, $v^y_{j,t+1} = \sigma^y_{j,t+1}\varepsilon^y_{j,t+1}$. Take logs:

$$\log[(v^y_{j,t+1})^2] = \log[(\sigma^y_{j,t+1})^2] + \log[(\varepsilon^y_{j,t+1})^2]$$
$$\log[(\sigma^y_{j,t+1})^2] = \alpha^y_j + \beta^y_j \log[(\sigma^y_{jt})^2] + (\tau^y_j)\eta_{j,t+1}.$$

- Has the state-space representation

$$z_{jt} = x_{jt} + \epsilon_{jt} \qquad \text{observation equation}$$
$$x_{jt} = \alpha_j + \beta_j x_{jt-1} + \tau_j \eta_{jt} \qquad \text{state equation}$$

- **Difficulty**: $\epsilon_{j,t} \equiv \log(\varepsilon^y_{j,t})^2 \sim \log \chi^2(1)$.
- **Solution**: Kim, Shephard, and Chib (1998, RES) MCMC mixture of normals approximation:

$$p(\epsilon) = \sum_{k=1}^{K} \pi_k \phi(\epsilon; m_k, s_k^2).$$

- Interweaving: Kastner-Fruhwrith-Schnattner (2013).

Computing Individual Uncertainty ($h = 1$)

- Using definition of forecast variance :

$$\begin{aligned}\Omega^y_{jt}(1) &= E[(\sigma^y_{j,t+1})^2(\varepsilon^y_{j,t+1})^2|I_t] \\ &= E[(\sigma^y_{j,t+1})^2|I_t] \\ &= \exp\left\{\alpha^y_j + \beta^y_j \log(\sigma^y_{jt})^2 + \frac{1}{2}(\tau^y_j)^2\right\}.\end{aligned}$$

- The last equality follows from the AR(1) law of motion for $\log(\sigma^y_{j,t+1})^2$, and the normality of $\eta_{j,t+1}$.
- Given estimates: $\hat{\alpha}^y_j$, $\hat{\beta}^y_j$, $(\hat{\tau}^y_j)^2$, and $\left\{\widehat{\log}(\sigma^y_{jt})^2\right\}_{t=1}^T$, compute $\hat{\Omega}^y_{jt}(1)$ using this expression.

Computing Individual Uncertainty ($h \geq 1$)

- Define $q = \max\left(lags_y, lags_F, lags_w, h\right)$
- Let $\mathcal{Z}_t \equiv (\hat{F}_t', W_t')'$ and define $\mathcal{F}_t \equiv (\mathcal{Z}_t, \ldots, \mathcal{Z}_{t-q+1})'$ and $Y_{jt} \equiv (y_{jt}, \ldots, y_{j,t-q+1})'$:

$$\begin{pmatrix} \mathcal{F}_t \\ Y_{jt} \end{pmatrix} = \begin{pmatrix} \Phi^F & 0 \\ \Lambda_j' & \Phi_j^Y \end{pmatrix} \begin{pmatrix} \mathcal{F}_{t-1} \\ Y_{j,t-1} \end{pmatrix} + \begin{pmatrix} V_t^{\mathcal{F}} \\ V_{jt}^Y \end{pmatrix}$$

$$\mathcal{Y}_{jt} = \Phi_j^{\mathcal{Y}} \mathcal{Y}_{j,t-1} + V_{jt}^{\mathcal{Y}}.$$

Computing Individual Uncertainty ($h \geq 1$)

