

# **What's News In Business Cycles?**

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April 19, 2010

# News as a Source of Business Cycles

- Theoretical papers:
  - Barro and King, (QJE, 1984); Beaudry and Portier (JET, 2007); Jaimovich and Rebelo (AER, 2009)
- Empirical papers: VAR estimation of anticipated shocks:
  - Cochrane (CRCSP, 1994); Beaudry and Portier (AER, 2006); Beaudry and Lucke (NBERMA, 2009); Eric Sims (2009)
- **This paper: Likelihood-based estimation of News shocks in the context of an optimizing DSGE model**

## The Model

Preferences:

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_t U(C_t - bC_{t-1} - \psi h_t^\theta S_t)$$

$$S_t = (C_t - bC_{t-1})^\gamma S_{t-1}^{1-\gamma}$$

Capital accumulation:

$$K_{t+1} = (1 - \delta(u_t))K_t + z_t^I I_t \left[ 1 - S \left( \frac{I_t}{I_{t-1}} \right) \right]$$

Production technology:

$$Y_t = z_t F(u_t K_t, X_t h_t, X_t L)$$

Resource constraint:

$$C_t + A_t I_t + G_t = Y_t$$

An exogenous wage markup:

$$\zeta_t \frac{\partial U'(V_t)}{\partial h_t} = \frac{\Lambda_t W_t}{1 + \mu_t}$$

## Introducing Anticipated Shocks

$$\ln x_t = \rho \ln x_{t-1} + \mu_t$$

$$\mu_t = \epsilon_{x,t}^0 + \epsilon_{x,t-4}^4 + \epsilon_{x,t-8}^8$$

$$\epsilon_{x,t}^i \sim \text{i.i.d. } N(0, \sigma_x^i), \quad i = 0, 4, 8$$

## Autoregressive Representation of Anticipated Shocks

$$\tilde{x}_{t+1} = M\tilde{x}_t + \eta\nu_{t+1}; \quad \nu_t \sim \text{i.i.d. } \mathcal{N}(0, I)$$

$$\begin{bmatrix} x_{t+1} \\ \epsilon_{x,t+1}^4 \\ \epsilon_{x,t}^4 \\ \epsilon_{x,t-1}^4 \\ \epsilon_{x,t-2}^4 \\ \epsilon_{x,t+1}^8 \\ \epsilon_{x,t}^8 \\ \epsilon_{x,t-1}^8 \\ \epsilon_{x,t-2}^8 \\ \epsilon_{x,t-3}^8 \\ \epsilon_{x,t-4}^8 \\ \epsilon_{x,t-5}^8 \\ \epsilon_{x,t-6}^8 \end{bmatrix} = \begin{bmatrix} \rho & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_t \\ \epsilon_{x,t}^4 \\ \epsilon_{x,t-1}^4 \\ \epsilon_{x,t-2}^4 \\ \epsilon_{x,t-3}^4 \\ \epsilon_{x,t}^8 \\ \epsilon_{x,t-1}^8 \\ \epsilon_{x,t-2}^8 \\ \epsilon_{x,t-3}^8 \\ \epsilon_{x,t-4}^8 \\ \epsilon_{x,t-5}^8 \\ \epsilon_{x,t-6}^8 \\ \epsilon_{x,t-7}^8 \end{bmatrix} + \begin{bmatrix} \sigma_x^0 & 0 & 0 \\ 0 & \sigma_x^4 & 0 \\ 0 & 0 & \sigma_x^8 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \nu_{t+1}^0 \\ \nu_{t+1}^4 \\ \nu_{t+1}^8 \end{bmatrix}$$

