Online Appendix for 'Is There a Single Shock that Drives the Majority of Business Cycle Fluctuations?'

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Abstract

This online appendix consists of the following appendices: an appendix detailing the VAR Bayesian estimation procedure; an appendix describing the DSGE model used for the Monte Carlo Simulation of Section 4 of the paper, including calibration details and additional simulation results from a model where IST news is the business cycle shock for both perfect- and imperfect-information structures (with the latter structure also used for simulation results from a model where the business cycle shock does not exist); an appendix with additional Monte Carlo results regarding the role of hours in the analysis; and an appendix presenting additional results from several robustness checks I ran to confirm that my benchmark results hold across various modifications and extensions of my benchmark setting.

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Appendix A Bayesian Estimation Procedure

The VAR given by Equation (4) of the paper can be written in matrix notation as follows:

$$Y = XB + U, \tag{A.1}$$

where $Y = [y_1, ..., y_T]'$, $X = [X_1, ..., X_T]'$, $X_t = [y_{t-1}, ..., y_{t-p}, 1]'$, $B = [B_1, ..., B_p, B_c]'$, k and p are the number of variables and lags, respectively, and $U = [u_1, ..., u_T]'$. B here represents the reduced form VAR coefficient matrix and Σ is the variance-covariance matrix of the reduced form VAR innovations. I follow the conventional approach of specifying a normal-inverse Wishart prior distribution for the reduced-form VAR parameters:

$$vec(B) \mid \Sigma \sim N(vec(\bar{B}_0), \Sigma \otimes N_0^{-1}), \tag{A.2}$$

$$\Sigma \sim IW_k(v_0 S_0, v_0), \tag{A.3}$$

where N_0 is a kpxkp positive definite matrix, S_0 is a kxk covariance matrix, and $v_o > 0$. As shown by Uhlig (1994), the latter prior implies the following posterior distribution:

$$vec(B) \mid \Sigma \sim N(vec(\bar{B}_T), \Sigma \otimes N_T^{-1}), \tag{A.4}$$

$$\Sigma \sim IW_k(v_T S_T, v_T), \tag{A.5}$$

where $v_T = T + v_0$, $N_T = N_0 + X'X$, $\bar{B}_T = N_T^{-1}(N_0\bar{B}_0 + X'X\hat{B}), S_T = \frac{v_0}{v_T}S_0 + \frac{T}{v_T}\hat{\Sigma} + \frac{1}{v_T}(\hat{B} - \bar{B}_0)'N_0 N_T^{-1}X'X(\hat{B} - \bar{B}_0)$, $\hat{B} = (X'X)^{-1}X'Y$, and $\hat{\Sigma} = (Y - X\hat{B})'(Y - X\hat{B})/T$.

I follow the sign restrictions literature and use a weak prior, i.e., $v_0 = 0$, $N_0 = 0$, and arbitrary S_0 and $\bar{B}_0$. This implies that the prior distribution is proportional to $|\Sigma|^{-(k+1)/2}$ and that $v_T = T$, $S_T = \hat{\Sigma}$, $\bar{B}_T = \hat{B}$, and $N_T = X'X$.

It is further assumed that there exists a linear mapping between the reduced-form innovations and economic shocks, e_t, given by

$$u_t = Ae_t. \tag{A.6}$$

The impact matrix A must satisfy $AA' = \Sigma$. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, C (e.g, the

Cholesky factor of Σ), the entire space of permissible impact matrices can be written as CD, where D is a k x k orthonormal matrix (i.e., $D' = D^{-1}$ and $DD' = I$, where I is the identity matrix). I follow the efficient method proposed by Rubio-Ramirez et al. (2010) for generating orthonormal matrices Ds and the associated identification, impact A matrices.

Formally, the posterior simulator for $\{B,\Sigma,D\}$ can be described as follows:

1. Draw Σ from an $IW_k(T\hat{\Sigma}, T)$ distribution.

2. Draw B from the conditional distribution $MN(\hat{B}, \Sigma \otimes (X'X)^{-1})$.

3. Draw D using the algorithm from Rubio-Ramirez et al. (2010) and compute the impact Matrix $A = CD$ where C is the Cholsky factor of Σ; then, use the matrix triplet $\{B,\Sigma,D\}$ to compute the impulse response function and forecast error variance contributions of e_t.

4. Keep $\{B,\Sigma,D\}$ if Restrictions 1 and 2 from Section 3 of the paper are met.

5. Repeat steps 1-4 a large number of times and collect the drawn $\{B,\Sigma,D\}$'s.

Appendix B Model

This appendix lays out a two-sector medium-scale DSGE model whose structure builds on Moura (2018), who extended the Smets and Wouters (2007) framework into an explicit two-sector structure that accommodates non-identical sector-specific production functions, sector-specific price and wage stickiness, and labor and capital reallocation frictions. Abstracting from these three elements altogether would result in perfect correspondence between RPI and IST at all horizons, while their presence results only in a long-run quantitative equivalence between RPI and IST. Hence, this modeling framework is suitable for my purposes as it accounts for RPI endogeneity in a structural manner and thus constitutes a valuable lens through which to examine the suitability of my identification procedure for answering the question posed in this paper's title. The main difference between my framework and that of Moura (2018) lies in my adding to the latter news shocks to both TFP and IST.

The general setup for both the consumption and investment sectors is very similar, with the only difference between them being the introduction of IST for the modeling of the investment sector. In what follows below I present the main building blocks of the model.

B.1 Households

There is a continuum of optimizing households, indexed by $j \in [0,1]$, that maximize their lifetime utility subject to their inter-temporal budget constraint and the sector-specific capital accumulation constraints by choosing consumption bundle $C_t(j)$; hours worked in the consumption sector $L_t^C(j)$ and hours worked in the investment sector $L_t^I(j)$, where the aggregate level of hours worked for each household is defined as $L_t(j) = \left[(L_t^C(j))^{1+\tau} + (L_t^I(j))^{1+\tau}\right]^{\frac{1}{1+\tau}}$ with $\tau \geq 0$; one-period securities bonds $B_{t+1}(j)$ with price equal to the inverse of next period's risk-free interest rate $(1/R_{t+1})$; investment bundle $I_t(j)$; next period's installed capital in the consumption sector $K_{t+1}^C(j)$ and corresponding installed capital in the investment sector $K_{t+1}^I(j)$; and capital utilization rate $u_t(j)$ where the aggregate level of capital services for each household is defined as $K_{t+1}^s(j) = \left[(K_{t+1}^{s,C}(j))^{1+\nu} + (K_{t+1}^{s,I}(j))^{1+\nu}\right]^{\frac{1}{1+\nu}}$ with $\nu \geq 0$ and $K_{t+1}^s(j) = u_t(j)K_{t+1}(j)$, $K_{t+1}^{s,C}(j) = u_t(j)K_{t+1}^C(j)$, $K_{t+1}^{s,I}(j) = u_t(j)K_{t+1}^I(j)$. Formally, this maximization problem can be written as

$$\max_{\left\{\substack{C_t(j),L_t^C(j),L_t^I(j),B_{t+1}(j),I_t(j),\\ K_{t+1}^C(j),K_{t+1}^I(j),K_{t+1}^I,(j)u_t(j)}\right\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \zeta_t \left[\frac{(C_t(j) - hC_{t-1})^{1-\sigma_c}}{1-\sigma_c} exp\left(\frac{\sigma_c - 1}{1+\sigma_l}\left[(L_t^C(j))^{1+\omega} + (L_t^I(j))^{1+\omega}\right]^{\frac{1+\sigma_l}{1+\omega}}\right)\right]$$

$$\begin{aligned}
s.t\ \ & C_t(j) + RPI_t I_t(j) + \frac{B_{t+1}(j)}{R_{t+1}P_t^C} - T_t \leq \frac{B_t(j)}{P_t^C} + \frac{W_t^{w,C}L_t^C(j) + W_t^{w,I}L_t^I(j)}{P_t^C} + \\
& + RPI_t\left[R_t^{K,C}u_t^C(j)K_t^C(j) + R_t^{K,I}u_t(j)K_t^I(j) - \psi(u_t(j))K_t^C(j) - \psi(u_t(j))K_t^I(j)\right] + \frac{Div_t}{P_t^C}, \qquad \text{(B.1)}\\
& K_{t+1} = (1-\delta)K_t + \left[1 - \Upsilon\left(\frac{I_t}{I_{t-1}}\right)\right] I_t,\\
& K_{t+1}^s(j) = \left[(K_{t+1}^{s,C}(j))^{1+\nu} + (K_{t+1}^{s,I}(j))^{1+\nu}\right]^{\frac{1}{1+\nu}},\\
& K_{t+1}^s(j) = u_t(j)K_{t+1}(j)\ K_{t+1}^{s,C}(j) = u_t(j)K_{t+1}^C(j)\ K_{t+1}^{s,I}(j) = u_t(j)K_{t+1}^I(j),
\end{aligned}$$

where ζ_t is an intertemporal preference shock; h is the external habit formation parameter; σ_c is the inverse elasticity of inter-temporal substitution; σ_l is the inverse Frisch elasticity of labor supply; T_t are lump-sum taxes; $W_t^{h,x}$ is hourly wage paid to households for working in sector x, with $x = C, I$; $K_t^{s,x}(j) = u_t(j)K_t^x(j)$ is capital services used in production in sector x, where $u_t^x(j)$ is the sector-specific capital utilization rate and $K_t^x(j)$ is sector-specific installed capital; RPI_t represents the relative price of investment, i.e., $\frac{P_t^I}{P_t^C}$, where P_t^C and P_t^I are the prices of consumption and investment bundles $C_t(j)$ and $I_t(j)$, respectively; $RPI_t R_t^{K,x} u_t^x(j) K_t^x(j)$ is income earned from renting capital from sector x with $R_t^{K,x}$ denoting the rental rate of capital services in sector x and $\psi(u_t(j))K_t^x(j)$ representing the resource cost of increasing the rate of capital utilization in sector x;[1] Div_t denotes total dividends distributed by imperfectly competitive retail firms and labour unions in the economy; Υ is the investment adjustment cost function, with $\Upsilon(\gamma) = \Upsilon'(\gamma) = 0$ and $\Upsilon''(\cdot) > 0$;[2] and δ is the capital depreciation rate.

Importantly, as in Horvath (2000), the above specification of the disutility of working implies imperfect labor mobility across sectors when $\omega > 0$, allowing for sectoral heterogeneity in wages and hours worked. And the similar specification of the aggregation of capital across sectors introduces frictions in the sectoral reallocation of capital.

B.2 Intermediate Labor Union Sector and Labor Packers

There is a continuum of intermediate sector-specific labor unions, that differentiate the labor services supplied by households and sell them to *labor packers* who then package and resell them to intermediate goods producers. It is assumed that these labor unions set nominal wages subject to Calvo frictions and that each labor union represents a different labor service; I index the continuum of these labor services by $l \in [0, 1]$.

Labor Packers. The labor packers in sector x, with $x = C, I$, maximize profits subject to a Dixit and Stiglitz (1977) aggregator:

$$\begin{aligned} &\max_{L_t^x, L_t^x(l)} W_t^x L_t^x - \int_0^1 W_t^x(l) L_t^x(l) dl \\ &s.t\ \ L_t^x = \left[\int_0^1 L_t^x(l)^{\frac{\phi^{w,x}-1}{\phi^{w,x}}} dl\right]^{\frac{\phi^{w,x}}{\phi^{w,x}-1}} \qquad , \end{aligned} \tag{B.2}$$

[1] I assume the following capital utilization cost function: $\psi(u_t(j)) = \frac{\omega}{2}(u_t(j) - 1)^2$.

[2] I assume the following investment adjustment cost function: $\Upsilon\left(\frac{I_t}{I_{t-1}}\right) = \frac{\varpi}{2}\left(\frac{I_t(j)}{I_{t-1}(j)} - 1\right)^2$.

where W_t^x and $W_t^x(l)$ are the prices of the composite and intermediate sector-specific labor services, respectively, and $\phi^{w,x} > 1$ the sector-specific elasticity of substitution among the different labor services. Combining the FOCs of Problem (B.2) gives

$$L_t^x(l) = L_t^x \left(\frac{W_t^x(l)}{W_t^x} \right)^{-\phi^{w,x}}. \tag{B.3}$$

Labor Unions. Sector-specific nominal wage rigidities are introduced into the model via a Calvo (1983) pricing scheme with partial indexation: unions in sector x have market power and can readjust wages with probability $1 - \xi_{w,x}$ in each period; for those unions that cannot readjust, $W_t^x(l)$ will get partially indexed to last period's consumption goods inflation $\pi_{t-1,C}$ (i.e., $\frac{P_{t-1}^C}{P_{t-2}^C}$). The optimal wage set by the union that is allowed to re-optimize its wage is obtained from solving the following optimization problem:

$$\begin{aligned} &\max_{\widetilde{W}_t^x(l)} \mathbb{E}_t \sum_{s=0}^{\infty} \xi_{w,x}^{t+s} \frac{\beta^{t+s} \Xi_{t+s} P_t^C}{\Xi_t P_{t+s}^C} \left[W_t^x(l) - W_{t+s}^{h,x} \right] L_{t+s}(l) \\ s.t \;\; & L_t^x(l) = L_t^x \left(\frac{W_t^x(l)}{W_t^x} \right)^{-\phi^{w,x}}, \\ & W_t^x(l) = \widetilde{W}_0^x(l) \prod_0^t \pi_{t,C}^{\iota_{w,x}}, \end{aligned} \tag{B.4}$$

where $\widetilde{W}_t^x(l)$ is the newly set wage; $\xi_{w,x}$ is the Calvo (1983) probability of being allowed to optimize one's wage; $\frac{\beta^{t+s}\Xi_{t+s}}{\Xi_t P_{t+s}}$ is the nominal discount factor for households, where $\Xi_t = \zeta_t (C_t - hC_{t-1})^{-\sigma_c}$ $exp\left(\frac{\sigma_c - 1}{1+\sigma_l} \left[(L_t^C(j))^{1+\omega} + (L_t^I(j))^{1+\omega} \right]^{\frac{1+\sigma_l}{1+\omega}} \right)$; and $0 \leq \iota_{w,x} < 1$ is the parameter governing the partial indexation mechanism.

B.3 Final Good Firms

The sector-specific final good Y_t^x $(x = C, I)$ is produced by final good firms as a composite made of a continuum of sector-specific intermediate goods, indexed by $i \in [0, 1]$. The final good is supplied to consumers, investors, and the government, and is purchased in a monopolistically competitive market from the intermediate goods firms, at monopolistic price $P^x(i)$.

All final good firms have access to a technology that allows them to transform intermediate goods into final goods via a Dixit and Stiglitz (1977) aggregator, leading to the following maximization problem facing final good firms:

$$
\begin{aligned}
&\max_{Y_t, Y_t(i)} P_t^x Y_t^x - \int_0^1 P_t^x(i) Y_t^x(i) di \\
&s.t \;\; Y_t^x = \left[\int_0^1 Y_t^x(i)^{\frac{\phi^{p,x}-1}{\phi^{p,x}}} di \right]^{\frac{\phi^{p,x}}{\phi^{p,x}-1}} \qquad ,
\end{aligned}
\tag{B.5}
$$

where P_t^x and $P_t^x(i)$ are the prices of the composite and intermediate produced goods in sector x, respectively, and $\phi^{p,x} > 1$ is the elasticity of substitution among the different goods. Combining the FOCs of Problem (B.5) gives

$$
Y_t^x(i) = Y_t^x \left(\frac{P_t^x(i)}{P_t^x} \right)^{-\phi^{p,x}}. \tag{B.6}
$$

B.4 Intermediate Goods Producers

There is a continuum of intermediate goods producers in both the consumption and investment sectors that produce good Y_t^x. Since the only effective asymmetry between the modeling of these two sectors lies in the technology used to produce the intermediate good, I proceed in this section by separately presenting the modeling of each sector's intermediate goods producers.

Consumption Sector. The intermediate goods producers in the consumption sector produce good $Y_t^C(i)$ using the following technology:

$$
Y_t^C(i) = A_t K_t^{s,C}(i)^{\alpha_C} L_t^C(i)^{1-\alpha_C} - \varphi_t^C, \tag{B.7}
$$

where A_t represent TFP in the economy; $K_t^{s,C}(i) = u_t(i) K_t^C(i)$ is capital services used in production, where $u_t(i)$ is the capital utilization rate and $K_t^C(i)$ is installed capital; $L_t^C(i)$ is the labor input; and φ_t^C is a deterministic fixed production cost with a trend that is included to ensure proper scaling of the fixed cost. I assume that intermediate goods producers are perfectly competitive in the input markets; they minimize costs by choosing L_t^C and $K_t^{s,C}$, taking wages and capital services rental rates as given, subject to the production function (B.7):

$$
\begin{aligned}
&\min_{L_t^C(i), K_t^{s,C}(i)} W_t^C L_t^C(i) - R_t^{k,C} K_t^{s,C}(i) \\
&s.t \;\; Y_t^C(i) = A_t K_t^{s,C}(i)_C^{\alpha} L_t^C(i)^{1-\alpha_C} - \varphi_t^C,
\end{aligned}
\tag{B.8}
$$

which yields the following FOCs:

$$(\partial L_t^C): \quad \Theta_t^C(i)(1-\alpha_C)A_t K_t^{s,C}(i)_C^{\alpha} L_t^C(i)^{-\alpha_C} = W_t^C, \tag{B.9}$$

$$(\partial K_t^{s,C}): \quad \Theta_t^C(i)\alpha_C A_t K_t^{s,C}(i)^{(\alpha_C-1)} L_t^C(i)^{(1-\alpha_C)} = R_t^{k,C}, \tag{B.10}$$

where Θ_t is the Lagrange multiplier associated with the production function and equals marginal cost MC_t^C, which is the same for all firms in the consumption sector and whose expression can be written as

$$MC_t^C = \frac{1}{A_t} W_t^{C\,1-\alpha_C} (R_t^{k,C})^{\alpha_C} \alpha_C^{-\alpha_C} (1-\alpha_C)^{(-1-\alpha_C)}. \tag{B.11}$$

Nominal price rigidities are introduced into the model via a Calvo (1983) pricing scheme with partial indexation: retail firms can readjust prices with probability $1-\xi_{p,C}$ in each period; for those firms that cannot readjust, $P_t^C(i)$ will get partially indexed to last period's consumption goods inflation $\pi_{t-1,C}$. The optimal price set by the firm that is allowed to re-optimise its price is obtained from solving the following optimization problem:

$$\begin{aligned}
&\max_{\widetilde{P}_t^C(i)} \mathbb{E}_t \sum_{s=0}^{\infty} \xi_{p,C}^{t+s} \frac{\beta^{t+s}\Xi_{t+s}P_t^C}{\Xi_t P_{t+s}^C} \left[P_t^C(i) - MC_{t+s}^C\right] Y_{t+s}^C(i) \\
s.t \;\; & Y_t^C(i) = Y_t^C \left(\frac{P_t^C(i)}{P_t^C}\right)^{-\phi^{p,C}}, \\
& P_t^C(i) = \widetilde{P}_0^C(i) \prod_0^t \pi_{t,C}{}^{\iota_{p,C}},
\end{aligned} \tag{B.12}$$

where $\widetilde{P}_t^C(i)$ is the newly set price, $\xi_{p,C}$ is the Calvo (1983) probability of being allowed to optimize one's price, $\frac{\beta^{t+s}\Xi_t}{\Xi_{t+s}P_{t+s}}$ is the nominal discount factor for households already defined above for Problem (B.4), $0 \leq \iota_{p,C} < 1$ is the parameter governing the partial indexation mechanism, and MC_t^C is the firm's nominal marginal cost.

Investment Sector. The intermediate goods producers in the investment sector produce good $Y_t^I(i)$ using the following technology:

$$Y_t^I(i) = A_t S_t K_t^{s,I}(i)^{\alpha_I} L_t^I(i)^{1-\alpha_I} - \varphi_t^I, \tag{B.13}$$

where A_t represent TFP in the economy; S_t is IST; $K_t^{s,I}(i) = u_t(i)K_t^I(i)$ is capital services used in production, where $u_t(i)$ is the capital utilization rate and $K_t^I(i)$ is installed capital; $L_t^I(i)$ is the labor input; and φ_t^I is a deterministic fixed production cost with a trend that is included to ensure proper scaling of the fixed cost. Apart from the presence of IST in the production function of intermediate firms in the investment sector, the modeling of these firms is prefectly symmetric with respect to that of intermediate firms in the consumption sector.

Specifically, I assume that intermediate goods producers are perfectly competitive in the input markets; they minimize costs by choosing L_t^I and $K_t^{s,I}$, taking wages and capital services rental rates as given, subject to the production function (B.7):

$$\begin{aligned} &\min_{L_t^I(i),K_t^{s,I}(i)} W_t^I L_t^I(i) - R_t^{k,I} K_t^{s,I}(i) \\ &s.t\ \ Y_t^I(i) = A_t S_t K_t^{s,I}(i)_I^{\alpha} L_t^I(i)^{1-\alpha_I} - \varphi_t^I, \end{aligned} \tag{B.14}$$

which yields the following FOCs:

$$(\partial L_t^I): \quad \Theta_t^I(i)(1-\alpha_I) A_t S_t K_t^{s,I}(i)_I^{\alpha} L_t^I(i)^{-\alpha_I} = W_t^I, \tag{B.15}$$

$$(\partial K_t^{s,I}): \quad \Theta_t^I(i)\alpha_I A_t S_t K_t^{s,I}(i)^{(\alpha_I-1)} L_t^I(i)^{(1-\alpha_I)} = R_t^{k,I}, \tag{B.16}$$

where Θ_t is the Lagrange multiplier associated with the production function and equals marginal cost MC_t^I, which is the same for all firms in the consumption sector and whose expression can be written as

$$MC_t^I = \frac{1}{A_t S_t} W_t^{I^{1-\alpha_I}} (R_t^{k,I})^{\alpha_I} \alpha_I^{-\alpha_I} (1-\alpha_I)^{(-1-\alpha_I)}. \tag{B.17}$$

Nominal price rigidities are introduced into the model via a Calvo (1983) pricing scheme with partial indexation: retail firms can readjust prices with probability $1-\xi_{p,I}$ in each period; for those firms that cannot readjust, $P_t^I(i)$ will get partially indexed to last period's consumption goods inflation $\pi_{t-1,I}$. The optimal price set by the firm that is allowed to re-optimise its price is obtained from solving the following optimization problem:

$$\begin{aligned} &\max_{\widetilde{P}_t^I(i)} \mathbb{E}_t \sum_{s=0}^{\infty} \xi_{p,I}^{t+s} \frac{\beta^{t+s}\Xi_{t+s} P_t^C}{\Xi_t P_{t+s}^C} \left[P_t^I(i) - MC_{t+s}^I \right] Y_{t+s}^I(i) \\ &s.t\ \ Y_t^I(i) = Y_t^I \left(\frac{P_t^I(i)}{P_t^I} \right)^{-\phi^{p,I}}, \\ &P_t^I(i) = \widetilde{P}_0^I(i) \prod_0^t \pi_{t,I}{}^{\iota_{p,I}}, \end{aligned} \tag{B.18}$$

where $\widetilde{P}_t^I(i)$ is the newly set price, $\xi_{p,I}$ is the Calvo (1983) probability of being allowed to optimize one's price, $\frac{\beta^{t+s}\Xi_t}{\Xi_{t+s}P_{t+s}}$ is the nominal discount factor for households already defined above for Problem (B.4), $0 \leq \iota_{p,I} < 1$ is the parameter governing the partial indexation mechanism, and MC_t^I is the firm's nominal marginal cost.

