

NO NEWS IS GOOD NEWS*

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ABSTRACT

We estimate a standard dynamic stochastic general equilibrium model under three different information structures to assess the importance of these informational assumptions. In the first information structure, agents receive news about future structural shocks, as in Beaudry and Portier (2006) and Schmitt-Grohé and Uribe (2012); in the second structure, agents observe noisy signals about current structural shocks; in the third structure, agents do *not* observe either news or noise. Data overwhelming support the noise-shock information structure. News (noise) shocks shift spectral power from the lower (higher) end to the higher (lower) end of the spectrum, which forces internal propagation mechanisms to work harder (less hard) in models with news (noise) shocks. That data prefer noise shocks and the reallocation of spectral power to the lower end connects to Granger’s (1966) “typical spectral shape” of macroeconomic variables. As a byproduct, the paper develops a novel estimation methodology for models with incomplete information.

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1 INTRODUCTION

[To be written.]

2 ANALYTICAL EXAMPLE

2.1 THE MODEL AND INFORMATION FLOWS Consider a standard growth model with a representative household that maximizes expected log utility, $E_0 \sum_{t=0}^{\infty} \beta^t \log(C)_t$, subject to $C_t + K_t \leq A_t K_{t-1}^\alpha$, where C_t , K_t , and Y_t denote time- t consumption, capital, and output, respectively, and A_t is an exogenous technology shock. As usual, $0 < \alpha < 1$ and $0 < \beta < 1$. Labor is supplied inelastically. The equilibrium conditions are well known and given by

$$\frac{1}{C_t} = \alpha\beta E_t \left[\frac{1}{C_{t+1}} \frac{Y_{t+1}}{K_t} \right] \quad (1)$$

$$C_t + K_t = Y_t = A_t K_{t-1}^\alpha. \quad (2)$$

Let A denote the steady state value of technology. The steady state capital stock is $K = [\alpha\beta A]^{1/(1-\alpha)}$. Let lower case letters denote percentage deviations from steady state values, $k_t = \log(K_t) - \log(K)$ and $a_t = \log(A_t) - \log(A)$. Log linearizing (1)–(2) yields an equilibrium that is characterized by a second-order difference equation in capital

$$\alpha\beta E_t(k_{t+1}) - (1 + \alpha^2\beta)k_t + \alpha k_{t-1} = \alpha\beta E_t(a_{t+1}) \quad (3)$$

Let a_t have the following moving-average structure

$$a_t = \theta\varepsilon_t + (1 - \theta)\varepsilon_{t-1} \quad (4)$$

where $\theta \in (0, 1)$ and is interpreted as a weight on the structural shock ε_t . Conditional on θ , there are two information sets that will yield different expectations about a_{t+1} (and hence k_{t+1}). Information set one, “news”, assumes that the structural innovations are contained in the agents’ information set, ε^t . Information set two, “noise”, assumes that the agents only observe a^t . With $\theta \geq 1/2$, the expectations $E[a_{t+1}|a^t]$ and $E[a_{t+1}|\varepsilon^t]$ are equivalent because (4) is a fundamental moving average representation. However, if $\theta < 1/2$ then $E[a_{t+1}|\varepsilon^t]$ is much more accurate than $E[a_{t+1}|a^t]$. This is because agents conditioning on a^t will not weight the shocks correctly, nor will they condition on the same set of shocks. They observe

$$\begin{aligned} a_t &= (1 - \theta)u_t + \theta u_{t-1} \\ u_t &= \left[\frac{(1 - \theta)L + \theta}{(1 - \theta) + \theta L} \right] \varepsilon_t \end{aligned} \quad (5)$$

And the expectations would differ according to

$$\begin{aligned} E_t[a_{t+1}|\varepsilon^t] &= (1 - \theta)\varepsilon_t \\ E_t[a_{t+1}|a^t] &= \theta u_t \end{aligned}$$

As $\theta \rightarrow 0$, the forecast $E_t[a_{t+1}|\varepsilon^t]$ is much more accurate than $E_t[a_{t+1}|a^t]$.

The equilibrium for each information set is given by

$$k_t = \alpha k_{t-1} + (1 - \theta)\varepsilon_t \quad (6)$$

$$k_t = \alpha k_{t-1} + \theta u_t \quad (7)$$

The difference between (6) and (7) looks innocuous but (5) suggests otherwise. Writing (7) in ε_t space gives

$$k_t = \theta \left[\frac{(1 - \theta)L + \theta}{(1 - \theta + \theta L)(1 - \alpha L)} \right] \varepsilon_t \quad (8)$$

Comparing (6) and (8), we see that the equilibrium goes from an AR(1) process to an ARMA(2,1). The additional persistence, an autoregressive coefficient of θ , is due entirely to the agents solving a signal extraction problem.

2.2 IMPULSE RESPONSES We use the following parameter values for the calibration of the analytical model above: (1) discount factor (β) to be 0.99; (2) capital share (α) to be 0.3; and (3) standard deviation of technology shock (σ_a) to be 1.

Based on these values, we consider four different values of the moving average parameter (θ) appeared in the technology shock process: $\theta = [0.95, 0.75, 0.25, 0.05]$. We solve the model under the set of given parameters using two different solution algorithms, ‘*gensys*’ assuming complete information and ‘*PIgensys*’ assuming partial information. For the partial information setup, we assume that agents can only observe the history of technology shocks (a^t).

Figure 1 display the impulse responses of technology shock and capital under the two different information assumptions of agents. What these results demonstrate is what the analytical derivation discerns. When θ is equal to 0.9 or 0.75, the capital impulse responses are identical across the two information specifications. However, the dynamics under partial information are not consistent with the theory when θ is smaller than 0.5, whereas the complete information solution still generates results discerned by the analytics. Furthermore, the pervert discounting problem under partial information is exacerbated as $\theta \rightarrow 0$. For $\theta = 0.05$, the partial information does basically nothing as the analytics allude. Agents are very uncertain about the contemporaneous shock, and they assign essentially no weight to this shock.

3 THE ESTIMATED MODEL

The main model to be estimated follows Schmitt-Grohé and Uribe (2012), which is a real business cycle model, augmented with several real rigidities, that is fit to U.S. data. The real rigidities include habit formation in consumption and leisure, variable capacity utilization, and investment adjustment costs. The equilibrium system of the model is log-linearized and solved using Sims’s (2001) algorithm.

3.1 MODEL DETAILS A representative household derives utility from consumption, C_t and leisure, ℓ_t , and maximizes its utility function given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{\{(C_t - \theta_c C_{t-1}) (\ell_t - \theta_\ell \ell_{t-1})^\chi\}^{1-\sigma} - 1}{1 - \sigma} \quad (9)$$

where β is the discount factor, θ_c and θ_ℓ determine the degree of internal habit formation, χ controls the marginal rate of substitution between consumption and leisure, and σ determines the intertemporal elasticity of substitution.

Households own physical capital and control both the size of the capital stock, K_t , and its utilization rate, u_t . The depreciation rate is an increasing, convex function of the rate of utilization

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

with $\delta_i > 0$ for $i = 1, 2, 3$.

The law of motion for capital is

$$K_{t+1} = [1 - \delta(u_t)] K_t + I_t \left[1 - S \left(\frac{I_t}{I_{t-1}} \right) \right] \quad (10)$$

where I_t denotes gross investment. Effective capital services supplied to firms at time t are $u_t K_t$. Investment adjustment costs, $S(\cdot)$, follow Christiano, Eichenbaum and Evans's (2005) quadratic specification

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

where $\kappa > 0$ is a parameter and μ^i denotes the steady-state growth rate of investment. $S(\cdot)$ satisfies $S(1) = S'(1) = 0$ and $S''(1) > 0$.

The production technology is

$$Y_t = z_t (u_t K_t^\alpha X_t h_t^{1-\alpha}) \quad (11)$$

where z_t is a transitory productivity shock, X_t is a permanent productivity shock, and h_t denotes hours worked, $h_t = 1 - \ell_t$.

The government consumes an exogenous and stochastic quantity of goods, G_t . The aggregate resource constraint is

$$C_t + A_t I_t + G_t = Y_t \quad (12)$$

where A_t is the rate of transformation between consumption and investment goods and is assumed to be exogenous and stochastic. A_t represents the relative price of investment goods in terms of consumption goods.

3.2 INFORMATION FLOWS The model consists of four exogenous shock processes: stationary neutral productivity shock, z_t ; nonstationary neutral productivity shock, X_t ; investment specific shock, A_t ; and a government spending shock, G_t . We examine five alternative specifications for the model's information structure.

The first information structure is the conventional one that appears throughout the modern macroeconomics literature. Each exogenous process follows a first-order autoregression with an *i.i.d.* innovation and the processes are mutually independent

$$\hat{\chi}_t = \rho_\chi \hat{\chi}_{t-1} + \varepsilon_{\chi,t} \quad (13)$$

where $\varepsilon_{\chi,t} \sim i.i.d. N(0, \sigma_\chi^2)$. In this specification, agents have no foresight about future realizations of these shocks. We call this ‘‘AR News.’’

The second structure simplifies the news process in Schmitt-Grohé and Uribe (2012) and is given by

$$\hat{\chi}_t = \rho \hat{\chi}_{t-1} + \varepsilon_{\chi,t}^0 + \varepsilon_{\chi,t-1}^1 + \varepsilon_{\chi,t-2}^2 + \varepsilon_{\chi,t-3}^3 \quad (14)$$

where $\varepsilon_{\chi,t}^j$ denotes the j -period anticipated changes in the log deviation of a variable from its steady state, denoted as $\hat{\chi}_t$, with $\chi_t = \{z_t, X_t, A_t, G_t\}$. These shocks are assumed to be independent across time and anticipation horizon, i.e., $E\varepsilon_{\chi,t}^j \varepsilon_{\chi,t-m}^k = 0$ for $k, j = 0, 1, 2, 3$ and $E\varepsilon_{\chi,t}^j \varepsilon_{\chi,t}^k = 0$ for any $k \neq j$. The information set of the agent consists of current and past realizations of the exogenous shocks $\varepsilon_{\chi,t}^j$. By observing $\varepsilon_{\chi,t}^2$, for example, agents know precisely how this shock will impinge upon χ_{t+2} and agents will respond as soon as the shock is observed. Agents do not have perfect foresight, however, because χ_t also contains a contemporaneous innovation. We refer to this information as ‘‘SGU News.’’