**Note:** A  $k$ -period anticipated shock generates  $k$  additional latent state variables.

# Seven Exogenous Driving Forces:

## 1. Stationary Neutral Productivity Shocks: $z_t$

$$Y_t = z_t F(u_t K_t, X_t h_t, X_t L)$$

$$\ln z_t = \rho_z \ln z_{t-1} + \mu_{z,t}$$

$$\mu_{z,t} = \epsilon_{z,t}^0 + \epsilon_{z,t-4}^4 + \epsilon_{z,t-8}^8$$

$$\epsilon_{z,t}^i \sim \text{i.i.d. } N(0, \sigma_z^i), \quad i = 0, 4, 8$$

## 2. Non-stationary Neutral Productivity Shocks: $X_t$

$$Y_t = z_t F(u_t K_t, X_t h_t, X_t L)$$

$$\mu_t^x \equiv \frac{X_t}{X_{t-1}}$$

$$\ln(\mu_t^x / \mu^x) = \rho_x \ln(\mu_{t-1}^x / \mu^x) + \epsilon_{x,t}^0 + \epsilon_{x,t-4}^4 + \epsilon_{x,t-8}^8$$

$$\epsilon_{x,t}^i \sim \text{i.i.d. } N(0, \sigma_x^i), \quad i = 0, 4, 8.$$



### 3. Stationary Investment-Specific Productivity Shocks: $z_t^I$

$$K_{t+1} = (1 - \delta(u_t))K_t + z_t^I I_t \left[ 1 - S \left( \frac{I_t}{I_{t-1}} \right) \right]$$

$$\ln z_t^I = \rho_{z^I} \ln z_{t-1}^I + \mu_{z^I,t}$$

$$\mu_{z^I,t} = \epsilon_{z^I,t}^0 + \epsilon_{z^I,t-4}^4 + \epsilon_{z^I,t-8}^8$$

$$\epsilon_{z^I,t}^i \sim \text{i.i.d. } N(0, \sigma_{z^I}^i), \quad i = 0, 4, 8$$

#### 4. Non-stationary Investment-Specific Productivity Shocks: $A_t$

$$C_t + A_t I_t + G_t = Y_t$$

$$A_t = A_{t-1} \mu_t^a$$

$$\ln(\mu_t^a / \mu^a) = \rho_a \ln(\mu_{t-1}^a / \mu^a) + \epsilon_{a,t}^0 + \epsilon_{a,t-4}^4 + \epsilon_{a,t-8}^8$$

$$\epsilon_{a,t}^i \sim \text{i.i.d. } N(0, \sigma_a^i), \quad i = 0, 4, 8.$$

## 5. Government Spending Shocks: $G_t$

$$C_t + A_t I_t + G_t = Y_t$$

$$g_t = \frac{G_t}{X_t^G}$$

$$X_t^G = (X_{t-1}^G)^{\rho_{xg}} (X_{t-1}^Y)^{1-\rho_{xg}}; \quad X_t^Y = A_t^{\alpha/(\alpha-1)} X_t$$

$$\ln(g_t/g) = \rho_g \ln(g_{t-1}/g) + \epsilon_{g,t}^0 + \epsilon_{g,t-4}^4 + \epsilon_{g,t-8}^8$$

$$\epsilon_{g,t}^i \sim \text{i.i.d. } N(0, \sigma_g^i), \quad i = 0, 4, 8.$$

## 6. Wage Markup Shocks: $\mu_t$

An exogenous wage markup:

$$\zeta_t \frac{\partial U'(V_t)}{\partial h_t} = \frac{\Lambda_t W_t}{1 + \mu_t}$$

$$\ln \mu_t / \mu = \rho_\mu \ln \mu_{t-1} / \mu + \mu_{\mu,t}$$

$$\mu_{\mu,t} = \epsilon_{\mu,t}^0 + \epsilon_{\mu,t-4}^4 + \epsilon_{\mu,t-8}^8$$

$$\epsilon_{\mu,t}^i \sim \text{i.i.d. } N(0, \sigma_\mu^i), \quad i = 0, 4, 8$$

## 7. Preference Shock: $\zeta_t$

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_t U(C_t - bC_{t-1} - \psi h_t^\theta S_t)$$

$$\ln \zeta_t = \rho_\zeta \ln \zeta_{t-1} + \mu_{\zeta,t}$$

$$\mu_{\zeta,t} = \epsilon_{\zeta,t}^0 + \epsilon_{\zeta,t-4}^4 + \epsilon_{\zeta,t-8}^8$$

$$\epsilon_{\zeta,t}^i \sim \text{i.i.d. } N(0, \sigma_\zeta^i), \quad i = 0, 4, 8$$