B.5 Aggregate Resource Constraints

Final output in the consumption sector may either be transformed into a single type of consumption good that is consumed by households or by the government, while final output in the investment sector may either be transformed into a single type of investment good that is consumed by households or by the government, or used up through capital utilization costs. In particular, the economy-wide resource constraints for consumption and investment sectors are given by

$$Y_t^C = C_t + G_t^C, \tag{B.19}$$

$$Y_t^I = I_t + G_t^I + \psi^d(u_t)K_t, \tag{B.20}$$

where G_t^C and G_t^I represent government spending on consumption and investment goods, respectively.

Nominal GDP is defined as $P_t^C(C_t + G_t^C) + P_t^I(I_t + G_t^I)$ where, as usual, capital utilization costs are accounted for as intermediate consumption and do not show up in GDP. Real GDP (Y_t) in consumption units is then given by

$$Y_t = C_t + G_t^C + RPI_t(I_t + G_t^I). \tag{B.21}$$

B.6 Monetary Policy

There is assumed to be a central bank that follows a nominal interest rate rule by adjusting its instrument in response to deviations of consumption goods inflation from steady state inflation as well as deviations of real GDP growth rate from its steady state growth rate μ, which is equal to $\mu = \mu_A + \alpha_C\mu_S$ where μ_A and μ_S are the steady state growth rates of TFP and IST, respectively. This Taylor-like policy rule is given by the following equation:

$$\frac{R_{t+1}}{R^*} = \left(\frac{R_t}{R^*}\right)_r^{\rho} \left[\left(\frac{\pi_{t,C}}{\pi_C^*}\right)^{r_\pi} \left(\frac{Y_t}{Y_{t-1}\mu}\right)^{r_y} \right]^{1-\rho_r} exp(\epsilon_t^R), \tag{B.22}$$

where R^* is the steady state nominal gross rate; parameter ρ_r determines the degree of interest rate smoothing; parameters r_π and r_y govern the strength of the responses of monetary policy to deviations of inflation and output growth from their target levels, respectively; and ϵ_R is a white noise monetary policy shock, i.e., $\epsilon_t^R \sim iid(0, \sigma_R)$.

B.7 Fiscal Policy

The government budget constraint is of the form

$$P_t^C G_t^C + P_t^I G_t^I + B_t = \frac{B_{t+1}}{R_{t+1}} + T_t, \tag{B.23}$$

where T_t are nominal lump-sum taxes that also appear in the households' budget constraint.

B.8 Shocks

I include in the model a total of 8 shocks: TFP surprise and news shocks, IST surprise and news shocks, monetary policy shocks, government consumption and investment shocks, and preference shocks. The monetary policy shock, ϵ_t^R, has already been introduced above in Equation (B.22). To define the other shocks, I now introduce the following stochastic processes for their corresponding fundamentals:

$$lnA_t = \mu_A t + lnA_{t-1} + z_{t-1}^A + \epsilon_t^{A,surprise},\ \epsilon_t^{A,surprise} \sim iid(0, \sigma_{A,surprise}); \tag{B.24}$$

$$z_t^A = \rho_{z,A} z_{t-1}^A + \epsilon_t^{A,news},\ \epsilon_t^{A,news} \sim iid(0, \sigma_{A,news}); \tag{B.25}$$

$$lnS_t = \mu_S t + lnS_{t-1} + z_{t-1}^S + \epsilon_t^{S,surprise},\ \epsilon_t^{S,surprise} \sim iid(0, \sigma_{S,surprise}); \tag{B.26}$$

$$z_t^S = \rho_{z,S} z_{t-1}^S + \epsilon_t^{S,news},\ \epsilon_t^{S,news} \sim iid(0, \sigma_{S,news}); \tag{B.27}$$

$$lnG_t^C = \mu t + \rho_{G,C} lnG_{t-1}^C + \epsilon_t^{G,C},\ \epsilon_t^{G,C} \sim iid(0, \sigma_{G,C}); \tag{B.28}$$

$$lnG_t^I = \mu_S t + \rho_{G,I} lnG_{t-1}^I + \epsilon_t^{G,I},\ \epsilon_t^{G,I} \sim iid(0, \sigma_{G,I}); \tag{B.29}$$

$$ln\zeta_t^I = \rho_\zeta ln\zeta_{t-1} + \epsilon_t^\zeta,\ \epsilon_t^\zeta \sim iid(0, \sigma_\zeta). \tag{B.30}$$

News shocks are defined here using a smooth news process by introducing stochastic drift terms (z_t^A for TFP and z_t^S for IST) whose persistence parameters ($\rho_{z,A}$ and $\rho_{z,S}$) determine the smoothness of the news shocks' effects on their corresponding fundamental (see, e.g., Leeper and Walker

(2011), Barsky and Sims (2011, 2012), and Leeper et al. (2013)). Note that the stochastic processes for TFP and IST are defined here in accordance with the general formulation from Equations (2) and (3) of the paper with the anticipation horizon set to $j = 1$ and the smoothness parameters $\rho_{z,A}$ and $\rho_{z,S}$ (which correspond to κ in Equation (2) from the paper) set to 0.6.

B.9 Baseline Calibration

I solve the model by log-linearizing its system of equilibrium equations about the steady state values of the variables. I calibrate the steady state growth rates of TFP and IST (μ_A and μ_S) to 0.27% and 1.03%, in accordance with the average growth rates of TFP and RPI in my empirical sample where the latter calibration is based on the long-run equivalence between IST and RPI.[3] The persistence parameters of the news shocks processes ($\rho_{z,A}$ and $\rho_{z,S}$) are both set to 0.6 and the standard deviations of the TFP news shock and IST news shock ($\epsilon_t^{A,news}$ and $\epsilon_t^{S,news}$) are set to 0.007 and 0.045, respectively. The news shocks' standard deviation calibration is set such that IST news shocks have a relatively dominant role, with IST news shocks explaining 57% of the two-year variation in output and a corresponding 21% share is explained by TFP news shocks.

All other parameters' calibration follows Moura (2018), taking the estimated mode posterior values for his estimated parameters and his calibration for the parameters he did not estimate. Table B.1 presents the calibration I use for the model's parameters excluding the shock processes' related parameters; these parameters are separately presented in Table B.2. This calibration underlies the Monte Carlo experiment of Section 4 from the paper.

Figures B.1a and B.1b, which depict the impulse responses and FEV contributions for IST news, TFP news, and monetary policy shocks, demonstrate that TFP news shocks produce positive impact comovement among the real aggregates (as so do monetary policy shocks, but these shocks account for a negligible share of output variation) whereas IST news shocks only raise consumption on impact while reducing output and investment and leaving hours largely unchanged.[4] This

[3] This implies a steady state real GDP growth rate of $\mu = \mu_A + \alpha_C \mu_S = 0.54\%$, where $\alpha_C = 0.35$ in accordance with the calibration from Moura (2018).

[4] As discussed in Moura (2018), price stickiness in the investment sector seems to be the main driver of the inability of unanticipated IST shocks to produce positive comovement, which is also naturally related to the corresponding failure of IST news shocks to do this. On Page 14 I discuss in more detail this failure as well as what calibration changes can be done to avoid it.

kind of setting, while stressing the difficulty of estimated state-of-the-art medium-scale DSGE models to produce business cycle driving IST news shocks, is valuable for my purposes as it constitutes a litmus test for my identification approach to avoid erroneously picking up a business cycle shock when one is not present in the true model.

Specifically, one may worry that such a setting would have my identification approach erroneously pick up a combination of comovement-producing shocks (TFP news and monetary policy shocks in this setting) and a dominant IST news shock (in terms of its FEV contributions, which are 57%, 63%, and 89% for the two-year variation in output, investment, and hours, respectively). This worry is based on the notion that the comovement-producing shocks comply with the comovement restriction part of identifying Restriction 1 from Section 3 of the paper, whereas the dominance of the IST news shock complies with its FEV restriction part; hence, my identification procedure would possibly pick up TFP news and monetary policy shocks to meet the comovement restriction, while picking up IST news shocks to meet the FEV restrictions, which would in turn leave us with some combination of three structural shocks. The results presented in Section 4 of the paper alleviate this concern by showing the strong unlikelihood of my baseline identification procedure to pick up a business cycle shock when such a shock does not exist.

I now turn to discussing a second Monte Carlo experiment where the business cycle shock truly exists and corresponds to IST news shocks, including explanations of the objective of this experiment, the alterations I make to the baseline calibration, and the simulation results.

B.10 Monte Carlo Experiment: A Model where IST News Shocks Comply With the Short-Run Restrictions

Objective. The evidence from Section 4 of the paper is based on a true data generating process (DGP) that delivers only partial compliance of the IST news shock with the identifying restrictions of my estimation procedure. Such a setting proved informative in showing the fairly strong capacity of my identification procedure to avoid spuriously identifying a business cycle shock when such a shock does not exist. This section aims at accomplishing a complementary objective in showing that my identification procedure can be successful in picking up a business cycle shock when such a shock truly exists in the true DGP.

Structural Model. To obtain the aforementioned goal, one needs a DSGE model with comovement-producing IST news shocks. However, this turns out to be quite a challenge in the context of estimated models. E.g., while employing the calibration used in Jaimovich and Rebelo (2009) generates positive business cycle comovement in response to IST news shocks, using the estimated parameters obtained in Khan and Tsoukalas (2011) (who embedded the preference structure from Jaimovich and Rebelo (2009) into a medium-scale DSGE model) does not deliver similar impulse responses. And, importantly, such estimated parameters do not produce significant FEV contributions for IST news shocks. The estimated, elaborate two-sector model of Moura (2018) is no exception in this regard as IST news shocks fail to produce positive comovement in his model (see Figure B.1a). Hence, to maintain the appealing structural framework of Moura (2018) while still encompassing IST news shocks that comply with Restrictions 1 and 2 from Section 3 of the paper, one must alter the calibration of this model's parameters.

Since my objective in this section is to produce a DSGE model based DGP with the IST news shock being the business cycle shock, but also at the same time maintain a reasonable calibration in terms of data fit and previous research, I try to alter as few as possible parameters' values. That said, in weighing the tradeoff between consistency with the DSGE literature and being able to obtain a suitable DGP for the sake of the sought after Monte Carlo experiment of this section, I place a much larger weight on the latter.

Specifically, I alter five parameters relative to the baseline calibration from Table B.1 (non-shock related parameters): I change the Calvo price rigidity parameter in the investment sector from 0.93 to 0, inverse elasticity of intertemporal substitution (σ_c) from 1.26 to 0.25, consumption habit formation (h) from 0.64 to 0, inverse Frisch elasticity (σ_l) from 1.23 to 100, and coefficient on output growth in the Taylor rule (r_y) from 0.72 to 0. Relative to the calibration of the shocks' standard deviations from Table B.2, I modify the baseline standard deviations by multiplying all of them by 25% except for that of the IST news shock, which I calibrate to 0.042. The changes in the parameters from Table B.1 generate an IST news shock that conforms to the impact comovement restriction while those in the shocks' standard deviations ensure that the IST news shock accounts for the bulk of the business cycle variation in the real aggregates and also that this shock has effects that are not overwhelmingly large. Some sacrifice was made particularly in terms of the RPI and investment responses, which are too large at longer horizons (also see Figure B.1a in the context of the baseline calibration, for which hours response at business cycle frequencies is also too large); but this cost is worthwhile incurring given the main purpose of the Monte Carlo experiment of this section which is to examine the capacity of my identification procedure to properly identify the business cycle shock when such a shock exists in a state-of-the-art structural framework.

I shall now briefly discuss the role of each change of the parameters from Table B.1. As already discussed by Liu et al. (2012) and Moura (2018) in the context of IST surprise shocks, price rigidity in the investment sector makes IST improvements less expansionary because these leave some of investment goods prices unchanged and thus relatively expensive with respect to the future, which in turn generates a large fall in investment demand owing to households being roughly indifferent to the timing of investment purchases. This mechanism, which is naturally also relevant to anticipated improvements in IST, also puts downward pressure on investment sector hours (which are mostly demand-driven in the short run). To eliminate this mechanism, I simply remove investment sector price rigidities from the model. Since IST news shocks persistently raise real interest rates in the baseline model, lowering σ_c makes consumption growth more responsive to IST news shocks which in turn allows investment to rise more on impact for a given output level; this lowering also limits the negative wealth effect of IST news shocks on hours which in turn helps to generate an impact rise in hours. To increase the impact rise in consumption which is diminished by the lowering of σ_c, I remove habit formation from the model as it allows for a less smooth consumption response and thus a greater impact rise. When $\sigma_c < 1$, households FOC with respect to consumption implies complementarity between consumption and leisure whose strength is governed by the inverse Frisch elasticity of labor supply; hence, raising the latter allows for more room for hours to rise in tandem with the rise in consumption. Lastly, I remove the responsiveness of interest rates to output growth in the Taylor-like rule so as to allow for a more accommodative monetary policy in the presence of a favorable IST news shock.

I now turn to discussing the results from the Monte Carlo experiments, again separating them (as in the experiments from Section 4 of the paper) into those obtained from imposing the long-run RPI restriction and those obtained from removing this restriction.

Baseline Case. As in the Monte Carlo experiment of Section 4 from the paper, I simulate 100 artificial data sets from the model and apply to each my estimation procedure where 10^5 posterior draws are taken in the Bayesian estimation. My focus is on comparing the average of the estimated median and 84th and 16th percentiles of the impulse responses and FEV contributions posterior distribution, where the average is taken over the 100 Monte Carlo simulations, to their corresponding theoretical counterparts from the model. Figures B.2a and B.2b show the mean estimated median and 84th and 16th percentile impulse responses and FEV contributions to the variables' variation of the identified business cycle shock over a ten year horizon, along with the corresponding true responses and contributions from the true model. It is apparent that the mean estimated median responses are quite close to their theoretical counterparts, especially at business cycle frequencies.[5] In accordance with this, the mean correlation between the estimated median business cycle shock series and the true IST news shock series is 90%.

It is also clear that at longer horizons there is a downward bias in the estimates of the non-stationary variables' impulse responses. Nevertheless, the estimated long-run effect on RPI (not shown in the figures) is still informative in facilitating the correct interpretation of the business cycle shock as an IST news shock, in terms of both the impulse responses and the FEVs with the former mean median estimate being -4.4% and the latter being 70.2%. Also worthwhile noting is the downward bias in the estimates of the FEVs from Figure B.2b,[6] which indicates that the empirical results of this paper can be seen as potentially conservative with respect to the true role of IST news shocks. Overall, it is clear that my identification procedure does a good job of identifying the business cycle shock as an IST news shock when such a correspondence truly exists in the DGP.

In the first row of Table B.3 I also present the share of simulation with null identification along with the corresponding admissibility rates. Clearly, this Monte Carlo experiment does not lead to

[5]Note that the true effect of IST news shocks on TFP is zero all horizons. I have experimented with DGPs where IST news shocks are allowed to have a meaningful delayed effect on TFP, as in the data, and found that these effects are also captured well by my identification procedure. To keep the experiment as simple as possible, I abstract from such effects in the Monte Carlo experiments presented here.

[6]The only exception is the FEV estimate for TFP which is upward biased. Nevertheless, as is clear from the first sub-figure of Figure B.2a, the zero effect on TFP is reasonably captured especially as the horizon advances.

any problem relating to null identification. While the mean admissibility rate is somewhat lower than its empirical counterpart (78.2×10^{-5} compared to 129.7×10^{-5}), over 25% of the simulations resulted in an admissibility rate of at least 100×10^{-5}, which is quite comparable to the empirical one; and 13% of them had an admissibility rate that exceeded the empirical one. Furthermore, I have also found that the Monte Carlo based admissibility rates are increasing in the dominance of the IST news shock in terms of the real aggregates' FEV shares it accounts for, which supports the notion that the results of this paper are likely the outcome of a correct identification. Put differently, taken together with both the Monte Carlo results from Section 4 of the paper as well as the empirical ones of Section 5, the results of this section highlight that it is very unlikely that a spurious identification of the business cycle shock is what is standing behind the empirical results of this paper.

Removing the Long-Run RPI Restriction. I now present results from the same experiment underlying Figures B.2a and B.2b, only that now I only impose Restriction 1 from Section 3 of the paper when applying my estimation procedure to the artificial data sets (i.e., I exclude the long-run restriction). Figures B.3a and B.3b present the results from this Monte Carlo experiment. While the mean estimated median responses and FEV contributions for RPI and TFP are reasonably close to their theoretical counterparts at short-run horizons and the mean correlation between the estimated median IST news shock series and the true IST news shock series (standing at 91%) is similar to that obtained from also imposing the long-run restriction, there is a very large downward bias in the estimated long-run effect and FEV contribution for RPI (not shown in the figures) with these standing at -2.5% and 36%. The latter significantly downward biased FEV estimate, which is roughly half of the corresponding estimate from also imposing the long-run restriction in the estimation procedure, makes it clear that there is an important cost resulting from not imposing the long-run RPI restriction in terms of properly identifying the long-run implications of the business cycle shock. Moreover, this estimated FEV number accords reasonably well with its empirical counterpart obtained when only imposing Restriction 1 in actual data. Overall, the results shown so far for this experiment raise confidence in the notion that the true DGP underlying the results of this paper is one where the business cycle shock is an IST news shock.

The second row of Table B.3 presents the share of simulations with null identification along with the corresponding mean admissibility rate. Here too there is no problem of null identification, which one should expect given the existence of a business cycle shock in the true DGP. Moreover, the mean admissability rate is roughly similar to its empirical counterpart. (Note that the much larger admissability rate obtained for this less restrictive estimation procedure relative to the baseline estimation stresses the relevance of the point raised in Footnote 12 of the paper that one need not use the size of the set of admissible models as an indication for the identifying restrictions' validity.) Hence, the results from both rows of Table B.3 accord well with the notion that it is very unlikely that a spurious, rather than correct, identification of the business cycle shock is what has generated the empirical results of this paper.

B.11 Monte Carlo Experiments: Imperfect-Information Structure

The results from the previous section, as well as those from Section 4 of the paper, are based on a full-information setting where news shocks are perfectly observed by agents. Nevertheless, one may argue that the simulation results could be sensitive to the presence of noise in signals of news shocks received by agents. To address this concern, this section presents an additional set of results from Monte Carlo experiments based on DSGE-generated artificial data that accounts for the presence of such noise.

Specifically, I follow the information structure from Barsky and Sims (2011) in modifying my baseline DSGE model such that agents observe only noisy signals of the stochastic drift terms for TFP (z_t^A) and IST (z_t^S):

$$s_t^A = z_t^A + n_t^A,\ n_t^A \sim iid(0, \sigma_{n^A}); \tag{B.31}$$

$$s_t^S = z_t^S + n_t^S,\ n_t^S \sim iid(0, \sigma_{n^S}); \tag{B.32}$$

where n_t^A and n_t^S are noise shocks of the TFP- and IST-news-related signals, respectively. I calibrate these noise shocks' standard deviations to be equal to their corresponding news shocks' standard deviations, i.e., $\sigma_{n^A} = \sigma_{A,news}$, $\sigma_{n^S} = \sigma_{S,news}$. This calibration can be viewed as agnostic in assuming equal levels of precision and noise embodied in the signals agents receive.[7] With this

[7]It can also be seen as a somewhat conservative calibration choice given that Barsky and Sims (2011)

modification of the information structure of the model in place, I proceed by solving the model for both the baseline calibration and the alternative one from Page 13 (with the additional calibration of the noise shocks' standard deviations as being equal to the corresponding news shocks' standard deviations)[8] and repeat my Monte Carlo experiments for artificial data from the imperfect-information version of the model. The solution assumes that agents use the Kalman filter to form forecasts of the unobserved stochastic drift terms for TFP and IST such that the solution to the signal extraction problem these agents solve is properly accounted for by the log-linearized solution of the model (see, e.g., Pearlman et al. (1986), Barsky and Sims (2011), Levine et al. (2012), and Blanchard et al. (2013).[9]

Figures B.4a and B.4b depict the impulse responses and FEV contributions for IST news, TFP news, and IST noise shocks. Exposition wise, the only difference between these figures and Figures B.1a and B.1b is that monetary policy shocks are replaced with IST noise shocks. (The former have very similar effects across the perfect- and imperfect-information models.) As in the perfect-information model, TFP news shocks produce positive impact comovement among the real aggregates (as so do monetary policy shocks, albeit not shown here) whereas IST news shocks only raise consumption while reducing output and investment and leaving hours largely unchanged. Nevertheless, it is noteworthy that the presence of noise shocks in the model (both TFP and IST noise shocks) reduces the impact effects of TFP and IST news shocks on the variables. And, notably, while having much less persistent effects than news shocks, noise shocks produce the same impact effect as news shocks owing to the assumption of equal standard deviations for both shock

estimate TFP signal precision to be 31% higher than its noisiness.

[8]For the alternative calibration (i.e., for which IST news is the business cycle shock), the imperfect-information structure significantly lowered the impact effects of IST news shocks thus causing difficulty for the identification procedure to pick up the business cycle shock. Hence, to address this issue and produce meaningful impact effects, I calibrated the standard deviation of the IST news shock to 0.07. Importantly, to still maintain a setting where I can test the robustness of the validity of my econometric approach to a meaningful imperfection in the information structure, I also calibrated the standard deviation of the IST noise shock to 0.07. Note that such calibration of equal variances of the news and noise shocks produces equal impact effects of these two shocks on all variables as agents can not distinguish between the two shocks on impact. And such a setting serves my purposes well in providing a suitable environment for testing the validity of my econometric approach in the presence of meaningful information partialness.

[9]The solution to both the perfect- and imperfect-information models is done in Dynare (Adjemian et al. (2011)), with the latter being based on MATLAB code which is integrated into Dynare and implements the solution techniques from Pearlman et al. (1986) for solving imperfect-information DSGE models (see Levine et al. (2019) for details).

types and the associated agents' inability to distinguish between the two shocks on impact. (While TFP noise shocks' effects are not shown in these figures, this impact equivalence result also applies to them.) This kind of setting constitutes an additional litmus test for my identification approach to avoid erroneously picking up a business cycle shock when one is not present in the true model.

I now turn to discussing the results from the Monte Carlo experiments for the imperfect-information model, again separating them (as in the experiments from Section 4 of the paper as well as the ones from previous section) into those obtained from imposing the long-run RPI restriction and those obtained from removing this restriction, while considering simulation results from both a model where IST news is the business cycle as well as a model where a business cycle shock does not exist.

Baseline Case. The share of simulations with null identification along with the corresponding mean admissibility rate appear in the first and third rows of Table B.4, whose expositional structure corresponds to that of Table B.3 (where the perfect-information based results for the alternative calibration from Page 13 are presented). Do note, however, that results for both the baseline and the alternative calibration are presented in Table B.4, with the first row corresponding to the former and the third row corresponding to the latter. Overall, the main message of the paper seems to be robust to allowing for imperfect-information structures. More specifically, applying the baseline estimation to artificial data from such structures still indicates a very low chance (1%) of spurious identification when the true model does not contain a business cycle shock while implying much higher admissibility rates that are broadly in line with observed ones when applied to a model where such a shock exists in the true model.