- Define $q = \max\left(lags_y, lags_F, lags_w, h\right)$
- Let $\mathcal{Z}_t \equiv (\hat{F}_t', W_t')'$ and define $\mathcal{F}_t \equiv (\mathcal{Z}_t, \ldots, \mathcal{Z}_{t-q+1})'$ and $Y_{jt} \equiv (y_{jt}, \ldots, y_{j,t-q+1})'$:

$$\begin{pmatrix} \mathcal{F}_t \\ Y_{jt} \end{pmatrix} = \begin{pmatrix} \Phi^F & 0 \\ \Lambda_j' & \Phi_j^Y \end{pmatrix} \begin{pmatrix} \mathcal{F}_{t-1} \\ Y_{j,t-1} \end{pmatrix} + \begin{pmatrix} V_t^{\mathcal{F}} \\ V_{jt}^Y \end{pmatrix}$$

$$\mathcal{Y}_{jt} = \Phi_j^{\mathcal{Y}} \mathcal{Y}_{j,t-1} + V_{jt}^{\mathcal{Y}}.$$

- *Forecast Error Variance* $\Omega_{jt}^{\mathcal{Y}}(h) \equiv E_t[(\mathcal{Y}_{j,t+h} - E_t[\mathcal{Y}_{j,t+h}])^2]$. The following recursion holds (with $\Omega_{jt}^{\mathcal{Y}}(0) \equiv 0$):

$$\Omega_{jt}^{\mathcal{Y}}(h) = \Phi_j^{\mathcal{Y}} \Omega_{jt}^{\mathcal{Y}}(h-1) \Phi_j^{\mathcal{Y}\prime} + E_t[V_{j,t+h}^{\mathcal{Y}} V_{j,t+h}^{\mathcal{Y}\prime}],$$

- Then h-period ahead uncertainty in y_{jt} is

$$\mathcal{U}_{jt}^{y}(h) = \sqrt{1_j' \mathcal{U}_{jt}^{\mathcal{Y}}(h) 1_j}.$$

1_j a selection vector picks out the element for uncertainty in $y_{j,t}$.

Sources of Uncertainty

- Forecast error variance is *not* equal to stochastic volatility in residuals v_{jt}^{y} *unless* $h = 1$.

$$\Omega_{jt}^{Y}(h) = \underbrace{\Phi_j^{Y}\Omega_{jt}^{Y}(h-1)\Phi_j^{Y\prime}}_{\text{autoregressive}} + \underbrace{\Omega_{jt}^{Z}(h-1)}_{\text{Factor}} + \underbrace{E_t(V_{jt+h}^{Y}V_{jt+h}^{Y\prime})}_{\text{stochastic volatility } Y}$$
$$+ \underbrace{2\Phi_j^{Y}\Omega_{jt}^{YZ}(h-1)}_{\text{covariance}}$$

Sources of Uncertainty

- Forecast error variance is *not* equal to stochastic volatility in residuals v_{jt}^{y} *unless* $h = 1$.

$$\Omega_{jt}^{Y}(h) = \underbrace{\Phi_j^{Y}\Omega_{jt}^{Y}(h-1)\Phi_j^{Y\prime}}_{\text{autoregressive}} + \underbrace{\Omega_{jt}^{Z}(h-1)}_{\text{Factor}} + \underbrace{E_t(V_{jt+h}^{Y}V_{jt+h}^{Y\prime})}_{\text{stochastic volatility } Y} + \underbrace{2\Phi_j^{Y}\Omega_{jt}^{YZ}(h-1)}_{\text{covariance}}$$

- **Autoregressive** component when $h > 1$

Sources of Uncertainty

- Forecast error variance is *not* equal to stochastic volatility in residuals v_{jt}^{y} *unless* $h = 1$.

$$\Omega_{jt}^{Y}(h) = \underbrace{\Phi_j^Y \Omega_{jt}^{Y}(h-1)\Phi_j^{Y\prime}}_{\text{autoregressive}} + \underbrace{\Omega_{jt}^{Z}(h-1)}_{\text{Factor}} + \underbrace{E_t(V_{jt+h}^{Y} V_{jt+h}^{Y\prime})}_{\text{stochastic volatility } Y}$$
$$+ \underbrace{2\Phi_j^Y \Omega_{jt}^{YZ}(h-1)}_{\text{covariance}}$$

- **Autoregressive** component when $h > 1$
- **Predictor** Uncertainty: *error in forecasting F_t and W_t* contribute to uncertainty when $h > 1$