The third information structure comes from the correlated news process in Walker and Leeper (2011) and is given by

$$\hat{\chi}_t = \rho \hat{\chi}_{t-1} + \phi_0 \varepsilon_{\chi,t} + \phi_1 \varepsilon_{\chi,t-1} + \phi_2 \varepsilon_{\chi,t-2} + \phi_3 \varepsilon_{\chi,t-3} \quad (15)$$

where ε_χ is normally distributed with mean zero and variance $\sigma_{\varepsilon_\chi}^2$. We assume agents observe current and past realizations of the shocks $\{\varepsilon_{\chi,t-j}\}_{j=0}^\infty$, and interpret the moving-average parameters as weights with restrictions $\sum_j \phi_j = 1$ and $\phi_j \geq 0$. Given that (15) is a function of past shocks, we allow for the possibility that by observing the shock directly, agents receive news about the future path of the χ_t process. We label this information setup ‘‘News.’’

The final structure, labeled ‘‘Noise’’, imposes partial information.¹ Agents do not observe any realizations of the exogenous shocks, but they know that the underlying exogenous processes are governed by the news specification in (Walker-Leeper) ‘‘News’’. Specifically, agents form expectations using observations on the six variables, $\{Y_t, C_t, I_t, G_t, h_t, A_t\}$. By taking the innovations out of the agents’ information sets, there are more shocks than observables and agents must solve a signal-extraction problem.²

4 ESTIMATION

We use Bayesian inference methods to construct the parameters’ posterior distribution, which is a combination of the likelihood function and prior information (see An and Schorfheide

¹Appendix B provides details of the estimation procedure under the partial information assumption.

²Related approaches appear in Pearlman, Currie, and Levine (1986), Collard, Dellas, and Smets (2009), Levine, Pearlman, Perendia, and Yang (2012), Rondina and Walker (2012), and Blanchard, L’Huillier, and Lorenzoni (2012).

(2007) for a survey). We estimate the model using six U.S. quarterly time series data ranging from 1955:1 to 2011:3: the log difference of real per capital GDP (YGR), real per capital consumption (CGR), real per capital investment (IGR), real per capital government spending (GGR), log hours worked (LH), and the log difference of the relative price of investment (AGR). A full description of the data used is given in Appendix A. We further assume that the six series are measured in percentages, and all of the series are observed with *i.i.d.* measurement error. Their relationship to the model variables is given by

$$\begin{bmatrix} \text{YGR}_t \\ \text{CGR}_t \\ \text{IGR}_t \\ \text{GGR}_t \\ \text{LH}_t \\ \text{AGR}_t \end{bmatrix} \times 100 = \begin{bmatrix} \Delta \log(Y_t) \\ \Delta \log(C_t) \\ \Delta \log(I_t) \\ \Delta \log(G_t) \\ \log(h_t) \\ \Delta \log(A_t) \end{bmatrix} + \begin{bmatrix} \epsilon_{Y,t}^{me} \\ \epsilon_{C,t}^{me} \\ \epsilon_{I,t}^{me} \\ \epsilon_{G,t}^{me} \\ \epsilon_{h,t}^{me} \\ \epsilon_{A,t}^{me} \end{bmatrix} \quad (16)$$

where $\epsilon_{X,t}^{me}$ denotes the *i.i.d.* measurement error of the variable X with mean zero and standard deviation σ_X^{me} .

4.1 PRIOR DISTRIBUTIONS We calibrate several parameters that are difficult to identify from the data, using a calibration largely drawn from Schmitt-Grohé and Uribe (2012). The subjective discount factor, β , is set to 0.973, which implies an annual steady-state real interest rate of 10.8 percent. The intertemporal elasticity of substitution, σ , is set to 2. The quarterly depreciation rate for capital, δ_0 , is set to 0.025 so that the annual depreciation rate is 10 percent. The capital income share of total output, α , is set to 0.3, implying a labor income share of 0.7. We calibrate the parameter δ_1 so that the steady-state capacity utilization, u , becomes unity.

The rest of the calibrated parameters are computed from the means of our data sample: The gross per capital GDP growth rate is 1.0040, the gross growth rate of relative price of investment is 0.9955, and the share of government consumption in GDP is 0.2.

Table 2 lists the prior distribution for all estimated parameters, both for models with *i.i.d.* and correlated news processes. The priors for the parameters used both for the *i.i.d.* and correlated news models in common and for the *i.i.d.* news process model are taken from Schmitt-Grohé and Uribe (2012).

Priors for the standard deviation of correlated news process are chosen to be fairly diffuse so that they are identical to that of the unanticipated component of corresponding shock as in Schmitt-Grohé and Uribe (2012). Priors for the moving average coefficient parameters of each news process ($\{\phi_i\}_{i=0,1,2,3}$), impose two conditions: non-negativity and sum-to-one constraints. To satisfy these constraints, we assigned a Dirichlet prior distribution, which is frequently used in statistical inference for positive variables summing to one (see Gelman, Carlin, Stern, and Rubin (2003)). The Dirichlet probability density function is defined by:

$$\mathcal{D}(\phi_i | \eta_0, \dots, \eta_3) = \frac{\Gamma(\sum_{i=0}^3 \eta_i)}{\prod_{i=0}^3 \Gamma(\eta_i)} \left(\prod_{i=0}^3 \phi_i^{\eta_i - 1} \right) \mathbf{1}_{\{\phi_i \geq 0; \sum_{i=0}^3 \phi_i = 1\}}(\phi_i)$$

where η_0, \dots, η_3 are the Dirichlet distribution parameters, $\Gamma(\cdot)$ is the Gamma function and $\mathbf{1}_A(\cdot)$ denotes the indicator function defined on the set A . We assume here that the moving

average coefficient parameters are a priori equiprobable (reflecting the absence of knowledge regarding these parameters) which corresponds to identical parameters $\{\eta_i = 1, \forall i = 0, \dots, 3\}$. As a result, the proposed prior for $\phi_i, i = 0, \dots, 3$ is a uniform distribution on the following simplex:

$$\mathbb{S} = \left\{ \phi_i; \phi_i \geq 0, i = 0, 1, 2, \sum_{i=0}^2 \phi_i \leq 1 \right\}.$$

4.2 BAYESIAN INFERENCE The posterior distribution is sampled by the Tailored randomized block MCMC (hereafter referred to as TaRB-MH) algorithm in Chib and Ramamurthy (2010). The estimation procedure of this method is different from the most popular sampling algorithm, the random walk Metropolis Hastings algorithm (RW-MH henceforth), in two dimensions—how to update the parameter vector drawn from a proposal density and to construct the proposal density. First, the TaRB-MH updates the parameters by randomly splitting them into several blocks, whereas the RW-MH does it for the entire parameter vector. Then the TaRB-MH conducts a separated MH to update each block indices, fixing parameters in other blocks at the previous step’s value. In doing so, the proposal density for each block is tailored to closely approximate the location and the curvature of the posterior density in that block.

For the estimation, we initialize the sampler at the prior mean of each parameter, set the number of initial burn-ins to be 1,000, and draw 20,000 posterior samples.

5 ESTIMATION RESULTS

5.1 POSTERIOR ESTIMATES Posterior estimates of the model parameters appear in Table 3 through 5. Focusing on the preference and technology parameters in Table 3, with the exception θ_l , habits in leisure, our median estimates are close to those that Schmitt-Grohé and Uribe (2012) report. The “News” specification delivers very similar estimates to “SGU News”, though the convexity of capacity utilization, δ_2 is about twice as large with “News”.

Major differences emerge from the “AR News” and the models with the partial information specification. Habit formation parameters for consumption and leisure are less than half of the estimates under either “SGU News” or “News”, with no overlap in the respective 90 percent probability bands. Still more striking is that investment adjustment costs, κ , are about 10 to 20 percent of the estimates under “SGU News” or “News”.

News specifications like “SGU News” or “News” are known to generate comovement problems. For example, news about higher future productivity increases consumption and leisure immediately, before the higher productivity is realized and output expands. Lower work effort when the news arrives reduces output, so consumption can increase only if investment falls. Data strongly suggest positive comovement between consumption and output, so friction parameters must be large to attenuate the negative comovement that news generates. Information structures “AR News” and the models with the partial information structures do not produce the perverse short-run comovements.

5.2 MODEL FIT It turns out that time series data strongly prefer the models with the partial information specifications in which agents never observe the news about exogenous

processes: no news is good news for model fit. In particular, the best-fitting model is the “Noise” structure. Tables 7 reports alternative measures of model fit. The only difference across the four models is their information structures, so model fit corresponds to an assessment of the information specifications. By any criterion, the data strongly prefer “Noise”. Next in the ordering comes “SGU News”, then “News”. “AR News” is consistently the least preferred specification.

Granger (1966) emphasizes that the “typical spectral shape” of macroeconomic time series allocates most of the spectral power to low frequencies. News processes like “SGU News” or “News” push spectral power into higher frequencies, which the estimation tries to correct through extraordinarily high degrees of frictions. Even massive frictions, though, cannot improve model fit relative to the models with the partial information specifications. It is also remarkable that the conventional AR specification for exogenous processes is the least preferred information structure.

