

What's News In Business Cycles*

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Abstract

In the context of a dynamic, stochastic, general equilibrium model, we perform classical maximum-likelihood and Bayesian estimations of the contribution of anticipated shocks to business cycles in the postwar United States. Our theoretical framework is a real-business-cycle model augmented with investment adjustment costs, variable capacity utilization, habit formation in consumption, and preferences featuring a parameter governing the strength of the wealth elasticity of labor supply. Business cycles are assumed to be driven by permanent and stationary neutral productivity shocks, permanent and stationary investment-specific shocks, government spending shocks, wage-markup shocks, and preference shocks. Each of these driving forces is buffeted by three types of structural innovations: unanticipated innovations and innovations anticipated four or eight quarters in advance. We find that anticipated shocks account for more than half of predicted aggregate fluctuations. (JEL E32, E13, C11, C51)

Keywords: Anticipated Shocks, Sources of Aggregate Fluctuations, Bayesian Estimation.

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1 Introduction

How important are anticipated shocks as a source of economic fluctuations? What type of anticipated shock is important? How many quarters in advance are the main drivers of business cycles anticipated? The literature extant has attempted to address these questions using vector autoregression (VAR) analysis. A central contribution of this paper is the insight that one can employ likelihood-based methods in combination with a dynamic stochastic general equilibrium (DSGE) model populated by forward-looking agents to identify and estimate the anticipated components of exogenous innovations in fundamentals. This is possible because forward-looking agents will in general react differently to news about future changes in different fundamentals as well as to news about a given fundamental with different anticipation horizons.

An important motivation for pursuing a model-based, full-information econometric strategy—as opposed to adopting a VAR approach—for the identification of anticipated shocks is that the equilibrium dynamics implied by DSGE models featuring shocks with multi-period anticipated components generally fail to have a representation that takes the form of a structural VAR system whose innovations are the structural shocks of the DSGE model. This problem arises even in cases in which the number of observables matches the total number of innovations in the model. The reason for this failure is that the presence of anticipated innovations with multi-period anticipation horizons introduces multiple latent state variables. We show in this paper that an innovation that is anticipated j periods in advance introduces j exogenous state variables. This proliferation of states makes it less likely that the dynamics of the observables possesses a VAR representation, hindering the ability of current and past values of a given set of observables to identify the underlying structural innovations. As a result, in general, a VAR methodology may not identify the anticipated component of structural shocks. Leeper, Walker, and Yang (2008) articulate the difficulties of extracting information about anticipated shocks via conventional VAR analysis in the context of a model with fiscal foresight.

An additional concern with existing VAR-based studies of anticipated shocks is that they have focused on identifying a single anticipated innovation—typically, anticipated innovations in total factor productivity. By contrast, our model-based full-information approach allows for the identification of anticipated components in multiple sources of uncertainty. Further, our proposed methodology makes it possible to distinguish between anticipation horizons and between stationary and nonstationary anticipated components.

Our assumed theoretical environment is a real-business-cycle model augmented with four real rigidities: internal habit formation in consumption, investment adjustment costs, vari-

able capacity utilization, and imperfect competition in labor markets. In addition, following Jaimovich and Rebelo (2009), the model specifies preferences featuring a parameter that governs the wealth elasticity of labor supply. The assumed real rigidities and preference specification are intended to overcome the well-known criticism raised by Barro and King (1984) regarding the ability of the neoclassical model to predict positive comovement between consumption, output, and employment in response to demand shocks (including anticipated movements in fundamentals).

In our model, business cycles are driven by seven structural shocks. Namely, stationary neutral productivity shocks, nonstationary neutral productivity shocks, stationary investment-specific productivity shocks, nonstationary investment-specific productivity shocks, government spending shocks, wage-markup shocks, and preference shocks. Our choice of shocks is guided by a growing model-based econometric literature showing that these shocks are important sources of business cycles in the postwar United States (see, for example, Smets and Wouters, 2007; and Justiniano, Primiceri, and Tambalotti, 2009).

The novel element in our theoretical formulation is the assumption that each of the seven structural shocks features an anticipated component and an unanticipated component. The anticipated component is, in turn, driven by innovations announced four or eight quarters in advance. This means that in any period t the innovation to the exogenous fundamentals of the economy can be expressed as the sum of three signals. One signal is received in period $t - 8$, the second in period $t - 4$, and the third in period t itself. Thus, the signal received in period $t - 4$ can be interpreted as a revision of the one received earlier in period $t - 8$. In turn, the signal received in period t can be viewed as a revision of the sum of the signals received in periods $t - 8$ and $t - 4$. It follows that the information received in periods $t - 8$ and $t - 4$ regarding the innovation to the exogenous state in period t represent noisy signals.

We apply Bayesian and classical likelihood-based methods to estimate the parameters defining the stochastic processes of anticipated and unanticipated shocks and other structural parameters. The resulting estimated DSGE model allows us to perform variance decompositions to identify what fraction of aggregate fluctuations can be accounted for by anticipated shocks. The main finding of this paper is that anticipated shocks are an important source of uncertainty: They explain about one half of the variances of output, hours, consumption, and investment. This result represents a sharp departure from the DSGE-model-based econometric literature on the sources of business cycles, which has implicitly attributed one hundred percent of aggregate fluctuations at business-cycle frequencies to unanticipated variations in economic fundamentals.

The fact that the DSGE-model-based econometric literature on the sources of business cycles has been mute about the role of anticipated shocks does not mean that business-

cycle researchers in general have not entertained the idea that changes in expectations about the future path of exogenous economic fundamentals may represent an important source of aggregate fluctuations. On the contrary, this idea has a long history in economics, going back at least to Pigou (1927). Recently, it has been revived by Cochrane (1994), who finds that contemporaneous shocks to technology, money, credit, and oil prices cannot account for the majority of observed aggregate fluctuations. Cochrane shows that VARs estimated using artificial data from a real-business-cycle model driven by contemporaneous and anticipated shocks to technology produce responses to consumption shocks that resemble the corresponding responses implied by VARs estimated on actual U.S. data. More recently, an influential contribution by Beaudry and Portier (2006) proposes an identification scheme for uncovering anticipated shocks in the context of a VAR model for total factor productivity and stock prices. Beaudry and Portier argue that innovations in the growth rate of total factor productivity are to a large extent anticipated and explain about half of the forecast error variance of consumption, output, and hours. Our approach to estimating the importance of anticipated shocks as a source of business-cycle fluctuations departs from that of Beaudry and Portier (2006) in two important dimensions: first our estimation is based on a formal dynamic, stochastic, optimizing, rational expectations model, and thus does not suffer from the aforementioned invertibility problem. Second, we employ a full information econometric approach to estimation, which allows us to identify simultaneously multiple distinct sources of anticipation.