## Interpretation as Technological Diffusion

Consider the technological diffusion

$$\ln X_t = \sum_{i=0}^{\infty} (1 - \phi^i) \nu_{t-i}$$

It can be written as

$$\ln(X_t/X_{t-1}) = \phi \ln(X_{t-1}/X_{t-2}) + (1 - \phi) \nu_{t-1}$$

This is a special case of our assumed process with

$$\rho_x = \phi$$

$$\sigma_x^1 = (1 - \phi) \sigma_\nu$$

$$\sigma_x^k = 0; \quad \text{for } k = 0, 2, 3$$

## Functional Forms

$$U(V) = \frac{V^{1-\sigma} - 1}{1 - \sigma}$$

$$F(a, b, c) = a^{\alpha_k} b^{\alpha_h} c^{1-\alpha_k-\alpha_h},$$

$$S(x) = \frac{\kappa}{2}(x - \mu^I)^2$$

$$\delta(u) = \delta_0 + \delta_1(u - 1) + \frac{\delta_2}{2}(u - 1)^2$$

## Calibration

$\beta$	$\sigma$	$\alpha_k$	$\alpha_h$	$\delta_0$	$u$	$\mu^y$	$\mu^a$	$G/Y$	$h$	$\mu$
0.99	1	0.23	0.67	0.025	1	1.0045	0.9957	0.2	0.2	1.15

**Seven Observables.** Sample: 1955Q1-2006Q4

1.  $\Delta \ln Y_t =$  Output Growth
2.  $\Delta \ln C_t =$  Consumption Growth
3.  $\Delta \ln(I_t A_t) =$  Investment Growth
4.  $\Delta \ln h_t =$  Hours Growth
5.  $\Delta \text{TFP} =$  TFP Growth
6.  $\Delta \ln G_t =$  Government Consumption Growth
7.  $\Delta \ln A_t =$  Growth Rate of the Price of Investment



## Prior Parameter Distributions

- All  $\sigma_j^i$  are gamma (m,m) distributions.
- The unanticipated innovation has variance of  $3\times$  the sum of the anticipated components:

