Quantifying the Effect of Noisy TFP News on Business Cycles

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- Changes in expectations as driver of aggregate fluctuations.
- Many representations : multiple equilibria and sunspot fluctuations, news and noise on economic fundamentals and modifications in market sentiments without any change in economic outcomes (see e.g. Benhabib, *et al.*, 2015, Beaudry and Portier, 2014, Lorenzoni, 2009, Angeletos and La'o, 2013, and Angeletos *et al.*, 2016).
- Impact on the usefulness of SVARs.
- Objective : disentangle surprise, news and noise in aggregate TFP.
- Methodological contribution : propose a simple approach based on projections.

- No consensus seems to emerge about the contribution of noisy news in TFP shock to aggregate fluctuations.
- DSGE models : Blanchard, L'Huillier and Lorenzoni (2013), Barsky and Sims (2012).
- SVARs using forward information or Bayesian SVARMA : Forni, Gambetti, Luca and Sala (2017), Chahrour and Jurado (2022) and Benati, Chan, Eisenstat and Koop (2020).

Introduction
Roadmap

- The identification Problem.
- Proposed Methodology
- Simulation Results.
- Applications : à venir

Problems in Quantifying the Importance of These Shocks

Structural Vector Autoregressive (SVAR) models are commonly used to quantify the contribution of structural shocks to business cycle fluctuations and to evaluate DSGE model implications.

Challenges arise in the presence of news and noise shocks :

- The innovations from a VAR on observables do not necessarily correspond to structural shocks.
- This occurs when the data-generating process has a **non-fundamental MA component**—i.e., the MA roots lie inside the unit circle—making it impossible to approximate the process with a finite-order AR representation.
- In the presence of **noise shocks**, the agent's signal is contaminated, leading to a **signal extraction problem** : even the agent cannot infer the true structural shock, and the econometrician cannot recover it from observables alone.

Challenges in Quantifying the Importance of These Shocks

Two key sources of identification problems :

- **News shocks :** When agents receive information about future fundamentals, the innovations from a VAR may not align with true structural shocks. This creates a *non-fundamentalness problem*, as the econometrician's information set is strictly smaller than that of the agents.
- **Noise shocks :** When signals are contaminated by noise, even agents cannot correctly identify structural shocks. In this case, the econometrician may have access to a *larger* information set—such as future realizations of fundamentals—which can be used to disentangle the effects of noise.

Specific Challenges and Solutions in Identifying These Shocks

Potential Solutions :

- **Non-fundamentalness due to news shocks :** The econometrician observes a smaller information set than economic agents. A possible solution is to expand the econometrician's information set, for example through the inclusion of common factors (Forni and Gambetti, 2014, *JME*).
- **Identification failure due to noise shocks :** The issue is more severe, as even agents cannot identify the true shocks. Solutions include :
  1. Estimating fully specified structural models (e.g., Blanchard, L'Huillier, and Lorenzoni, 2013 ; Barsky and Sims, 2012).
  2. Using future realizations of fundamentals—this relies on the concept of *recoverability* (Chahrour and Jurado, 2022).

Summary : In the first case, the econometrician is less informed than agents. In the second case, the econometrician uses additional information—such as future fundamentals—not available to agents.

ABCD Representation

To study the conditions under which structural shocks can be recovered from observables, we express the system in its general state-space (ABCD) form :

$$x_t = Ax_{t-1} + B\varepsilon_t,$$
$$y_t = Cx_{t-1} + D\varepsilon_t,$$

where x_t is the vector of state variables, y_t the vector of observables, and ε_t the vector of structural shocks. We first consider the simple case where the matrix D is invertible.

ABCD Representation

Question : Is it possible to recover the system's dynamics and the underlying structural shocks from a VAR estimated on the observables y_t ?

We consider a VAR representation for the observables :

$$y_t = F(L)\, y_{t-1} + u_t,$$

where $F(L)$ is an infinite-order lag polynomial and u_t are the reduced-form innovations.

- Can we recover the structural shocks ε_t from the VAR innovations u_t ?
- If the state variables x_t are observed, the system is trivially recoverable.

The Poor Man's Condition : ABCD (Fernandez-Villaverde et al., 2007)

We examine the simple case where the matrix D is invertible. Implication : same number of shocks as observables.

$$\varepsilon_t = D^{-1}\left(y_t - Cx_{t-1}\right).$$

This yields :

$$x_t = \left(A - BD^{-1}C\right)x_{t-1} + BD^{-1}y_t$$

$$x_t = \left(A - BD^{-1}C\right)^{t-1}x_0 + \sum_{i=0}^{t-1}\left(A - BD^{-1}C\right)^{i-1}BD^{-1}y_{t-i}.$$

If $\lim_{t\to\infty}\left(A - BD^{-1}C\right)^{t-1} = 0$, the observables perfectly reveal the states x_t.

The Poor Man's Condition : ABCD (Fernandez-Villaverde et al., 2007)

We then obtain a VAR(∞) representation in terms of the observables y_t and the structural shocks :

$$y_t = C \sum_{i=0}^{\infty} \left(A - BD^{-1}C \right)^{i-1} BD^{-1} y_{t-i-1} + D\varepsilon_t.$$

If the matrix $A - BD^{-1}C$ is not stable, one cannot recover the structural shocks from a VAR on the observables.

The Poor Man's Condition : ABCD (Fernandez-Villaverde et al., 2007)

Sufficient condition for fundamentalness :

All eigenvalues of the matrix $(A - BD^{-1}C)$ are strictly less than one in absolute value.

This condition ensures that the structural shocks ε_t can be recovered from the VAR innovations based on the observables y_t.

Implication : If the condition is not satisfied, the econometrician can attempt to restore fundamentalness by enriching the information set—for example, by including latent factors as proposed in Forni et al. 2014.

The Problem with Noise Shocks

The presence of noise shocks implies that the matrix D is **singular** (non-invertible).

This is because agents respond to a signal that combines both news and noise shocks, making their behavior observationally equivalent across the two. Consequently, the mapping from structural shocks to observables is not one-to-one :

$$s_t = \varepsilon_t^{\text{news}} + \varepsilon_t^{\text{noise}}$$

implies that the effect of these two shocks on observables is collinear in D, leading to a rank-deficient matrix.

Signal Extraction Problem

We consider a simple information structure in which agents observe a noisy signal about future technology growth.

$$\Delta z_t = \varepsilon^{\text{news}}_{t-q}, \qquad s_t = \varepsilon^{\text{news}}_t + \varepsilon^{\text{noise}}_t,$$

where :

- $\varepsilon^{\text{news}}_t$ represents the anticipated (*news*) component about future productivity,
- $\varepsilon^{\text{noise}}_t$ is a noise component in the signal, uncorrelated with fundamentals.