The present paper is related to Davis (2007) who in independent and contemporaneous work estimates using full-information likelihood-based methods the effects of anticipated shocks in a model with nominal rigidities.¹ Davis finds that anticipated shocks explain about half of the volatility of output growth, which is consistent with the results reported in this paper. His results suggest that the most important source of anticipated shocks are anticipated changes in the relative price of investment. This prominence of the relative price of investment as a source of business cycles is in line with the findings reported in Justiniano, Primiceri, and Tambalotti (2009), who restrict attention to unanticipated innovations in this relative price. By contrast, we find that variations in the relative price of investment, whether anticipated or unanticipated, have a negligible effect on business cycles. We argue that in the context of structural DSGE models estimated using Bayesian methods, this discrepancy is explained to a large extent by whether the set of observables used for estimation includes or not the price of investment. Our econometric analysis does include this variable as an observable. By contrast, Davis (2007) and Justiniano, Primiceri, and Tambalotti (2009),

¹Our work is also related to Fujiwara et al. (2008). These authors estimate and compare the role of anticipated shocks in Japan and the United States.

do not include the price of investment as an observable. Our econometric strategy imposes more discipline on the predicted movements of the relative price of investment than does the strategy that omits it from the set of observables, as it forces the predicted movements in the relative price of investment to mimic those observed in actual data. The benefit of excluding the price of investment from the set of observables is that it allows the estimation procedure to pick freely the parameters defining its law of motion to match movements in other endogenous variables included in the set of observables. But this freedom comes at a cost. For instance, the model estimated by Justiniano, Primiceri, and Tambalotti (2009) predicts a standard deviation of the relative price of investment at least four times as large as its empirical counterpart.

Our model features a preference specification containing a parameter that governs the magnitude of the wealth elasticity of labor supply. In a recent theoretical paper, Jaimovich and Rebelo (2009) argue that a value of this parameter consistent with a low wealth elasticity of labor supply, in combination with other real rigidities of the type discussed above, facilitates positive comovement of output, hours, and consumption in response to anticipated productivity shocks. To our knowledge, the present investigation presents the first econometric estimate of this key parameter of the Jaimovich-Rebelo preference specification. Our estimates deliver a negligible wealth elasticity of labor supply, providing empirical support for the preference specification originally proposed by Greenwood, Hercowitz, and Huffman (1988).

Our estimation results shed light on the debate on whether government spending shocks are mostly anticipated or unanticipated. In our model government spending, like all other exogenous variables considered, is subject to unanticipated innovations as well as to innovations that are anticipated either four or eight quarters. In the literature that uses the narrative approach to the identification of government spending shocks, for example Ramey and Shapiro (1998), a central argument is that changes in government spending are known several quarters before they result in actual increases in spending. By contrast, Blanchard and Perotti (2002) identify government spending shocks that are by construction unanticipated. Our methodology allows us to jointly evaluate the relative importance of both types of government spending shock. We find that 60 percent of the variance of government spending is due to anticipated shocks and 40 percent is due to unanticipated shocks. Furthermore, we find that government spending shocks account for close to ten percent of the variance of output growth. This magnitude is standard in the literature. The novel insight emerging from our econometric estimation is that two thirds of this fraction is attributable to anticipated innovations and one third to surprise movements in government spending.

The remainder of the paper is organized in six sections. Section 2 illustrates the ability

of our full-information, likelihood-based econometric approach to identify the anticipated component of shocks. It studies a small artificial economy driven by three innovations two of which are anticipated. The artificial model is estimated using two observables. Section 3 presents the theoretical model. Section 4 explains how to introduce anticipated disturbances into the model and derives the autoregressive representation of the exogenous stochastic state variables. This section also demonstrates that our framework can accommodate revisions in expectations, such as anticipated increases in productivity that fail to materialize. Section 5 presents classical and Bayesian likelihood-based estimations of the structural parameters of the model defining the stochastic processes of the anticipated and unanticipated components of the assumed sources of business cycles. This section also provides measures of the model's ability to fit the data. Section 6 contains the central result of the paper, namely, that anticipated shocks account for about half of the predicted variance of output, consumption, investment, and hours. We convey this result through a number of perspectives, including variance decompositions of growth rates and HP filtered model predictions into their anticipated and unanticipated components and spectral analysis. The section also explores two variations of the baseline setup. One variation consists in enriching the set of observables by adding data on stock prices. The second variation considers a more parsimonious version of both the set of observables and the theoretical model. Specifically, it eliminates total factor productivity from the set of observables and preference shocks, markup shocks, and shocks to the marginal efficiency of investment from the set of driving forces. In addition, in this section, we relate the findings of our paper to those obtained using a structural VAR approach to the identification of anticipated shocks. Finally, section 7 concludes.

2 Identification of Anticipated Shocks: An Illustrative Example

Our full-information, likelihood-based, empirical strategy for identifying the standard deviations of the anticipated and unanticipated components of each source of uncertainty exploits the fact that in the theoretical model the observable variables react differently to anticipated and unanticipated shocks. To illustrate the potential of our empirical strategy to identify the parameters that govern the distributions of the underlying shocks, we present an estimation of these parameters based on artificial data generated from a small model featuring disturbances anticipated 0, 1, and 2 periods.²

²We thank our editor, Harald Uhlig, for suggesting this example.

The model is given by

$$\begin{aligned}x_t &= \rho_x x_{t-1} + \epsilon_t^0 + \epsilon_{t-1}^1 + \epsilon_{t-2}^2, \\y_t &= \rho_y y_{t-1} + \epsilon_t^1,\end{aligned}$$

and

$$z_t = \epsilon_t^2,$$

where $\epsilon_t^i \sim N(0, \sigma_i^2)$ is an i.i.d. random innovation in x_t that is announced in period t but materializes in a change in x only in period $t + i$. The other variables of the model change in anticipation of future changes in x . Specifically, the variable y_t responds to one-period anticipated innovations in x , and the variable z_t responds to two-period anticipated innovations in x .

We create an identification problem similar to the one that emerges in the economic model analyzed in later sections, by assuming that the econometrician can only observe two variables, x_t and v_t . The variable v_t is a linear combination of y_t and z_t and is given by

$$v_t = y_t + z_t.$$

That is, the econometrician cannot observe y_t and z_t separately. However, we assume that the econometrician knows both the structure of the model and that v_t is linked to y_t and z_t by the above relationship. The econometric problem consists in estimating the three parameters σ_0 , σ_1 , and σ_2 , defining the standard deviations of the unanticipated, one-period-anticipated, and two-period-anticipated innovations in x_t . We set ρ_x and ρ_y at 0.9 and 0.5, respectively.

The top row of figure 1 displays the true impulse responses of the observables x_t and v_t to unit innovations in each of the three shocks, ϵ_t^0 , ϵ_t^1 , and ϵ_t^2 . Note that the impulse responses of x_t are copies of each other, simply shifted one period to the right. This feature of the model may raise the question of whether the econometrician will be able to correctly identify the parameters of interest with a sample of observations on x_t and v_t . The intuition for why identification may be possible in spite of the seemingly unrevealing aspect of the impulse responses of the observables is that each of the three shocks has a distinct effect on the joint behavior of the two observables. The virtue of the simple example economy at hand is that these effects can be easily discerned: first, the shock ϵ_t^2 is the only disturbance that has a purely temporary effect on v_t . Second, the shock ϵ_t^1 is the only innovation that has a persistent effect on v_t . And third, ϵ_t^0 is the only shock that affects x_t but not v_t . Thus knowledge of the underlying data generating process should allow for the design of a successful econometric strategy to identify the volatilities of the three underlying sources of uncertainty. Next, we substantiate this conjecture by formally estimating the example

economy using Bayesian methods on simulated data for x_t and v_t .