Figures B.5a and B.5b present the mean estimated median and 84th and 16th percentile impulse responses and FEV contributions to the variables' variation of the identified business cycle shock over a ten year horizon, along with the corresponding true responses and contributions from the true model, for the simulation from the imperfect-information model where IST news is the business cycle shock. Importantly, the mean estimated median responses are quite close to their theoretical counterparts, especially at business cycle frequencies, indicating the validity of my econometric approach for identifying the business cycle shock is robust to the presence of meaningful information partialness. The mean correlation between the estimated median business cycle shock series and the true IST news shock series is 83%, which is somewhat lower than the baseline 90% obtained from the baseline full-information case but is still sufficiently high to warrant confidence in the ability of my identification procedure to pick up the business cycle shock also in the presence of an imperfect-information structure.

Removing the Long-Run RPI Restriction. The second and fourth rows of Table B.4 present the share of simulations with null identification along with the corresponding mean admissibility rate for the baseline and alternative calibration cases from applying an estimation that excludes the long-run restriction. While here too there is no problem of null identification for the case where a true business cycle shock does exist (fourth row), with the mean admissability rate being roughly similar to its empirical counterpart, the risk of spurious identification (second row and first column, i.e., 20%) is much greater than that observed for the baseline estimation case from the first row (20 times as much). Similar to the perfect-information model case, this emphasizes one dimension of the added value from imposing the long-run restriction (Restriction 2), which is related to the significantly reduced risk of spurious identification when the true DGP does not contain a single business cycle shock. (The other dimension is discussed below with respect to the long-run downward bias in the estimated FEV share for RPI.) Lastly, it is also worthwhile noting that the very low admissibility rate reported in the second row and second column of Table B.4 (2.9×10^{-5}) relative to its empirical counterpart (reported in Section 6.2 of the paper) is also not supportive (like that from the first row) of the notion that it is likely that the true DGP behaves similarly to that implied by a DSGE model where no business cycle shock exists.

Figures B.6a and B.6b present results from the same experiment underlying Figures B.5a and B.5b, only that now I only impose Restriction 1 from Section 3 of the paper when applying my estimation procedure to the artificial data sets (i.e., I exclude the long-run restriction). While the mean estimated median responses and FEV contributions for RPI and TFP are reasonably close to their theoretical counterparts at short-run horizons and the mean correlation between the estimated median IST news shock series and the true IST news shock series (82%) is similar to that obtained from also imposing the long-run restriction, there is a very large downward bias in the estimated long-run effect and FEV contribution for RPI (not shown in the figures) with these standing at -3.6% and 33%. The latter significantly downward biased FEV estimate, which is roughly half of the corresponding estimate from also imposing the long-run restriction (Restriction 2) in the estimation procedure, makes it clear that there is an important cost resulting from not imposing the long-run RPI restriction in terms of properly identifying the long-run implications of the business cycle shock also in the imperfect-information model case (similar results obtained from the perfect-information case). Moreover, this estimated FEV number accords reasonably well with its empirical counterpart obtained when only imposing Restriction 1 to actual data. Overall, the results from this section (in accordance with those from the perfect-information case) raise confidence in the notion that the true DGP underlying the results of this paper is one where the business cycle shock is an IST news shock.

Table B.1: **Model Parameterization: Non-Shock Related Parameters**.

Parameter	Description	Value
β	Subjective discount factor	0.998
δ	Depreciation rate	0.025
$\phi^{w,C};\phi^{w,I};\phi^{p,C};\phi^{p,I}$	Labor and goods market elasticity of substitution	10
π_C^*	Steady state gross C inflation	1.011
μ_A	Steady state TFP gross growth rate	1.0027
μ_S	Steady state IST gross growth rate	1.013
α_C,α_I	Capital share	0.35;0.35
$\frac{G^C}{Y^C}$	Steady state government consumption share	0.23
$\frac{G^I}{Y^I}$	Steady state government investment share	0.15
σ_c	Inverse elasticity of inter-temporal substitution	1.26
h	Habit formation parameter	0.64
σ_l	Inverse Frisch elasticity	1.23
$\xi_{p,C};\xi_{p,I}$	Degree of nominal rigidities in the goods market	0.78;0.93
$\xi_{w,C};\xi_{w,I}$	Degree of nominal rigidities in the labor market	0.85;0.98
$\iota_{p,C};\iota_{p,I}$	Degree of price indexation to past inflation	0.18;0.13
$\iota_{w,C};\iota_{w,I}$	Degree of wage indexation to past inflation	0.11;0.18
ω	Capital utilization elasticity	0.94
ϖ	Steady-state elasticity of the investment adjustment cost function	3.97
τ	Reallocation cost: Labor	2.77
ν	Reallocation cost: Capital	0.12
r_π	Coefficient on inflation in the interest rate rule	1.91
r_y	Coefficient on output growth in the interest rate rule	0.72
ρ_R	Degree of interest rate smoothing	0.77

Notes: The table consists of the non-shock parameters' values used for the model described in Appendix B. This calibration underlies the Monte Carlo experiment of Section 4 from the paper. The third column shows the values for both the consumption and investment sectors, whenever such a distinction applies.

Table B.2: **Model Parameterization: Shock Related Parameters**.

Parameter	Description	Value
$\rho_{z,A}$	TFP news shock persistence	0.6
$\rho_{z,S}$	IST news shock persistence	0.6
$\rho_{G,C}$	Government consumption shock persistence	0.97
$\rho_{G,I}$	Government investment shock persistence	0.96
ρ_{ζ}	Preference shock persistence	0.93
$\sigma_{A,surprise}$	TFP surprise shock standard deviation	0.00902
$\sigma_{S,surprise}$	IST surprise shock standard deviation	0.0202
$\sigma_{A,news}$	TFP news shock standard deviation	0.007
$\sigma_{S,news}$	IST news shock standard deviation	0.045
σ_{R}	Monetary policy shock standard deviation	0.00253
$\sigma_{G,C}$	Government consumption shock standard deviation	0.0125
$\sigma_{G,I}$	Government investment shock standard deviation	0.0262
σ_{ζ}	Preference shock standard deviation	0.0219

Notes: The table consists of the shock parameters' values used for the model described in Appendix B. This calibration underlies the Monte Carlo experiment of Section 4 from the paper.

Table B.3: **DSGE Model Based Monte Carlo Experiment: IST News Constitutes the Business Cycle Shock.**

	Null Identification	Admissibility Rate
Alternative Calibration: With Long-Run RPI Restriction	0%	78.2×10^{-5}
Alternative Calibration: Without Long-Run RPI Restriction	0%	1688×10^{-5}

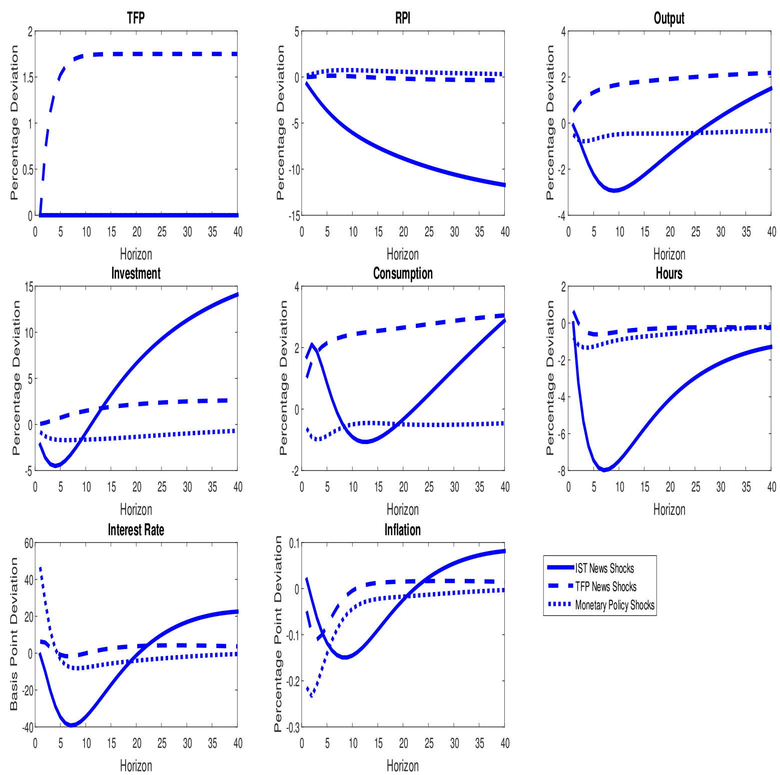
Notes: This table presents the share of simulations in which identification was null (first column) along with the average admissibility rate (average number of admissible models divided by total number of posterior draws (10^5)) for the simulations that did produce a non-null set of admissible models (second column). A total of 100 simulations were conducted (corresponding to 100 artificial data sets from the DSGE model described in Appendix B) with the first row of the table providing results from applying my baseline identification procedure to each data set using the alternative calibration from Page 13 which results in IST news being the business cycle shock; and the second row providing results from applying the baseline procedure but without imposing the long-run RPI restriction (Restriction 2 from Section 3 of the paper) while again using the alternative calibration from Page 13 which results in IST news being the business cycle shock.

Table B.4: **DSGE Model Based Monte Carlo Experiments: Imperfect-Information Structure.**

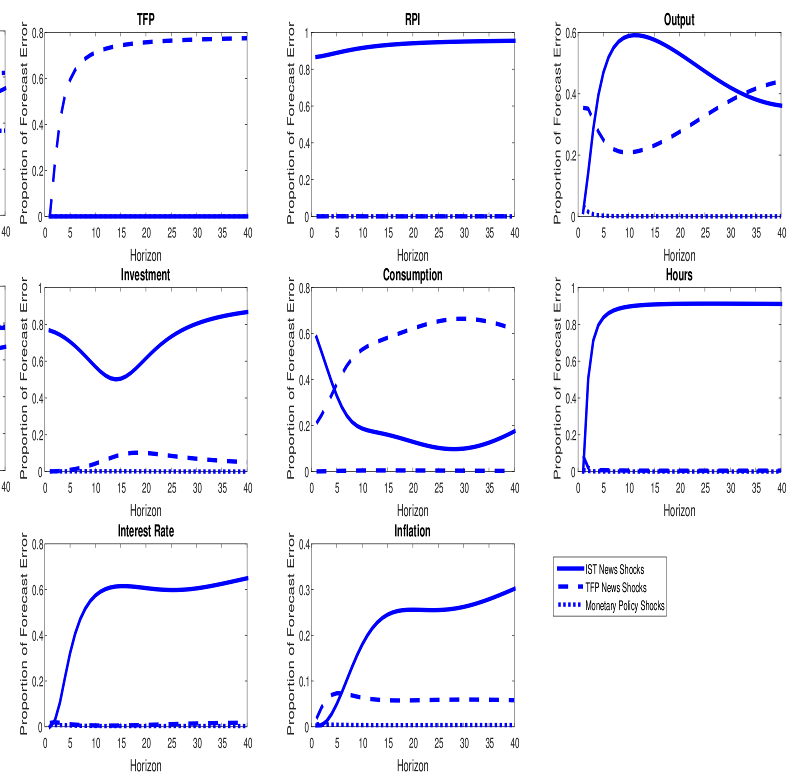
	Null Identification	Admissibility Rate
Baseline Calibration: With Long-Run RPI Restriction	99%	1×10^{-5}
Baseline Calibration: Without Long-Run RPI Restriction	80%	2.9×10^{-5}
Alternative Calibration: With Long-Run RPI Restriction	0%	129.7×10^{-5}
Alternative Calibration: Without Long-Run RPI Restriction	0%	2376×10^{-5}

Notes: This table presents the share of simulations in which identification was null (first column) along with the average admissibility rate (average number of admissible models divided by total number of posterior draws (10^5)) for the simulations that did produce a non-null set of admissible models (second column). A total of 100 simulations were conducted, corresponding to 100 artificial data sets from the DSGE model described in Appendix B where the information structure is now imperfect as described in Appendix B.11. The first row of the table providing results from applying my baseline identification procedure to each data set using the baseline calibration (assuming noise shocks' standard deviations that are equal to their corresponding news shocks' standard deviations); the second row providing results from applying the baseline procedure but without imposing the long-run RPI restriction while using the baseline calibration; and the third and fourth rows corresponding to results from applying the baseline estimation procedure and the one without imposing the long-run RPI restriction to each data set, respectively, using the alterative calibration described in Page 13 with the only difference being that the standard deviation of the IST news shocks (as well as that of the IST noise shock) is set to 0.07 (the standard deviation of the TFP noise shock is set equal to that of the TFP news shock from alternative calibration from Page 13).

Figure B.1: **DSGE Model: (a) Impulse Responses; (b) Contribution to FEV.**



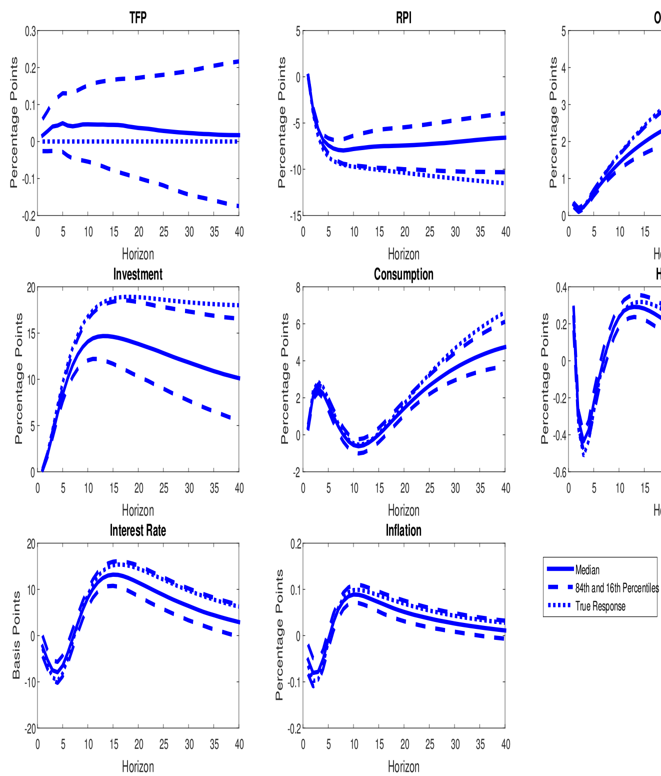
(a) Theoretical Impulse Responses to IST News, TFP News, and Monetary Policy Shocks.



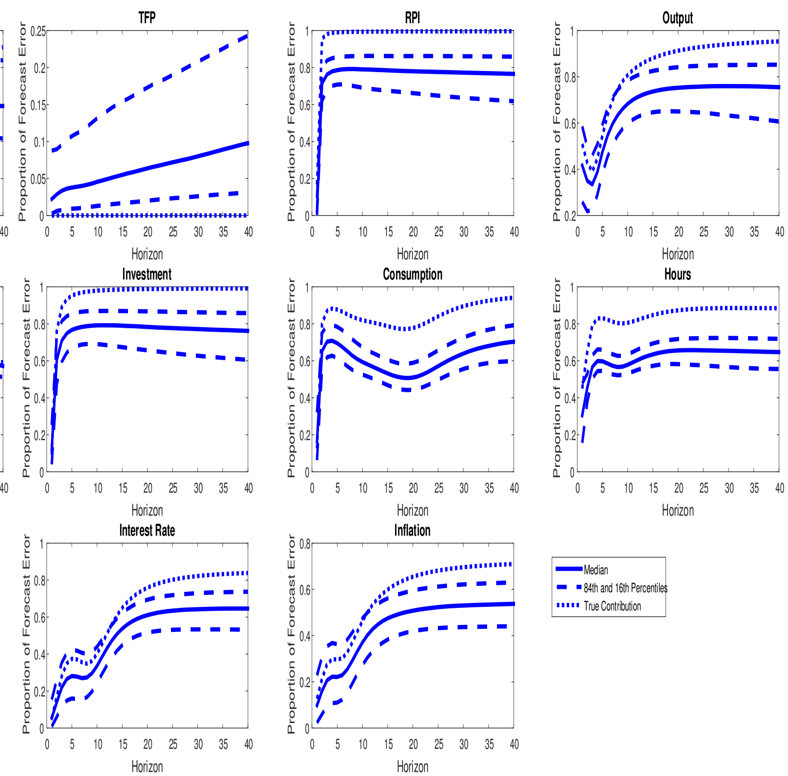
(b) Theoretical Contribution of IST News, TFP News, and Monetary Policy Shocks to the FEV of the Variables.

Notes: Panel (a): The solid, dashed, and dotted line are the impulse responses to IST news, TFP news, and monetary policy shocks, respectively, from the DSGE model (described in Appendix B) used for the Monte Carlo experiment from Section 4 of the paper. Responses are in terms of deviations from steady state values. Panel (b): The solid, dashed, and dotted line are the FEV contributions of IST news, TFP news, and monetary policy shocks, respectively, from the DSGE model (described in Appendix B) used for the Monte Carlo experiment from Section 4 of the paper.

Figure B.2: **Monte Carlo Evidence from a DSGE Model: Baseline Estimation Procedure: (a) Impulse Responses; (b) Contribution to FEV.**



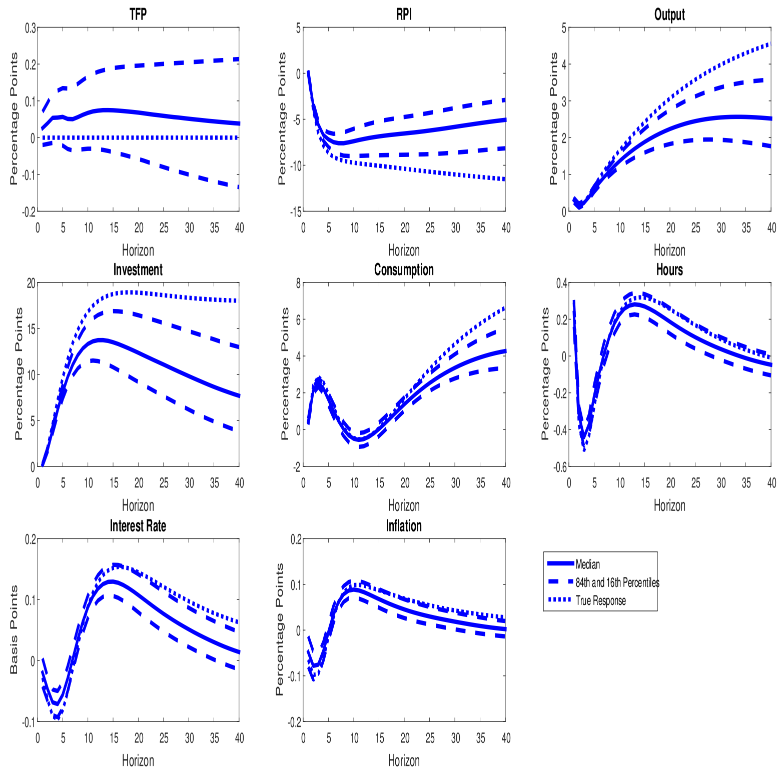
(a) The Mean Estimated Median and 84th and 16th Percentiles of Impulse Responses and the True Impulse Responses.



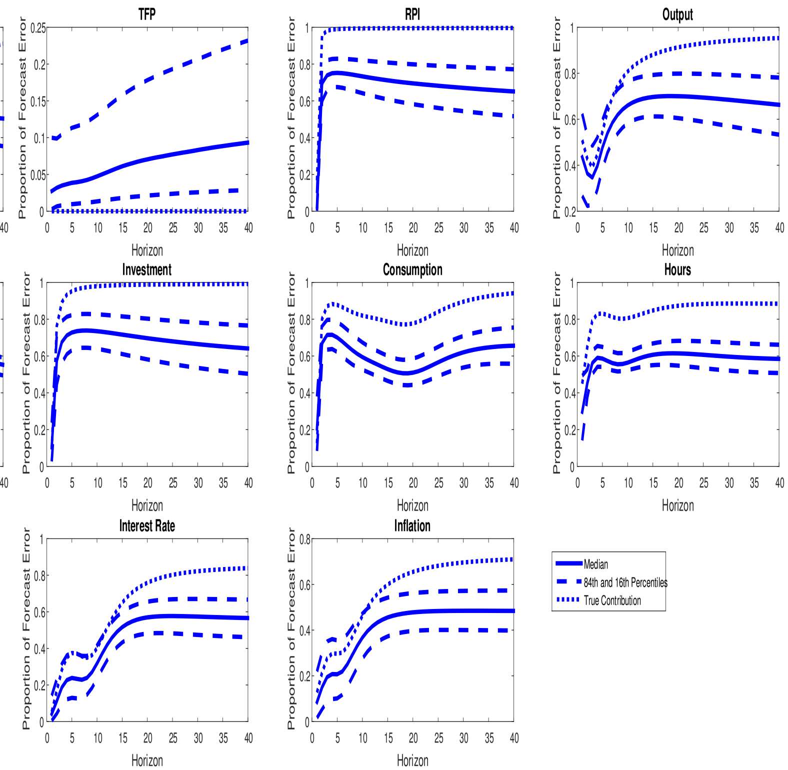
(b) The Mean Estimated Median and 84th and 16th Percentiles of FEV Contributions and the True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from applying the baseline estimation procedure to artificial data sets generated from the DSGE model described in Appendix B with the alternative calibration from Page 13. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true impulse responses. Responses are in terms of deviations from steady state values. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true contribution.

Figure B.3: **Monte Carlo Evidence from a DSGE Model: Estimation Procedure Without Long-Run Restriction: (a) Impulse Responses; (b) Contribution to FEV.**



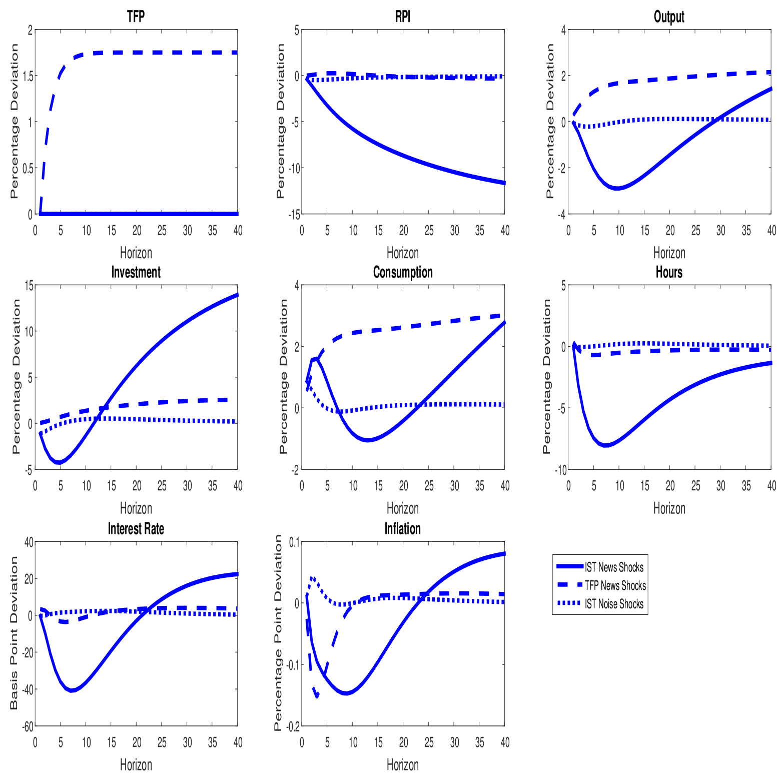
(a) The Mean Estimated Median and 84th and 16th Percentiles of Impulse Responses and the True Impulse Responses.