At time t, agents observe s_t and the past history $\mathcal{I}_t = \{s_t, s_{t-1}, \dots\}$. They form the best estimate (in the mean-square-error sense) of the true news shock :

$$\widehat{\varepsilon}^{\text{news}}_t = \mathbb{E}_t[\varepsilon^{\text{news}}_t \mid s_t].$$

Signal Extraction Problem

Given the linear structure of the signal, the optimal estimate is :

$$\widehat{\varepsilon}_t^{\text{news}} = \frac{\mathrm{Cov}(\varepsilon_t^{\text{news}}, s_t)}{\mathrm{Var}(s_t)}\, s_t = \frac{\sigma^2_{news}}{\sigma^2_{news} + \sigma^2_{noise}}\, s_t.$$

The coefficient

$$\kappa = \frac{\sigma^2_{news}}{\sigma^2_{news} + \sigma^2_{noise}}$$

measures the *informativeness* of the signal :

- If $\sigma^2_{noise} = 0$, the signal is perfectly informative, so $\widehat{\varepsilon}_t^{\text{news}} = \varepsilon_t^{\text{news}}$.
- If $\sigma^2_{noise} \to \infty$, the signal conveys no information, so $\widehat{\varepsilon}_t^{\text{news}} = 0$.

Solution : The econometrician can use **future realizations** of fundamentals (e.g., TFP) to distinguish between news and noise. This approach relies on the concept of *recoverability* introduced by Chahrour and Jurado (2021).

Data-Generating Process (DGP)

We consider the following Structural Moving Average (SMA) representation for the $n \times 1$ vector of variables :

$$X_t = \Theta_1(L)u_t + \Theta_2(L)\epsilon_t + \Theta_3(L)\nu_t + \Theta_4(L)\chi_t, \tag{1}$$

- $X_t = (\Delta z_t, y_t, x_t')'$, where :
  - Δz_t : Total Factor Productivity (TFP) growth
  - y_t : Variable of interest
  - x_t : $(n-2) \times 1$ vector of additional observables
- Structural shocks :
  - u_t : Non-anticipated (surprise) technology shock
  - ϵ_t : Anticipated (news) technology shock
  - ν_t : Noise shock
  - χ_t : Other orthogonal structural shocks
- $\Theta_i(L)$ are lag polynomials capturing the dynamic propagation of each shock.

We define the normalized vector of structural shocks as :

$$\eta_t = (u_t, \epsilon_t, \nu_t, \chi_t')', \quad \text{with } E[\eta_t] = 0, \quad E[\eta_t \eta_t'] = I.$$

The Setup : TFP

TFP as an Exogenous Univariate Process

The total factor productivity (TFP) growth process is composed of two orthogonal components :

$$\Delta z_t = \Delta z_t^{(1)} + \Delta z_t^{(2)},$$

where :

$$\Delta z_t^{(1)} = a(L)u_t, \quad \Delta z_t^{(2)} = b(L)\varepsilon_{t-q}, \quad (q > 0).$$

- u_t : Non-anticipated (surprise) technology shock
- ε_t : Anticipated (news) technology shock
- u_t and ε_t are uncorrelated at all leads and lags :

$$E[u_t \varepsilon_{t-k}] = 0 \quad \forall k \in \mathbb{Z}$$

- Their variances are σ_u^2 and σ_ε^2, respectively

The lag polynomials are defined as :

$$a(L) = \sum_{i=0}^{m} a_i L^i, \quad b(L) = \sum_{i=0}^{n} b_i L^i$$

The Setup : Signal

Agents observe a noisy signal about future TFP developments.

The observed signal s_t combines a true news shock and a noise component :

$$s_t = \varepsilon_t + \nu_t \tag{2}$$

- ε_t : News shock about future TFP
- ν_t : Noise shock — white noise with variance σ_ν^2, unrelated to fundamentals
- ν_t is orthogonal to both u_t and ε_t at all leads and lags :

$$E[\nu_t u_{t-k}] = E[\nu_t \varepsilon_{t-k}] = 0 \quad \forall k \in \mathbb{Z}$$

- The noise shock ν_t captures *extrinsic uncertainty* — variations in beliefs or expectations unrelated to actual economic fundamentals.

Proposed Strategy : Retrieving the Non-Anticipated TFP Shock

To recover the non-anticipated (surprise) component of TFP, we exploit the structure of the data-generating process (DGP) and rely on a projection approach.

The vector X_t may include business cycle indicators or common factors to account for missing information. Including such variables helps reduce the risk of non-fundamental representations.

Step 1 : Identification of the surprise TFP shock
We estimate the surprise component u_t using the following local projection :

$$\Delta z_t = \Psi_z(L) X_{t-1} + u_t,$$

where :

- $\Psi_z(L)$: Lag polynomial capturing the predictive content of observables X_{t-1}
- u_t : Non-anticipated (surprise) TFP shock, assumed to be orthogonal to X_{t-1}

Remark : This step is unnecessary if TFP is driven by a single structural shock (e.g., pure news), in which case Δz_t already captures the structural variation.

Proposed Strategy : Effects of Non-Anticipated and Anticipated Shocks

We consider the following moving-average (MA) representation for the variable of interest y_t :

$$y_t = \Theta_{21}(L)\, u_t + \Theta_{22}(L)\, \varepsilon_t + \Theta_{23}(L)\, \nu_t + \Theta_{24}(L)\, \chi_t,$$

where :

- u_t : Non-anticipated (*surprise*) technology shock,
- ε_t : Anticipated (*news*) technology shock,
- ν_t : Noise shock (irrelevant to fundamentals but influential on expectations),
- χ_t : Other orthogonal structural shocks.

Objective : Estimate the impulse response functions (IRFs) of y_t with respect to :

1. ε_t : News about future total factor productivity (TFP),
2. ν_t : Noise in the signal that affects beliefs but not fundamentals,

in a way that is robust to the presence (or absence) of surprise shocks.

Proposed Strategy : The Effect of Non-Anticipated Shocks

The dynamic impact of non-anticipated (surprise) technology shocks can be estimated using the following local projection :

$$y_{t+h} = \beta_h \Delta z_t + \Psi(L) X_{t-1} + v_{t+h},$$

where :

- y_{t+h} : Variable of interest at horizon h
- Δz_t : Observed TFP growth, assumed to reflect only the surprise component contemporaneously
- X_{t-1} : Vector of lagged controls (e.g., observables or estimated factors)
- $\Psi(L)$: Lag polynomial of order p
- v_{t+h} : Projection residual

Identification Assumption : Only the non-anticipated shock u_t contemporaneously affects Δz_t. Under this assumption, β_h consistently estimates the impulse response of y_{t+h} to a surprise technology shock.