We consider two cases, each representing a different economy. The two economies differ in the relative importance of the three underlying shocks. In one case, the innovations display very different relative standard deviations. Specifically, in this case we assume that $\sigma_2 = 0.8$, $\sigma_1 = \sigma_2/2$, and $\sigma_0 = \sigma_2/4$. In the second case, all innovations are assumed to share the same standard deviation, which we set at 0.8. In each case, we produce an artificial data set of 250 observations of the observables x_t and v_t . We then estimate σ_i for $i = 0, 1, 2$ using Bayesian methods. For both economies we adopt gamma prior distributions with mean 0.5 and standard deviation 0.2. The second and third rows of figure 1 display for each of the three parameters being estimated (σ_0 , σ_1 , and σ_2) its posterior density, its prior density, and its true value. Posterior densities are calculated using 500,000 draws from the posterior distribution. The Bayesian estimation strategy does a remarkable job at uncovering the true values of the parameters in question. In the economy in which $(\sigma_0, \sigma_1, \sigma_2) = (0.2, 0.4, 0.8)$, shown in the second row of figure 1 the posterior means are, respectively (0.24, 0.4, 0.79), with standard deviations (0.06, 0.02, 0.04). And in the economy in which $(\sigma_0, \sigma_1, \sigma_2) = (0.8, 0.8, 0.8)$, shown in the bottom row of figure 1, the posterior means are, respectively (0.75, 0.73, 0.77), with standard deviations (0.07, 0.04, 0.05). (The posterior medians are very close to the respective posterior means.) Although one cannot derive general conclusions from this example, it certainly suggests that the identification of the standard deviations of the anticipated and unanticipated components of shocks is possible when there are fewer observables than shocks and even when the impulse responses of some of the observables to shocks hitting the economy at different anticipation horizons are shifted copies of one another.

3 The Model

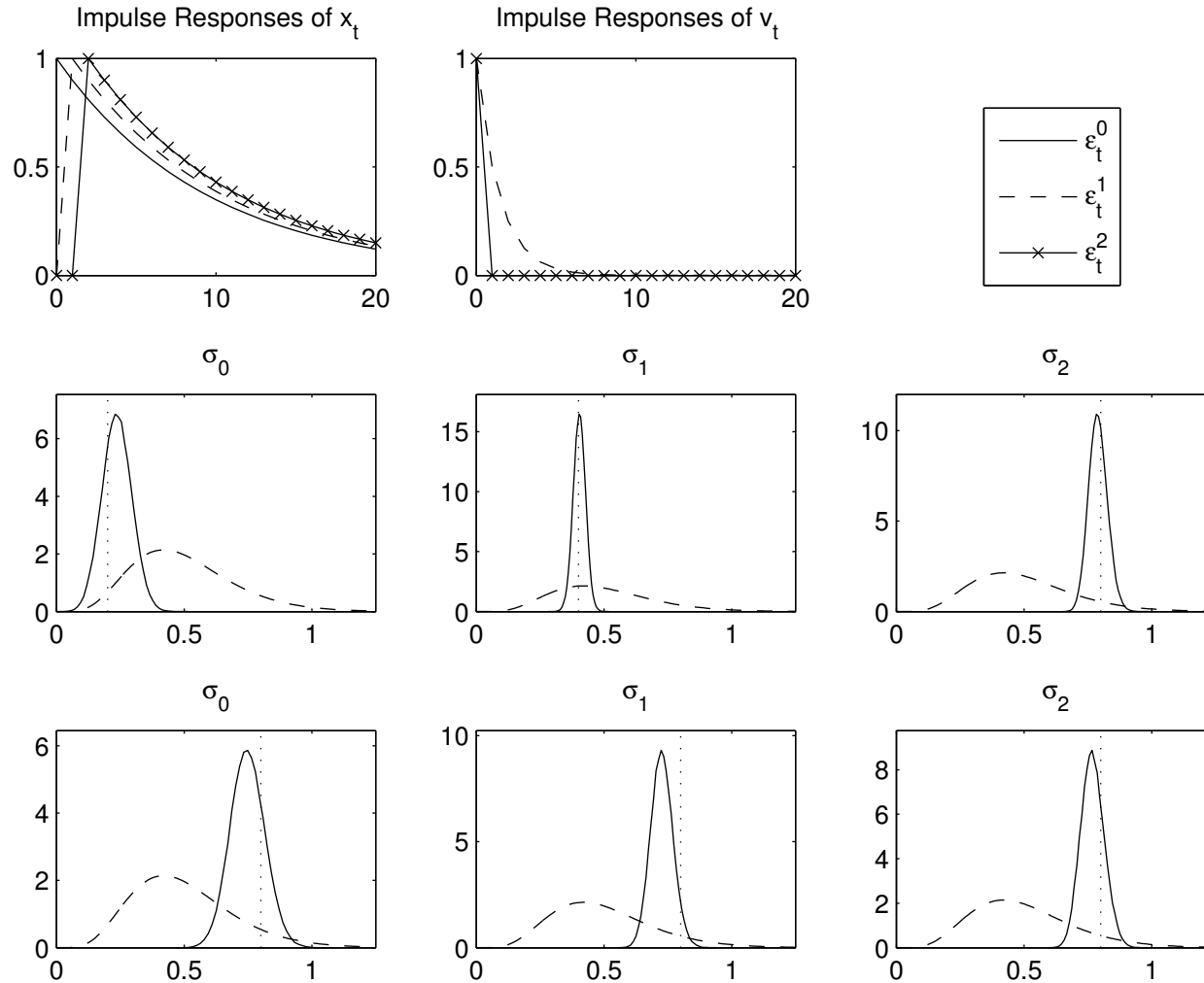
Consider an economy populated by a large number of identical, infinitely lived agents with preferences described by the lifetime utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_t U(V_t), \tag{1}$$

where U denotes a period utility function, which we assume to belong to the CRRA family

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

Figure 1: Identification in the Example Economy



Note: The top panels show the true impulse responses of the observables to a unit impulse in each of the three innovations. Each panel in the second and third rows of the figure plots with a solid line the posterior density, with a broken line the prior density, and with a dotted line the true value of σ_i for $i = 0, 1, 2$. Posterior densities are calculated using 500,000 draws from the posterior distribution of the respective parameter. The second row corresponds to the case in which the true parameter values are $\sigma_2 = 2\sigma_1 = 4\sigma_0 = 0.8$. The bottom row corresponds to the case in which the true parameter values are $\sigma_2 = \sigma_1 = \sigma_0 = 0.8$.