6 FREQUENCY DOMAIN DECOMPOSITIONS

In order to reveal the role of various information flows (AR News, SGU News, News, and Noise) in the DSGE model, we conduct frequency domain analyses of those four model variables. In doing so, we have two objectives. First, we focus on how each information flow alters the spectral power of model-generated observable variables—output, consumption, investment, government spending, hours, and relative price of investment. Second, we evaluate the model fit by making a comparison of the spectral densities of each model variables to that of the raw data used for the estimation. For this task, we employ a Bayesian Monte Carlo method to simulate data using the posterior parameters estimated.

Specifically, we conduct the following steps to estimate the empirical spectral densities of each DSGE model embedded with a differently specified information flow.

- Step 1: Bayesian Simulation Method

There are two steps needed to solve the DSGE models and simulate data from them. The first step is to solve the DSGE models using the estimated posterior parameter values. We solve the log-linearized DSGE models using Chris Sims’ (2001) *gensys* algorithm. Then we simulate data corresponding to the six observables used for the Bayesian estimation. In particular, we apply a Monte Carlo simulation method to generate a sample of length 227, which is the same as the number of observation of raw data used for the estimation, after a hundred burn-ins to preclude a data dependency on initial values. Finally, we remove deterministic trend from the simulated data by subtracting the quadratic trend of each series to ensure stationarity.³

- Step 2: Spectral Density Estimation

The next step is to estimate the spectral density of each simulated variable. More specifically, we calculate periodogram of each series by using the Welch’s (1967) averaged periodogram method. Then we obtain spectral density estimates by normalizing the periodogram so that the area under the curve becomes unity.

³However, our empirical results are robust across different detrending methods (e.g. linear trend.)

We iterate Step 1 and 2 for the number of posterior draws (20,000 draws) and calculate the mean and 90% interval spectral densities of each variable.

6.1 EMPIRICAL ASPECTS OF SGU NEWS As displayed in Figure 2, embedding the news structure as in Schmitt-Grohé and Uribe (2008) strongly influences the equilibrium dynamics. For the two technology shocks, the information structures makes the equilibrium dynamics of investment relatively more persistent as the foresight horizon increases. This is a notable finding since these two shocks are the main driving force of the model in terms of forecasting error variance decompositions.

At the same time, however, this is inconsistent with the main finding from the main conclusion from the theoretical model in Section 2. What the simple model delivers is that foresight with respect to technology generates a powerful wealth effect that produces a negative response to capital (and subsequently output) over the anticipation horizon. With foresight, future enhancements in technology are known and an anticipated positive technology shock increases future income and wealth, but not current income. In order to smooth consumption, agents raise current consumption and decrease saving. These additional fluctuations in capital tilts the spectrum so that higher frequencies are given relatively more weight.

Note that the estimated model involves a massive amount of real rigidities, whereas none of these frictions are embedded in the simple model. Accordingly, we reestimate the model with “SGU News” with the real frictions are wiped out (i.e., $\theta_c = \theta_\ell = \kappa = 0$) and conduct the frequency domain analyses. Figure 3 plots the model-implied spectrum with no real frictions. Regardless of the type of shocks, there is no clear spectral pattern emerged from the additional news structure. This finding illustrates that the persistence of equilibrium dynamics relies heavily on real rigidities, such as habit formation, variable capital utilization, and investment adjustment costs.

6.2 EMPIRICAL ASPECTS OF THE NOISE SPECIFICATIONS Figure 4 shows the model-implied spectrums of the key macroeconomic variables across various information assumptions, as well as their comparison to the actual data spectrum. The “SGU News” model consistently overestimates the lower frequency components of consumption and investment, thus output. When it comes to the “News” specification, even massive real frictions cannot make the equilibrium dynamics more persistent relative to “AR News”. On the other hand, the “Noise” structure tilts the output and consumption spectrums so that lower frequencies are given relatively more weight, with far less reliance on real rigidities. The news models better perform in matching the data-consistent spectral shape of hours than the other specifications.

7 UNCONDITIONAL MOMENTS

Table 8, and Figures 5 through 7 compare the unconditional moments of the model-implied data to those of actual time series. Table 8, in specific, reports the standard deviations of the actual data and the distributions from the model-simulated variables’ standard deviation. The “Noise” model-implied standard deviations of all the variables considered nest that of

the actual data in its 90% posterior intervals. In contrast, the news models significantly overestimate them.

Figures 5 through 7 show the actual data autocorrelations, as well as the means and 95th percentile intervals of the distributions from the model-implied variables' autocorrelations, for the “AR News”, “SGU News”, and “Noise” specifications. As the figures demonstrate, the overall fit of “SGU News”—in terms of their ability to replicate the autocorrelation structure observed in the data—is somewhat worse than the other two specifications.

8 CONCLUSION

In this paper, we mainly do two things. We provide theory to understand how the different informational assumptions alter equilibrium dynamics. Then we estimate a standard RBC Model assuming four information structures for the representative agent. Several findings emerge. First of all, noise shocks fit data substantially better. Second, noise shocks generate dynamics more consistent with Granger’s (1966) typical spectral shape of economic variable. Third, noise (news) shocks reallocate spectral power to the lower (higher) end of the spectrum. Finally, news shocks require internal propagation to work harder (e.g., habit formation) to match persistence observed in the actual time series.

The findings in this paper have implications that extend beyond the exercises performed here. More complicated models that are used to draw policy conclusions also employ frictions of various kinds—real, nominal, financial—to improve model fit. Those frictions play critical roles in optimal policy calculations. Our findings suggest that information structures deserve careful scrutiny.

A THE DATA

We construct the six observable variables by following the data description in Schmitt-Grohé and Uribe (2008). All components of the U.S. national income account are obtained from the National Income and Product Accounts (NIPA) tables available at Bureau of Economic Analysis website (<http://www.bea.gov/national/nipaweb/SelectTable.asp>).

- **Real Gross Domestic Product.** BEA, NIPA table 1.1.6., line 1, billions of chained 2005 dollars seasonally adjusted at annual rate.
- **Gross Domestic Product.** BEA, NIPA table 1.1.5., line 1, billions of dollars, seasonally adjusted at annual rates.
- **Personal Consumption Expenditure.** Personal consumption expenditure is defined as personal consumption expenditure on nondurable goods (BEA, NIPA table 1.1.5., line 5, billions of dollars, seasonally adjusted at annual rate) and personal consumption expenditure on services (BEA, NIPA table 1.1.5., line 6, billions of dollars, seasonally adjusted at annual rate).
- **Gross Private Domestic Investment.** Gross private domestic investment is defined as gross private domestic investment, fixed investment, nonresidential (BEA, NIPA table 1.1.5., line 9, billions of dollars, seasonally adjusted at annual rate) and gross private domestic investment, fixed investment, residential (BEA, NIPA table 1.1.5., line 12, billions of dollars, seasonally adjusted at annual rate).
- **Government Expenditure.** Government expenditure is defined as government consumption expenditure (BEA, NIPA table 3.9.5., line 2, billions of dollars, seasonally adjusted at annual rate) and government gross investment (BEA, NIPA table 3.9.5., line 3, billions of dollars, seasonally adjusted at annual rate).
- **Civilian Noninstitutional Population Over 16.** BLS, LNU00000000Q. Downloaded from www.bls.gov.
- **Nonfarm Business Hours Worked.** BLS, PRS85006033, seasonally adjusted, index 2005=100. Downloaded from www.bls.gov.
- **GDP Deflator** = $\text{Gross Domestic Product} / \text{Real Gross Domestic Product}$.
- **Real Per Capita GDP** = $\text{Real Gross Domestic Product} / \text{Civilian Noninstitutional Population Over 16}$.
- **Real Per Capita Consumption** = $\text{Personal Consumption Expenditure} / [\text{Civilian Noninstitutional Population Over 16} \times \text{GDP Deflator}]$.
- **Real Per Capita Investment** = $\text{Gross Private Domestic Investment} / [\text{Civilian Noninstitutional Population Over 16} \times \text{GDP Deflator}]$.
- **Real Per Capita Government Expenditure** = $\text{Government Expenditure} / [\text{Civilian Noninstitutional Population Over 16} \times \text{GDP Deflator}]$.

- **Per Capita Hours** = Nonfarm Business Hours Worked / Civilian Noninstitutional Population Over 16.

Finally, the relative price of investment is defined as the ratio of the chain weighted deflators for consumption and investment. Schmitt-Grohé and Uribe (2008) construct the deflator for investment by using the price series for producer durable equipment in Gordon (1990), as later updated by Cummins and Violante (2002). However, this deflator is only available until the end of 2006. In order to include the recent sample for this series, we construct the NIPA-based deflators for consumption and investment as in Justiniano, Primiceri, and Tambalotti (2011) and extend the original data in Schmitt-Grohé and Uribe (2008) by using the growth rate of the relative price of investment calculated from the NIPA-based deflators. The correlation coefficient between the two relative price of investment series is 0.99 over the sample period from 1955 to 2006.

B ESTIMATION PROCEDURE UNDER PARTIAL INFORMATION

This section outlines how to implement a DSGE model estimation under the partial information setup. As described in Pearlman, Currie, and Levine (1986) (PCL hereafter), the state space setup for an rational expectation (RE) system is given as:

$$A_0 X_{t+1,t} + A_1 X_t = A_2 X_{t-1} + C + \Psi \varepsilon_t \quad (17)$$

where X is a vector of the variables in the model, $X_{t+1,t}$ is the expected value of the model variables using the information set up to time t (i.e. $X_{t+1,t} \equiv E_t X_{t+1}$), ε is a vector of the exogenous random variables, C is a vector of constants, and Ψ is a matrix defining the standard deviation of exogenous shocks. Under the partial information setup, agents do not have full information about the underlying system and they only observe some of the economic variables. The corresponding measurement equation for agents is given as:

$$m_t = LX_t + v_t \quad (18)$$

where m is a vector of variables observed by agents, L is a selection matrix, and v is a vector of measurement errors.