This assumption aligns with frameworks such as which model TFP as reacting contemporaneously only to unanticipated innovations.

The Effect of Anticipated Shocks

To identify the impact of anticipated shocks (news shocks) on the variable of interest, consider the case where non-anticipated shocks affect TFP. The IRFs can be derived using the following local projection :

$$y_{t+h} = \beta_{h,z}\Delta z_{t+q} + \sum_{j=0}^{q} \delta_h \hat{u}_{t+j} + \Psi(L)X_{t-1} + v_{t+h}, \tag{3}$$

where $\Psi(L)$ is a lag polynomial of order p applied to X_{t-1}, and $\hat{u}_{t+1}$ is obtained as :

$$\hat{u}_{t+j} = \Delta z_{t+j} - \mathrm{Proj}(\Delta z_{t+j} \mid X_{t+j-1}, \dots, X_{t+j-p}).$$

The estimated parameters $\hat{\beta}_{h,z}$ from this projection directly provide the IRFs of the news shock on y_t.

The Effect of Anticipated Shocks

Applying the Frisch-Waugh-Lovell theorem, we obtain :

$$\beta_{h,z} b_q = \Theta_{h,22}.$$

To demonstrate this, define $y_{t+h}^{\perp}$ and $\Delta Z_{t+q}^{\perp}$ as :

$$y_{t+h}^{\perp} = y_{t+h} - \mathrm{Proj}[y_{t+h} \mid X_{t-1}, \ldots, X_{t-p}, u_{t+q}, \ldots, u_t],$$

$$\Delta z_{t+q}^{\perp} = \Delta z_{t+q} - \mathrm{Proj}[\Delta z_{t+1} \mid X_{t-1}, \ldots, X_{t-p}, u_{t+q}, \ldots, u_t].$$

Under invertibility, we have $\Delta z_{t+q}^{\perp} = b_q \epsilon_t$. Using the Frisch-Waugh-Lovell theorem :

$$\beta_{h,z} = \frac{E[y_{t+h}^{\perp} \Delta z_{t+q}^{\perp}]}{E[(\Delta z_{t+q}^{\perp})^2]}.$$

Substituting $\Delta z_{t+q}^{\perp} = b_q \epsilon_t$, we get :

$$\beta_{h,z} = \frac{\left[\Theta_{h,22} b_q \sigma_{\epsilon}^2\right]}{b_q^2 \sigma_{\epsilon}^2}.$$

The Effect of Anticipated Shocks :

Thus, simplifying further :

$$\beta_{h,z} = \frac{\Theta_{h,22} b_q \sigma_\epsilon^2}{b_q^2 \sigma_\epsilon^2} = \frac{\Theta_{h,22}}{b_q}.$$

In the case where no non-anticipated shocks affect TFP, as in Forni et al. (2017) and Charour and Jurado (2022), the local projection (3) remains the same, except that the terms $\hat{u}_{t+j}$ are omitted.

The Effect of Anticipated Shocks : Choosing the Lead-Time q

- The key question concerns the choice of the lead-time q (i.e., the term Δz_{t+q} in the projection).
- The estimation strategy relies on the following regression :

$$\Delta Z_{t+h} = \beta_h s_t + \Psi(L) X_{t-1} + v_{t+h}, \tag{4}$$

Frisch–Waugh–Lovell Theorem :

$$\beta_h = \frac{\mathbb{E}\left[\Delta Z_{t+h}^{\perp} s_t^{\perp}\right]}{\mathbb{E}\left[(s_t^{\perp})^2\right]},$$

where $\Delta Z_{t+h}^{\perp}$ and $s_t^{\perp}$ denote residuals orthogonalized with respect to the control set X_{t-1}.

Operational rule for choosing q :

1. For each candidate $q \in \{0, 1, \ldots, \bar{q}\}$, estimate the sequence $\{\hat{\beta}_h(q)\}_{h=0}^{\bar{h}}$.
2. Let $h(q)$ denote the horizon such that $\hat{\beta}_h(q)$ is statistically significant (e.g., at the 5% level).
3. Select
$$q^{\star} := \arg\min_q h(q),$$
corresponding to the earliest horizon at which a significant effect is detected.

The Effect of Anticipated Shocks : Choosing the Lead-Time q

Why this strategy works :

Suppose the following process for TFP :

$$\Delta z_t = \Delta u_t + b_q \varepsilon_{t-q},$$

where ε_{t-q} represents the anticipated (news) component and Δu_t the unanticipated (surprise) component.

Then, the covariance between future TFP growth and the signal $s_t = \varepsilon_t + \nu_t$ satisfies :

$$\begin{aligned}
\mathbb{E}(\Delta z_{t+h}\, s_t) &= \mathbb{E}[(\Delta u_t + \varepsilon_{t-q})(\varepsilon_t + \nu_t)] = 0, && h < q, \\
\mathbb{E}(\Delta z_{t+h}\, s_t) &= \mathbb{E}[(\Delta u_{t+q} + \varepsilon_t)(\varepsilon_t + \nu_t)] = b_q \sigma_\varepsilon^2, && h = q, \\
\mathbb{E}(\Delta z_{t+h}\, s_t) &= \mathbb{E}[(\Delta u_{t+h} + \varepsilon_{t-q+h})(\varepsilon_t + \nu_t)] = 0, && h > q.
\end{aligned}$$

Implication : Under this data-generating process, the regression in Equation (4) asymptotically selects, with probability one, the lead term Δz_{t+q} corresponding to the true anticipation horizon.

The Effect of Anticipated Shocks : Choosing the Lead-Time q

Illustrative process for TFP :

$$\Delta z_t = \Delta u_t + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2},$$

where ε_{t-j} represents anticipated shocks (news) at horizons $j = 1, 2$, and Δu_t is the unanticipated component.