with $\sigma > 0$. The variable ζ_t denotes an exogenous and stochastic preference shock in period t . This type of disturbance has been identified as an important driver of consumption fluctuations in most existing econometric estimations of DSGE macroeconomic models (e.g., Smets and Wouters, 2007; Justiniano, Primiceri, and Tambalotti, 2008). The argument of the period utility function, V_t , is assumed to be given by

$$V_t = C_t - bC_{t-1} - \psi h_t^\theta S_t, \quad (2)$$

where C_t denotes private consumption in period t , h_t denotes hours worked in period t , and S_t is a geometric average of current and past habit-adjusted consumption levels. The law of motion of S_t is postulated to be

$$S_t = (C_t - bC_{t-1})^\gamma S_{t-1}^{1-\gamma}. \quad (3)$$

The parameter $\beta \in (0, 1)$ denotes the subjective discount factor, $b \in [0, 1)$ governs the degree of internal habit formation, $\theta > 1$ determines the Frisch elasticity of labor supply in the special case in which $\gamma = b = 0$, and $\psi > 0$ is a scale parameter. This preference specification was suggested in a recent paper by Jaimovich and Rebelo (2009). It introduces the parameter $\gamma \in (0, 1]$ governing the magnitude of the wealth elasticity of labor supply while preserving compatibility with long-run balanced growth. We modify the Jaimovich-Rebelo preference specification to allow for internal habit formation in consumption. As $\gamma \rightarrow 0$, the argument of the period utility function becomes linear in habit-adjusted consumption and a function of hours worked, which, in the absence of habit formation, is the preference specification considered by Greenwood, Hercowitz, and Huffman (1988). This special case induces a supply of labor that depends only on the current real wage, and, importantly, is independent of the marginal utility of income. As a result, when γ and b are both small, anticipated changes in income will not affect current labor supply. As γ increases, the wealth elasticity of labor supply rises. In the polar case in which γ is unity, V_t becomes a product of habit-adjusted consumption and a function of hours worked, which is the preference specification most commonly studied in the closed-economy business-cycle literature. Because no econometric evidence exists on the value of the parameter γ , an important byproduct of our investigation is to obtain an estimate of this parameter.

Households are assumed to own physical capital. The capital stock, denoted K_t , is assumed to evolve over time according to the following law of motion

$$K_{t+1} = (1 - \delta(u_t))K_t + z_t^I I_t \left[1 - S \left(\frac{I_t}{I_{t-1}} \right) \right], \quad (4)$$

where I_t denotes gross investment. Owners of physical capital can control the intensity with which the capital stock is utilized. Formally, we let u_t measure capacity utilization in period t . The effective amount of capital services supplied to firms in period t is given by $u_t K_t$. We assume that increasing the intensity of capital utilization entails a cost in the form of a faster rate of depreciation. Specifically, we assume that the depreciation rate, given by $\delta(u_t)$, is an increasing and convex function of the rate of capacity utilization. We adopt a quadratic form for the function δ :

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

with $\delta_0, \delta_1, \delta_2 > 0$. The parameter δ_2 defines the sensitivity of capacity utilization to variations in the rental rate of capital. The parameter δ_1 governs the steady-state level of u_t . We will set this parameter at a value consistent with a unit steady-state value of u_t . And the parameter δ_0 corresponds to the rate of depreciation of the capital stock in a deterministic steady state in which u_t is unity.

The function S introduces investment adjustment costs of the form proposed by Christiano, Eichenbaum, and Evans (2005). We assume that the function S evaluated at the steady-state growth rate of investment satisfies $S = S' = 0$ and $S'' > 0$. We will focus on a quadratic specification of S :

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

where $\kappa > 0$ is a parameter and μ^i denotes the steady-state growth rate of investment. The technology transforming investment goods into capital goods is subject to a transitory exogenous disturbance denoted by z_t^I . This type of shock has recently been identified as an important source of aggregate fluctuations by Justiniano, Primiceri, and Tambalotti (2009).

The sequential budget constraint of the household is given by

$$C_t + A_t I_t + T_t = W_t^* h_t + r_t u_t K_t + P_t. \quad (5)$$

The left-hand side of this expression represents the uses of income, given by consumption, investment, and taxes. The variable A_t is an exogenous stochastic productivity shock shifting the technical rate of transformation of consumption goods into investment goods. In a decentralized competitive equilibrium A_t coincides with the relative price of new investment goods in terms of consumption goods. The variable T_t denotes lump-sum taxes. The right-hand side of the budget constraint represents the sources of income, which consist of wage income, capital income, and lump-sum profits from the ownership of firms and membership in a labor union. The variable W_t^* denotes the wage rate received by households, the variable

r_t denotes the rental rate of an effective unit of capital, and the variable P_t denotes profits.

The household's optimization problem consists in choosing a set of stochastic processes $\{C_t, h_t, S_t, V_t, I_t, K_{t+1}, u_t\}_{t=0}^{\infty}$ to maximize (1) subject to (2)-(5), taking as given the stochastic processes $\{\zeta_t, z_t^I, A_t, r_t, W_t^*, T_t, P_t\}_{t=0}^{\infty}$, and the initial conditions C_{-1}, S_{-1}, I_{-1} , and K_0 .

Motivated by earlier DSGE-based econometric studies of the U.S. business cycle (e.g., Smets and Wouters, 2007), we introduce an exogenously time-varying markup in wages. This type of shock has been found to explain a large fraction of fluctuations in hours worked over the business cycle. To introduce a time-varying wage markup, we model the labor market as imperfectly competitive. On the demand side of this market, we assume that final-goods-producing firms demand a composite labor input given by $h_t^c = \left[\int_0^1 h_{jt}^{\frac{1}{1+\mu_t}} dj \right]^{1+\mu_t}$, where h_{jt} denotes the differentiated labor input of type $j \in [0, 1]$, and μ_t denotes the markup in wages. We assume that μ_t is exogenous and stochastic. Let W_{jt} denote the wage posted by workers of type j . The labor-cost minimization problem of a firm demanding h_t^c units of the composite labor input is then given by $\min_{\{h_{jt}\}} \int_0^1 W_{jt} h_{jt} dj$ subject to $\left[\int_0^1 h_{jt}^{\frac{1}{1+\mu_t}} dj \right]^{1+\mu_t} \geq h_t^c$. The solution of this cost minimization problem implies a demand for labor of type j of the form $h_{jt} = h_t^c \left(\frac{W_{jt}}{W_t} \right)^{-\frac{1+\mu_t}{\mu_t}}$, where $W_t = \left[\int_0^1 W_{jt}^{-\frac{1}{\mu_t}} dj \right]^{-\mu_t}$, denotes the cost of one unit of the composite labor input.