B.1 SOLVING THE MODEL USING PI_GENSYSTM PI_gensys.m is a MATLAB program written by Chris A. Sims to solve stochastic linear RE models under the partial information setup. The program **PI_gensys.m** is called from MATLAB by a statement of the form:

$$\begin{aligned} & [G_1, CC, M, N, T_1, T_2, gev, eu, DD, E_2, E_5, Gamma, FLRANK] \\ & = \text{PI_gensys}(A_0, A_1, A_2, A_3, C, \Psi, \sim, \sim, \sim, \sim, \sim) \end{aligned}$$

The output of the program determines the coefficients in a “solved” system of the form

$$Y_t = G_1 Y_{t-1} + M \varepsilon_{t+1} + CC \quad (19)$$

where the vector Y and the matrix M are defined as:

$$Y_t \equiv \begin{bmatrix} \varepsilon_{t+1} \\ s_t \\ x_t \\ x_{t+1,t} \end{bmatrix}, \quad M = \begin{bmatrix} I \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

and CC is zero in most cases. Here s denote a vector of backward-looking variables whereas x denote is a vector of forward-looking variables in the system.

In order to describe the measurement equation corresponding to (19), rewriting the equation using partitioned matrices of G_1 as:

$$\begin{bmatrix} \varepsilon_{t+1} \\ s_t \\ x_t \\ x_{t+1,t} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ G_{10} & G_{11} & G_{12} & G_{13} \\ 0 & 0 & 0 & I \\ G_{20} & G_{21} & G_{22} & G_{23} \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ s_{t-1} \\ x_{t-1} \\ x_t \end{bmatrix} + \begin{bmatrix} I \\ 0 \\ 0 \\ 0 \end{bmatrix} \varepsilon_{t+1}$$

Define a vector z that includes all the elements of a vector Y except for the expected values on x 's, i.e.,

$$z_{t+1} \equiv \begin{bmatrix} \varepsilon_{t+1} \\ s_t \\ x_t \end{bmatrix}$$

Define $L_1 = LT_1$ and $L_2 = LT_2$. The measurement equation is then written as:

$$m_t = [K_1 \quad K_2] \begin{bmatrix} z_t \\ x_t \end{bmatrix} + v_t$$

where $K_1 = [L_1G_{10} \quad L_1G_{11} \quad L_1G_{12}]$, $K_2 = L_1G_{13} + L_2$, and v_t is a vector of measurement errors.

Like the gensys.m program, the returned value 'eu' is a 2×1 vector whose first element characterizes existence of an equilibrium (1 if true and 0 is false) and whose second element characterizes uniqueness of the equilibrium (1 if true and 0 if false). The scalar value 'FL_RANK' characterizes the number of forward-looking variable in the system which is the dimension of the vector x .

B.2 REDUCED-FORM SOLUTION FOR THE STATE SPACE REPRESENTATION Define a vector of forecast errors of z as:

$$\tilde{z}_t \equiv z_t - E_{t-1}z_t$$

Partition the state space representation (19) as:

$$\begin{bmatrix} z_{t+1} \\ x_{t+1,t} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} z_t \\ x_t \end{bmatrix} + \begin{bmatrix} M_1 \\ M_2 \end{bmatrix} \varepsilon_{t+1}$$

As shown in Levine, Pearlman, Perendia, and Yang (2012), the reduced-form solution is given by:

$$\begin{aligned} \text{System: } z_{t+1} = & C z_t + (A - C) \tilde{z}_t \\ & + (C - A) P D' (D P D' + V)^{-1} (D \tilde{z}_t + v_t) + u_{t+1} \end{aligned} \quad (20)$$

$$\text{Innovation: } \tilde{z}_{t+1} = A \tilde{z}_t - A P D' (D P D' + V)^{-1} (D \tilde{z}_t + v_t) + u_{t+1} \quad (21)$$

$$\begin{aligned} \text{Measurement: } m_t = & E z_t + (D - E) \tilde{z}_t + v_t \\ & - (D - E) P D' (D P D' + V)^{-1} (D \tilde{z}_t + v_t) \end{aligned} \quad (22)$$

where $C = A_{11} - A_{12}N$, $A = A_{11} - A_{12}A_{22}^{-1}A_{21}$, $E = K_1 - K_2N$, $D = K_1 - K_2A_{22}^{-1}A_{21}$, V is the covariance matrix of the measurement errors, and P is the solution of the Riccati equation given by

$$P = A P A' - A P D' (D P D' + V)^{-1} D P A' + U \quad (23)$$

and $U \equiv \text{cov}(u_t)$ is the covariance matrix of the exogenous shocks to the system. The equations (20) to (22) display that the model solution is a joint function of z and \tilde{z} , in that the law-of-motion of the system is affected by how agents update estimates of the model variables as well as the lagged values of the model variables.

In sum, the reduced-form solution above can be written as:

$$\begin{aligned} \underbrace{\begin{bmatrix} z_{t+1} \\ \tilde{z}_{t+1} \end{bmatrix}}_{\equiv Z_{t+1}} = & \underbrace{\begin{bmatrix} C & (A - C)(I - P D' (D P D' + V)^{-1} D) \\ 0 & A(I - P D' (D P D' + V)^{-1} D) \end{bmatrix}}_{\equiv \Gamma} \begin{bmatrix} z_t \\ \tilde{z}_t \end{bmatrix} \\ & + \underbrace{\begin{bmatrix} -(A - F) P H' (H P H' + V)^{-1} \\ A P H' (H P H' + V)^{-1} \end{bmatrix}}_{\equiv \Pi} v_t + u_{t+1} \end{aligned} \quad (24)$$

with the measurement equation

$$\begin{aligned} m_t = & \underbrace{\begin{bmatrix} E & (D - E)(I - P D' (D P D' + V)^{-1} D) \end{bmatrix}}_{\equiv \Phi} \begin{bmatrix} z_t \\ \tilde{z}_t \end{bmatrix} \\ & + \underbrace{(I - (D - E) P D' (D P D' + V)^{-1})}_{\equiv S} v_t \end{aligned} \quad (25)$$

B.3 LIKELIHOOD EVALUATION USING KALMAN FILTER Pearlman, Currie, and Levine (1986) show that

$$\text{cov} \begin{bmatrix} z_t \\ \tilde{z}_t \end{bmatrix} = \begin{bmatrix} P + Q & P \\ P & P \end{bmatrix} \equiv \mathcal{P} \quad (26)$$

where Q is a solution of the Lyapunov equation

$$Q = CQC' + CPD'(DPD' + V)^{-1}DPC' \quad (27)$$

The Kalman filtering equation is given by

$$Z_{t+1,t} = \Gamma Z_{t,t-1} + \Gamma \mathcal{P}_t \Phi' (\Phi \mathcal{P}_t \Phi' + \mathcal{S}V\mathcal{S}')^{-1} e_t \quad (28)$$

where $e_t = m_t - \Phi Z_{t,t-1}$. The updating equation for the covariance matrix of the error e_t becomes

$$\mathcal{P}_{t+1} = \Gamma \mathcal{P}_t \Gamma' - \Gamma \mathcal{P}_t \Phi' (\Phi \mathcal{P}_t \Phi' + \mathcal{S}V\mathcal{S}')^{-1} \Phi \mathcal{P}_t \Gamma' + U \quad (29)$$

The Kalman filtering can be implemented recursively by initializing the state vector Z and the covariance matrix \mathcal{P} . The system is initialized at

$$Z_{1,0} = 0 \quad \text{and} \quad \mathcal{P}_1 = \mathcal{P}$$

where \mathcal{P} is the steady state of the Riccati equation (26).

C TABLES

Parameter	Value	Description
β	0.973	Subjective discount factor
σ	2	Intertemporal elasticity of substitution
α	0.3	Capital share
δ_0	0.025	Steady-state depreciation rate
u	1	Steady-state capacity utilization rate
μ^y	1.004	Steady-state gross per capital GDP growth rate rate
μ^a	0.9955	Steady-state gross growth rate of price of investment
G/Y	0.2	Steady-state share of government consumption in GDP

Table 1: Calibrated parameters. The time unit is one quarter.