Then, the covariance between future TFP growth and the signal $s_t = \varepsilon_t + \nu_t$ satisfies :

$$\begin{aligned}
\mathbb{E}(\Delta z_{t+h}\, s_t) &= \mathbb{E}[(\Delta u_t + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2})(\varepsilon_t + \nu_t)] = 0, && h = 0,\\
\mathbb{E}(\Delta z_{t+h}\, s_t) &= \mathbb{E}[(\Delta u_{t+1} + b_1 \varepsilon_{t} + b_2 \varepsilon_{t-1})(\varepsilon_t + \nu_t)] = b_1 \sigma_\varepsilon^2, && h = 1,\\
\mathbb{E}(\Delta z_{t+h}\, s_t) &= \mathbb{E}[(\Delta u_{t+2} + b_1 \varepsilon_{t+1} + b_2 \varepsilon_{t})(\varepsilon_t + \nu_t)] = b_2 \sigma_\varepsilon^2, && h = 2,\\
\mathbb{E}(\Delta z_{t+h}\, s_t) &= \mathbb{E}[(\Delta u_{t+h} + b_1 \varepsilon_{t+h-1} + b_2 \varepsilon_{t+h-2})(\varepsilon_t + \nu_t)] = 0, && h > 2.
\end{aligned}$$

Interpretation :

- The covariance becomes positive at horizon $h = 1$, when news ε_t first affects future TFP growth through the term $b_1 \varepsilon_t$.
- Therefore, the estimation strategy correctly identifies the first anticipation horizon and selects : $q = 1$.

Why the Strategy Selects the Correct q

Specification (Blanchard, L'Huillier, and Lorenzoni, 2013) :

$$z_t^{(1)} = \rho z_{t-1}^{(1)} + u_t, \qquad \Delta z_t^{(2)} = \rho\, \Delta z_{t-1}^{(2)} + \varepsilon_{t-q},$$

with $\sigma_u^2 = \dfrac{\rho\,\sigma_\varepsilon^2}{(1-\rho)^2}$ so that total TFP,

$$z_t = z_t^{(1)} + z_t^{(2)},$$

follows a random walk.

Let the signal be $s_t = \varepsilon_t + \nu_t$. The covariance between TFP growth and the signal satisfies :

$$\mathbb{E}(\Delta z_{t+h}\, s_t) = \begin{cases} 0, & h < q, \\ \sigma_\varepsilon^2\, \rho^{\,h-q}, & h \geq q. \end{cases}$$

Interpretation :

- Before horizon q, no information about future productivity growth is available, so the covariance is zero.
- At $h = q$, news about future TFP (ε_t) starts affecting expectations, producing a positive covariance that decays geometrically with $\rho^{\,h-q}$.
- Therefore, the estimation strategy detects the first horizon with a significant effect and correctly identifies : $q^\star = q$.

The Effect of the Noise Shock

To estimate the dynamic impact of a noise shock, we use the following local projection equation :

$$y_{t+h} = \beta_{h,s} s_t + \delta \Delta z_{t+q} + \Psi_0 \tilde{X}_t + \Psi(L) X_{t-1} + v_{t+h}, \tag{5}$$

where :

- $s_t = \varepsilon_t + \nu_t$: Observed signal combining news and noise
- Δz_{t+q} : Future TFP used to partial out the news component
- $\tilde{X}_t$: Additional controls to purge s_t of other structural signals. For instance, Forni et al.2017 et al. propose an ordering that includes the federal funds rate to filter out signals related to monetary policy.
- X_{t-1} : Standard control variables (lags, observables)

Orthogonalization and Interpretation of the Noise IRF

The coefficient $\hat{\beta}_{h,s}$ from equation (5) estimates the impulse response of y_t to a noise shock, after controlling for the news and other confounding sources.

By the Frisch-Waugh-Lovell theorem :

$$\beta_{h,s} = \frac{\mathbb{E}\left[y_{t+h}^{\perp} s_t^{\perp}\right]}{\mathbb{E}\left[(s_t^{\perp})^2\right]} = \frac{\Theta_{h,23}\, \sigma_{\nu}^2}{\sigma_{s^{\perp}}^2},$$

where :

- $s_t^{\perp}$: Component of s_t orthogonal to future TFP (i.e., isolating the noise)
- $\Theta_{h,23}$: Moving average coefficient for noise shock at horizon h
- $\sigma_{s^{\perp}}^2 = \sigma_{\nu}^2$: Variance of the orthogonalized signal

This approach isolates the part of the signal that moves beliefs without affecting fundamentals.

The Choice of the Signal

- The signal s_t is not directly observable, but can be inferred from observable variables or projections.

- **Forni et al. (2017)** propose that an observed variable must be *sufficiently informative* to unveil the underlying signal.

- In their empirical application, they use the **expected business conditions over the next 12 months** ($E12M$), a component of the *University of Michigan Consumer Sentiment Survey*.
  - $E12M$ is ordered **second** in their VAR, immediately after the indicator of the technology process.
  - They also assess robustness to alternative variable orderings.

- Alternative indicators of expected business conditions can also be used. For instance, the **Index of Consumer Sentiment (ICS, five-year horizon)** from the same University of Michigan Survey captures households' expectations about business or financial conditions over the next five years.

- **Chahrour and Jurado (2022)** instead use the **expectation of TFP**, $E_t[z_{t+h}]$, computed from a VAR, as an indicator revealing noise :
  - This is obtained by subtracting $E_t[z_{t+h}]$ from its projection onto the lags, contemporaneous values, and leads of observed TFP.
  - A VAR including all variables in X_t is estimated to compute $E_t[z_{t+h}]$.

Simulations : Canonical RBC

The representative agent maximizes

$$U_0 = E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_t + \theta_t \ln(1 - N_t)\right]$$

subject to the constraint

$$C_t + I_t + G_t \leq Y_t$$

where

$$Y_t = K_t^{1-\alpha} (Z_t N_t)^{\alpha}$$

and

$$K_{t+1} = (1 - \delta) K_t + I_t$$

Simulations : Canonical RBC

We simulate a canonical RBC model that includes :

- Anticipated and unanticipated technology shocks
- Noisy signals about future productivity
- Government spending following an AR(1) process
- Preference shocks

TFP process (in logs, $z_t = \ln Z_t$) :

$$\Delta z_t = \Delta z_t^{(1)} + \Delta z_t^{(2)},$$

with :

$$z_t^{(1)} = \rho z_{t-1}^{(1)} + u_t, \quad \Delta z_t^{(2)} = \rho \Delta z_{t-1}^{(2)} + \varepsilon_{t-q}, \quad (q \geq 0),$$

where u_t is a surprise (non-anticipated) shock and ε_{t-q} is a news shock received at time $t - q$.

Signal process :

$$S_t = \rho S_{t-1} + \varepsilon_t + \nu_t$$

- ν_t : Noise shock unrelated to fundamentals
- S_t : Confidence or sentiment signal observed by agents

We estimate a VAR including : TFP, the signal S_t, consumption, and hours worked.