The supply side of the labor market consists of monopolistically competitive labor unions selling differentiated labor services to firms. The problem of the seller of labor of type j is to choose W_{jt} to maximize $(W_{jt} - W_t^*)h_{jt}$, subject to the above labor demand schedule. Using that schedule to eliminate the labor input, h_{jt} from the objective function, the maximization problem of labor union j takes the form $\max_{W_{jt}} (W_{jt} - W_t^*)h_t^c \left(\frac{W_{jt}}{W_t} \right)^{-\frac{1+\mu_t}{\mu_t}}$. The optimality condition associated with this problem is $W_t^* = \frac{W_{jt}}{1+\mu_t}$. It follows from this expression that the wage rate the union pays to its members is smaller than the wage rate firms pay to the unions. Also apparent from this expression is that all labor unions charge the same wage rate W_t . In turn, the fact that all type of labor command the same wage implies, by the demand functions for specialized labor services, that firms will demand identical quantities of each type of labor, $h_{jt} = h_t^c$ for all j . Profits of union j , given by $\mu_t/(1 + \mu_t)W_{jt}h_{jt}$, are assumed to be rebated to households in a lump-sum fashion. Finally, in equilibrium, we have that the total number of hours allocated by the unions must equal total labor supply, or $\int_0^1 h_{jt} dj = h_t$, which, since $h_{jt} = h_t^c$ for all j , implies that $h_t^c = h_t$. This completes the description of the labor market.

Output, denoted Y_t , is produced with a homogeneous-of-degree-one production function

that takes as inputs capital, labor services, and a fixed factor that can be interpreted as land or organizational capital. The fixed factor of production introduces decreasing returns to scale in the variable factors of production. Jaimovich and Rebelo (2009) suggest that a small amount of decreasing returns to scale allows for a positive response of the value of the firm to future expected increases in productivity. The production technology is buffeted by a transitory productivity shock denoted z_t and by a permanent productivity shock denoted X_t . Formally, the production function is given by

$$Y_t = z_t F(u_t K_t, X_t h_t, X_t L), \quad (6)$$

where F is taken to be of the Cobb-Douglas form: $F(a, b, c) = a^{\alpha_k} b^{\alpha_h} c^{1-\alpha_k-\alpha_h}$, where $\alpha_k, \alpha_h \in (0, 1)$ are parameters satisfying $\alpha_k + \alpha_h \leq 1$.

The government is assumed to consume an exogenous and stochastic amount of goods G_t each period and to finance these expenditures by levying lump-sum taxes.

A competitive equilibrium is a set of stochastic processes $\{C_t, h_t, I_t, K_{t+1}, Y_t, u_t, Q_t, \Lambda_t, S_t, V_t, \Pi_t\}_{t=0}^{\infty}$ satisfying

$$\begin{aligned} K_{t+1} &= (1 - \delta(u_t))K_t + z_t^I I_t \left[1 - S \left(\frac{I_t}{I_{t-1}} \right) \right] \\ C_t + A_t I_t + G_t &= Y_t \\ Y_t &= z_t F(u_t K_t, X_t h_t, X_t L) \\ V_t &= (C_t - bC_{t-1}) - \psi h_t^\theta S_t \\ S_t &= (C_t - bC_{t-1})^\gamma S_{t-1}^{1-\gamma} \\ \left[\zeta_t U'(V_t) - \Pi_t \gamma \frac{S_t}{C_t - bC_{t-1}} \right] - \beta b E_t \left[\zeta_{t+1} U'(V_{t+1}) - \Pi_{t+1} \gamma \frac{S_{t+1}}{C_{t+1} - bC_t} \right] &= \Lambda_t \\ \theta \psi \zeta_t U'(V_t) h_t^{\theta-1} S_t &= \Lambda_t \frac{z_t X_t F_2(u_t K_t, X_t h_t, X_t L)}{1 + \mu_t} \\ \Pi_t &= \psi \zeta_t U'(V_t) h_t^\theta + \beta (1 - \gamma) E_t \Pi_{t+1} \frac{S_{t+1}}{S_t} \\ Q_t \Lambda_t &= \beta E_t \Lambda_{t+1} [z_{t+1} u_{t+1} F_1(u_{t+1} K_{t+1}, X_{t+1} h_{t+1}, X_{t+1} L) + Q_{t+1} (1 - \delta(u_{t+1}))] \\ z_t F_1(u_t K_t, X_t h_t, X_t L) &= Q_t \delta'(u_t) \\ A_t \Lambda_t &= Q_t \Lambda_t z_t^I \left[1 - S \left(\frac{I_t}{I_{t-1}} \right) - \frac{I_t}{I_{t-1}} S' \left(\frac{I_t}{I_{t-1}} \right) \right] + \beta E_t Q_{t+1} \Lambda_{t+1} z_{t+1}^I \left(\frac{I_{t+1}}{I_t} \right)^2 S' \left(\frac{I_{t+1}}{I_t} \right), \end{aligned}$$

given the set of exogenous stochastic processes $\{z_t, X_t, G_t, A_t, z_t^I, \zeta_t, \mu_t\}_{t=0}^{\infty}$, and the initial

conditions K_0 , I_{-1} , C_{-1} , and S_{-1} . The variables Λ_t , Π_t , and $Q_t\Lambda_t$ represent, respectively, the Lagrange multiplier associated with the sequential budget constraint, the evolution of S_t , and the evolution of physical capital in the household's optimization problem.

The variable Q_t can be interpreted as the relative price of installed capital in period t available for production in period $t + 1$ in terms of consumption goods of period t . This relative price is also known as marginal Tobin's Q. A related concept is the value of the firm. Let V_t^F denote the value of the firm at the beginning of period t . Then one can write V_t^F recursively as: $V_t^F = Y_t - W_t h_t - A_t I_t + \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t} V_{t+1}^F$. The above expression states that the value of the firm equals the present discounted value of current and future expected dividends. Note that we use the representative household's intertemporal marginal rate of substitution to discount the future value of the firm. This choice of a discount factor is justified on the ground that firms are owned by households.

4 Introducing Anticipated Shocks

Our model of the business cycle is driven by seven exogenous forces: the stationary neutral productivity shock z_t , the nonstationary neutral productivity shock X_t , the stationary investment-specific productivity shock z_t^I , the nonstationary investment-specific productivity shock A_t , the government spending shock G_t , the wage-markup shock μ_t , and the preference shock ζ_t . We assume that all of these forces are subject to anticipated as well as unanticipated innovations. We study a formulation with four and eight-quarter anticipated shocks. This choice is motivated by two considerations. First, we would like to capture a relatively long anticipation horizon (in this case, two years). Second, to keep the computational time needed to econometrically estimate the model at a manageable level, we wish to avoid the proliferation of state variables that results as the anticipation horizon is enlarged. Our current specification requires 84 more exogenous state variables than an identical model without anticipated shocks. In general, an innovation that is anticipated k periods introduces k additional state variables.³

To illustrate the way we introduce anticipated shocks, consider a generic exogenous process x_t . We assume that x_t evolves over time according to the law of motion:

$$x_t = \rho x_{t-1} + \epsilon_t.$$

³In an earlier version of this paper, we considered a version of this model with only four shocks and anticipation horizons of 1, 2, and 3 quarters. In this formulation, the number of exogenous states induced by anticipation was only 24.