Sources of Uncertainty

- Forecast error variance is *not* equal to stochastic volatility in residuals v_{jt}^{y} *unless* $h = 1$.

$$\Omega_{jt}^{Y}(h) = \underbrace{\Phi_j^Y \Omega_{jt}^{Y}(h-1) \Phi_j^{Y\prime}}_{\text{autoregressive}} + \underbrace{\Omega_{jt}^{Z}(h-1)}_{\text{Factor}} + \underbrace{E_t(V_{jt+h}^{Y} V_{jt+h}^{Y\prime})}_{\text{stochastic volatility } Y}$$
$$+ \underbrace{2\Phi_j^Y \Omega_{jt}^{YZ}(h-1)}_{\text{covariance}}$$

- **Autoregressive** component when $h > 1$
- **Predictor** Uncertainty: *error in forecasting F_t and W_t* contribute to uncertainty when $h > 1$
- **Covariance** component: $\text{cov}(y_{t+h} - y_{t+h|t}, F_{t+h} - F_{t+h|t})$, non-zero when $h > 2$.

Variance Decomposition with $U_M(12)$ and $U_F(12)$

- Variance Decomposition with $U_M(12)$ and $U_F(12)$

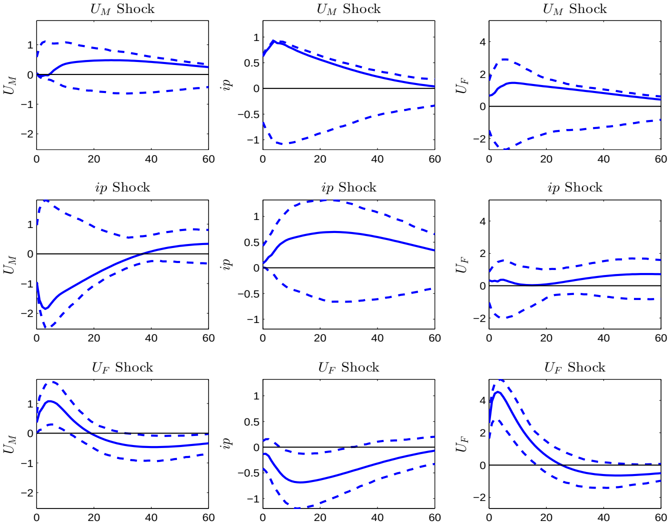
	SVAR $(U_M(12), ip, U_F(12))'$		
	Fraction variation in $U_M(12)$		
s	$U_M(12)$ Shock	*ip* Shock	$U_F(12)$ Shock
1	0.548	0.432	0.020
12	0.763	0.219	0.018
∞	0.635	0.206	0.159
$s_{\max}$	0.813	0.432	0.165
	[0.48, 0.94]	[0.17, 0.66]	[0.06, 0.51]
	Fraction variation in *ip*		
s	$U_M(12)$ Shock	*ip* Shock	$U_F(12)$ Shock
1	0.379	0.591	0.030
12	0.124	0.757	0.119
∞	0.202	0.697	0.101
$s_{\max}$	0.382	0.772	0.145
	[0.20, 0.71]	[0.42, 0.93]	[0.04, 0.59]
	Fraction variation in $U_F(12)$		
s	$U_M(12)$ Shock	*ip* Shock	$U_F(12)$ Shock
1	0.091	0.002	0.907
12	0.165	0.017	0.819
∞	0.200	0.162	0.638
$s_{\max}$	0.206	0.162	0.907
	[0.04, 0.71]	[0.05, 0.46]	[0.37, 0.99]