Alternative Strategies

- **Forni et al. (2017) :** TFP growth is assumed to be driven exclusively by *news shocks* about future fundamentals. The structural equation is :

$$\Delta z_t = b(L)\epsilon_{t-q}$$

where ϵ_{t-q} denotes a news shock received at time t about fundamentals materializing at $t + q$, and $c(L)$ is a distributed lag polynomial.

- **Chahrour and Jurado (2021) :** TFP itself is the fundamental process. The dynamics are given by :

$$\Delta z_t = b(L)\epsilon_t$$

where ϵ_t is the fundamental shock directly affecting TFP at time t.

Important : Both frameworks abstract from non-anticipated (surprise) shocks.

Recovering Noise Shocks under Recoverability

How can we retrieve the noise shocks under the recoverability condition ?

Example : a simplification of Forni et al. (2017)

Assume the following data-generating process (DGP) for TFP :

$$\Delta z_t = \epsilon_{t-1}$$

and the signal observed by agents :

$$s_t = \nu_t + \epsilon_t$$

Then, under recoverability :

$$E_{t-1}\Delta z_t = \frac{\sigma_\epsilon^2}{\sigma_s^2} s_{t-1} = \frac{\sigma_\epsilon^2}{\sigma_s^2}(\nu_{t-1} + \epsilon_{t-1})$$

So the forecast error is :

$$\Delta z_t - E_{t-1}\Delta z_t = u_t = \epsilon_{t-1} - \frac{\sigma_\epsilon^2}{\sigma_s^2}(\nu_{t-1} + \epsilon_{t-1})$$

Insight : If we know the ratio $\frac{\sigma_\epsilon^2}{\sigma_s^2}$, we can recover the news and noise shocks using future values of u_t and s_t.

Recovering Noise Shocks under Recoverability

How can we retrieve noise shocks under the recoverability condition ?

Example : Chahrour and Jurado (2021)

Assume the following data-generating process (DGP) for TFP :

$$\Delta z_t = b(L)\epsilon_t$$

and the signal observed by agents :

$$s_t = \nu_t + \epsilon_t$$

Under the recoverability condition, for a given horizon h, the following moment inequality must hold :

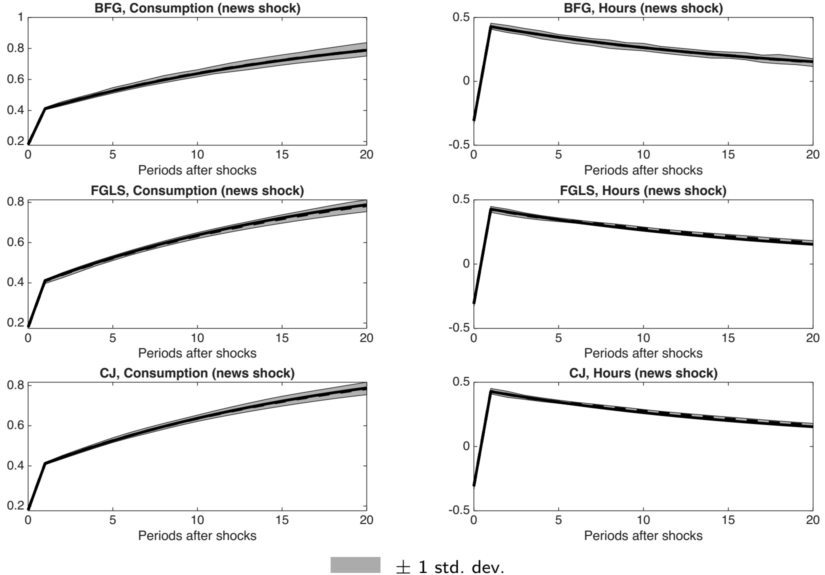
$$\mathbb{E}\left[\left(\mathbb{E}_t \Delta z_{t+h} - \Delta z_{t+h}\right)\nu_t\right] \geq 0$$

They use a VAR to estimate forecasts of TFP.

The identification strategy assumes that the spectral density matrix of the joint process is **lower-triangular**, enabling separation of noise from news shocks.