We impose the following structure on the error term ϵ_t :

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

where $\epsilon_{x,t}^j$ for $j = 0, 4$, and 8 denotes j -period anticipated changes in the level of x_t . This notation follows Ravn, Schmitt-Grohé, and Uribe (2007). For example, $\epsilon_{x,t-4}^4$ is an innovation to the level of x_t that materializes in period t , but that agents learn about in period $t - 4$. Therefore, $\epsilon_{x,t-4}^4$ is in the period $t - 4$ information set of economic agents but results in an actual change in the variable x_t only in period t . We thus say that $\epsilon_{x,t-4}^4$ is a 4-period anticipated innovation in x_t . The disturbance $\epsilon_{x,t}^j$ has mean zero, standard deviation σ_x^j , and is uncorrelated across time and across anticipation horizon. That is, $E\epsilon_{x,t}^j\epsilon_{x,t-m}^k = 0$ for $k, j = 0, 4, 8$ and $m > 0$, and $E\epsilon_{x,t}^j\epsilon_{x,t}^k = 0$ for any $k \neq j$. These assumptions imply that the error term ϵ_t is unconditionally mean zero and serially uncorrelated, that is, $E\epsilon_t = 0$ and $E\epsilon_t\epsilon_{t-m} = 0$ for $m > 0$. Moreover, the error term ϵ_t is unforecastable given only past realizations of itself. That is, $E(\epsilon_{t+m}|\epsilon_t, \epsilon_{t-1}, \dots) = 0$, for $m > 0$. Note that the proposed process for ϵ_t does not contain any moving average component.

The key departure of this paper from standard business-cycle analysis is the assumption that economic agents have an information set larger than one simply containing current and past realizations of ϵ_t . In particular, agents are assumed to observe in period t current and past values of the innovations $\epsilon_{x,t}^0$, $\epsilon_{x,t}^4$, and $\epsilon_{x,t}^8$. That is, agents can forecast future values of ϵ_t as follows:

$$E_t\epsilon_{t+k} = \begin{cases} \epsilon_{x,t+k-4}^4 + \epsilon_{x,t+k-8}^8 & \text{if } 1 \leq k \leq 4 \\ \epsilon_{x,t+k-8}^8 & \text{if } 4 < k \leq 8 \\ 0 & \text{if } k > 8 \end{cases}$$

Because agents are forward looking, they use the information contained in the realizations of the various innovations $\epsilon_{x,t}^j$ in their current choices of consumption, investment, hours worked, and asset holdings. It is precisely this forward-looking behavior of economic agents that allows an econometrician to identify the volatilities of the anticipated innovations $\epsilon_{x,t}^j$, even though the econometrician himself cannot directly observe these innovations.

4.1 Autoregressive Representation of Anticipated Shocks

The law of motion of the exogenous process x_t can be written recursively as:

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

which is a first-order linear stochastic difference equation of the form

$$\tilde{x}_{t+1} = M\tilde{x}_t + \eta\nu_{t+1}.$$

The vector of innovations ν_t is normal i.i.d. with mean zero and variance-covariance matrix equal to the identity matrix.

We apply the stochastic and informational structure described above to each of the seven driving forces in our model. Specifically, the stationary neutral productivity shock is assumed to obey the following law of motion

$$\ln z_t = \rho_z \ln z_{t-1} + \epsilon_{z,t}^0 + \epsilon_{z,t-4}^4 + \epsilon_{z,t-8}^8$$

where $\epsilon_{z,t}^i$ is an i.i.d. normal innovation with mean 0 and standard deviation σ_z^i for $i = 0, 4, 8$.

The natural logarithm of the nonstationary neutral productivity shock X_t is assumed to follow a random walk process with drift of the form

$$\ln X_t = \ln X_{t-1} + \ln \mu_t^x,$$

where the natural logarithm of the gross growth rate of X_t , denoted μ_t^x , is a stationary autoregressive process of the form

$$\ln(\mu_t^x/\mu^x) = \rho_x \ln(\mu_{t-1}^x/\mu^x) + \epsilon_{x,t}^0 + \epsilon_{x,t-4}^4 + \epsilon_{x,t-8}^8, \quad (7)$$

where $\epsilon_{x,t}^i$ is an i.i.d. process distributed normally with mean zero and standard deviation σ_x^i , for $i = 0, 4, 8$. The parameter μ^x governs the drift in the level of the nonstationary component of labor augmenting technological change.

The investment-specific productivity shock A_t is also assumed to possess a stochastic trend. Formally, we assume that

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

with the gross growth rate of A_t , denoted μ_t^a , following the stationary autoregressive process

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

The innovations $\epsilon_{a,t}^i$ are assumed to be i.i.d. normal with mean zero and standard deviation σ_a^i for $i = 0, 4, 8$. The parameter μ^a represents the drift in the price of investment.

Similarly, the stationary investment-specific productivity shock obeys the law of motion

$$\ln z_t^I = \rho_{z^I} \ln z_{t-1}^I + \epsilon_{z^I,t}^0 + \epsilon_{z^I,t-4}^4 + \epsilon_{z^I,t-8}^8.$$

The innovations $\epsilon_{z^I,t}^i$ are assumed to be i.i.d. normal with mean zero and standard deviation $\sigma_{z^I}^i$ for $i = 0, 4, 8$.

We assume that government spending, G_t , displays a stochastic trend given by X_t^G . We let $g_t \equiv G_t / X_t^G$ denote detrended government spending. The trend in government spending is assumed to be cointegrated with the trend in output, denoted X_t^Y . This assumption ensures that the share of government spending in output is stationary. However, we allow for the possibility that the trend in government spending is smoother than the trend in output. Specifically, we assume that

$$X_t^G = (X_{t-1}^G)^{\rho_{xg}} (X_{t-1}^Y)^{1-\rho_{xg}},$$

where $\rho_{xg} \in [0, 1)$ is a parameter governing the smoothness of the trend in government spending. In the present model, the trend in output can be shown to be given by $X_t^Y = X_t A_t^{\alpha_k / (\alpha_k - 1)}$. Log deviations of government spending from trend are assumed to follow the autoregressive process

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

where $\epsilon_{g,t}^i$ is assumed to be an i.i.d. normal innovation with mean 0 and standard deviation σ_g^i , for $i = 0, 4, 8$. Notice that X_t^G resides in the information set of period $t - 1$. This fact to-

gether with the assumption that g_t is autoregressive, implies the absence of contemporaneous feedback from any endogenous or exogenous variable to the level of government spending. At the same time, the maintained specification of the government spending process allows for lagged feedback from changes in the trend path of output.

Finally, the stochastic processes of the preference shock and the wage markup are given by

$$\ln \zeta_t = \rho_\zeta \ln \zeta_{t-1} + \epsilon_{\zeta,t}^0 + \epsilon_{\zeta,t-4}^4 + \epsilon_{\zeta,t-8}^8$$

and

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

The innovations $\epsilon_{\zeta,t}^i$ and $\epsilon_{\mu,t}^i$ are assumed to be i.i.d. normal with mean zero and standard deviations σ_{ζ}^i and σ_{μ}^i , respectively, for $i = 0, 4, 8$.

The central goal of our investigation is to econometrically estimate the standard deviations of the anticipated components of each of the seven exogenous shocks, σ_j^4 and σ_j^8 , for $j = z, x, a, z^I, g, \zeta, \mu$.