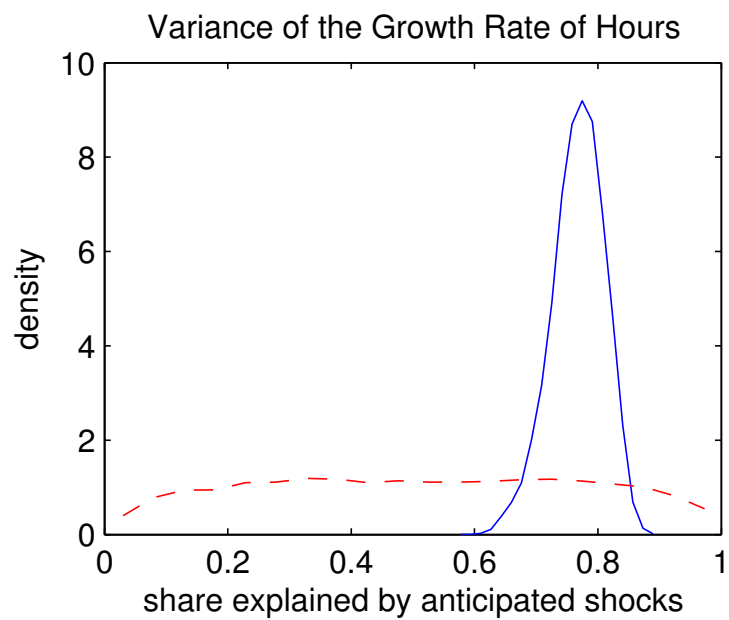
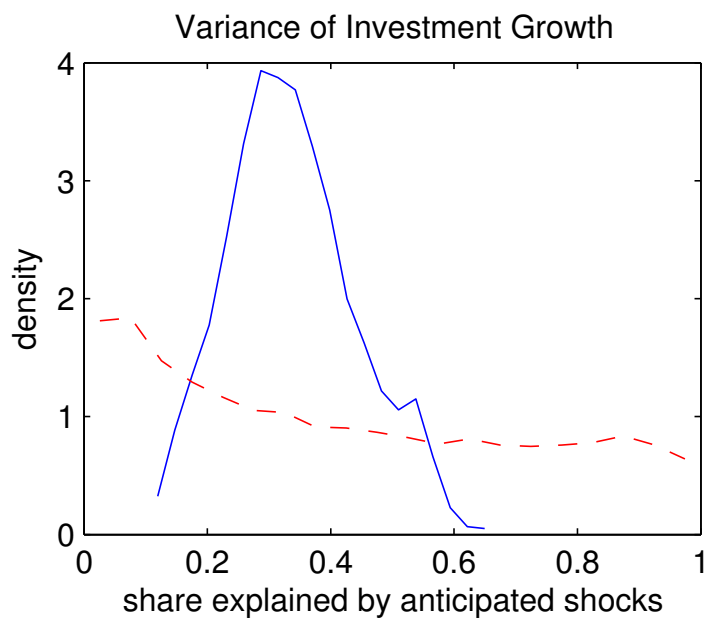
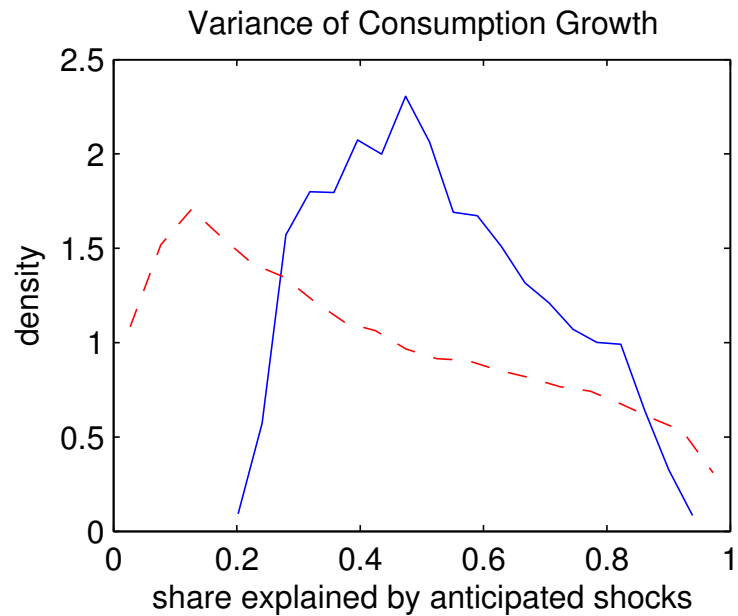
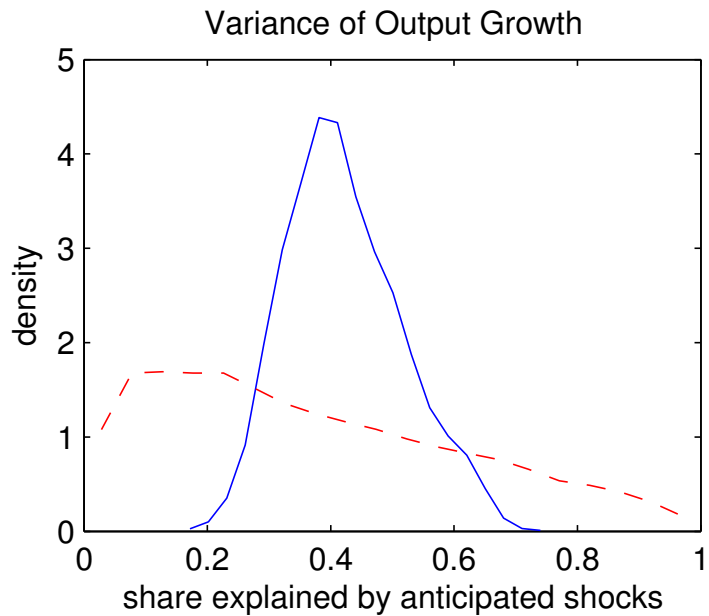
$$\frac{(\sigma_w^0)^2}{(\sigma_w^0)^2 + (\sigma_w^4)^2 + (\sigma_w^8)^2} = 0.75; \quad w = z, x, z^I, a, g, \mu, \zeta.$$

- The Jaimovich-Rebelo parameter  $\gamma$  has a uniform prior over the unit interval.
- All serial correlations beta prior distributions.