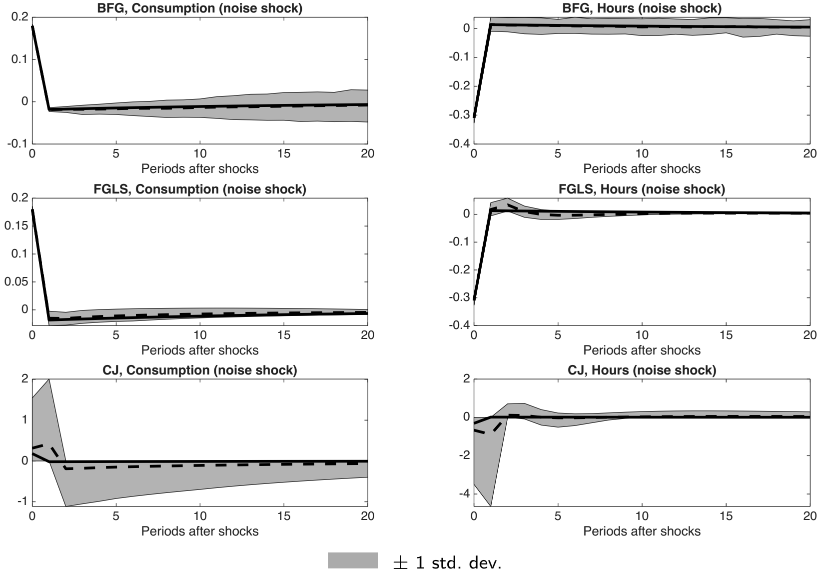
Simulation Results

Figure 1 – $T = 2500$, no surprise shock, $q = 1$



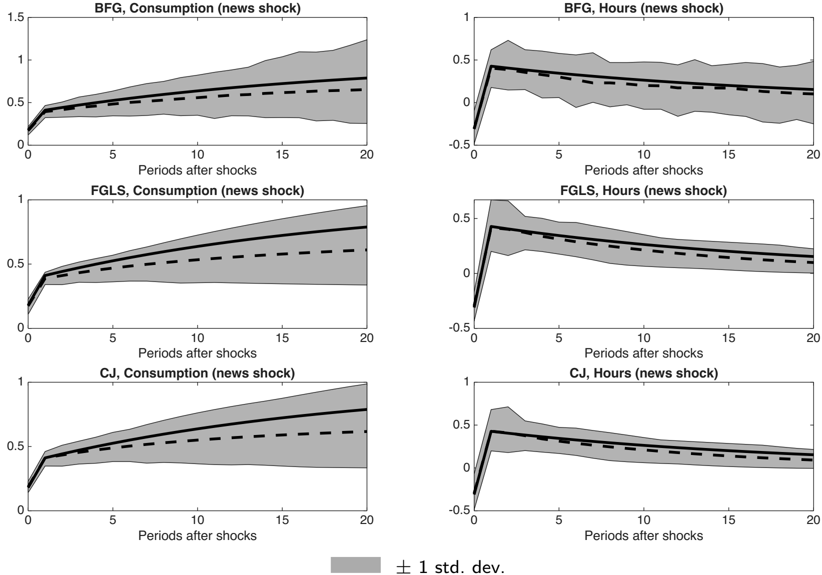
Simulation Results

Figure 2 – $T = 2500$, no surprise shock, $q = 1$



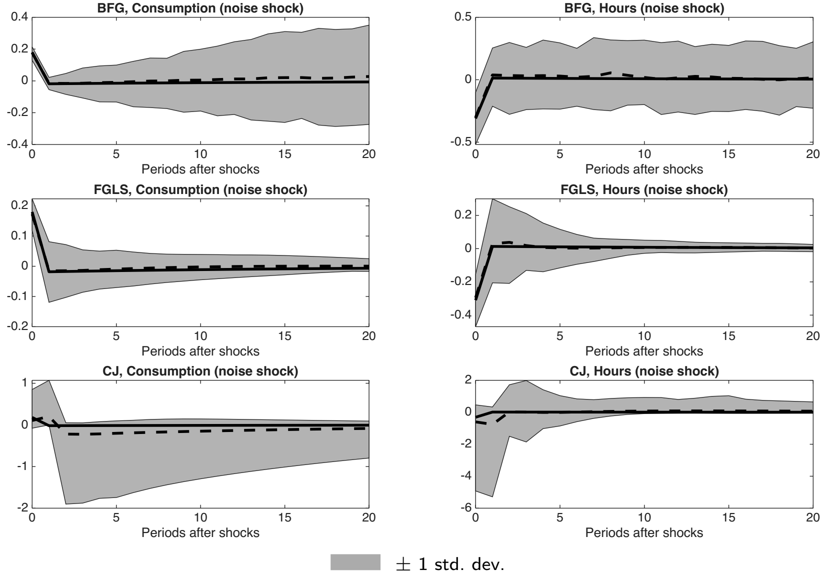
Simulation Results

Figure 3 – $T = 250$, no surprise shock, $q = 1$



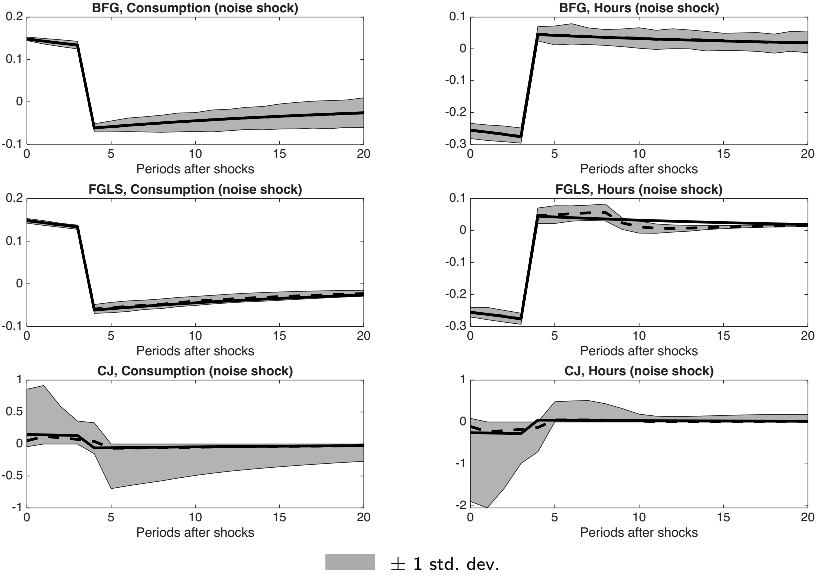
Simulation Results

Figure 4 – $T = 250$, no surprise shock, $q = 1$



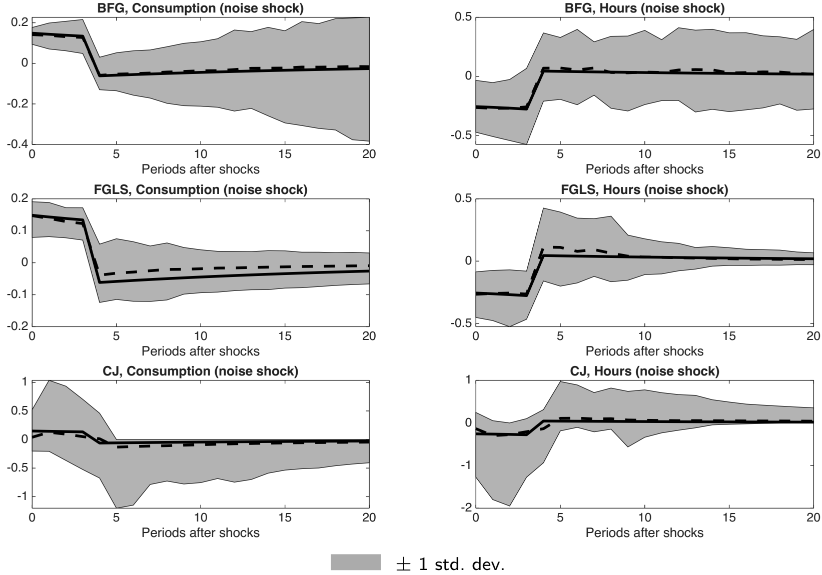
Simulation Results

Figure 5 – $T = 2500$, no surprise shock, $q = 4$



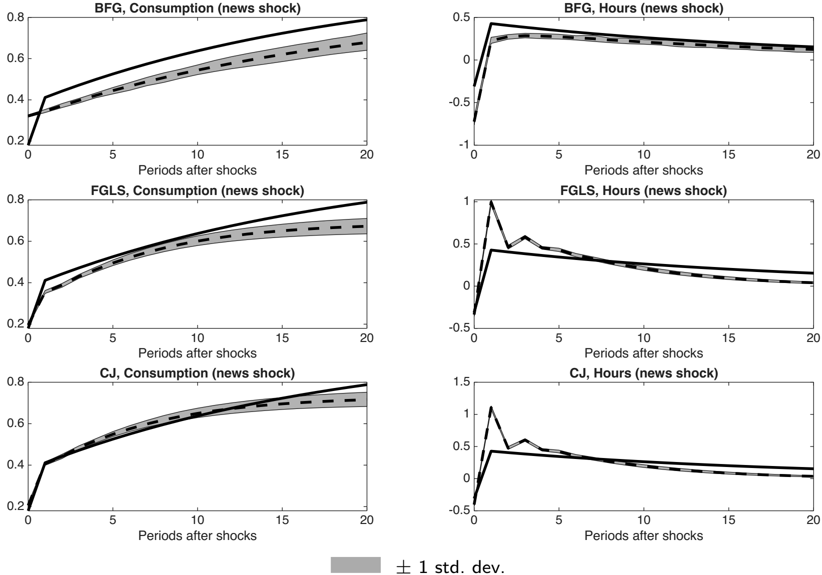
Simulation Results

Figure 6 – $T = 250$, no surprise shock, $q = 4$