4.2 Accommodating Revisions and Noisy Signals

The structure given above to anticipated and unanticipated innovations is flexible enough to accommodate revisions in announcements. These revisions capture situations such as announced productivity improvements that do not pan out or wage negotiations that start out as promising for workers (i.e., the announcement of a future increase in wage markups) but then go sour.

Consider, for example, a positive realization of the innovation $\epsilon_{z,t}^8$. This shock represents the announcement in period t of an improvement in productivity that will take place in period $t + 8$. Under our formulation, this announcement is subject to two revisions. The first revision takes place in period $t + 4$. Suppose for instance that the realization of $\epsilon_{z,t+4}^4$ is negative. This is equivalent to the announcement that the productivity improvement announced in period t will not materialized as expected. At this point, the economy may enter into a recession even though non of the economic fundamentals has changed. The second revision of the announcement of period t occurs in period $t + 8$. Suppose that the realization of $\epsilon_{z,t+8}^0$ is negative and offsets the prior two announcements $\epsilon_{z,t}^8 + \epsilon_{z,t+4}^4$. This is a situation in which agents learn that the earlier optimistic outlook for productivity did not pan out at all. The economy my experience at this point a double dip recession. Like the one that took place in period $t + 4$, the $t + 8$ recession occurs without any changes in observed economic fundamentals.

Further, the information structure we consider has the interpretation of noisy signals on

fundamentals. For instance, in period t , agents receive a signal $\epsilon_{z,t}^8$ regarding the level of productivity in period $t + 8$. But this signal is noisy in the sense that it is revised in period $t + 4$ by the innovation $\epsilon_{z,t+4}^4$. In turn, the combined signal $\epsilon_{z,t}^8 + \epsilon_{z,t+4}^4$ is itself noisy in the sense that it is subject to the revision $\epsilon_{z,t+8}^0$ in period $t + 8$.⁴

4.3 Inducing Stationarity and Solution Method

The exogenous forcing processes X_t and A_t display stochastic trends. These random trends are inherited by the endogenous variables of the model. We focus our attention on equilibrium fluctuations around these stochastic trends. To this end, we perform a stationarity-inducing transformation of the endogenous variables by dividing them by their trend component. This transformation is available in an unpublished technical appendix.

We compute a log-linear approximation to the equilibrium dynamics of the model. We have already shown how to express the law of motion of the exogenous driving forces of the model in a first-order autoregressive form. Then, using familiar perturbation techniques (e.g., Schmitt-Grohé and Uribe, 2004), one can write the equilibrium dynamics of the model up to first order as

$$x_{t+1} = h_x x_t + \eta \epsilon_{t+1}, \quad (8)$$

$$y_t = g_x x_t + \xi m_t, \quad (9)$$

where x_t is a vector of endogenous and exogenous state variables, y_t is the vector of observables, ϵ_t is a vector of structural disturbances distributed $N(0, I)$, and m_t is a vector of measurement errors distributed $N(0, I)$. The matrices h_x , g_x , η , and ξ are functions of the structural parameters of the model.

5 Estimating Anticipated Shocks

We use Bayesian methods and classical maximum likelihood to estimate a subset of the deep structural parameters of the model. Of particular importance among the estimated parameters are those defining the stochastic processes of unanticipated and anticipated innovations. The parameters that are not estimated are calibrated in a standard fashion.

Table 1 presents the values assigned to the calibrated parameters. The time unit is defined to be one quarter. We assign a value of 1 to σ , the parameter defining the curvature of the period utility function. This value is standard in the business-cycle literature. Following Jaimovich and Rebelo (2009), we assume a mild degree of decreasing returns to scale of 10

⁴We thank an anonymous referee for suggesting the noisy-signal interpretation of our maintained information structure.

Table 1: Calibrated Parameters

Parameter	Value	Description
β	0.99	Subjective discount factor
σ	1	Intertemporal elasticity of substitution
α_k	0.225	Capital share
α_h	0.675	Labor share
δ_0	0.025	Steady-state depreciation rate
u	1	Steady-state capacity utilization rate
μ^y	1.0045	Steady-state gross per capita GDP growth rate
μ^a	0.9957	Steady-state gross growth rate of price of investment
G/Y	0.2	Steady-state share of government consumption in GDP
h	0.2	Steady-state hours
μ	0.15	Steady-state wage markup

Note: The time unit is one quarter.

percent. We set the capital elasticity of the production function, α_k , to 0.225. This value, together with the assumed degree of decreasing returns to scale, implies that the labor share is 0.67, which is in line with existing business cycle studies. We assume a depreciation rate of 2.5 percent per quarter. We calibrate the parameter δ_1 to ensure that capacity utilization, u , equals unity in the steady state. We set the discount factor β at 0.99, a value commonly used in related studies. We calibrate the steady-state growth rates of per capita output and of the relative price of investment, μ^y and μ^a , respectively, to be 0.45 and -0.45 percent per quarter. These two figures correspond to the average growth rates of per capita output and the price of investment over the period 1955:Q1 to 2006:Q4. Following Justiniano, Primiceri, and Tambalotti (2009), we set the steady-state wage markup, μ , at 15 percent. We set the parameter ψ of the utility function at a value consistent with a steady-state fraction of time dedicated to remunerated labor of 20 percent. Finally, we set the share of government purchases in output equal to 20 percent, which is in line with the average government spending share in our sample.

5.1 Bayesian and Classical Maximum Likelihood Estimation

We perform classical maximum likelihood and Bayesian estimations of the noncalibrated structural parameters of the model. Specifically, given the system of linear stochastic difference equations (8) and (9) describing the equilibrium dynamics of the model up to first order, it is straightforward to numerically evaluate the likelihood function of the data given the vector of estimated parameters, which we denote by $L(Y|\Theta)$, where Y is the data sam-

ple and Θ is the vector of parameters to be estimated. This object is the basis of our maximum likelihood estimation of the parameter vector Θ . Given a prior parameter distribution $P(\Theta)$, the posterior likelihood function of the parameter Θ given the data, which we denote by $\mathcal{L}(\Theta|Y)$, is proportional to the product $L(Y|\Theta)P(\Theta)$. This object forms the basis of our Bayesian estimation. In particular, following the methodology described in An and Schorfheide (2007), we use the Metropolis-Hastings algorithm to obtain draws from the posterior distribution of Θ .

The vector of estimated parameters, Θ , contains the parameters defining the stochastic process for anticipated and unanticipated innovations, namely, ρ_j and σ_j^i for $i = 0, 4, 8$ and $j = z, x, z^I, a, g, \mu, \zeta$. In addition, the parameter vector Θ includes the parameter ρ_{xg} , governing the smoothness in the trend component of government spending, the parameter γ related to the wealth elasticity of labor supply, the preference parameter b defining habits in consumption, the preference parameter θ related to the Frisch elasticity of labor supply, the parameter δ_2 governing the convexity of the cost of adjusting capacity utilization, and the parameter κ , governing the cost of adjusting investment.