## Model Predictions

Statistic	$g^y$	$g^c$	$g^i$	$g^h$	$g^g$	$g^{tfp}$	$g^{pa}$
	Standard Deviations						
Data	0.91	0.51	2.28	0.84	1.14	0.75	0.41
Model – Bayesian Estimation	0.73	0.58	2.69	0.85	1.13	0.79	0.40
Model – ML Estimation	0.67	0.53	2.28	0.79	1.01	0.76	0.36
	Correlations with Output Growth						
Data	1.00	0.50	0.69	0.72	0.25	0.40	-0.12
Model – Bayesian Estimation	1.00	0.58	0.69	0.42	0.33	0.28	0.01
Model – ML Estimation	1.00	0.60	0.67	0.38	0.34	0.22	0.04
	Autocorrelations						
Data	0.28	0.20	0.53	0.60	0.05	-0.01	0.49
Model – Bayesian Estimation	0.43	0.39	0.60	0.14	0.02	0.03	0.47
Model – ML Estimation	0.36	0.34	0.52	0.09	0.03	0.05	0.48

Note: Bayesian estimates are medians of 500,000 draws from the posterior distributions of the corresponding population second moments.



## Share of Variance Explained by Anticipated Shocks

Specification	$g^Y$	$g^C$	$g^I$	$g^h$
1. Bayesian Estimation	0.41	0.50	0.33	0.77
2. Maximum Likelihood Estimation	0.49	0.70	0.41	0.72
3. Stock Prices Observable	0.68	0.83	0.69	0.55
4. HP Filtered Predictions	0.48	0.59	0.49	0.84
5. Parsimonious Model	0.68	0.68	0.69	0.69

## To which extent are government spending shocks, $g_t$ , anticipated?

Variance Decomposition				
Innovation	Bayesian		MLE	
	$g^Y$	$g^g$	$g^Y$	$g^g$
Total	0.09	0.95	0.11	0.96
$\epsilon_{g^0}$	0.03	0.37	0.03	0.25
$\epsilon_{g^4}$	0.04	0.35	0.08	0.71
$\epsilon_{g^8}$	0.02	0.23	0.00	0.00

Note: For the Bayesian estimation figures correspond to the mean of 500,000 draws from the posterior distribution of the variance decomposition.

## How important are shocks to the price of investment?

- Our estimates: share of  $\text{var}(g^y)$  explained by  $\epsilon_a^i$  is zero
- Justiniano et al.: share of  $\text{var}(g^y)$  explained by  $\epsilon_a^i > 60\%$ .
- What explains the difference in results? Observability of rel. price of investment. Observable in our paper but not in JPT.