	SVAR $(U_M(12), emp, U_F(12))'$		
	Fraction variation in $U_M(12)$		
s	$U_M(12)$ Shock	*emp* Shock	$U_F(12)$ Shock
1	0.621	0.360	0.019
12	0.776	0.212	0.012
∞	0.682	0.135	0.183
$s_{\max}$	0.682	0.135	0.183
	[0.37, 0.96]	[0.10, 0.62]	[0.09, 0.52]
	Fraction variation in *emp*		
s	$U_M(12)$ Shock	*emp* Shock	$U_F(12)$ Shock
1	0.342	0.355	0.303
12	0.076	0.433	0.491
∞	0.269	0.482	0.250
$s_{\max}$	0.342	0.482	0.519
	[0.23, 0.76]	[0.17, 0.86]	[0.18, 0.88]
	Fraction variation in $U_F(12)$		
s	$U_M(12)$ Shock	*emp* Shock	$U_F(12)$ Shock
1	0.273	0.090	0.637
12	0.389	0.108	0.503
∞	0.448	0.165	0.387
$s_{\max}$	0.464	0.165	0.637
	[0.09, 0.76]	[0.04, 0.59]	[0.20, 0.94]

	SVAR $(U_M(12), Q_1, U_F(12))'$		
	Fraction variation in $U_M(12)$		
s	$U_M(12)$ Shock	Q_1 Shock	$U_F(12)$ Shock
1	0.590	0.381	0.029
12	0.801	0.168	0.031
∞	0.692	0.202	0.106
$s_{\max}$	0.868	0.388	0.107
	[0.48, 0.95]	[0.17, 0.61]	[0.04, 0.49]
	Fraction variation in Q_1		
s	$U_M(12)$ Shock	Q_1 Shock	$U_F(12)$ Shock
1	0.384	0.602	0.014
12	0.099	0.748	0.154
∞	0.256	0.623	0.121
$s_{\max}$	0.388	0.751	0.210
	[0.23, 0.75]	[0.41, 0.96]	[0.05, 0.66]
	Fraction variation in $U_F(12)$		
s	$U_M(12)$ Shock	Q_1 Shock	$U_F(12)$ Shock
1	0.059	0.001	0.940
12	0.127	0.016	0.858
∞	0.178	0.151	0.671
$s_{\max}$	0.178	0.151	0.945
	[0.04, 0.69]	[0.05, 0.48]	[0.40, 0.99]

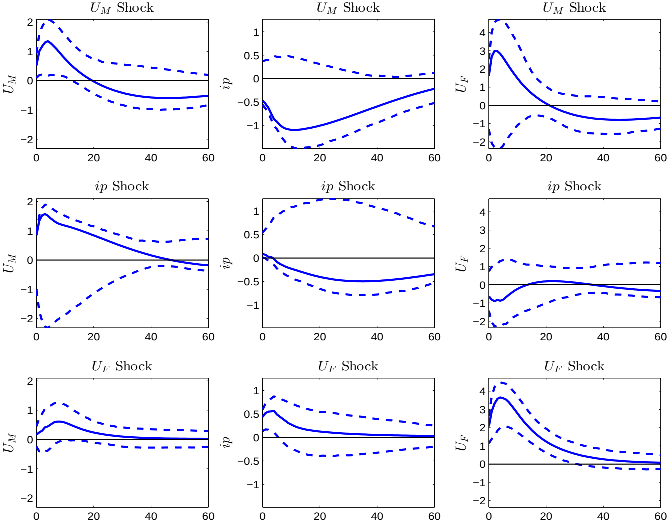
Note: Each panel shows the fraction of s-step-ahead forecast-error variance of the variable given in the panel title that is explained by the shock named in the column heading. The row denoted "$s = s_{max}$ "reports the maximum fraction (across all VAR forecast horizons m) of forecast error variance explained by the shock listed in the column heading. The numbers in parentheses represent the 5th and 95th percentiles of these statistics from bootstrapped samples. The data are monthly and span the period 1960:07 to 2015:04.