	Dist.	Mean	Std.	Min	Max
Common Parameters					
κ , investment adjustment cost	Gamma	4.0	1.0	0	∞
χ , preference	Gamma	4.0	1.0	0	∞
ρ_{xg} , serial correlation in the trend component of govt. spending	Beta*	0.7	0.2	0	0.99
ρ_g , serial correlation in govt. spending shock	Beta*	0.7	0.2	0	0.99
ρ_z , serial correlation in stationary technology shock	Beta*	0.7	0.2	0	0.99
ρ_x , serial correlation in non-stationary technology shock	Beta*	0	0.1	-0.5	0.5
ρ_a , serial correlation in investment-specific productivity shock	Beta*	0.5	0.1	0	0.7
θ_c , habit parameter in consumption	Beta*	0.5	0.1	0	0.99
θ_ℓ , habit parameter in leisure	Beta*	0.5	0.1	0	0.99
δ_2 , convexity of the cost of adjusting capacity utilization	Uniform			0.01	10
σ_y^{me} , std. of measurement error for per capital GDP growth rate	Uniform			0	$\frac{1}{4}\hat{\sigma}_y$
σ_c^{me} , std. of measurement error for per capital consumption growth rate	Uniform			0	$\frac{1}{4}\hat{\sigma}_c$
σ_i^{me} , std. of measurement error for per capital investment growth rate	Uniform			0	$\frac{1}{4}\hat{\sigma}_i$
σ_g^{me} , std. of measurement error for per capital govt. spending growth rate	Uniform			0	$\frac{1}{4}\hat{\sigma}_g$
σ_h^{me} , std. of measurement error for logged per capital hours worked	Uniform			0	$\frac{1}{4}\hat{\sigma}_h$
σ_a^{me} , std. of measurement error for the price of investment growth rate	Uniform			0	$\frac{1}{4}\hat{\sigma}_a$
Parameters for “SGU” News Model					
σ_j^0 , std. of unanticipated shock to the variable j	Uniform			0	$5\sqrt{3}$
σ_j^1 , std. of shock to the variable j anticipated 1 quarter ahead	Uniform			0	$5\sqrt{3}$
σ_j^2 , std. of shock to the variable j anticipated 2 quarters ahead	Uniform			0	$5\sqrt{3}$
σ_j^3 , std. of shock to the variable j anticipated 3 quarters ahead	Uniform			0	$5\sqrt{3}$
Parameters for “News” and “Noise” Models					
σ_j , std. of moving-average component of shock to the variable j	Uniform			0	$5\sqrt{3}$
$\phi_{0,j}$, weight of unanticipated shock to the variable j				0	1
$\phi_{1,j}$, weight of shock to the variable j anticipated 1 quarter ahead	Dirichlet			0	1
$\phi_{2,j}$, weight of shock to the variable j anticipated 2 quarters ahead				0	1
$\phi_{3,j}$, weight of shock to the variable j anticipated 3 quarters ahead				0	1

Table 2: Prior distributions for estimated parameters for the models with various information specifications. Note that $j = \{g, z, x, a\}$ and Beta* indicates that a linear transformation of the parameter has a beta prior distribution. Imposing a Dirichlet prior ensures that $\phi_{i,j} \geq 0, \forall i = 0, \dots, 3$ and $\sum_{i=0}^3 \phi_{i,j} = 1$.

	AR News	SGU News	News	Noise
Preference and technology				
θ_c (habit in consumption)	0.29 [0.23, 0.34]	0.90 [0.88, 0.92]	0.89 [0.87, 0.91]	0.43 [0.35, 0.50]
θ_ℓ (habit in leisure)	0.24 [0.16, 0.33]	0.89 [0.87, 0.90]	0.89 [0.87, 0.91]	0.19 [0.11, 0.29]
χ (preference)	15.89 [13.13, 18.90]	8.34 [6.71, 9.93]	9.64 [7.44, 12.04]	6.14 [4.32, 8.15]
κ (investment adjust. cost)	0.43 [0.30, 0.58]	4.84 [3.77, 5.89]	4.71 [3.61, 5.86]	0.94 [0.69, 1.23]
δ_2 (convexity of capacity util.)	0.07 [0.07, 0.07]	0.10 [0.08, 0.12]	0.21 [0.17, 0.26]	0.07 [0.07, 0.07]
Stationary neutral technology shock				
ρ_z (AR coeff.)	0.93 [0.91, 0.95]	0.99 [0.99, 0.99]	0.99 [0.99, 0.99]	0.71 [0.56, 0.84]
σ_z^0 (unanticipated std)	0.48 [0.41, 0.57]	0.23 [0.01, 0.51]	2.92 [2.54, 3.38]	0.94 [0.89, 0.98]
σ_z^1 (1-qtr anticipated std)		0.22 [0.02, 0.52]		
σ_z^2 (2-qtr anticipated std)		0.55 [0.04, 1.52]		
σ_z^3 (3-qtr anticipated std)		4.19 [3.61, 4.75]		
Non-stationary technology shock				
ρ_x (AR coeff.)	0.40 [0.35, 0.44]	0.25 [0.15, 0.33]	0.38 [0.30, 0.43]	0.12 [-0.06, 0.28]
σ_x^0 (unanticipated std)	0.56 [0.48, 0.65]	1.88 [1.49, 2.25]	3.29 [2.83, 3.78]	0.93 [0.74, 1.13]
σ_x^1 (1-qtr anticipated std)		0.71 [0.03, 1.72]		
σ_x^2 (2-qtr anticipated std)		2.43 [1.74, 3.05]		
σ_x^3 (3-qtr anticipated std)		2.80 [2.22, 3.44]		

Table 3: Posterior distributions. The reported numbers are the posterior median estimates and the square brackets indicate the 5% and 95% of posterior distribution.

	AR News	SGU News	News	Noise
Investment-specific productivity shock				
ρ_a (AR coeff.)	0.35 [0.28, 0.43]	0.47 [0.37, 0.57]	0.44 [0.31, 0.55]	0.33 [0.20, 0.44]
σ_a^0 (unanticipated std)	0.41 [0.37, 0.45]	0.22 [0.02, 0.37]	0.45 [0.39, 0.53]	0.74 [0.49, 0.82]
σ_a^1 (1-qtr anticipated std)		0.16 [0.01, 0.35]		
σ_a^2 (2-qtr anticipated std)		0.15 [0.02, 0.33]		
σ_a^3 (3-qtr anticipated std)		0.17 [0.02, 0.36]		
Government spending shock				
ρ_g (AR coeff.)	0.98 [0.97, 0.99]	0.98 [0.97, 0.99]	0.96 [0.95, 0.97]	0.93 [0.77, 0.98]
ρ_{xg} (govt. spen. trend AR coeff.)	0.86 [0.68, 0.99]	0.99 [0.99, 0.99]	0.84 [0.77, 0.92]	0.92 [0.76, 0.99]
σ_g^0 (unanticipated std)	1.10 [1.02, 1.20]	0.46 [0.03, 1.00]	3.74 [2.98, 4.51]	1.19 [1.01, 1.43]
σ_g^1 (1-qtr anticipated std)		0.45 [0.07, 0.90]		
σ_g^2 (2-qtr anticipated std)		0.59 [0.07, 1.02]		
σ_g^3 (3-qtr anticipated std)		0.40 [0.05, 0.93]		

Table 4: Posterior distributions (continued). The reported numbers are the posterior median estimates and the square brackets indicate the 5% and 95% of posterior distribution.

MA parameters of “News” and “Noise” models												
		News	Noise		News	Noise		News	Noise		News	Noise
MA(0)	θ_z^0	0.01 [0.00, 0.03]	0.01 [0.00, 0.03]	θ_x^0	0.00 [0.00, 0.01]	0.02 [0.00, 0.10]	θ_a^0	0.90 [0.78, 0.98]	0.25 [0.03, 0.39]	θ_g^0	0.19 [0.11, 0.25]	0.90 [0.78, 0.99]
MA(1)	θ_z^1	0.01 [0.00, 0.04]	0.98 [0.94, 1.00]	θ_x^1	0.34 [0.14, 0.51]	0.72 [0.49, 0.94]	θ_a^1	0.02 [0.00, 0.08]	0.07 [0.00, 0.25]	θ_g^1	0.16 [0.07, 0.24]	0.02 [0.00, 0.10]
MA(2)	θ_z^2	0.01 [0.00, 0.02]	0.01 [0.00, 0.02]	θ_x^2	0.28 [0.01, 0.60]	0.07 [0.00, 0.26]	θ_a^2	0.08 [0.00, 0.17]	0.66 [0.53, 0.92]	θ_g^2	0.37 [0.22, 0.50]	0.02 [0.00, 0.09]
MA(3)	θ_z^3	0.98 [0.94, 1.00]	0.00 [0.00, 0.02]	θ_x^3	0.38 [0.19, 0.54]	0.19 [0.01, 0.43]	θ_a^3	0.01 [0.00, 0.03]	0.03 [0.00, 0.11]	θ_g^3	0.28 [0.12, 0.44]	0.05 [0.00, 0.16]

Table 5: Posterior distributions (continued). The reported numbers are the posterior median estimates and the square brackets indicate the 5% and 95% of posterior distribution. Each column of the MA parameters may not sum to 1.0 due to rounding.

Model	Log Marginal Data Density	Bayes Factor Versus SGU News Model	DIC Statistic	BPIC Statistic
AR News	-2635.05	exp [462.88]	5048.59	5056.21
SGU News	-2155.83	1.00	4103.46	4102.70
News	-2464.04	exp [281.70]	4656.71	4645.97
Noise	-1950.61	exp [-231.73]	3616.37	3578.79

Table 6: Log marginal data densities relative to the SGU News model, and deviance information criterion (DIC) and Bayesian predictive information criterion (BPIC) of each model. The log marginal data densities are computed based on Geweke’s (1999) modified harmonic mean estimator.

Model	Log Marginal Data Density	Bayes Factor Versus SGU News Model	DIC Statistic	BPIC Statistic
AR News	-2662.36	exp [-60.31]	5164.17	5169.26
SGU News	-2703.35	1.00	5174.08	5187.27
News	-2692.59	exp [-37.23]	5065.32	5034.91
Noise	-2098.27	exp [-624.40]	4000.97	3779.78

Table 7: Log marginal data densities relative to the SGU News model, and deviance information criterion (DIC) and Bayesian predictive information criterion (BPIC) of each model with no real frictions (i.e., $\theta_c = \theta_\ell = \kappa = 0$). The log marginal data densities are computed based on Geweke’s (1999) modified harmonic mean estimator.