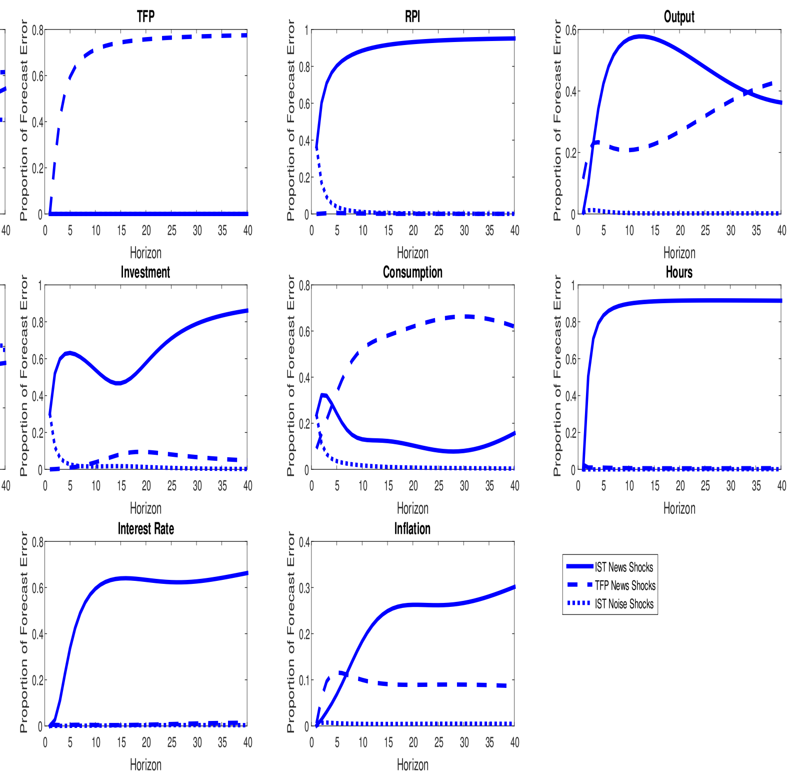
(b) The Mean Estimated Median and 84th and 16th Percentiles of FEV Contributions and the True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from applying an estimation procedure that excludes the long-run restriction to artificial data sets generated from the DSGE model described in Appendix B with the alternative calibration from Page 13. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true impulse responses. Responses are in terms of deviations from steady state values. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true contribution.

Figure B.4: **DSGE Model with Imperfect-Information Structure: (a) Impulse Responses; (b) Contribution to FEV.**



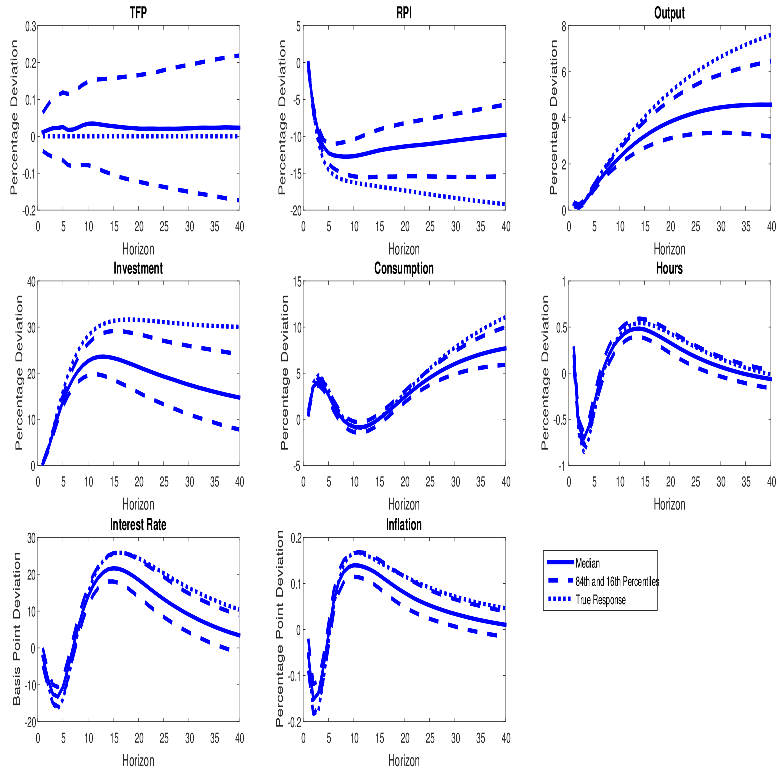
(a) Theoretical Impulse Responses to IST News, TFP News, and IST Noise Shocks.



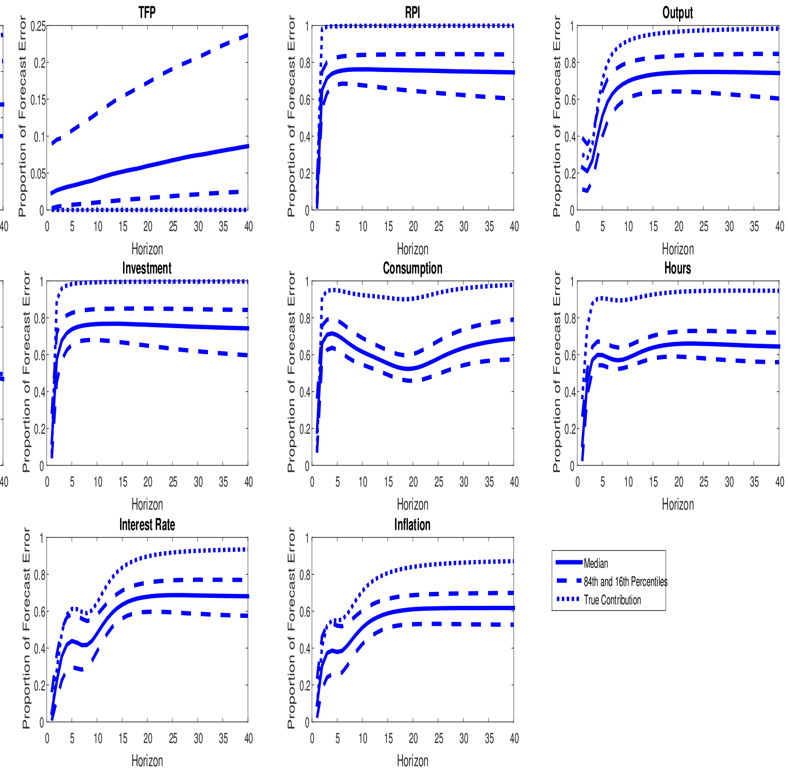
(b) Theoretical Contribution of IST News, TFP News, and IST Noise Shocks to the FEV of the Variables.

Notes: Panel (a): The solid, dashed, and dotted line are the impulse responses to IST news, TFP news, and IST noise shocks, respectively, from the DSGE model described in Appendix B only modified to contain an imperfect-information structure as detailed in Appendix B.11. Responses are in terms of deviations from steady state values. Panel (b): The solid, dashed, and dotted line are the FEV contributions of IST news, TFP news, and IST noise shocks, respectively, from the DSGE model described in Appendix B only modified to contain an imperfect-information structure as detailed in Appendix B.11.

Figure B.5: **Monte Carlo Evidence from a DSGE Model with Imperfect-Information Structure: Baseline Estimation Procedure: (a) Impulse Responses; (b) Contribution to FEV.**



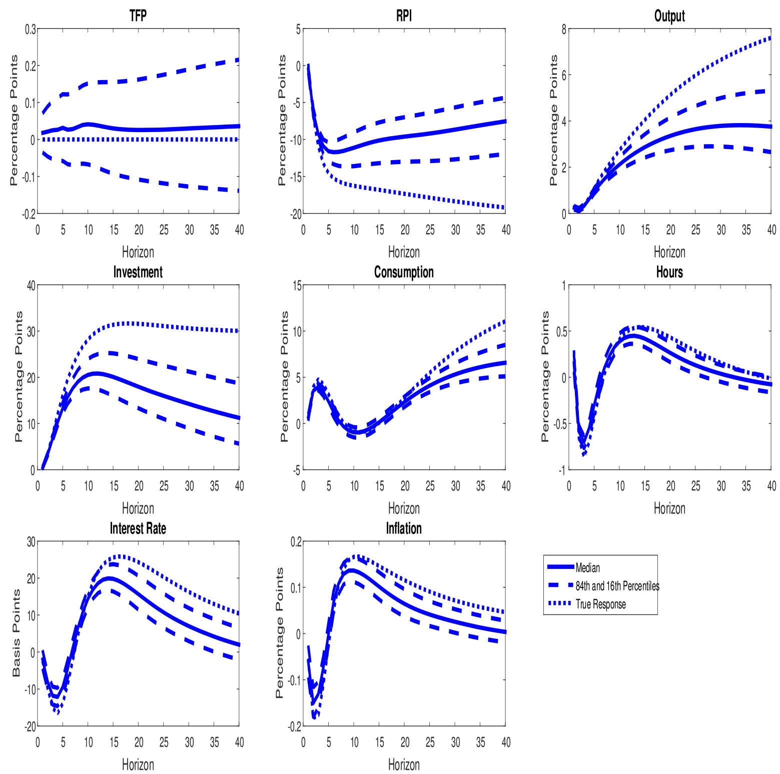
(a) The Mean Estimated Median and 84th and 16th Percentiles of Impulse Responses and the True Impulse Responses.



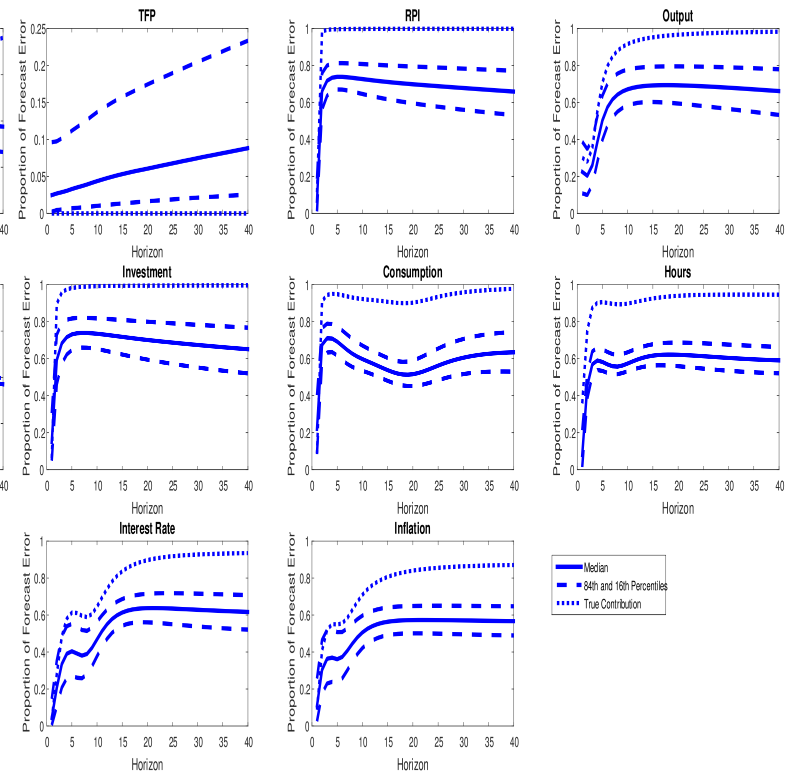
(b) The Mean Estimated Median and 84th and 16th Percentiles of FEV Contributions and the True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from applying the baseline estimation procedure to artificial data sets generated from the DSGE model described in Appendix B where the information structure is now imperfect as described in Appendix B.11. The calibration follows the alternative calibration from Page 13 with the only difference being that the standard deviation of the IST news shocks (as well as that of the IST noise shock) is set to 0.07; the standard deviation of the TFP noise shock is set equal to that of the TFP news shock from the alternative calibration from Page 13. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true impulse responses. Responses are in terms of deviations from steady state values. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true contribution.

Figure B.6: **Monte Carlo Evidence from a DSGE Model with Imperfect-Information Structure: Estimation Procedure Without Long-Run Restriction: (a) Impulse Responses; (b) Contribution to FEV.**



(a) The Mean Estimated Median and 84th and 16th Percentiles of Impulse Responses and the True Impulse Responses.



(b) The Mean Estimated Median and 84th and 16th Percentiles of FEV Contributions and the True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from applying an estimation procedure that excludes the long-run restriction to artificial data sets generated from the DSGE model described in Appendix B where the information structure is now imperfect as described in Appendix B.11. The calibration follows the alternative calibration from Page 13 with the only difference being that the standard deviation of the IST news shocks (as well as that of the IST noise shock) is set to 0.07; the standard deviation of the TFP noise shock is set equal to that of the TFP news shock from the alternative calibration from Page 13. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true impulse responses. Responses are in terms of deviations from steady state values. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the true contribution.

Appendix C The Role of Hours in the Analysis

In Section 6.1 of the paper I presented Monte Carlo evidence suggesting that it is very much possible that applying an erroneous differenced hours VAR specification to the actual data could result in the negligible long-run FEV shares I find when specifying hours in first-differences, supporting the view that the actual data is likely generated by a stationary hours based data generating process (DGP). In this appendix I augment this evidence with further evidence on the likelihood of a stationary hours based DGP, while providing additional technical details on the DGP used as well as touching upon the issue of removing hours from the VAR.

C.1 Stationary Hours Based DGP

In the experiment from Section 6.1 of the paper, I generated 100 artificial data sets from VARs that are identical to my empirical VAR, i.e., with hours worked in levels and which comply with Restrictions 1 and 2 from Section 3 of the paper, and applied my identification procedure (based on 10^5 posterior draws) to each artificial data set using a VAR that includes hours in first-differences. The second experiment whose results are presented in this section is identical to the first only that I apply my identification procedure to each artificial data set using a VAR that includes hours in levels, rather than first-differences. While the objective of the first experiment was to study the long-run estimation bias from erroneously entering hours in first-differences in the VAR, that of the second experiment considered here is to examine the identification precision from correctly specifying hours in levels.[10]

To mimic as much as possible the low-frequency aspects of the actual data used in my empiri-

[10] I refrain from focusing on Monte Carlo experiments based on DGPs where hours are differenced as these were found to encompass the following data-inconsistent features: on average, they produce small low-frequency correlations between hours worked and the growth rates of RPI, TFP, output, and consumption (and significantly negative, rather than positive, correlation with investment growth), which is in stark contrast to the actual low-frequency correlations observed in the data and the correspondingly consistent average correlations produced by stationary hours DGPs; applying differenced hours VAR estimation to artificial data generated from differenced hours DGPs that do comply with the low-frequency nature of the data mostly results in null set identification, making it unlikely that a differenced hours DGP could have produced the non-empty set of admissible models obtained from applying the differenced specification to actual data; and hours exhibit a significant long-run response to the business cycle shock, which is strongly at odds with economic theory. Taken together, these facts indicate that differenced hours based DGPs are very unlikely to have generated the actual data that we observe in reality.

cal analysis, I only consider artificial data sets for which the following low-frequency correlations hold (with resect to variables' HP trends): *i*) RPI growth rate is negatively correlated with TFP, output, investment, and consumption growth rates as well as hours in levels; *ii*) TFP growth rate is positively correlated with output, investment, and consumption growth rates as well as hours in levels; *iii*) RPI (TFP) growth rate is positively (negatively) correlated with hours in first-differences; and *iv*) RPI growth rate is more correlated with hours in levels in absolute terms than the corresponding correlation between TFP growth rate and hours in levels. Importantly, the estimation bias is similar when these low-frequency correlations are not restricted to hold for the artificial data sets. That said, ensuring that these low-frequency features hold is important for making the associated Monte Carlo experiments more realistic in terms of being based on artificial data that share common low-frequency features with the actual, empirical data.[11]

Figures C.1a and C.1b correspond to Figures 3a and 3b from the paper with the only difference being that they are based on correctly specifying hours in levels in the estimated VARs. Clearly, the mean estimated median responses and FEV contributions for RPI and TFP are now very close to the corresponding mean true counterparts, which is in stark contrast to the results from Figures 3a and 3b from the paper. Taken together, the Monte Carlo results presented here as well as in Section 6.1 of the paper emphasize that correctly specifying hours in levels is crucial to structurally interpreting the business cycle shock in an appropriate manner.

C.2 Removing Hours from the VAR

Figures C.2a and C.2b present impulse response and FEV results, respectively, from removing hours from the VAR. These results are similar to those from the first-differenced-hours based ones in that the business cycle shock does not seem to matter for RPI variation at any frequency in a meaningful way, accounting for only 2% of the long-run variation in RPI (not shown in Figure C.2b). Also note that the business cycle shock is not meaningful for TFP variation, ultimately only accounting for 5% of its long-run variation.

[11] I only restrict the sign of these low-frequency correlation, rather than resorting to more restrictive bounds, so as to refrain from overly restraining the DGP. Notably, Restriction *iii* ensures that the low-frequency correlation of hours with RPI and TFP growth rates is eliminated once hours are considered in first-differences.

At first pass, these results appear to undermine the main message of the paper because they emphasize that the baseline results are sensitive not only to the way hours are specified in the VAR (see Section 6.1 in the paper) but also to their exclusion. As the baseline results of any empirical work should not rely on the inclusion of one particular variable (as central as that variable may be), can there still be merit to my empirical analysis after visually inspecting the results from Figure C.2b? I believe that there is and shall argue below that in fact these results have led me to conduct additional experiments and tests which ultimately maintain and even bolster the confidence in the notion that it is quite unlikely that a DGP where IST news is not the business cycle shock has generated the results of this paper.

More generally, I structure my argument that the validity of my results still remains despite the findings from Figure C.2b along three dimensions. The first is that removing hours from the VAR effectively prevents from the low-frequency correlation between hours and RPI and TFP growth rates to be accounted for, thus producing significant downward bias in RPI and TFP responses (much like when hours are inserted in first-differences, which also prevents from these correlations to be accounted for). The second dimension concerns the plausibility that a DGP containing hours and a business-cycle-driving IST news shock could have generated results of the kind shown in Figure C.2b. The last dimension pertains to the robustness of the results from the levels-VAR specification to excluding hours.

Low-Frequency Correlation. The crux of this part of my argument lies in the assertion that other variables' low-frequency variation does not pick up the important low-frequency comovement between hours and RPI and TFP growth rates in a satisfactory way, thus resulting in the exclusion of hours from the VAR doing similar damage from an identification standpoint as inserting it in first-differences does. (Here I continue to rely on the important result from Gospodinov et al. (2011) that not accounting for such low-frequency correlations can result in severe estimation bias.)

To establish this assertion, I present in Table C.1 the low-frequency correlation of hours with growth rates of RPI and TFP in both raw form and partialed out form. While the former was already shown in Table 6 of the paper (and shown again here for convenience), the latter represents partial correlations after controlling for the effects of the HP trends of the growth rates of output, investment, consumption, and TFP (RPI) with the corresponding numbers shown in the first (second) column. The purpose of this step is to examine to what extent the strong low-frequency correlation between hours and RPI and TFP growth rates can be accounted for by information contained in the low-frequency variation in the other non-stationary variables in my analysis. The lower the partial correlations are relative to the raw ones, the more informative the low-frequency variation in the other variables is for the low-frequency comovement between hours and RPI and TFP growth rates.

For the hours-RPI case, the partial correlation (-85%) from Table C.1 is actually even higher in absolute terms than the raw one (-74%), indicating that the other variables are entirely incapable of picking up the low-frequency comovment between hours and RPI growth; this indicates that removing hours from the VAR is expected to lead to significant bias in RPI responses. For the hours-TFP case, while the partial correlation (36%) is lower than the raw one (52%), the wedge between the two still implies a far from perfect capacity of the other variables to pick up the low-frequency comovement between hours and TFP growth. All in all, the results from Table C.1 are consistent with the notion that the low-frequency comovement between hours and the growth rates of RPI and TFP is sufficiently autonomous so that the other variables in the baseline VAR are not capable of eliminating the estimation bias resulting from the exclusion of hours.

Implications for Plausibility of Structural Interpretation. This part of my argument uses the results from Figures C.2a and C.2b as the basis for an additional litmus test for the plausibility of my IST-news-based interpretation of this paper's results. I conduct the following test to gauge the level of this plausibility. This test generates 100 artificial data sets from stationary VARs that include hours and comply with Restrictions 1 and 2 from Section 3 of the paper (like the baseline empirical VAR) and applies to them the non-hours-stationary-VAR estimation procedure that also underlies the results from Figures C.2b and C.2b.

The results from this experiment are shown in Figures C.3a and C.3b, which show the mean estimated median and 84th and 16th percentile impulse responses and FEV contributions to the variables' variation of the identified business cycle shock over a ten year horizon, along with the corresponding mean true responses and contributions from the true model. It is apparent that the mean estimated median responses and FEV contributions for RPI and TFP are significantly downward biased. E.g., while the true FEV contributions to RPI and TFP 10-year variation are 57% and 31%, respectively, the corresponding average estimated median contributions are 23% and 11%. The numbers for the long-run horizon (not directly shown in the figures) are even further apart with 80% and 60% being the true long-run contributions for RPI and TFP compared to corresponding mean estimated median long-run contributions of 33% and 15%.

Moreover, reflective of the aforementioned severe downward bias in the estimation of the long-run contributions to RPI and TFP variation, the proportions of Monte Carlo simulations where estimated median long-run contributions to RPI and TFP FEVs are both below 0.1 and 0.05 are 40% and 23%, respectively. (I.e., for 40 and 23 out of the 100 considered artificial data sets, my identification produces an estimated median long-run RPI and TFP FEV contribution of less than 0.1 and 0.05.) In the actual data the estimated long-run FEV shares for RPI and TFP are 2% and 5%; hence, the significant aforementioned 40% and 23% proportions indicate that it is very much possible that applying a non-hours-VAR specification to the actual data could result in the small long-run FEV shares I find when excluding hours from my baseline VAR, supporting the view that the actual data is likely generated by an IST-news-driven DGP which includes hours. In other words, these proportions stress that there is a rather strong likelihood of erroneously inferring that the business cycle shock is unrelated to long-run movements in RPI and TFP when using a VAR that excludes hours.

Levels-VAR Without Hours. Notwithstanding the importance of my baseline choice of stationary VAR specification and associated long-run restrictions for the structural interpretation of this paper's results, it was still rather encouraging that a simple levels-VAR (which allows for silence on the issue of cointegration and first-differencing issues) that includes hours still produced meaningful RPI and TFP FEV shares at advanced horizons (see Figure D.6b). Since the basis for the first dimension of my argument stems from first-differencing non-stationary variables, a basic litmus test for the validity of this part of the argument is that a levels-VAR that excludes hours produces results that are comparable to those from including it. Otherwise, there must be an additional factor driving the sensitivity of the baseline results to excluding hours, which would in turn undermine my claim that this sensitivity does not reduce the validity of my empirical analysis.