IRF for SVAR $(U_M, ip, U_F)'$ using VXO in Z_1



Note: Bootstrapped 90 percent error bands appear as dashed lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. Z_1 is created by using VXO and Z_2 is generated by using r_p, $\alpha = 0.94$. The correlation $\rho\left(Z_{1t}, \hat{e}_{Mt}\right) = 0.1650$, $\rho\left(Z_{1t}, \hat{e}_{Ft}\right) = 0.1299$ and $\rho\left(Z_{2t}, \hat{e}_{Ft}\right) = -0.1662$. The sample is from 1962:07 to 2015:04.

IRF for SVAR $(U_M, ip, U_F)'$ using VXO in Z_2



Note: Bootstrapped 90 percent error bands appear as dashed lines. Responses to one standard deviation shocks are reported. Response units are reported in percentage points. Z_1 is generated by using r_p, $\alpha = 0.94$ and Z_2 is created by using VXO. The correlation $\rho(Z_{1t}, \hat{e}_{Mt}) = -0.1115$, $\rho(Z_{1t}, \hat{e}_{Ft}) = -0.1491$ and $\rho(Z_{2t}, \hat{e}_{Ft}) = 0.1969$. The sample is from 1962:07 to 2015:04.

6 Survived Solutions for System $(U_M, ip, U_F)'$

- 6 Survived Solutions for System $(U_M, ip, U_F)'$

Panel A: Summary of Results from 6 Solutions

	Summary Statistics of $\hat{e} = (e_M, e_Y, e_F)$		Instrument Relevance			
Case	Skewness	Kurtosis	$\hat{c}_1$	$\hat{c}_2$	$\hat{c}_3$	C
Baseline	$(0.48, -0.42, -1.70)$	$(5.87, 6.05, 19.65)$	-0.07	-0.17	-0.16	0.134
Sol #1	$(0.33, -0.46, -1.82)$	$(5.71, 6.54, 20.68)$	-0.07	-0.17	-0.16	0.135
Sol #2	$(0.50, -0.43, -1.77)$	$(5.88, 6.28, 20.08)$	-0.08	-0.17	-0.16	0.135
Sol #3	$(0.36, -0.46, -1.81)$	$(5.74, 6.49, 20.59)$	-0.07	-0.17	-0.16	0.135
Sol #4	$(0.32, -0.45, -1.78)$	$(5.69, 6.39, 20.41)$	-0.07	-0.17	-0.16	0.134
Sol #5	$(0.30, -0.44, -1.74)$	$(5.66, 6.37, 19.86)$	-0.08	-0.17	-0.15	0.134

Panel B: Correlation Matrix of $\hat{e}$

$$\hat{e}_M: \begin{pmatrix} 1 & 0.991 & 0.998 & 0.994 & 0.989 & 0.987 \\ & 1 & 0.985 & 0.999 & 0.999 & 0.999 \\ & & 1 & 0.988 & 0.982 & 0.983 \\ & & & 1 & 0.999 & 0.998 \\ & & & & 1 & 0.998 \\ & & & & & 1 \end{pmatrix}$$

$$\hat{e}_Y: \begin{pmatrix} 1 & 0.985 & 0.995 & 0.988 & 0.987 & 0.987 \\ & 1 & 0.986 & 0.999 & 0.999 & 0.998 \\ & & 1 & 0.990 & 0.984 & 0.982 \\ & & & 1 & 0.999 & 0.998 \\ & & & & 1 & 0.999 \\ & & & & & 1 \end{pmatrix}$$

$$\hat{e}_M: \begin{pmatrix} 1 & 0.993 & 0.994 & 0.995 & 0.998 & 0.996 \\ & 1 & 0.998 & 0.999 & 0.999 & 0.997 \\ & & 1 & 0.999 & 0.997 & 0.999 \\ & & & 1 & 0.999 & 0.998 \\ & & & & 1 & 0.998 \\ & & & & & 1 \end{pmatrix}$$

Note: Panel A reports the skewness and kurtosis of $\hat{e}$ and instrument relevance for 6 survived solutions in system $(U_M, ip, U_F)'$. Panel B reports the matrix of correlation $\hat{e}$ across 6 solutions. The monthly data span the period 1960:07 to 2015:04.