	Raw Data	AR News	SGU News	News	Noise
Output	0.86	0.44 [0.34, 0.55]	5.37 [3.97, 7.15]	4.80 [3.54, 6.63]	0.73 [0.60, 0.92]
Consumption	0.50	0.34 [0.26, 0.44]	3.20 [2.42, 4.20]	3.06 [2.29, 4.20]	0.55 [0.44, 0.73]
Investment	2.20	1.26 [0.95, 1.68]	23.33 [17.18, 31.22]	20.05 [14.59, 28.31]	2.75 [2.24, 3.40]
Hours	1.87	0.43 [0.31, 0.56]	6.00 [3.98, 8.78]	3.88 [2.75, 5.62]	0.83 [0.57, 2.49]

Table 8: Unconditional moments of raw data and model-generated data. The reported numbers are the posterior median estimates and the square brackets indicate the 5% and 95% of posterior distribution. Each series is detrended by the Hodrick-Prescott filter.

D FIGURES

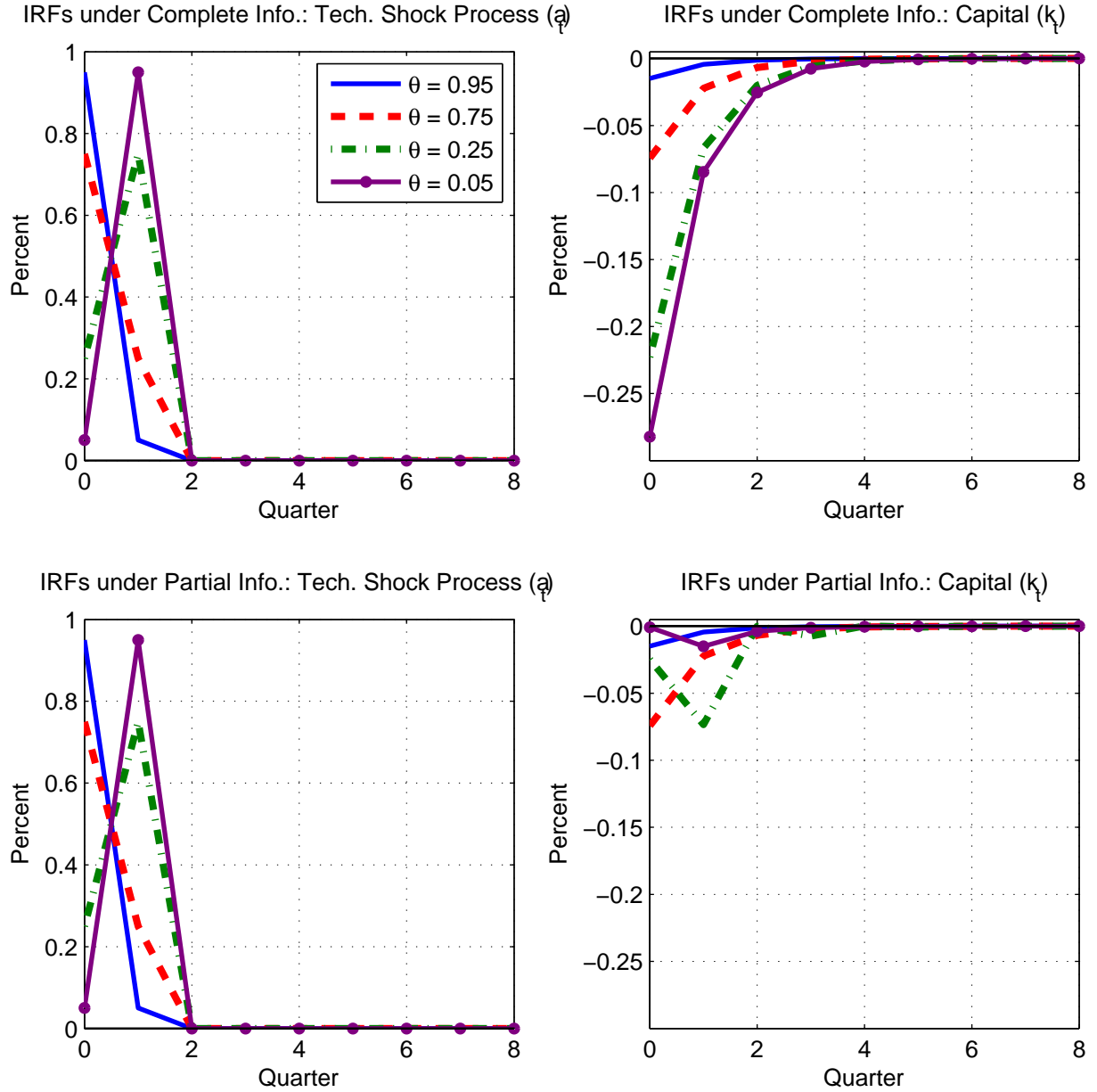


Figure 1: Impulse responses of technology shock process and capital to a one standard deviation shock in technology under agents' complete information assumption (first row) and those under agents' partial information information assumption (second row).

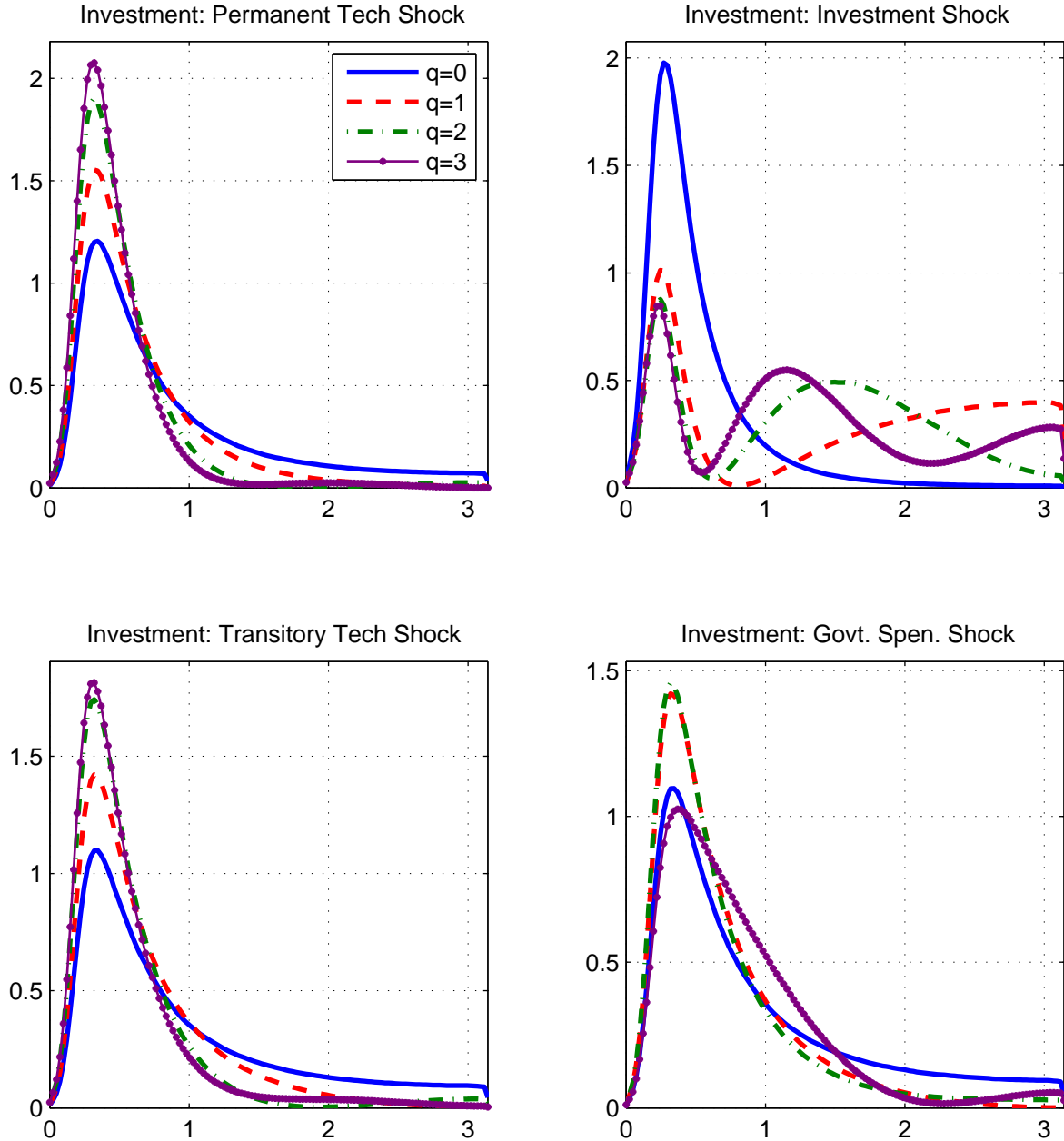


Figure 2: Estimated median spectral densities of investment from the SGU News specification. The model-generated series are simulated by the corresponding exogenous shock anticipated q -period ahead. Then each series is detrended by the Hodrick-Prescott filter.