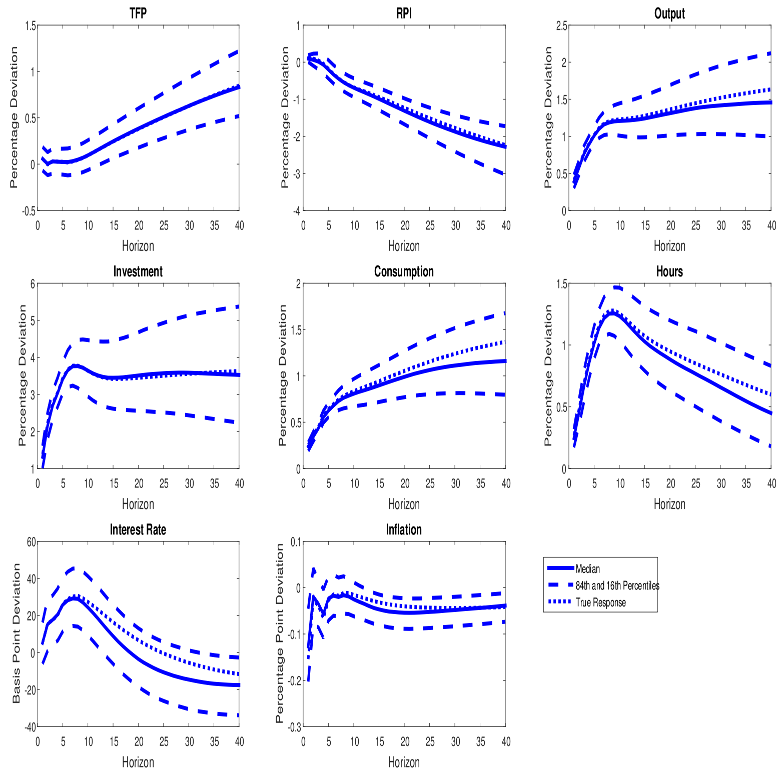
Figures C.4a and C.4b present the impulse response and FEV results from a levels-VAR that excludes hours. Importantly, RPI and TFP FEV shares are still meaningful, reaching 37% and 33% at the ten-year horizon, respectively, with these numbers being comparable to the corresponding numbers from the levels-VAR that includes hours (44% and 28%). The similarity of the results from the non-hours-levels-VAR with respect to those from the levels-VAR with hours increases the confidence in the view that what is really driving the sensitivity of the baseline results to the exclusion of hours is the issue of the low-frequency correlations between hours and RPI and TFP growth rates and the fact that this exclusion prevents from these correlations to be properly accounted for in the estimation.

Table C.1: **Low-Frequency Raw and Partial Correlation of Hours Worked with RPI and TFP Growth Rates.**

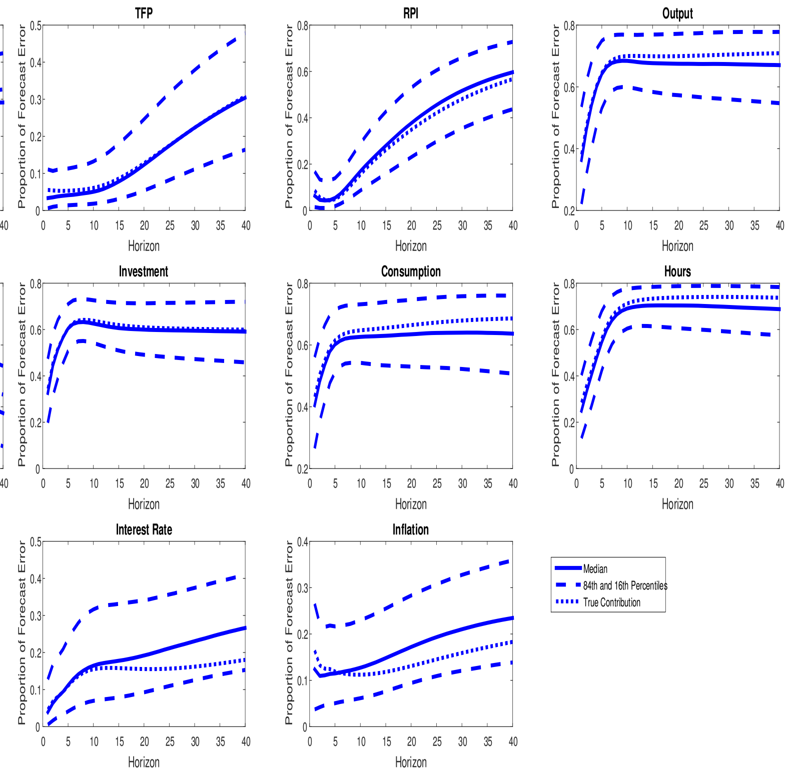
	HP-Trend of RPI Growth	HP-Trend of TFP Growth
Raw Correlation	-74%	52%
Partial Correlation	-85%	36%

Notes: This table presents the correlations (in %) of the HP-trends of hours worked in logs with the HP-trends of the log-first-differences of RPI and TFP both in raw form (first row) and partialed out form. The latter represents partial correlations after controlling for the effects of the HP-trends of the growth rates of output, investment, consumption, and TFP (RPI) for the numbers in the first (second) column.

Figure C.1: **Monte Carlo Evidence from a Stationary Hours Specification: (a) Impulse Responses; (b) Contribution to FEV.**



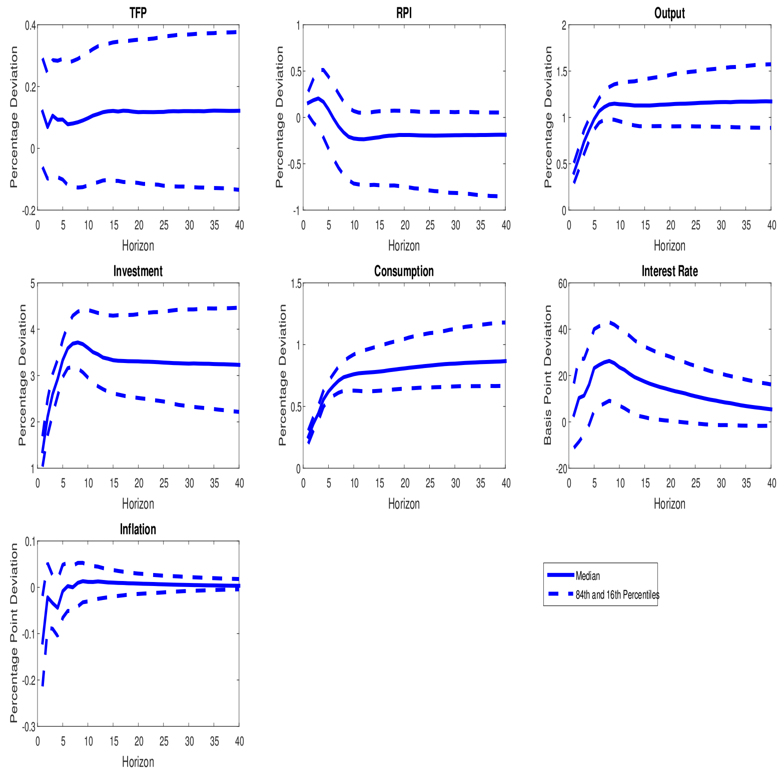
(a) The Mean Estimated Median and 84th and 16th percentile Impulse Responses and the Mean True Impulse Responses.



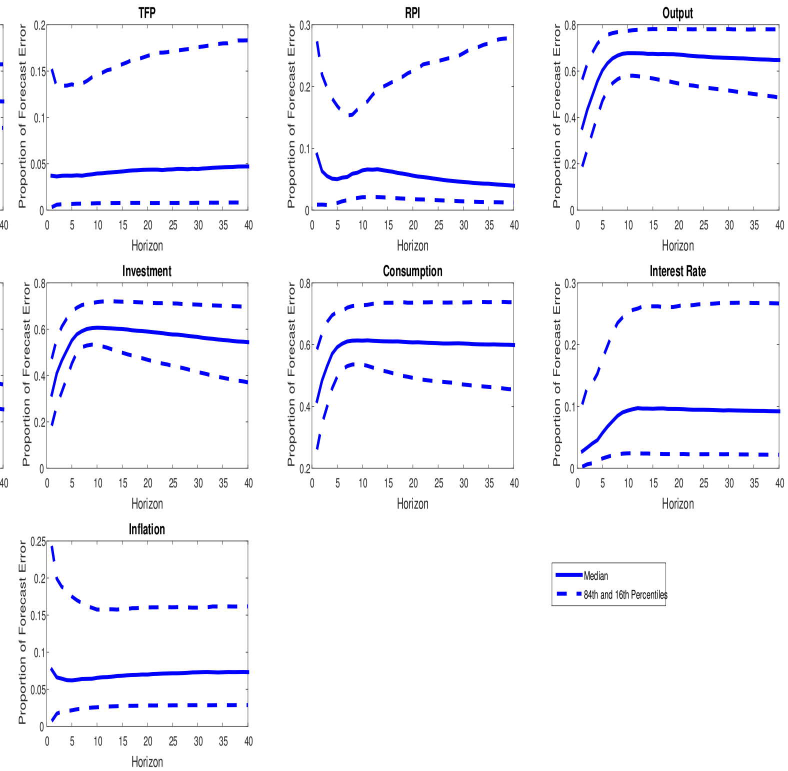
(b) The Mean Estimated Median and 84th and 16th Percentiles FEV Contributions and the Mean True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from estimating a levels hours VAR specification with artificial data sets generated from a levels hours VAR. Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true impulse response across the data generating processes. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations,the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true contribution across the data generating processes.

Figure C.2: **Removing Hours from the Baseline VAR: (a) Impulse Responses; (b) Contribution to FEV.**



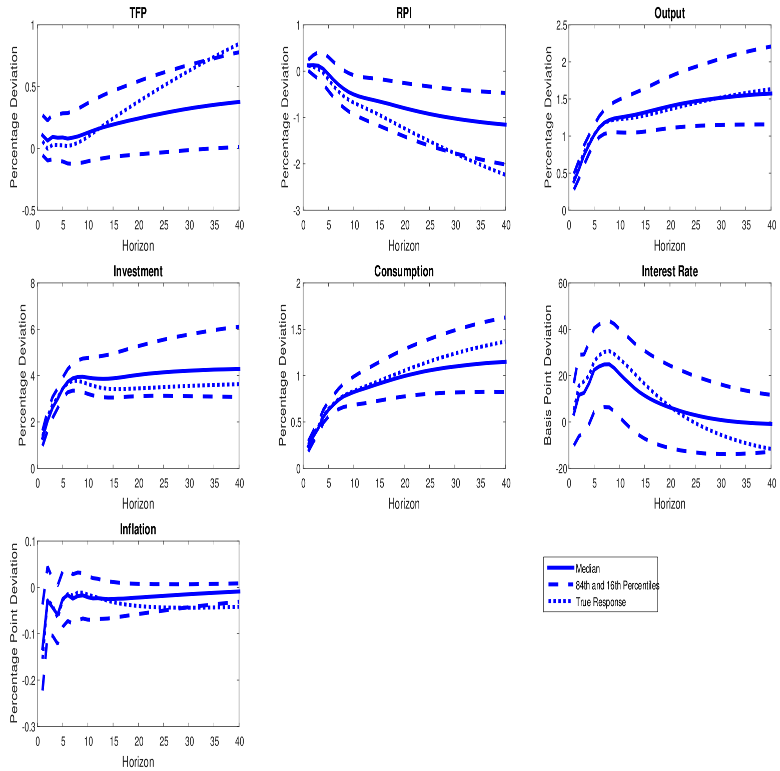
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



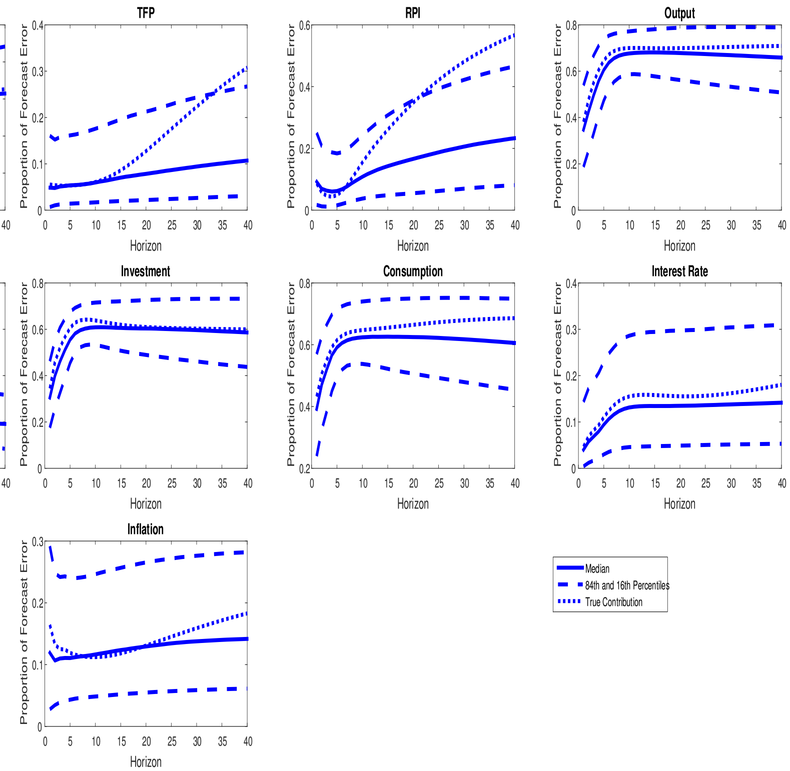
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from excluding hours from the baseline VAR. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from excluding hours from the baseline VAR.

Figure C.3: **Monte Carlo Evidence from a Non-Hours VAR: (a) Impulse Responses; (b) Contribution to FEV.**



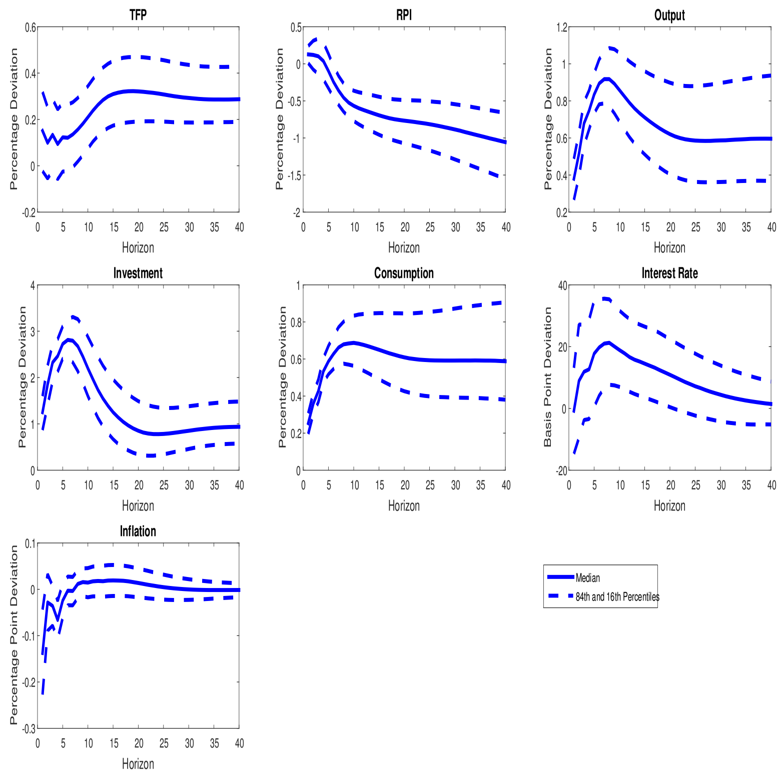
(a) The Mean Estimated Median and 84th and 16th percentile Impulse Responses and the Mean True Impulse Responses.



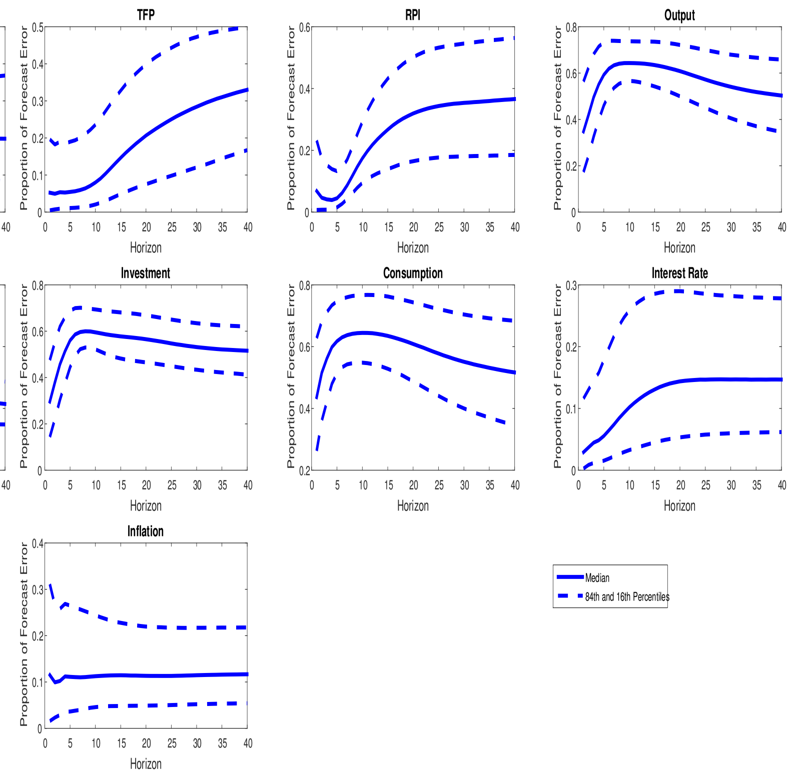
(b) The Mean Estimated Median and 84th and 16th Percentiles FEV Contributions and the Mean True FEV Contributions.

Notes: This figure presents Monte Carlo evidence on the identification of the business cycle shock from estimating a non-hours-VAR with artificial data sets generated from a VAR that includes hours (i.e., baseline VAR). Panel (a): The solid line is the average estimated median impulse response across monte carlo simulations, the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true impulse response across the data generating processes. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the average estimated median FEV contribution across monte carlo simulations,the dashed lines are the 84th and 16th mean estimated percentiles, and the dotted line represents the average true contribution across the data generating processes.

Figure C.4: **Removing Hours from the Levels VAR: (a) Impulse Responses; (b) Contribution to FEV.**



(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a *levels* VAR that excludes hours worked. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a *levels* VAR excludes hours worked.

Appendix D Robustness Analysis

This appendix examines the robustness of the baseline results along eight additional dimensions beyond the two already considered in Section 6 of the paper. The first speaks to the possibility that there may not exist a perfect linear mapping between VAR innovations and economic shocks. The second is that over the entire sample period VAR innovations may not be homoscedastic and VAR coefficients may not be stable. The third relates to the inclusion of stock prices in the VAR. The fourth concerns the potential implications of the financial crisis and zero lower bound (ZLB) periods for my results. The fifth pertains to the stationary specification choice used in my baseline VAR. The sixth and seventh concern the robustness of the results to using Fernald (2014)'s investment TFP measure and a PCE-based inflation measure, respectively. And the eighth deals with imposing the impact positive response restriction only on consumption.

D.1 Addressing Potential Invertibility Issues

As emphasized in Fernandez-Villaverde et al. (2007), for there to be a linear mapping between VAR innovations to economic shocks, as it is assumed in Mapping (A.6), the observables ought to be capable of perfectly forecasting any unobserved state variables present in the true model. If this is the case, the moving average (MA) process of the true model is said to be invertible, or fundamental.

Given that non-invertibility is fundamentally a product of informational deficiency, one practical approach to testing whether non-invertibility is affecting one's results is by checking whether the VAR contains sufficient information such that the true MA process is invertible. Following this reasoning, Forni and Gambetti (2014) have developed a formal statistical test of the null hypothesis of invertibility that is based on checking for orthogonality of the identified shock at hand with respect to the past values of the principal components of a large macroeconomic data set. Forni and Gambetti (2014) have shown that the null of invertibility is rejected if and only if orthogonality is rejected, in which case the identified shock cannot be considered a structural shock.

To conduct the invertibility test for my identified business cycle shock, I extract the principal components from the large quarterly FRED-QD database consisting of 254 quarterly macroeconomic and financial series, all of which have been transformed to induce stationarity.[12] The series span the period 1959:Q1-2015:Q3. Consistent with the invertibility test proposed and used in Forni and Gambetti (2014) and Forni et al. (2014), Table D.4 reports the p-values of the F-test of the regression of the median business cycle shock series on three lags of the first n principal components, where n goes from 1 to 8. I truncate n at 8 as the first eight principal components explain 53% of the total variance of the FRED-QD data set. In all specifications the null of invertibility cannot be rejected at the 5% level, indicating that the identified business cycle shock passes the invertibility test.

Moreover, Table D.4 also reports the R^2s associated with each regression in line with the important message from Beaudry et al. (2015) that one must look at the explanatory power of lagged principal components in addition to the standard F-test p-values so as to ascertain the quantitative importance of any potential non-invertibility. Beaudry et al. (2015) show that non-invertibility is likely to be quantitatively unimportant in terms of its effect on identification precision even for R^2s in the order of 0.2. Hence, that the R^2s of my regressions never exceed 0.14 is encouraging and enhances confidence that the results of this paper are not driven by potential non-invertibility.

D.2 Results for Post-1982 Sub-Sample

One may be concerned that the VAR coefficients might not be stable over the entire sample period. Moreover, the VAR innovations may not be homoscedastic. Hence, I now present results from applying my methodology to a post-1982 sub-sample where it is demonstrated that these sub-sample results, which are much less likely to suffer from potential coefficient instability or heteroscedasticity (see, e.g., Stock and Watson (2007)), are essentially the same as the large sample results.

Figures D.1a and D.1b show the impulse responses and FEV contributions from this exercise; and the first and second rows of Tables D.1, D.2, and D.3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this

[12] The data was downloaded from Michael McCracken's webpage at https://research.stlouisfed.org/econ/mccracken/fred-databases/.

period, respectively. The figures are based on 10^6 randomly generated models from which a total of 2436 admissible models were collected. It is apparent the main results are unchanged for the post-1982 sub-sample period: the business cycle shock accounts for 81% and 54% of the long-run variation in RPI and TFP, respectively, significantly reducing the former while raising the latter, and exhibits a strong boom-bust behavior in the late 1990s and early 2000s period while being a major driver of investment variation over this period.

D.3 Adding Stock Prices to the VAR

Given this paper's IST-news-based interpretation of the business cycle shock and given that it is fairly reasonable to assume that stock prices contain information about future IST progress, a natural extension of the benchmark analysis would be to add stock prices to the baseline VAR. If the business cycle shock were truly an IST news shock, then we should expect to see a significant response of stock prices to this shock on impact. Moreover, since the late 1990s and early 2000s period was characterized by a boom-bust pattern in stock markets, adding stock price to the baseline VAR would allow to examine the contribution of the business cycle shock to this boom-bust pattern and further establish the IST-news-based interpretation of the business cycle shock.