**Relation To VAR Evidence on Anticipated Productivity Growth Shocks:** Beaudry and Portier (BP), *AER* 2006

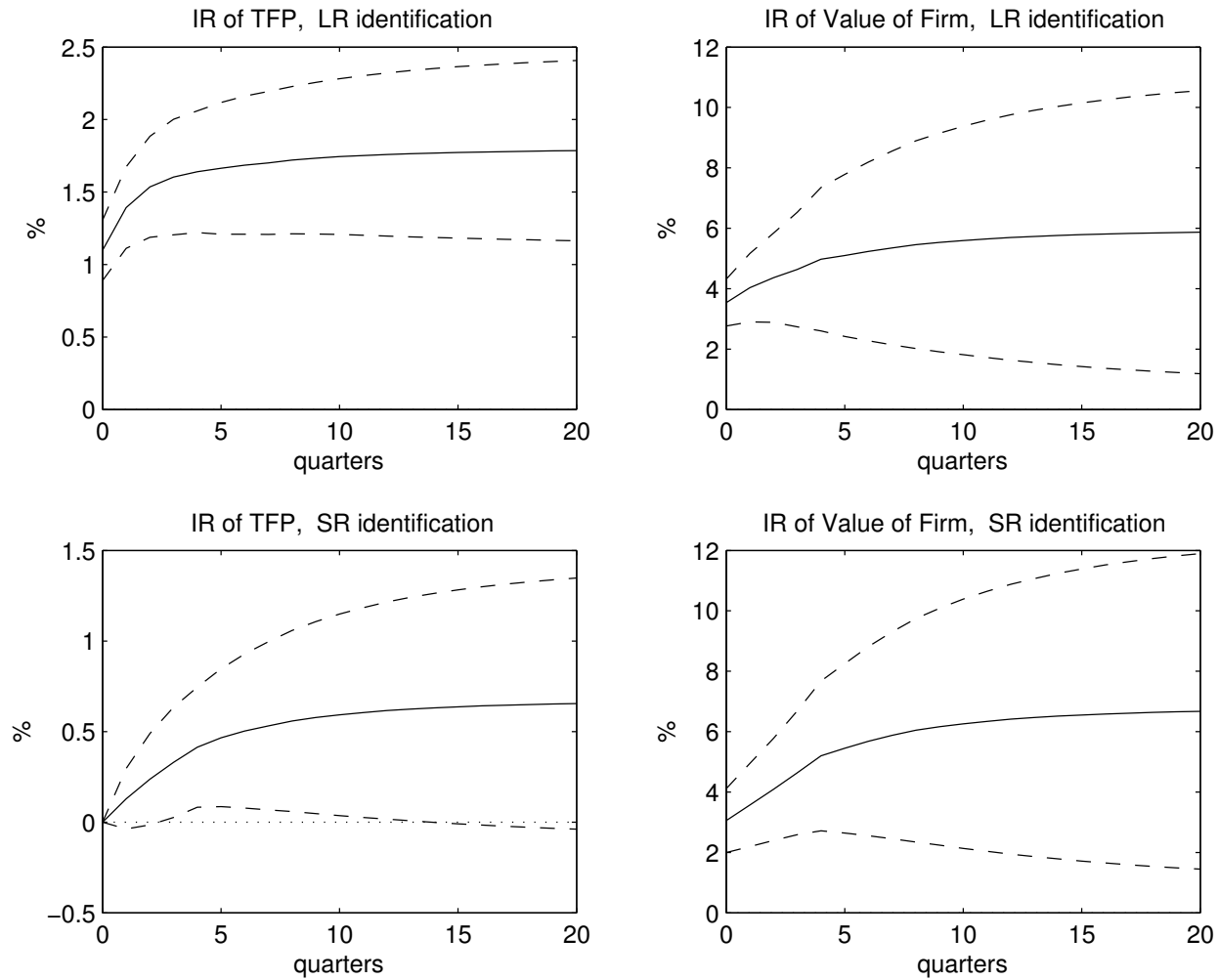
$$\begin{bmatrix} \Delta \ln TFP_t \\ \Delta \ln SP_t \end{bmatrix} = C(L) \begin{bmatrix} \epsilon_t^1 \\ \epsilon_t^2 \end{bmatrix}$$

**A BP News Shock Satisfies Simultaneously:**

- It does not affect TFP contemporaneously
- It does affect TFP in the long run.

Note: Our model **does not have** a BP-style bivariate VAR representation.

# Beaudry-Portier-Style VAR Regressions: Parsimonious Model





## Summary of Main Findings

1. In the context of our estimated model anticipated shocks explain about half of the movements in aggregate variables at business-cycle frequency.
2. In a parsimonious model, the most important anticipated shocks are innovations to TFP.
3. The estimated importance of shocks to the price of investment is zero when this variable is treated as an observable in the estimation.
4. Government spending shocks have an important anticipated component.

**EXTRAS**

## Identification of Anticipated Shocks: An Illustrative Example

- Model:  $x_t = 0.9x_{t-1} + \epsilon_t^0 + \epsilon_{t-1}^1 + \epsilon_{t-2}^2$

$$y_t = 0.5y_{t-1} + \epsilon_t^1$$

$$z_t = \epsilon_t^2$$

- Observables:  $x_t$  and  $v_t \equiv y_t + z_t$
- Case 1: True values:  $(\sigma_0, \sigma_1, \sigma_2) = (0.2, 0.4, 0.8)$ , prior are gamma(.5,.2), posterior means (0.24, 0.4, 0.79) posterior standard deviations (0.06, 0.02, 0.04).
- Case 2: True values:  $(\sigma_0, \sigma_1, \sigma_2) = (0.8, 0.8, 0.8)$ , prior are gamma(.5,.2), posterior means (0.75, 0.73, 0.77) posterior standard deviations (0.07, 0.04, 0.05).