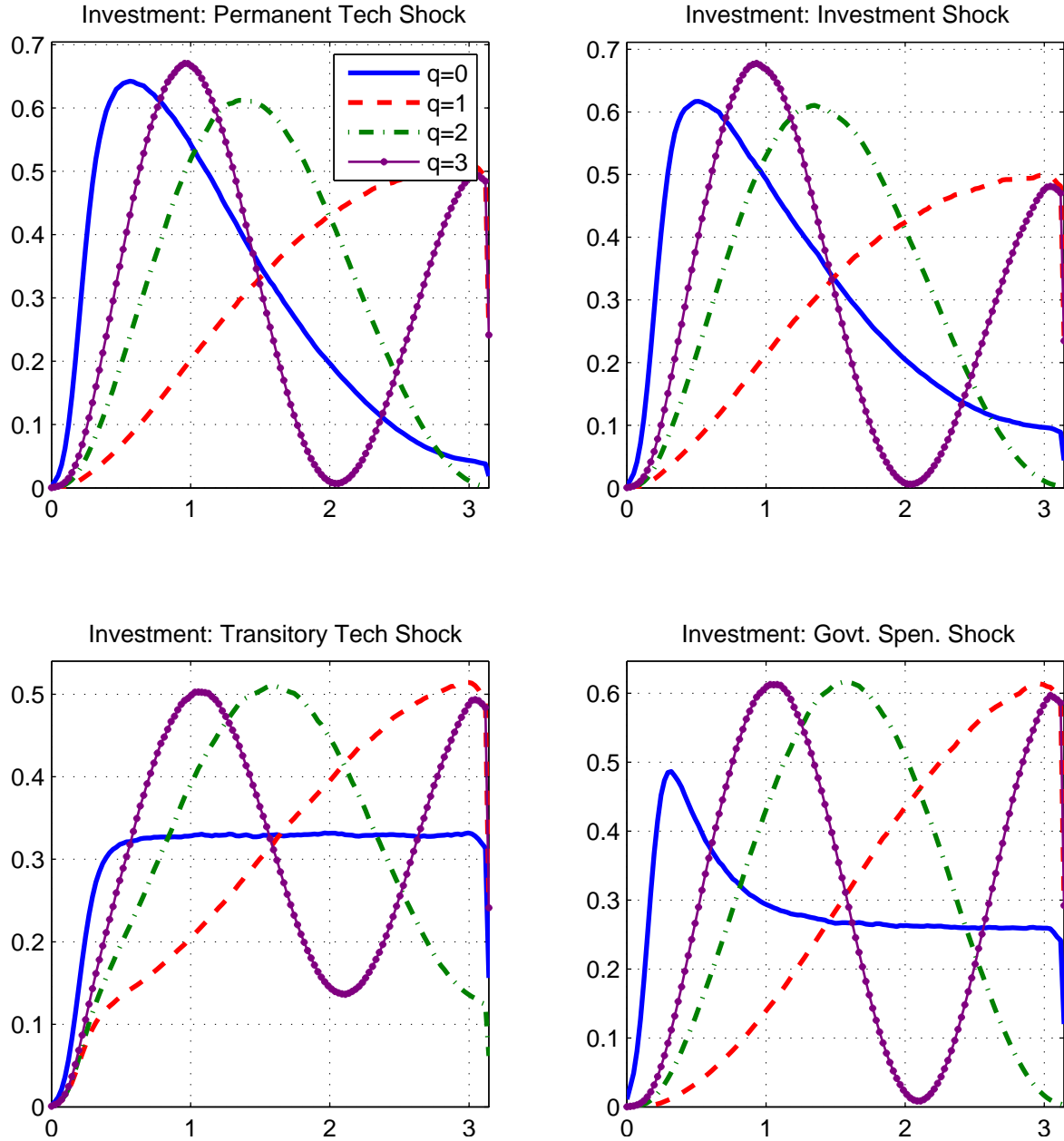


Figure 3: Estimated median spectral densities of investment from the SGU News specification with no real frictions (i.e., $\theta_c = \theta_\ell = \kappa = 0$). The model-generated series are simulated by the corresponding exogenous shock anticipated q -period ahead. Then each series is detrended by the Hodrick-Prescott filter.

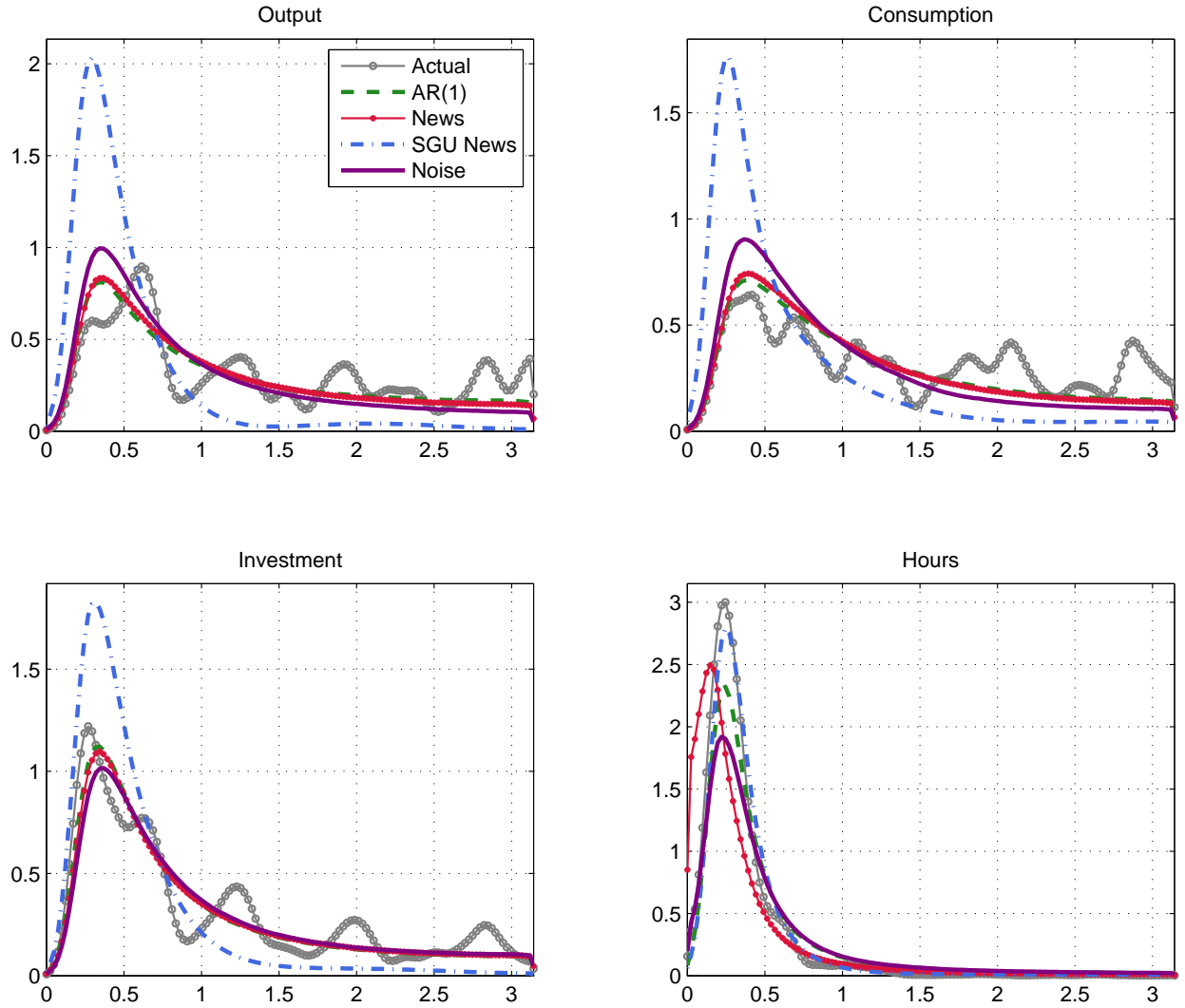


Figure 4: Spectral densities of raw data and estimated median spectral densities of investment across the three different information flows: Raw data (solid lines with circles), AR News (dashed lines), News (solid lines with stars), SGU News (dotted-dashed lines), and Noise (solid lines). The model-generated series are simulated jointly by all the exogenous shocks. Then each series is detrended by the Hodrick-Prescott filter.