Toward this end, I add to the baseline VAR the log-first-difference of the real S&P 500 Index, obtained from Robert Shiller's website. This series is converted to quarterly frequency by averaging over the monthly observations from each quarter. Figures D.2a and D.2b show the impulse responses and FEV contributions from this exercise; and the third and fourth rows of Tables D.1, D.2, and D.3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Moreover, Table D.5 shows the contribution of the business cycle shock to stock prices variation over the boom-bust period. Results are based on 10^6 randomly generated models from which a total of 338 admissible models were collected.

It is apparent that all of the baseline results are robust to the inclusion of stock prices in the VAR. Interestingly, the business cycle shock generates a significant impact jump in stock prices and is also an important driver of their business cycle variation, confirming the view that stock prices contain valuable information about the future value of IST. Specifically, the median contribution of the business cycle shock to the two-year variation in stock prices is 41% and the median impact effect of the shock on stock prices is highly significant at 3.2%. Moreover, as Table D.5 confirms, the business cycle shock played a major role in driving stock prices during the boom-bust period with median contributions of 62% of the late 1990's boom in stock prices and 30% of the decline in the bust period.[13] Overall, the results support the interpretation of the business cycle shock as representing an IST news shock.

Notably, in standard macro models IST news shocks lower Tobin's *marginal* q (the value of an additional unit of installed capital), which at first pass seems to imply that the positive impact rise in stock prices from Figure D.2a is at odds with theory. However, Jaimovich and Rebelo (2009) argue that this does not necessarily mean that IST news shocks should reduce Tobin's *average* q (the ratio of firm value to the capital stock), which is what is commonly thought of as corresponding to stock prices. The reason for this is that with the standard Christiano et al. (2005)-type investment adjustment costs Tobin's average and marginal q are not equal. Jaimovich and Rebelo (2009) show that the value of the firm can be written as the sum of two components, the first corresponding to the value of the capital stock and the second representing the value of investment. And, while IST (as well as TFP) news shocks reduce the first component, they raise the second one.

For the calibration in Jaimovich and Rebelo (2009), the first component's response dominates the second one's such that firm value drops in response to both IST and TFP news shocks. But Jaimovich and Rebelo (2009) report that this can be overturned quite easily by introducing decreasing returns to scale into the production function, with the value of the firm rising in response to IST/TFP news shocks when the degree of returns to scale is lower than 0.9. So one need not view the stock price impact response result as necessarily theory-inconsistent as it seems that reasonable alterations of standard settings can make it more in line with theory.

[13] Relative to steady state growth as computed from the sample's average growth rate of stock prices, the stock market grew by 52% in the period 1997-1999 and lost 53% of its value in the subsequent bust period.

D.4 Financial Crisis and ZLB Periods

The inclusion of the financial crisis period (2008-2009) and associated ZLB period (2009-2014) in my baseline sample could potentially affect this paper's results through three main channels. The first is that the Great Recession period was a very unique episode in terms of the large credit supply shocks it saw; one may also want to consider results that are based on more normal, non-crisis periods. The second is that the ZLB period constitutes a structural change in the U.S. economy and therefore may bias my estimation. And the third is that my interest rate variable, the 3-month T-Bill rate, remains roughly constant during the ZLB period which in turn may also potentially bias my results. To address these three concerns, I proceed in three steps. First, I show results from a sample that excludes the financial crisis and ZLB periods, i.e., 1959-2007. Second, I use the WU and XIA (2016) shadow rate series instead of the three month T-Bill rate while running the estimation over the same sample as I do in my baseline estimation. Lastly, instead of using a short-term government bond yield which was constrained by zero during the ZLB period, I use the 10-year Treasury rate which was unconstrained during this period. The first exercise addresses the concern related to the first two aforementioned channels; and the next two address the concern pertaining to the third channel. I now turn to presenting the results from these three estimation exercises.

Results from a 1959-2007 Sample. Figures D.3a and D.3b show the impulse responses and FEV contributions from the 1959-2007 sample based estimation; and the fifth and sixth rows of Tables D.1, D.2, and D.3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Results are based on 10^6 randomly generated models from which a total of 365 admissible models were collected.

It is apparent that the IST-news-based interpretation of the business cycle shock is also borne out by the results of this specification, with the business cycle shock continuing to account for most of the long-run variation in RPI and the significant boom-bust nature of this shock in the late 1990s-early 2000s period remaining intact. These results are especially encouraging in confirming that my baseline results are insensitive to the exclusion of the Great Recession period and the apparent important role of the business cycle shock in driving it, as indicated by the historical decomposition results from Table 5 of the paper. Also worthwhile noting is the fact that the exclusion of the financial crisis and ZLB periods has no bearing on the significant rise in interest rates observed for the baseline case.

Results from Using the WU and XIA (2016) Shadow Rate Series. The results from replacing the baseline three month T-Bill rate with the shadow rate from WU and XIA (2016) appear in Figures D.4a and D.4b and the seventh and eighth rows of Tables D.1, D.2, and D.3. The sample used for this estimation, as dictated by the sample coverage of the shadow rate series, is 1960:Q1-2015:Q4 where quarterly values are averages of raw monthly values of this series. Results are based on 10^6 randomly generated models from which a total of 915 admissible models were collected.

Notably, this replacement has little effect on the baseline results and the associated IST-news-based interpretation of the business cycle shock. Moreover, the shadow rate, which serves as a better proxy for the stance of monetary policy in a ZLB environment than standard short-term interest rates, rises significantly in response to the business cycle shock in largely similar fashion to the baseline case. This rise is also somewhat stronger than that from the baseline specification, which is to be expected given that the shadow rate fluctuates in the ZLB period as opposed to the three month T-Bill rate.

Results from Using the 10-year Treasury Rate. The results from replacing the baseline three month T-Bill rate with the 10-year Treasury Rate are shown in Figures D.5a and D.5b and the ninth and tenth rows of Tables D.1, D.2, and D.3. Results are based on 10^6 randomly generated models from which a total of 1027 admissible models were collected.

Here too one can think of the long-term, 10-year Treasury rate as a better measure of the true stance of monetary policy in a ZLB environment than common short-term interest rates but in more general terms it effectively captures markets' perceptions of the future stance of monetary policy. As such, its insignificant rise observed from Figure D.5a serves as evidence that the contractionary nature of monetary policy in response to the business cycle shock is insufficiently persistent to generate a significant rise in long-term interest rates. Nevertheless, the clear robustness of the results regarding the long-run implications and late 1990s-early 2000s boom-bust behavior of this shock informs us that the validity of the IST-news-based interpretation of the business cycle shock maintains also for this specification.

D.5 Alternatives to the Stationary VAR Specification

My opting to specify a stationary VAR where TFP, RPI, output, consumption, and investment are log-first-differenced in the VAR can be warranted on the basis of both the evidence that *i*) statistical cointegration tests could not reject the null of no cointegration among the non-stationary variables in my VAR and that *ii*) hours should be treated as a stationary variable that should accordingly be kept in levels in the VAR, as well as the importance of being able to have meaningful inference about the long-run implications of the identified business cycle shock for its structural interpretation.

Nevertheless, one may still raise the concern that my estimation could potentially be biased owing to its abstraction from theoretically sound cointegrating relations between the non-stationary variables in my VAR (e.g., stationary consumption- and investment-output ratios). There are two possible ways to address this concern. The first is to estimate the VAR in levels. Such a non-stationary specification does not come without cost: it completely disables proper inference about the long-run implications of the business cycle shock which turns out to be crucial for the structural interpretation of this shock. That said, it does have merit in demonstrating what comes out of both not taking a stand on the cointegration structure among the non-stationary variables (or lack thereof) as well as removing the long-run restriction (Restriction 2 from Section 3 of the paper), where the latter was already done but in the context of the baseline stationary VAR.

The second involves including in the VAR the logs of the consumption and investment shares of output, which are generally stationary in standard DSGE models and whose inclusion therefore accounts for any potential omission of theory-consistent cointegration structure. While including both ratios in real terms in place of consumption and investment also yielded results which are consistent with an IST-news-based interpretation of the business cycle shock, I proceeded with only making the former replacement (i.e., keeping investment) while adding to the VAR the nominal investment share of GDP for two reasons. The first is the clear non-stationarity of the real investment share of output for my sample. The second reason, which can be viewed as the root cause of the first reason, is that in the presence of a stochastically trending IST the real investment share of output is not stationary whereas the nominal one is (see, e.g., the model from Moura (2018) which also serves as the underlying framework of the Monte Carlo experiments of Section 4 of the paper and the additional ones from Appendices B.10 and B.11). I now turn to presenting the results from these two estimation exercises.

VAR in Levels. The results from the levels VAR appear in Figures D.6a and D.6b (impulse responses and FEVs) and the first two rows of Table D.6 (boom-bust behavior of the business cycle shock in terms of mean realizations and contribution to investment variation). Results are based on 10^6 randomly generated models from which a total of 25092 admissible models were collected.

The results appear quite similar to those from the stationary VAR without the long-run restriction (see Figures 4a and 4b and Tables 7 and 8 from the paper). As in the latter case, the quantitative difference between the RPI responses across the baseline and levels VAR specification need not be taken to mean a lack of robustness; instead, they should be expected given that effectively the levels VAR specification is equivalent to the stationary VAR without the long-run restriction in terms of both specifications not being capable of revealing the truth about the long-run implications of the business cycle shock. And, still, that 44% of the 10-year variation in RPI is accounted for by the business cycle shock along with a significant boom-bust behavior in the late 1990s-early 2000s period is consistent with an IST-news-based interpretation of the business cycle shock also in the levels VAR specification.

Including Consumption and Investment Shares of Output. The results from replacing the log-first-difference of consumption with the log-level of the real consumption-output ratio and adding the nominal investment-output ratio are shown in Figures D.7a and D.7b and the eleventh and twelfth rows of Tables D.1, D.2, and D.3. In this estimation I use a nine-variable VAR where only TFP, RPI, output, and investment are first-differenced while the other five variables are kept in levels (real consumption share of output, hours, inflation, interest rates, and the nominal investment share of output). Note that the response of consumption is constructed as the sum of the responses of output and the real consumption share of output, which in turn allows me to impose the baseline impact restriction and two-year 50% FEV restriction on consumption. Results are based on 10^6 randomly generated models from which a total of 252 admissible models were collected.

The results are similar to the baseline ones, with the IST-news-based interpretation of the business cycle shock continuing to be valid. This is encouraging in alleviating the concern that not accounting for theory-consistent cointegration has meaningful consequences for my results.

D.6 Fernald (2014)'s Investment TFP Measure

In addition to providing an aggregate utilization-adjusted TFP series, Fernald (2014) also constructs quarterly sectoral TFP series which are in turn based on an equality between RPI and IST that yields non-utilization-adjusted sectoral TFP measures. Effectively, the ratio between the non-utilization-adjusted consumption and investment TFP measures from Fernald (2014) is simply the ratio of investment prices, where the investment sector corresponds to consumer durables and equipment and intellectual property investment, to consumption prices with the consumption sector defined as everything that is not in the investment sector. As with the aggregate TFP measure, Fernald (2014) also provides utilization-adjusted sectoral TFP measures with the investment TFP one potentially serving as a good proxy for IST if perfect correspondence between RPI and IST were in place. It is therefore of interest to examine the robustness of my baseline results to replacing RPI with Fernald (2014)'s utilization-adjusted investment TFP measure.

Figures D.8a and D.8b show the impulse responses and FEV contributions from replacing my baseline RPI measure with the aforementioned investment TFP measure; and the thirteenth and fourteenth rows of Tables D.1, D.2, and D.3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Results are based on 10^6 randomly generated models from which a total of 906 admissible models were collected.

The baseline results are clearly robust to this replacement, with most of the long-run variation in the investment TFP measure being accounted for by the business cycle shock and the latter continuing to exhibit a significant boom-bust pattern in the late 1990s-early 2000s period.

D.7 Alternative Inflation Measure

The fall in inflation that takes place in response to the business cycle shock is an interesting result informing us that the business cycle shock does not appear to be a *pure* demand shock. To have more confidence in this result, it could prove useful to examine the robustness of this inflation decline to using an alternative common measure of inflation based on the personal consumption expenditures (PCE) deflator. (The Federal Reserve actually states its goal for inflation in terms of the PCE deflator.)

Figures D.9a and D.9b show the impulse responses and FEV contributions from replacing my baseline CPI-based inflation measure with the PCE-deflator-based inflation measure (defined as log-first-differences of the PCE deflator); and the fifteenth and sixteenth rows of Tables D.1, D.2, and D.3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Results are based on 10^6 randomly generated models from which a total of 1427 admissible models were collected.

The baseline results are robust to this replacement, with this alternative inflation measure also significantly falling in response to the business cycle shock. Moreover, the long-run behavior of RPI and the boom-bust nature of the business cycle shock in the late 1990s-early 2000s period continue to hold also for this alternative specification.

D.8 Imposing the Impact Restriction Only on Consumption

This paper's interpretation of the business cycle shock as a general purpose technology (GPT) news shock, where the manifestation of this shock takes place in the investment-specific goods sector through IST news shocks, associates the business cycle shock with delayed movements in TFP which reflect the GPT nature of this shock. As such, this shock contains elements shared also by the commonly studied TFP news shock, which in turn raises the concern that the impact response restriction part of Restriction 1 from Section 3 of the paper (i.e., that all real aggregates rise on impact) may be overly restrictive. Specifically, contrasting earlier empirical results from Beaudry and Portier (2006) which indicated that TFP news shocks produce business cycle comovement, Barsky and Sims (2011) argue that TFP news shocks only raise consumption on impact while failing to do so for output, investment, and hours (which is broadly consistent with responses from a standard RBC model). Hence, my identification and interpretation of the business cycle shock may be biased by the additional three impact restrictions on the latter three aggregates.

To address this concern, I have repeated my baseline estimation procedure with only imposing that consumption rise on impact while leaving the impact responses of the other three aggregates unrestricted. Figures D.10a and D.10b show the impulse responses and FEV contributions from this estimation exercise; and the seventeenth and eighteenth rows of Tables D.1, D.2, and D.3 depict the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock, the business cycle shock's mean realizations of the boom-bust period, and its contribution to the variation in investment over this period, respectively. Results are based on 10^6 randomly generated models from which a total of 1299 admissible models were collected.

It is clear that the baseline results are robust to my removal of the restrictions on the impact response of output, investment, and hours, with results being very similar both quantitatively and qualitatively to the baseline ones. This strong similarity indicates that this paper's structural interpretation of the business cycle shock is robust to letting the data freely determine the impact responses of these three aggregates and renders it unlikely that my baseline three impact restriction for these variables are erroneous.

Table D.1: **Long-Run Implications of Business Cycle Shock for RPI and TFP.**

	Impulse Response	Forecast Error Variance Contribution
Post-1982 VAR: RPI	-2.2% [-5.1%,-1.3%]	81% [67%,88%]
Post-1982 VAR: TFP	0.8% [0.3%,2%]	54% [17%,78%]
VAR With Stock Prices: RPI	-2.7% [-6.3%,-1.7%]	81% [66%,88%]
VAR With Stock Prices: TFP	1.2% [0.6%,3.2%]	57% [32%,77%]
1959-2007 Sample: RPI	-2.6% [-5.9%,-1.6%]	81% [64%,88%]
1959-2007 Sample: TFP	0.9% [0.4%,2.4%]	51% [19%,78%]
Shadow Rate: RPI	-2.8% [-6.2%,-1.6%]	80% [60%,88%]
Shadow Rate: TFP	1.2% [0.5%,3.3%]	59% [27%,79%]
10-Year Treasury Rate: RPI	-2.4% [-4.8%,-1.5%]	78% [61%,87%]
10-Year Treasury Rate: TFP	1.1% [0.5%,2.7%]	55% [23%,79%]
Imposing Cointegration: RPI	-2.4% [-4.5%,-1.5%]	76% [56%,87%]
Imposing Cointegration: TFP	1% [0.4%,2.2%]	47% [18%,73%]
Investment TFP: RPI	2.7% [1.6%,5.6%]	78% [54%,87%]
Investment TFP: TFP	1.2% [0.6%,2.9%]	64% [35%,82%]
Alternative Inflation Measure: RPI	-2.5% [-5%,-1.5%]	80% [62%,88%]
Alternative Inflation Measure: TFP	1.1% [0.5%,2.6%]	55% [22%,78%]
Only Consumption Restriction: RPI	-2.5% [-5.1%,-1.6%]	81% [62%,88%]
Only Consumption Restriction: TFP	1.1% [0.5%,2.7%]	55% [24%,78%]

Notes: This table presents the median and 16th and 84th percentiles of the long-run impulse responses and FEV shares of RPI and TFP due to the business cycle shock in alternative model specifications relative to the baseline one (see Appendix D). The 16th and 84th percentiles appear in squared brackets next to the median estimate.

Table D.2: **Mean Realization of Business Cycle Shock and Other Long-Run (Non-Business-Cycle) RPI Shock in Boom-Bust Period.**

	Business Cycle Shock	Other Long-Run Shock
Post-1982 VAR: Boom Period Mean Realization	0.38 [0.18,0.58]	-0.02 [-0.29,0.25]
Post-1982 VAR: Bust Period Mean Realization	-0.35 [-0.57,-0.12]	0.06 [-0.33,0.45]
VAR With Stock Prices: Boom Period Mean Realization	0.38 [0.21,0.57]	-0.04 [-0.31,0.23]
VAR With Stock Prices: Bust Period Mean Realization	-0.37 [-0.59,-0.17]	-0.01 [-0.45,0.37]
1959-2007 Sample: Boom Period Mean Realization	0.52 [0.35,0.70]	0.01 [-0.25,0.23]
1959-2007 Sample: Bust Period Mean Realization	-0.39 [-0.56,-0.20]	-0.05 [-0.38,0.24]
Shadow Rate: Boom Period Mean Realization	0.43 [0.27,0.59]	0.08 [-0.18,0.31]
Shadow Rate: Bust Period Mean Realization	-0.42 [-0.61,-0.24]	-0.01 [-0.35,0.26]
10-Year Treasury Rate: Boom Period Mean Realization	0.38 [0.21,0.57]	0.04 [-0.31,0.23]
10-Year Treasury Rate: Bust Period Mean Realization	-0.37 [-0.59,-0.17]	-0.01 [-0.45,0.37]
Imposing Cointegration: Boom Period Mean Realization	0.49 [0.33,0.65]	-0.08 [-0.29,0.18]
Imposing Cointegration: Bust Period Mean Realization	-0.33 [-0.53,-0.11]	0.11 [-0.35,0.46]
Investment TFP: Boom Period Mean Realization	0.47 [0.31,0.63]	-0.01 [-0.26,0.27]
Investment TFP: Bust Period Mean Realization	-0.43 [-0.60,-0.25]	0.08 [-0.26,0.38]
Alternative Inflation Measure: Boom Period Mean Realization	0.50 [0.33,0.66]	0.06 [-0.22,0.32]
Alternative Inflation Measure: Bust Period Mean Realization	-0.36 [-0.55,-0.19]	-0.04 [-0.37,0.28]
Only Consumption Restriction: Boom Period Mean Realization	0.49 [0.33,0.65]	0.01 [-0.27,0.30]
Only Consumption Restriction: Bust Period Mean Realization	-0.38 [-0.56,-0.20]	-0.10 [-0.40,0.21]

Notes: This table presents the median and 16th and 84th percentiles of the mean realization of the business cycle shock and the other shock driving long-run RPI variation in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods. Results shown are for alternative model specifications relative to the baseline one (see Appendix D).

Table D.3: **Contribution of Business Cycle Shock and Other Long-Run (Non-Business-Cycle) RPI Shock to Investment Boom-Bust Episode.**

	Business Cycle Shock	Other Long-Run Shock
Post-1982 VAR: Boom Period Contribution	88% [32%,144%]	20% [-14%,69%]
Post-1982 VAR: Bust Period Contribution	138% [62%,213%]	5% [-60%,60%]
VAR With Stock Prices: Boom Period Contribution	84% [47%,121%]	10% [-10%,47%]
VAR With Stock Prices: Bust Period Contribution	169% [96%,241%]	11% [-39%,53%]
1959-2007 Sample: Boom Period Contribution	93% [55%,131%]	1% [-25%,23%]
1959-2007 Sample: Bust Period Contribution	120% [61%,184%]	-5% [-38%,24%]
Shadow Rate: Boom Period Contribution	83% [48%,116%]	10% [-12%,41%]
Shadow Rate: Bust Period Contribution	175% [112%,237%]	2% [-37%,41%]
10-Year Treasury Rate: Boom Period Contribution	84% [47%,121%]	10% [-10%,47%]
10-Year Treasury Rate: Bust Period Contribution	169% [96%,241%]	11% [-39%,53%]
Imposing Cointegration: Boom Period Contribution	54% [26%,84%]	8% [-9%,31%]
Imposing Cointegration: Bust Period Contribution	140% [85%,194%]	-5% [-43%,31%]
Investment TFP: Boom Period Contribution	88% [52%,124%]	5% [-17%,32%]
Investment TFP: Bust Period Contribution	163% [101%,223%]	3% [-32%,41%]
Alternative Inflation Measure: Boom Period Contribution	97% [63%,136%]	10% [-12%,42%]
Alternative Inflation Measure: Bust Period Contribution	165% [101%,232%]	-3% [-45%,42%]
Only Consumption Restriction: Boom Period Contribution	97% [61%,135%]	7% [-13%,37%]
Only Consumption Restriction: Bust Period Contribution	160% [92%,224%]	-1% [-40%,38%]

Notes: This table presents the median and 16th and 84th percentiles of the contribution (in %) of the business cycle shock and the other long-run RPI shock to the change in investment in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods. Results shown are for alternative model specifications relative to the baseline one (see Appendix D). The contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ investment\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rates are the average growth rates for the sample periods underlying the specifications' estimation (apart for the post-1982, 1959-2007, and shadow rate specifications, all specifications are based on the baseline 1959:Q1-2017:Q3 sample). Note that a relative contribution of 100% implies that all of the gain or loss in investment is accounted for by the shock.

Table D.4: **F-Test and R^2 of Regression of Business Cycle Shock Series on Lagged Principal Components.**

	Principal Components (from 1 to n)							
	1	2	3	4	5	6	7	8
P-Value	0.83	0.12	0.13	0.06	0.09	0.07	0.12	0.12
R^2	0	0.05	0.06	0.09	0.10	0.12	0.13	0.14

Notes: Column n reports the p-value of the F-test as well as the R^2 of the regression of the median business cycle shock series on three lags of the first n principle components extracted from the FRED-QD comprehensive quarterly data set, where n goes from 1 to 8.