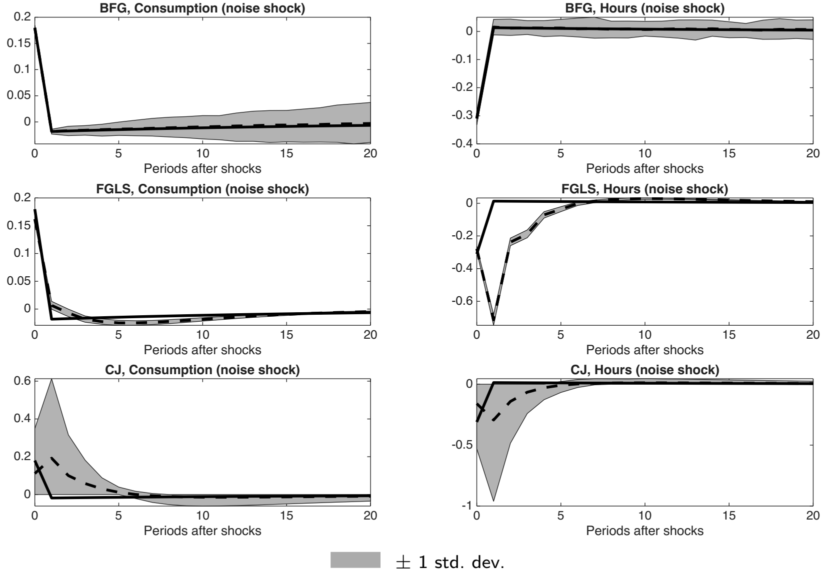
Simulation Results

Figure 7 – $T = 2500$, with surprise shock, $q = 1$



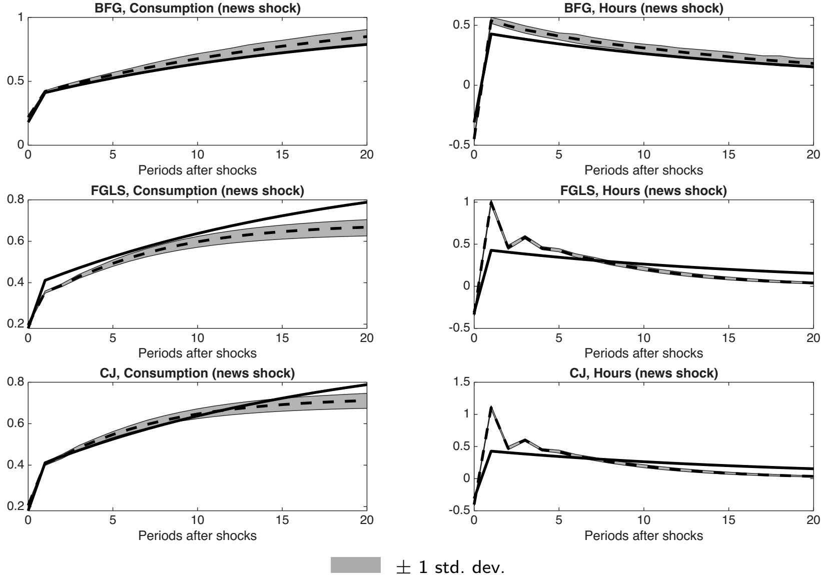
Simulation Results

Figure 8 – $T = 2500$, with surprise shock, $q = 1$



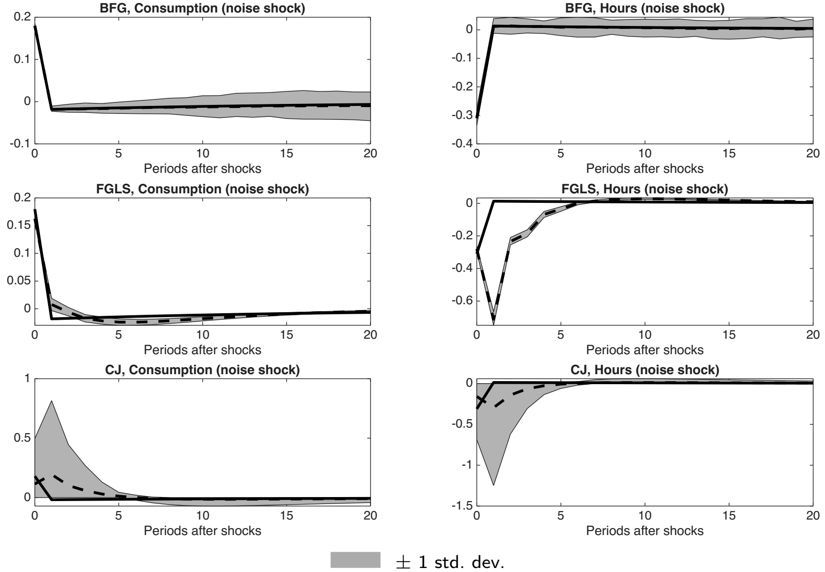
Simulation Results

Figure 9 – $T = 2500$, with surprise shock and 5 variables, $q = 1$



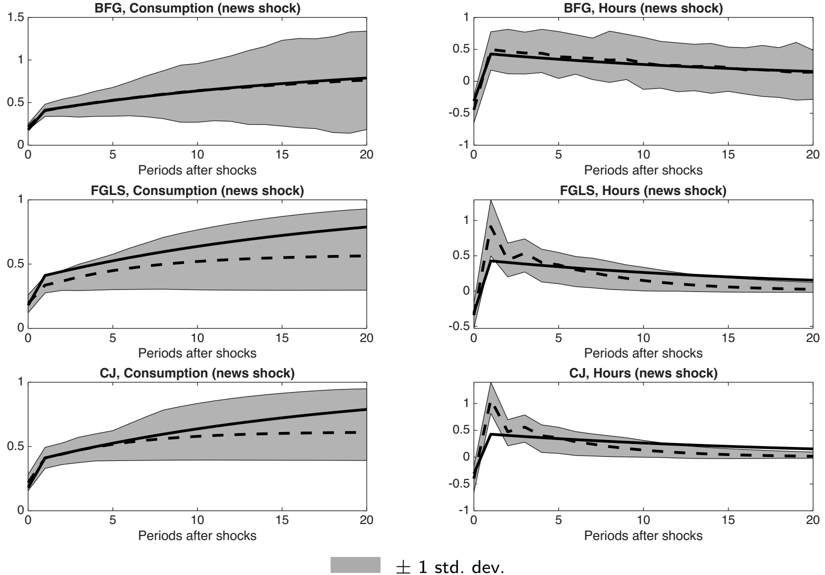
Simulation Results

Figure 10 – $T = 2500$, with surprise shock and 5 variables, $q = 1$



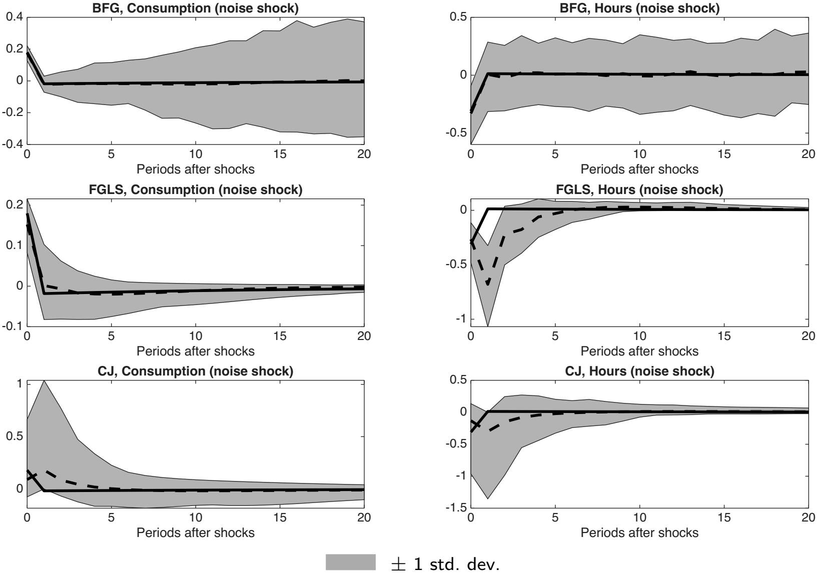
Simulation Results

Figure 11 – $T = 250$, with surprise shock and 5 variables, $q = 1$



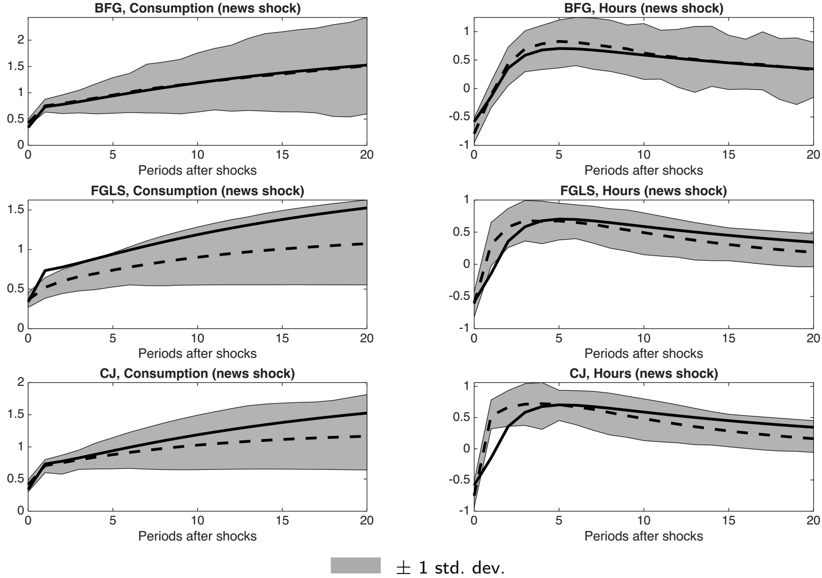
Simulation Results