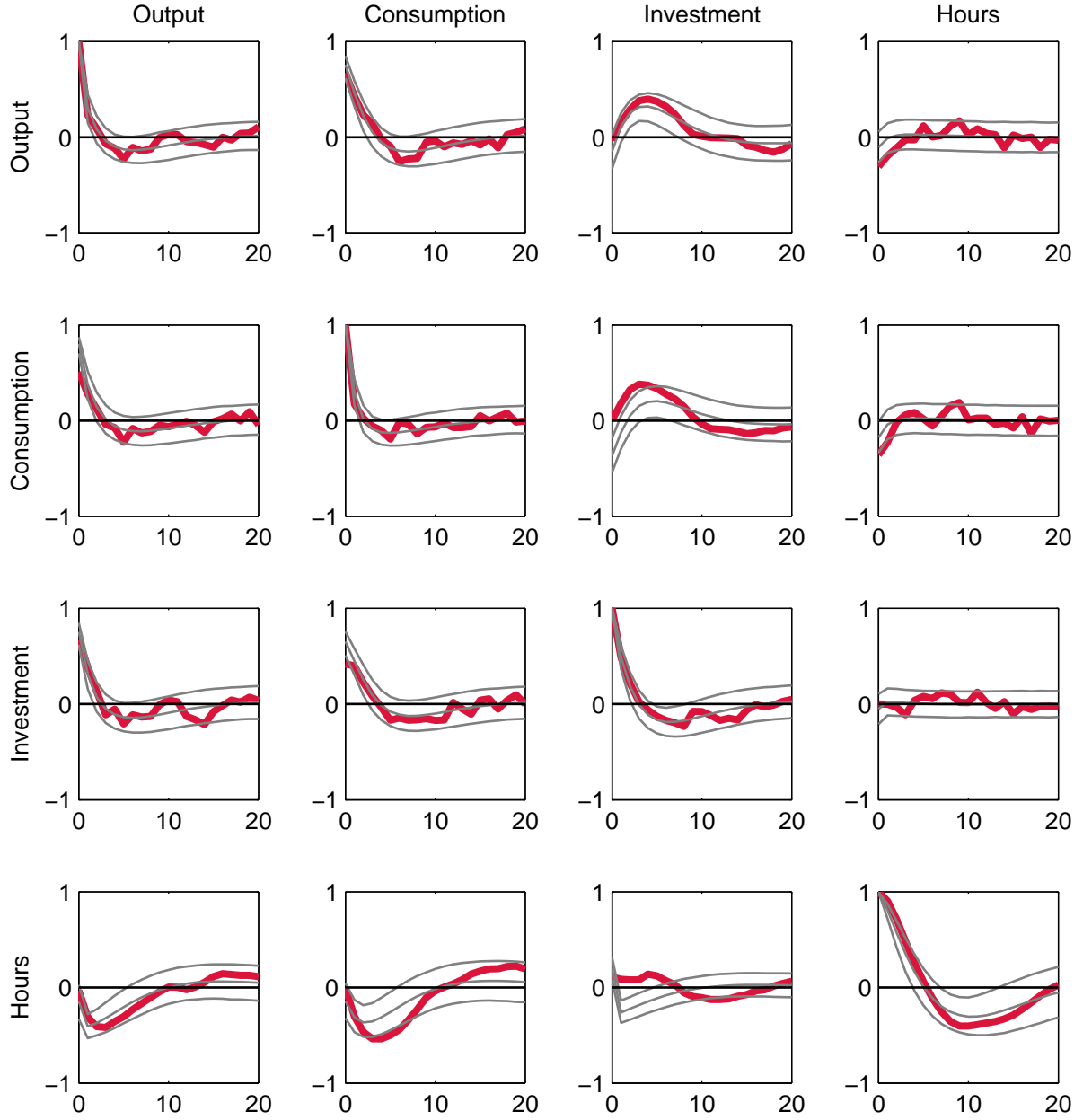


Figure 5: Auto- and cross-correlations of raw data (thick solid lines) and of AR News' medians and 90 percent coverage percentiles of the distributions (thin solid lines). Each series is detrended by the Hodrick-Prescott filter.

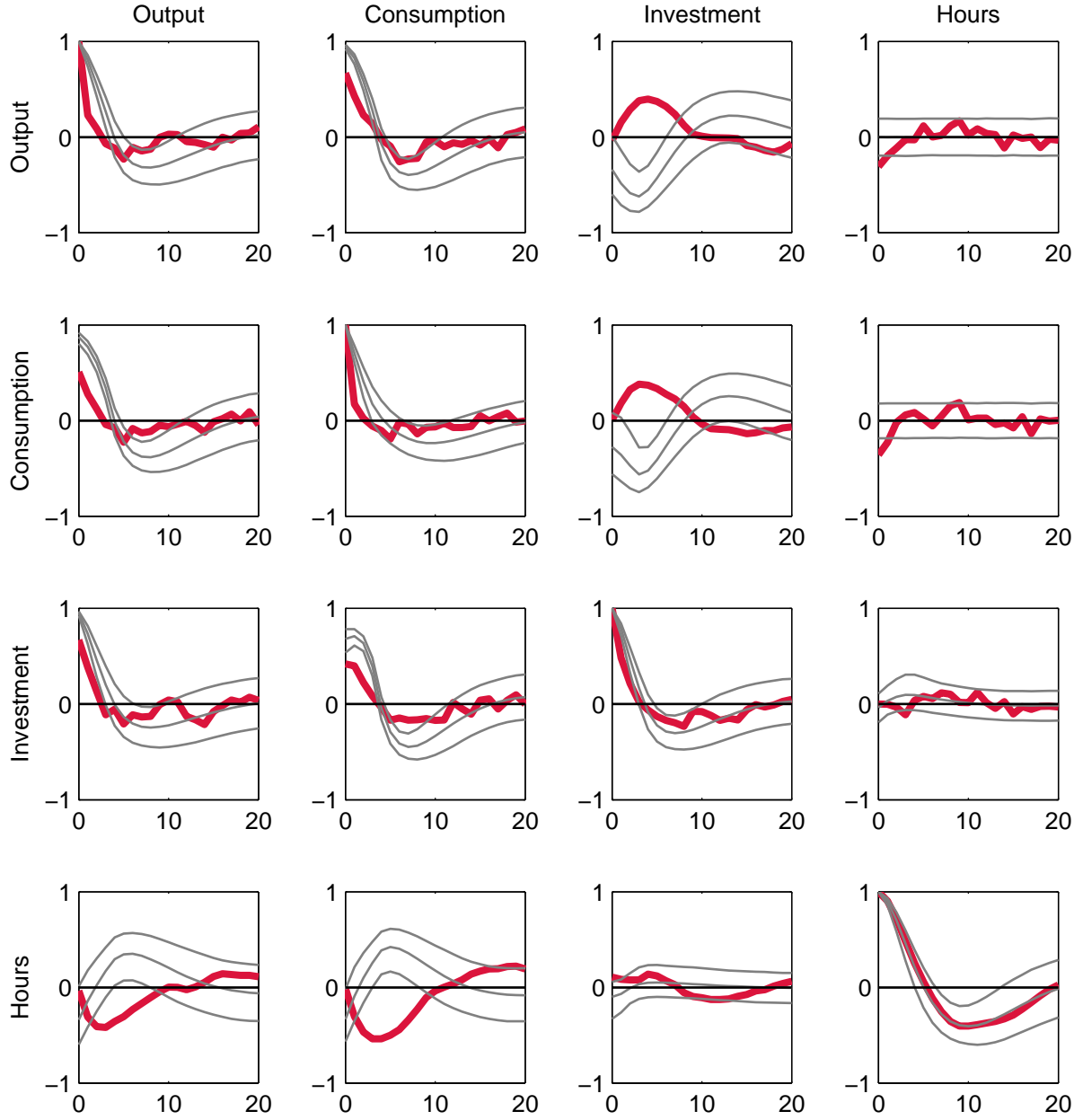


Figure 6: Auto- and cross-correlations of raw data (thick solid lines) and of SGU News' medians and 90 percent coverage percentiles of the distributions (thin solid lines). Each series is detrended by the Hodrick-Prescott filter.

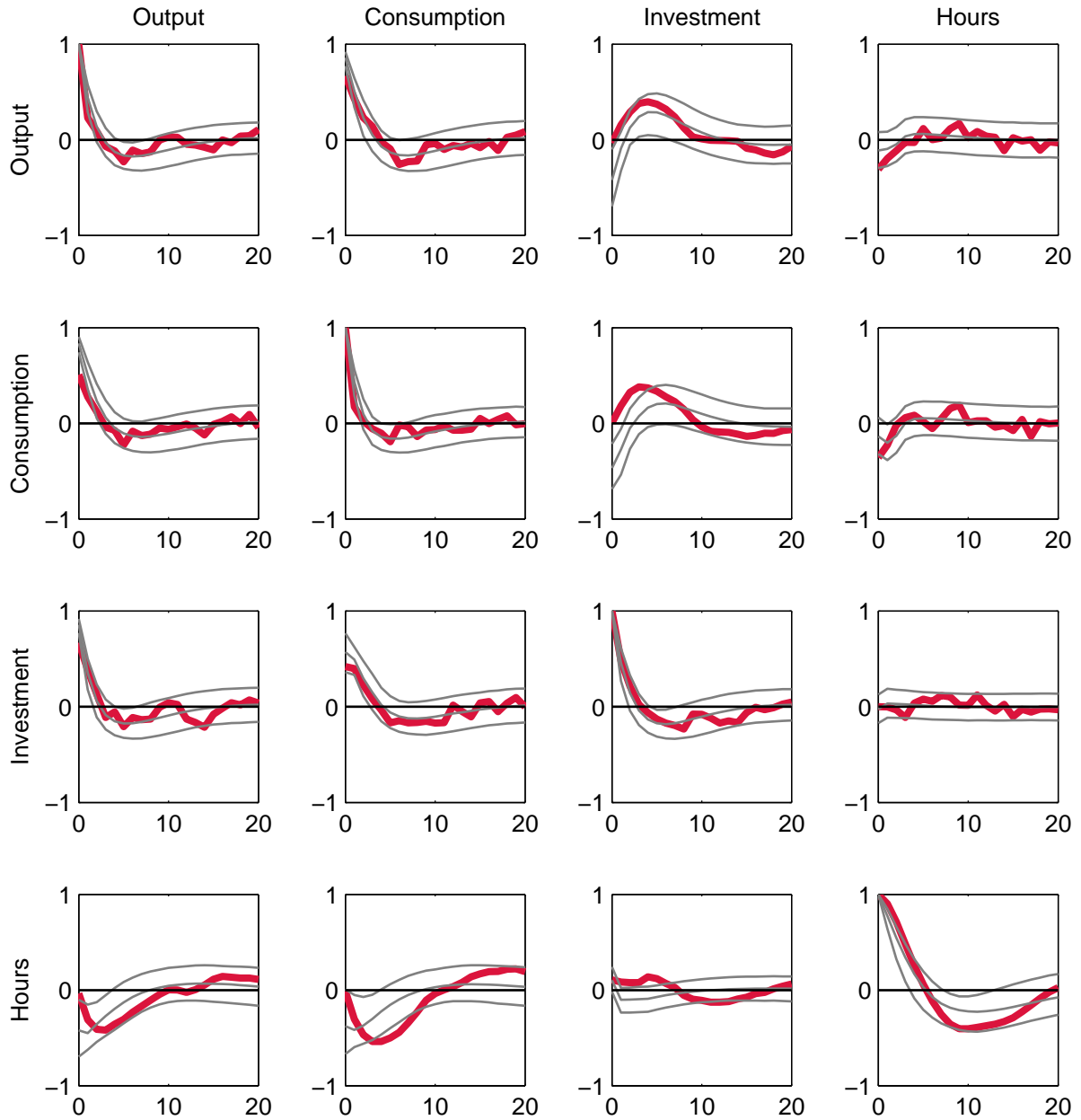


Figure 7: Auto- and cross-correlations of raw data (thick solid lines) and of Noise's medians and 90 percent coverage percentiles of the distributions (thin solid lines). Each series is detrended by the Hodrick-Prescott filter.

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