Table D.5: **Contribution of Business Cycle Shock and Other Long-Run (Non-Business-Cycle) RPI Shock to Stock Prices Boom-Bust Episode.**

	Business Cycle Shock	Other Long-Run Shock
VAR With Stock Prices: Boom Period Contribution	62% [28%,103%]	13% [-8%,50%]
VAR With Stock Prices: Bust Period Contribution	30% [5%,59%]	6% [-8%,27%]

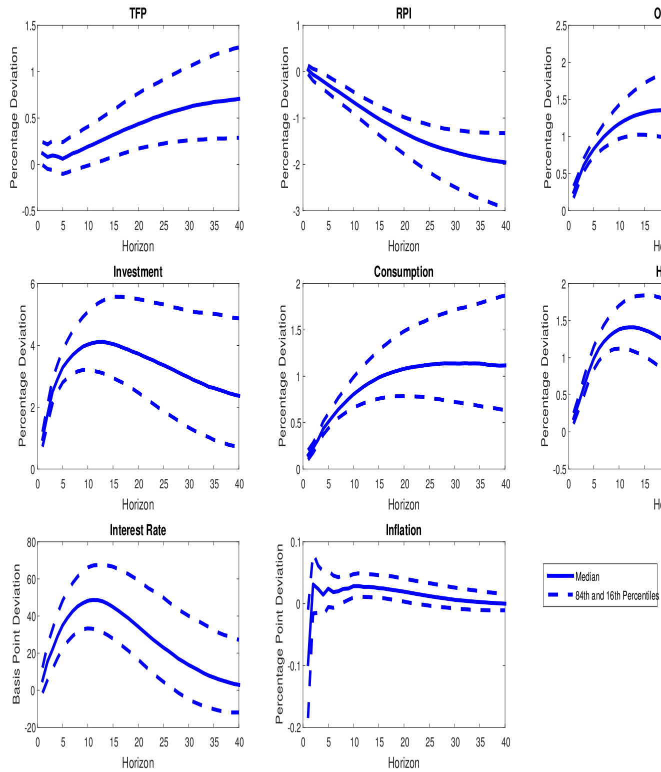
Notes: This table presents the median and 16th and 84th percentiles of the contribution (in %) of the business cycle shock and the other long-run RPI shock to the change in stock prices in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods from a VAR that includes stock prices. The contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ stock\ prices\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rate for stock prices is assumed to be 2.8%, which is the average growth rate in the sample period. Note that a relative contribution of 100% implies that all of the gain or loss in stock prices is accounted for by the shock.

Table D.6: **Levels VAR: Mean Realization of Business Cycle Shock and Contribution to Investment Variation in Boom-Bust Period.**

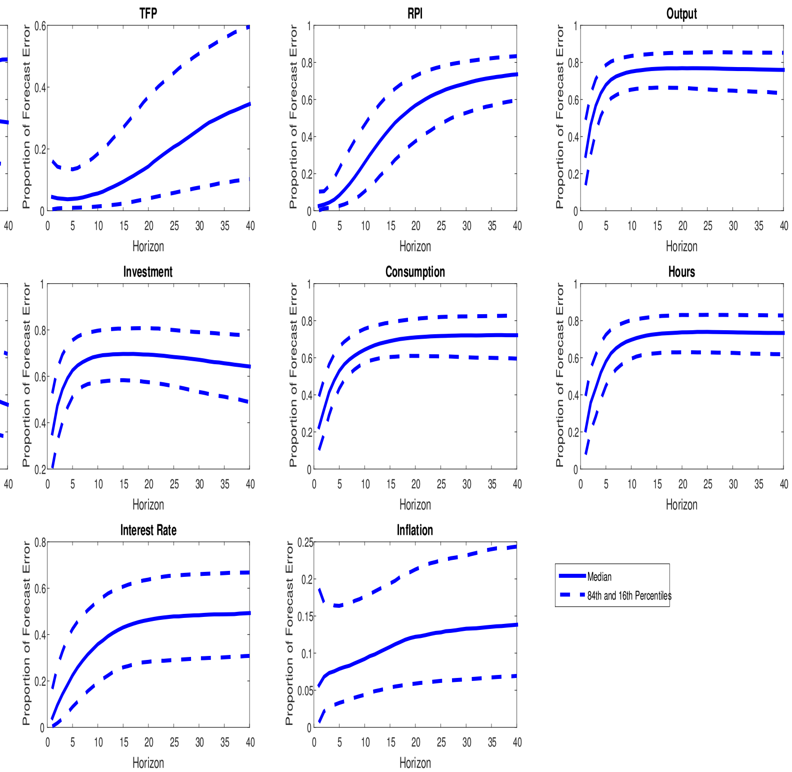
	Mean Realization	Contribution to Investment Variation
Levels VAR: Boom Period	0.51 [0.30,0.72]	68% [30%,105%]
Levels VAR: Bust Period	-0.25 [-0.45,-0.05]	120% [69%,171%]

Notes: This table presents the median and 16th and 84th percentiles of the mean realization of the business cycle shock and the contribution (in %) of this shock to the change in investment in the boom (1997:Q1-1999:Q4) and bust (2000:Q1-2003:Q1) periods from an estimation of a VAR in levels. Since for a level-VAR the long-run restriction is meaningless, this restriction is not imposed upon in the estimation. The contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ investment\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rate for investment is assumed to be 2.8%, which is the average growth rate for the sample period. Note that a relative contribution of 100% implies that all of the gain or loss in investment is accounted for by the shock.

Figure D.1: **Post-1982 VAR: (a) Impulse Responses; (b) Contribution to FEV.**



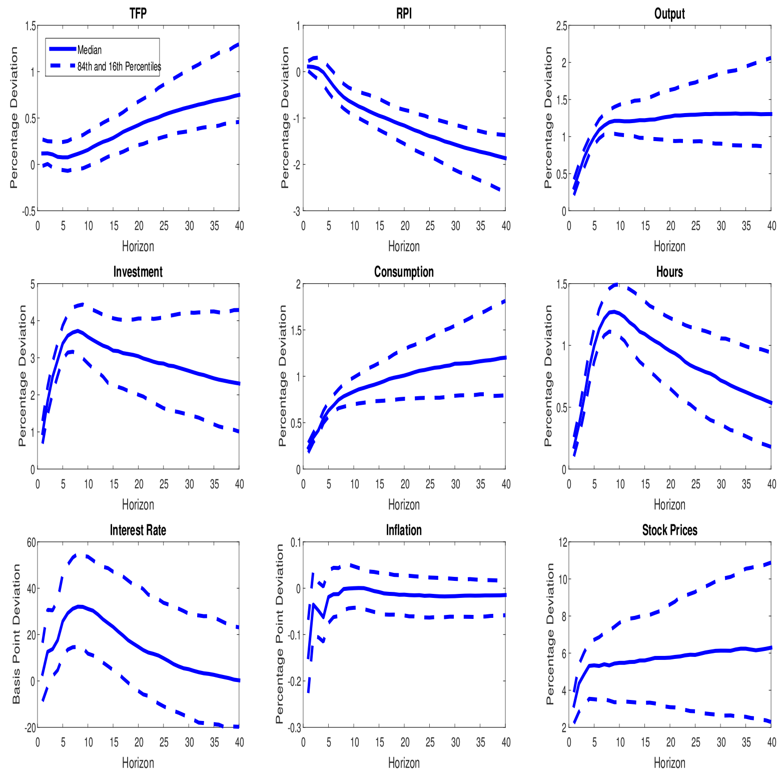
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



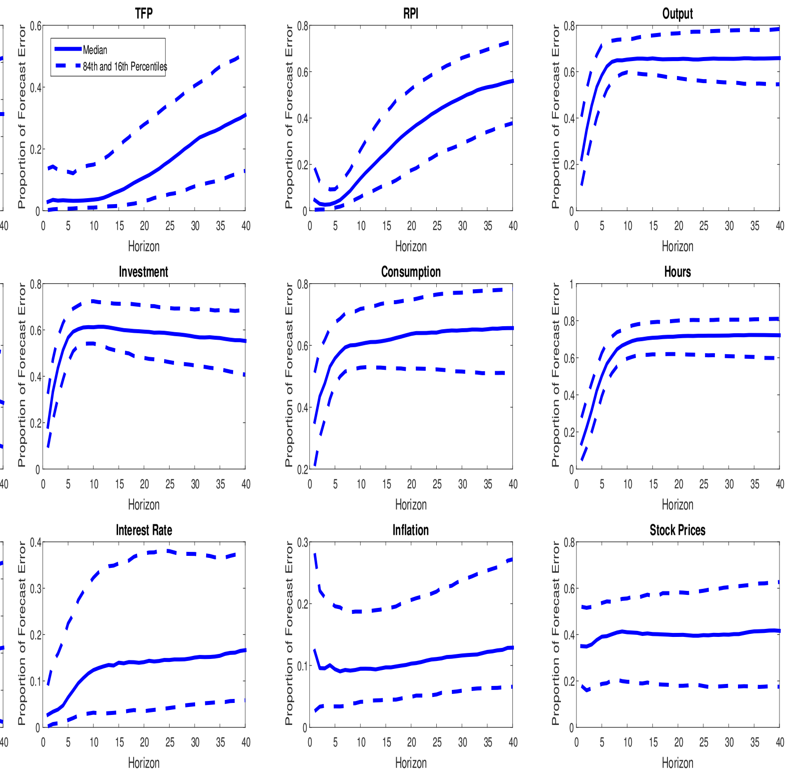
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a post-1982 VAR. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a post-1982 VAR.

Figure D.2: **VAR With Stock Prices: (a) Impulse Responses; (b) Contribution to FEV.**



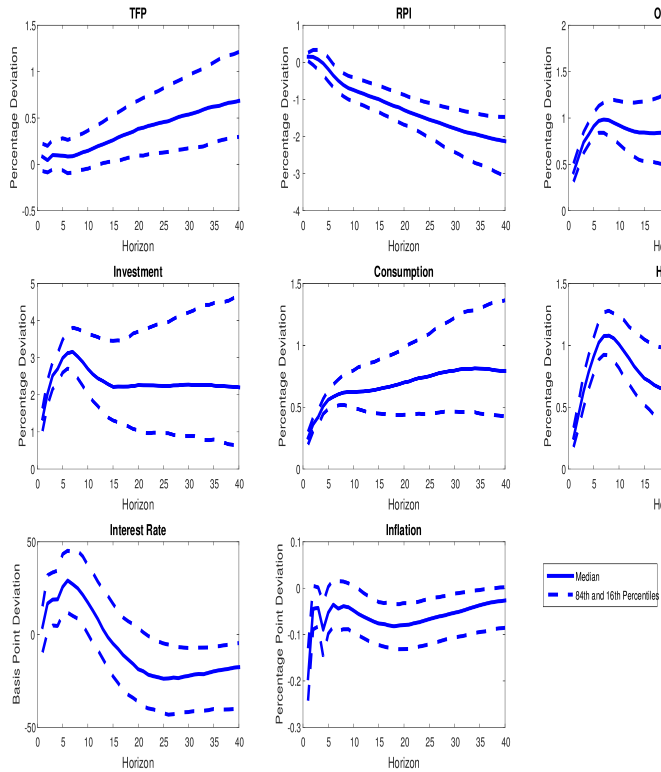
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



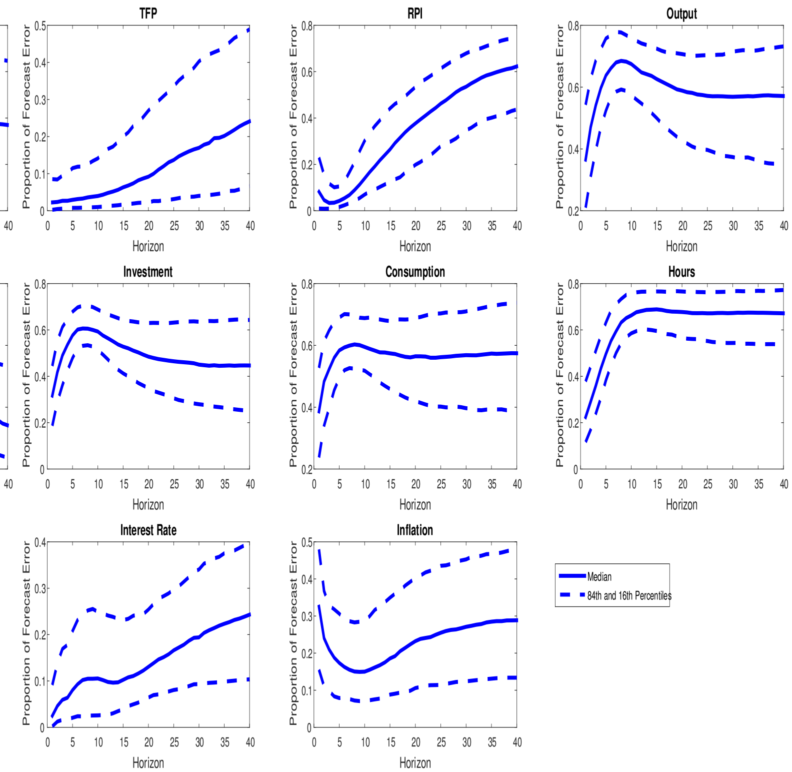
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a VAR that includes stock prices. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a VAR that includes stock prices.

Figure D.3: **1959-2007 Sample: (a) Impulse Responses; (b) Contribution to FEV.**



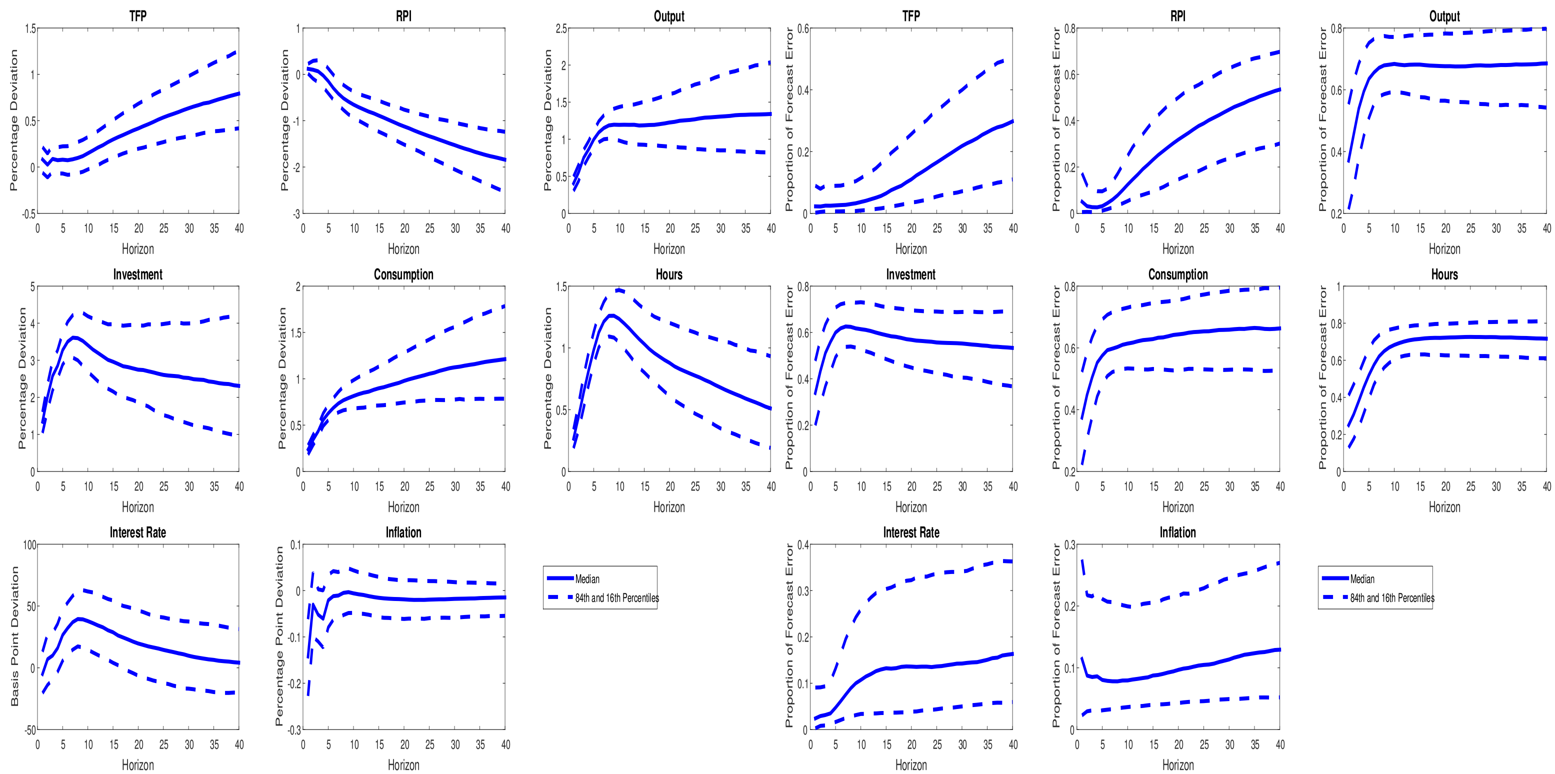
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a 1959-2007 VAR. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a 1959-2007 VAR.

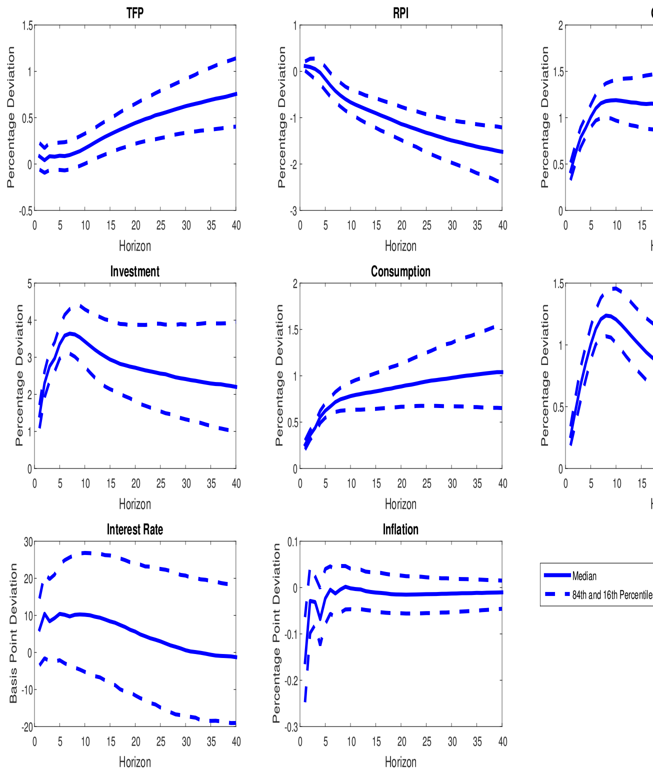
Figure D.4: **Shadow Rate: (a) Impulse Responses; (b) Contribution to FEV.**



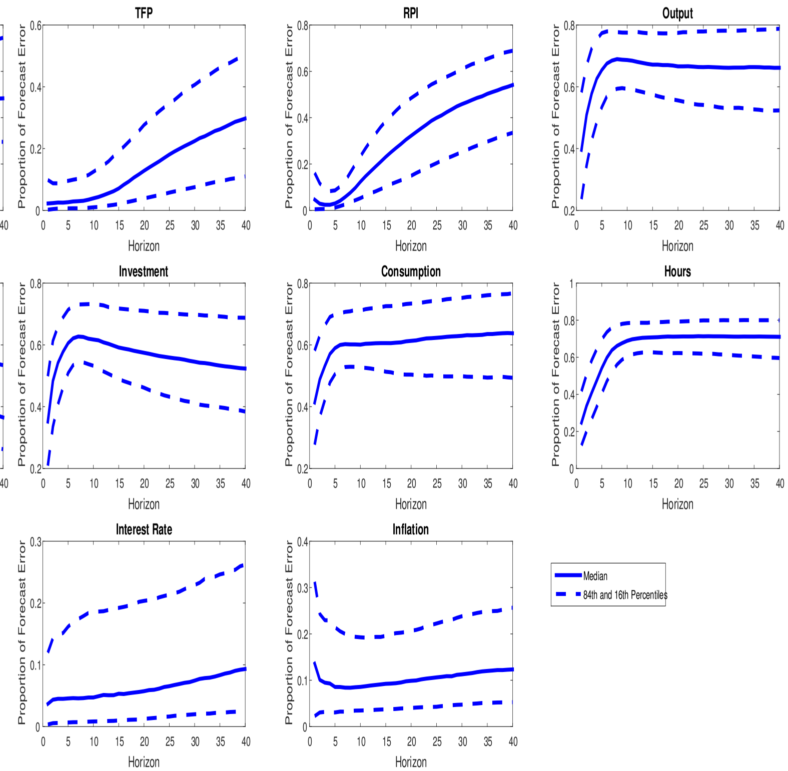
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock. **(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.**

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the three month T-Bill rate with the shadow rate from WU and XIA (2016). Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the three month T-Bill rate with the shadow rate from WU and XIA (2016).

Figure D.5: **10-Year Treasury Rate: (a) Impulse Responses; (b) Contribution to FEV.**



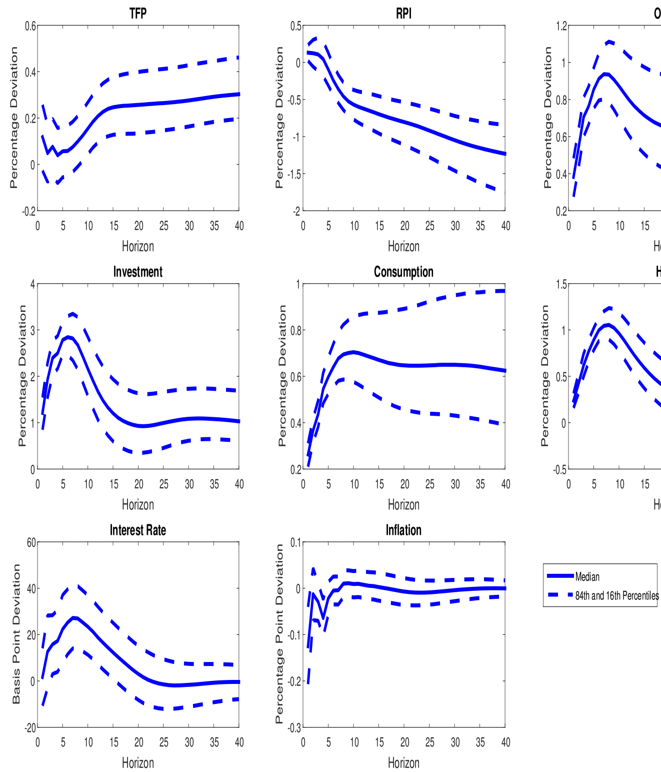
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



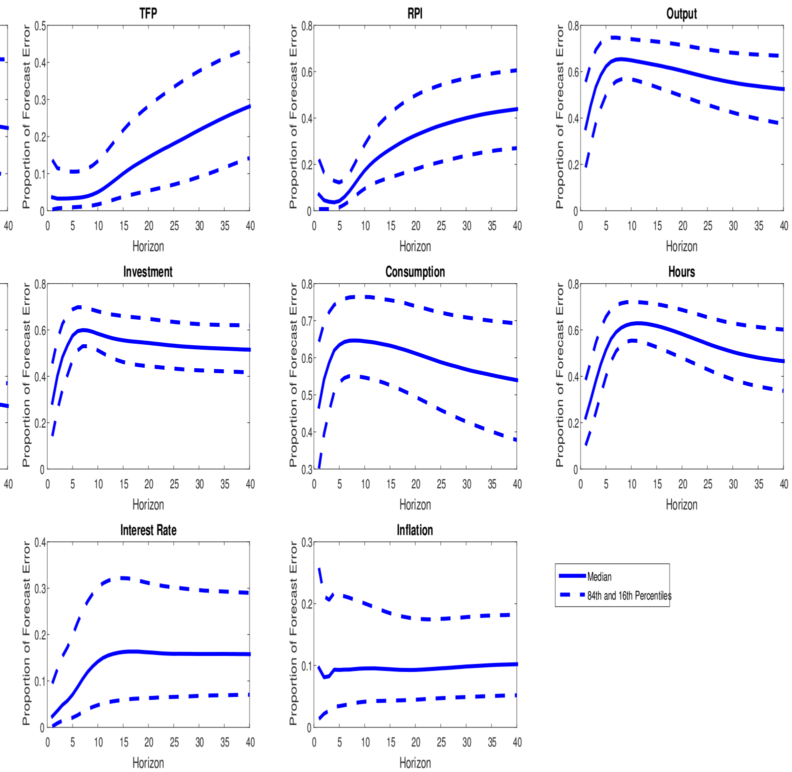
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the three month T-Bill rate with the 10-year treasury rate. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the three month T-Bill rate with the 10-year treasury rate.