Figure 12 – $T = 250$, with surprise shock and 5 variables, $q = 1$



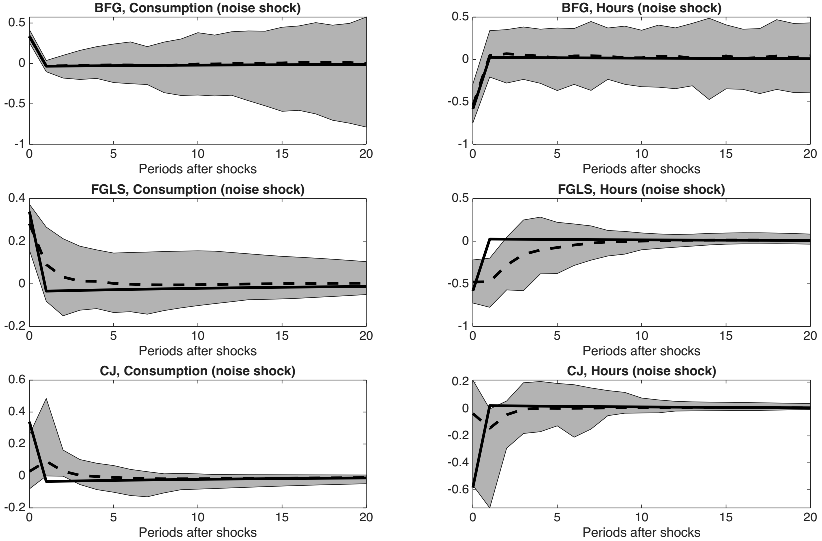
Simulation Results

Figure 13 – $T = 250$, with surprise shock and 5 variables, $q = 1$, $\rho = .5$



Simulation Results

Figure 14 – $T = 250$, with surprise shock and 5 variables, $q = 1$, $\rho = .5$



$\pm$ 1 std. dev.

Conclusion

Proposed Strategy : A simple and unified approach to identify **surprise**, **news**, and **noise** shocks related to economic fundamentals using local projections and future information.

Next Steps :

- Extend simulations to richer dynamic environments (e.g., Smets and Wouters model)
- Implement the strategy on real-world macroeconomic data