Figure D.6: **Levels VAR: (a) Impulse Responses; (b) Contribution to FEV.**



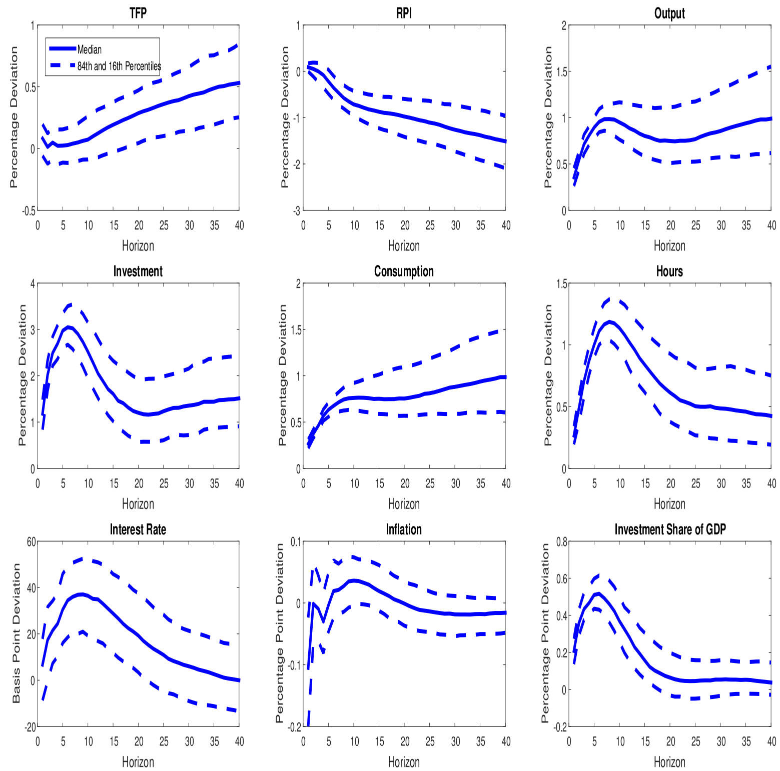
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



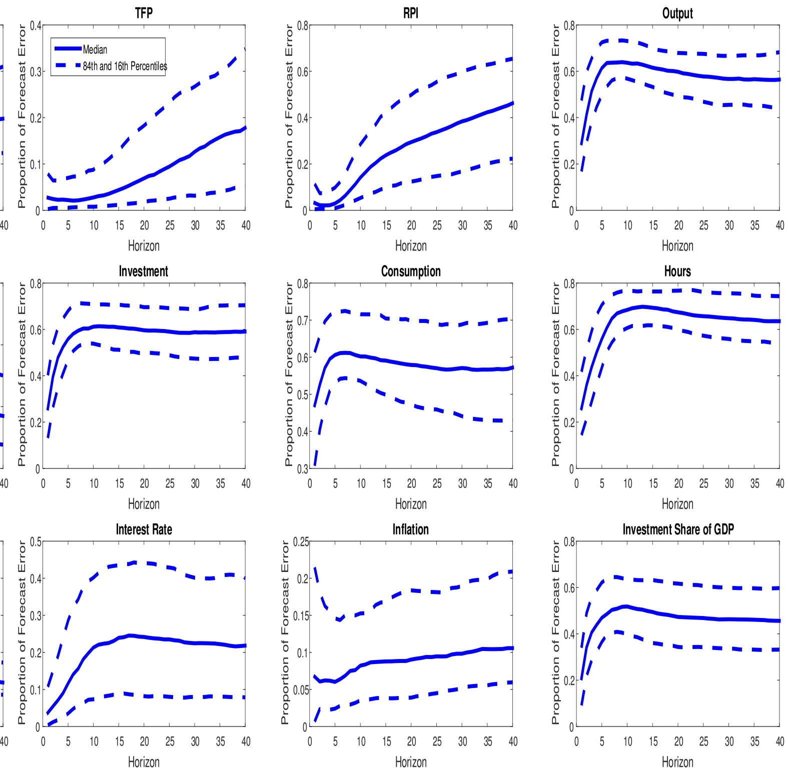
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from a levels VAR. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from a levels VAR.

Figure D.7: **Imposing Cointegration: (a) Impulse Responses; (b) Contribution to FEV.**



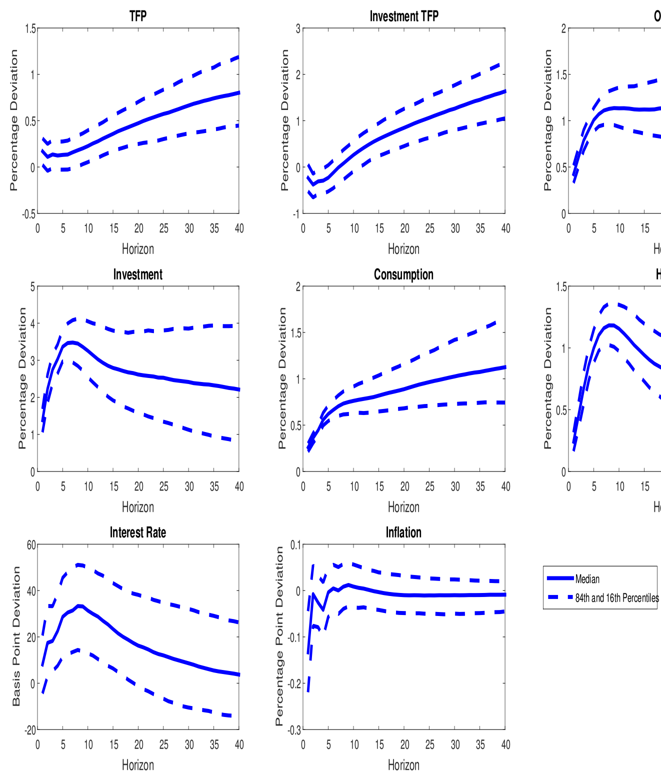
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



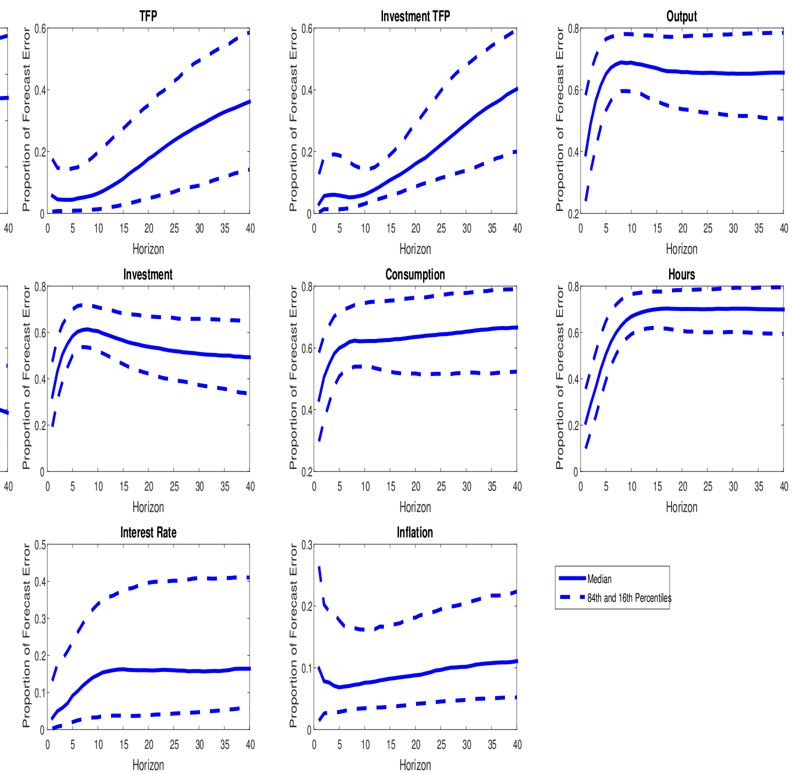
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the log-first-difference of consumption with the log-level of the real consumption-output ratio and adding the nominal investment-output ratio. In this estimation I use a nine-variable VAR where only TFP, RPI, output, and investment are first-differenced while the other five variables are kept in levels (real consumption share of output, hours, inflation, interest rates, and the nominal investment share of output). Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the log-first-difference of consumption with the log-level of the real consumption-output ratio and adding the nominal investment-output ratio. In this estimation I use a nine-variable VAR where only TFP, RPI, output, and investment are first-differenced while the other five variables are kept in levels (real consumption share of output, hours, inflation, interest rates, and the nominal investment share of output).

Figure D.8: **Fernald (2014)'s Investment TFP: (a) Impulse Responses; (b) Contribution to FEV.**



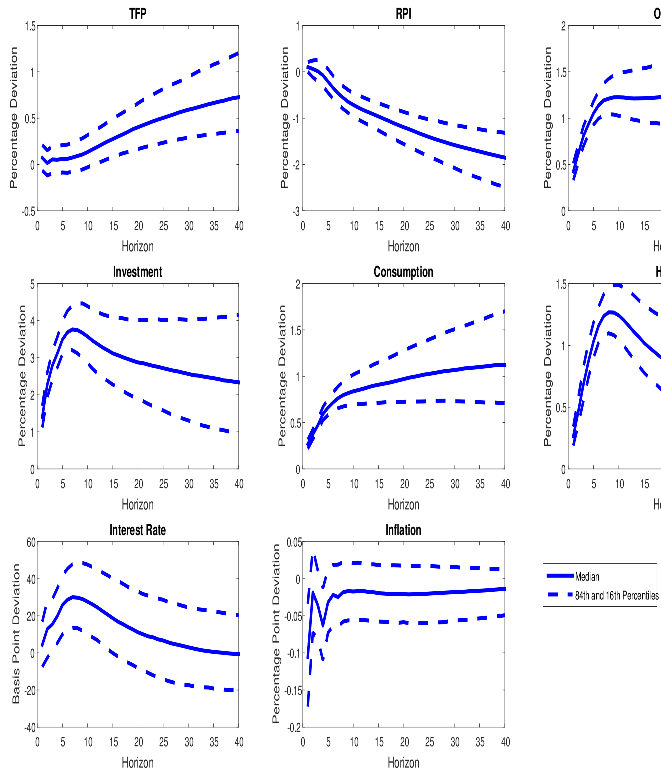
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



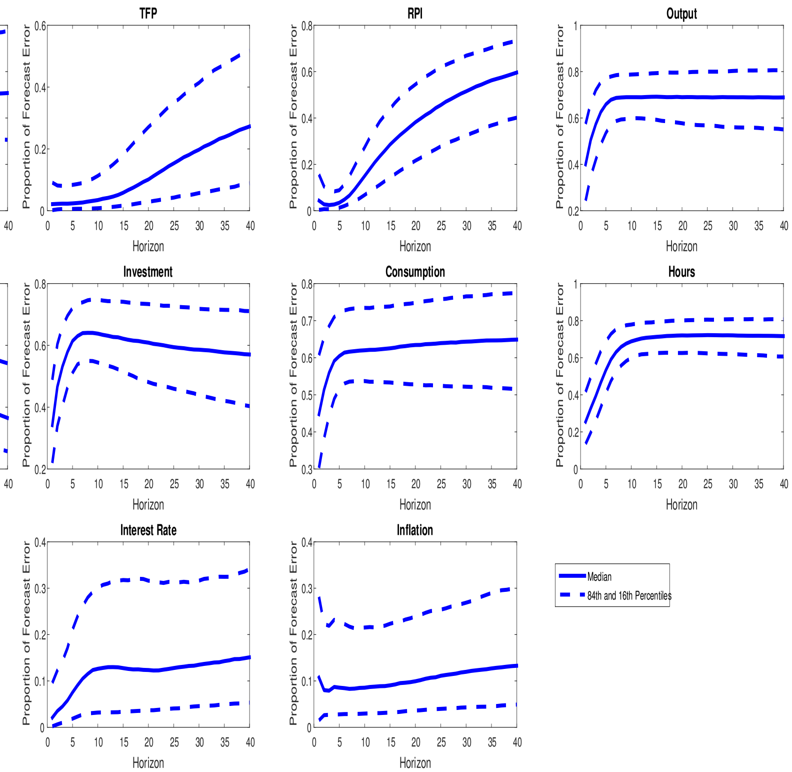
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing RPI with Fernald (2014)'s Investment TFP measure. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing RPI with Fernald (2014)'s Investment TFP measure.

Figure D.9: **PCE Deflator: (a) Impulse Responses; (b) Contribution to FEV.**



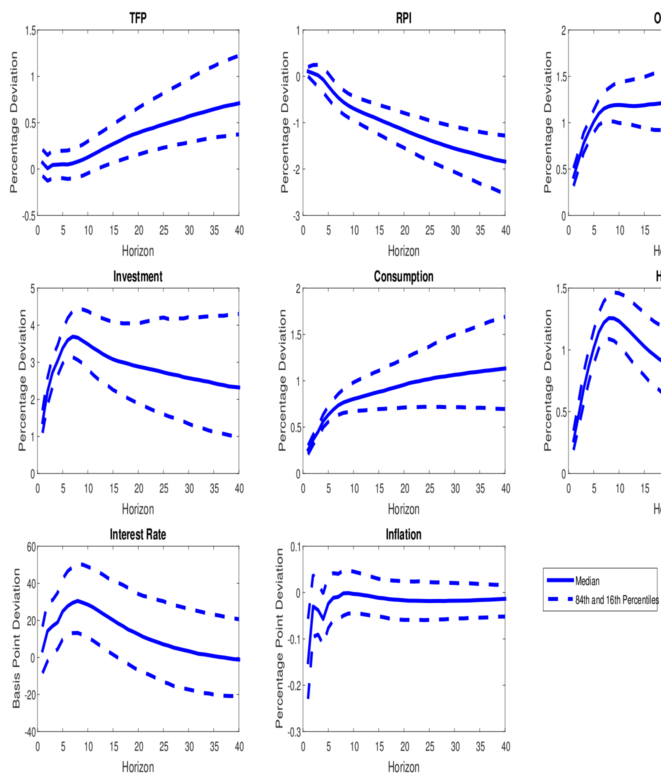
(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



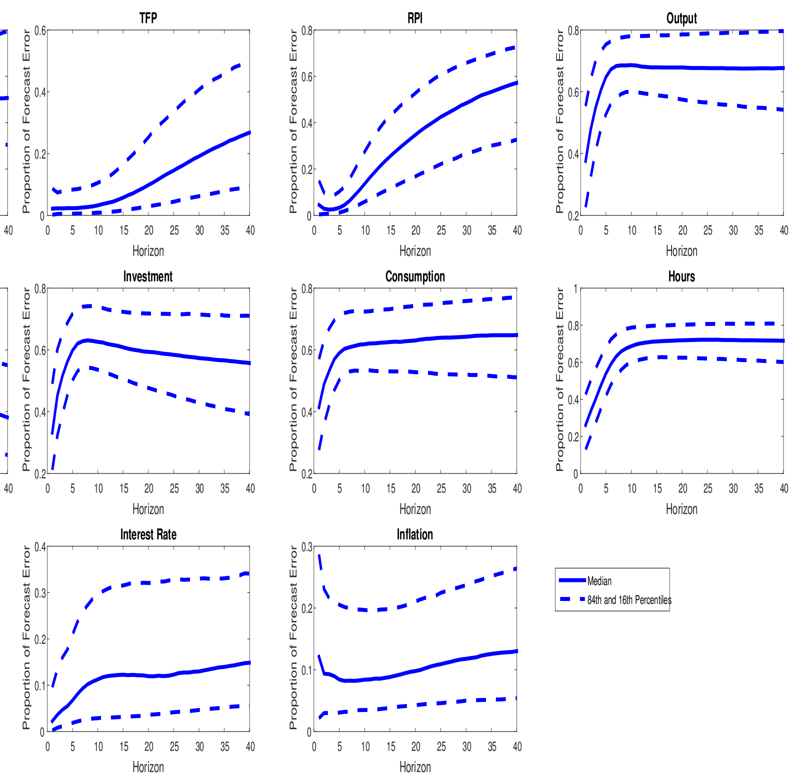
(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from replacing the CPI-based inflation measure with the PCE-based one (log-first-differences of the PCE deflator). Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from replacing the CPI-based inflation measure with the PCE-based one (log-first-differences of the PCE deflator).

Figure D.10: **Imposing the Impact Restriction Only on Consumption: (a) Impulse Responses; (b) Contribution to FEV.**



(a) The Median and 84th and 16th percentiles of the Impulse Responses to the Business Cycle Shock.



(b) The Median and 84th and 16th Percentiles of the Contribution of the Business Cycle Shock to the FEV of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 84th and 16th percentiles of the posterior distributions of impulse responses from imposing only on consumption to rise on impact while leaving the impact response of the other three aggregates unrestricted. Responses are in terms of deviations from pre-shock values. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 84th and 16th percentiles of the posterior distribution of FEV contributions from imposing only on consumption to rise on impact while leaving the impact response of the other three aggregates unrestricted.

References

Adjemian, S., Bastani, H., Juillard, M., Karamé, F., Maih, J., Mihoubi, F., Perendia, G., Pfeifer, J., Ratto, M. and Villemot, S.: 2011, Dynare: Reference Manual Version 4, *Dynare Working Papers 1*, CEPREMAP.

Barsky, R. and Sims, E.: 2011, News shocks and business cycles, *Journal of Monetary Economics* **58**(3), 235–249.

Barsky, R. and Sims, E.: 2012, Information, animal spirits, and the meaning of innovations in consumer confidence, *American Economic Review* **102**(4), 1343–1377.

Beaudry, P., Fève, P., Guay, A. and Portier, F.: 2015, When is nonfundamentalness in VARs a real problem? an application to news shocks, *Working Paper 21466*, National Bureau of Economic Research.

Beaudry, P. and Portier, F.: 2006, Stock prices, news, and economic fluctuations, *American Economic Review* **96**(4), 1293–1307.

Blanchard, O. J., L'Huillier, J.-P. and Lorenzoni, G.: 2013, News, noise, and fluctuations: An empirical exploration, *American Economic Review* **103**(7), 3045–70.

Calvo, G. A.: 1983, Staggered prices in a utility-maximizing framework, *Journal of monetary Economics* **12**(3), 383–398.

Christiano, L., Eichenbaum, M. and Evans, C.: 2005, Nominal rigidities and the dynamic effects of a shock to monetary policy, *Journal of Political Economy* **113**(1), 1–45.

Dixit, A. K. and Stiglitz, J. E.: 1977, Monopolistic competition and optimum product diversity, *The American Economic Review* **67**(3), 297–308.

Fernald, J.: 2014, A quarterly utilization-adjusted series on total factor productivity, *Technical report*, Federal Reserve Bank of San Francisco.

Fernandez-Villaverde, J., Rubio-Ramirez, J., Sargent, T. and Watson, M.: 2007, ABCs (and Ds) for understanding VARs, *American Economic Review* **97**(3), 1021–1026.

Forni, M. and Gambetti, L.: 2014, Sufficient information in structural vars, *Journal of Monetary Economics* **66**, 124 – 136.

Forni, M., Gambetti, L. and Sala, L.: 2014, No news in business cycles, *The Economic Journal* **124**(581), 1168–1191.

Gospodinov, N., Maynard, A. and Pesavento, E.: 2011, Sensitivity of impulse responses to small low-frequency comovements: Reconciling the evidence on the effects of technology shocks, *Journal of Business & Economic Statistics* **29**(4), 455–467.

Horvath, M.: 2000, Sectoral shocks and aggregate fluctuations, *Journal of Monetary Economics* **45**(1), 69–106.

Jaimovich, N. and Rebelo, S.: 2009, Can news about the future drive the business cycle?, *American Economic Review* **99**(4), 1097–1118.

Khan, H. and Tsoukalas, J.: 2011, Investment shocks and the comovement problem, *Journal of Economic Dynamics and Control* **35**(1), 115–130.

Leeper, E. M., Walker, T. B. and Yang, S. S.: 2013, Fiscal foresight and information flows, *Econometrica* **81**(3), 1115–1145.

Leeper, E. and Walker, T.: 2011, Information flows and news driven business cycles, *Review of Economic Dynamics* **14**(1), 55–71.

Levine, P., Pearlman, J., Perendia, G. and Yang, B.: 2012, Endogenous persistence in an estimated dsge model under imperfect information*, *The Economic Journal* **122**(565), 1287–1312.

Levine, P., Pearlman, J. and Yang, B.: 2019, Solution, simulation and estimation of dsge models under imperfect information in dynare, *Technical report*, Technical report, University of Surrey.

Liu, Z., Fernald, J., Basu, S. et al.: 2012, Technology shocks in a two-sector dsge model, *2012 Meeting Papers*, number 1017, Society for Economic Dynamics.

Moura, A.: 2018, Investment shocks, sticky prices, and the endogenous relative price of investment, *Review of Economic Dynamics* **27**, 48–63.

Pearlman, J., Currie, D. and Levine, P.: 1986, Rational expectations models with partial information, *Economic Modelling* **3**(2), 90–105.

Rubio-Ramirez, J., Waggoner, D. and Zha, T.: 2010, Structural vector autoregressions: Theory for identification and algorithms for inference, *Review of Economic Studies* **77**(2), 665–696.

Smets, F. and Wouters, R.: 2007, Shocks and frictions in the us business cycle: A bayesian dsge approach, *American Economic Review* **97**(3), 586–606.

Stock, J. and Watson, M.: 2007, Why has U.S. inflation become harder to forecast?, *Journal of Money, Credit and Banking* **39**(2), 3–33.

Uhlig, H.: 1994, What macroeconomists should know about unit roots: A bayesian perspective, *Econometric Theory* **10**(3/4), 645–671.

WU, J. C. and XIA, F. D.: 2016, Measuring the macroeconomic impact of monetary policy at the zero lower bound, *Journal of Money, Credit and Banking* **48**(2-3), 253–291.