We estimate the model on U.S. quarterly data ranging from 1955:Q1 to 2006:Q4. The data include seven time series: the per capita growth rates of real GDP, real consumption, real investment, real government expenditure, and hours, and the growth rates of total factor productivity and the relative price of investment. Our set of observables differs from those employed in existing likelihood-based estimates of DSGE macroeconomic models in that it includes both a time series for total factor productivity and a time series for the relative price of investment. Naturally, the inclusion of these two time series restricts the freedom of neutral and investment specific productivity shocks to explain the behavior of observables other than total factor productivity and the relative price of investment themselves. This is because the estimation procedure has a tendency to pick stochastic processes for neutral and investment-specific productivity shocks geared towards accounting for movements in total factor productivity and the price of investment.

We assume that output growth is measured with error. Allowing for measurement error in output is required by the fact that, up to first order, the resource constraint of the model economy postulates a linear restriction among the seven observables. Formally, the vector

of observable variables is given by

$$\text{vector of observables} = \begin{bmatrix} \Delta \ln(Y_t) \\ \Delta \ln(C_t) \\ \Delta \ln(A_t I_t) \\ \Delta \ln(h_t) \\ \Delta \ln(G_t) \\ \Delta \ln(TFP_t) \\ \Delta \ln(A_t) \end{bmatrix} \times 100 + \begin{bmatrix} \epsilon_{y,t}^{me} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

where Δ denotes the temporal difference operator, and $TFP_t \equiv z_t X_t^{1-\alpha_k}$ denotes total factor productivity. The measurement error in output growth, $\epsilon_{y,t}^{me}$, is assumed to be an i.i.d. innovation with mean zero and standard deviation σ_{gy}^{me} . The appendix provides more detailed information about the data used in the estimation of the model. The vector of estimated parameters Θ also includes the standard deviation of the measurement error, σ_{gy}^{me} .

Table 2 displays the assumed prior distribution $P(\Theta)$ of the estimated structural parameters contained in the vector Θ . We assume gamma distributions for the standard deviations of all 21 innovations of the model. The reason why we use gamma distributions instead of inverse-gamma distributions, which are more commonly used as priors for standard deviations, is to allow for a positive density at zero for the standard deviations of anticipated shocks. In this way, our priors allow for the possibility that individual anticipated shocks not matter at all. For each of the seven shocks in the model, the prior distributions of the standard deviations of the two anticipated components are assumed to be identical. We assume that for each of the seven shocks the variance of the unanticipated component is three times as large as the sum of the variances of both anticipated components—or, equivalently the variance of the unanticipated component equals 75 percent of the total variance of the shock. Formally, at the mean of the prior distributions, we have that

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

We believe that this specification of priors represents a conservative stance with regard to the importance of anticipated shocks. We set the total prior variance of the seven shocks so that the model predictions for standard deviations, serial correlations, and correlations with output growth of the seven observables are broadly in line with the data when the remaining structural parameters are set at their maximum-likelihood point estimates. We complete the specification of the prior distributions of the standard deviations of the 21 innovations by imposing a common unit coefficient of variation on all of these distributions. This choice

Table 2: Parameter Estimation

Parameter	Bayesian Estimation							ML Estimation	
	Prior Distribution			Posterior Distribution				Point Est.	Std.
	Distribution	Mean	Std.	Median	Std.	5%	95%		
θ	Gamma*	4.00	1.00	4.74	0.59	3.88	5.83	5.39	0.85
γ	Uniform	0.50	0.29	0.00	0.00	0.00	0.01	0.00	0.00
κ	Gamma	4.00	1.00	9.11	1.05	7.41	10.91	25.07	2.25
δ_2/δ_1	Inv. Gamma	1.00	1.00	0.34	0.08	0.23	0.50	0.44	0.15
b	Beta	0.50	0.20	0.91	0.01	0.89	0.93	0.94	0.01
ρ_{xg}	Beta	0.70	0.20	0.72	0.14	0.44	0.88	0.74	0.17
ρ_z	Beta	0.70	0.20	0.92	0.04	0.85	0.96	0.96	0.03
σ_z^0	Gamma	1.50	1.50	0.65	0.06	0.54	0.74	0.62	0.09
σ_z^4	Gamma	0.61	0.61	0.11	0.10	0.01	0.31	0.11	0.08
σ_z^8	Gamma	0.61	0.61	0.09	0.08	0.01	0.27	0.11	0.08
ρ_a	Beta	0.50	0.20	0.48	0.06	0.38	0.58	0.48	0.06
σ_a^0	Gamma	0.31	0.31	0.21	0.10	0.02	0.35	0.16	0.09
σ_a^4	Gamma	0.13	0.13	0.16	0.11	0.01	0.34	0.20	0.10
σ_a^8	Gamma	0.13	0.13	0.16	0.11	0.01	0.33	0.19	0.10
ρ_g	Beta	0.70	0.20	0.96	0.02	0.93	0.99	0.96	0.02
σ_g^0	Gamma	1.05	1.05	0.62	0.33	0.06	1.07	0.53	0.31
σ_g^4	Gamma	0.43	0.43	0.57	0.34	0.04	1.07	0.69	0.31
σ_g^8	Gamma	0.43	0.43	0.37	0.32	0.03	1.00	0.43	0.29
ρ_x	Beta*	0.20	0.20	0.38	0.12	0.12	0.49	0.27	0.16
σ_x^0	Gamma	0.45	0.45	0.38	0.11	0.22	0.57	0.45	0.16
σ_x^4	Gamma	0.19	0.19	0.08	0.09	0.01	0.28	0.12	0.09
σ_x^8	Gamma	0.19	0.19	0.10	0.09	0.01	0.27	0.12	0.09
ρ_w	Beta	0.70	0.20	0.98	0.01	0.95	1.00	0.98	0.01
σ_w^0	Gamma	1.19	1.19	0.50	0.38	0.04	1.24	1.51	1.00
σ_w^4	Gamma	0.49	0.49	4.79	0.92	3.18	5.70	3.93	1.12
σ_w^8	Gamma	0.49	0.49	0.51	0.93	0.04	2.85	3.20	1.26
ρ_ζ	Beta	0.50	0.20	0.17	0.07	0.07	0.30	0.10	0.07
σ_ζ^0	Gamma	6.30	6.30	4.03	1.38	1.20	6.02	2.83	1.79
σ_ζ^4	Gamma	2.57	2.57	1.89	1.48	0.17	4.84	2.76	1.99
σ_ζ^8	Gamma	2.57	2.57	2.21	1.55	0.14	4.85	5.34	1.51
ρ_{z^i}	Beta	0.50	0.20	0.47	0.13	0.22	0.64	0.21	0.10
σ_{z^i}	Gamma	17.15	17.15	11.72	1.79	8.90	14.94	34.81	4.03
$\sigma_{z^i}^4$	Gamma	7.00	7.00	1.93	1.92	0.16	6.15	11.99	4.47
$\sigma_{z^i}^8$	Gamma	7.00	7.00	5.50	2.51	1.71	10.58	14.91	2.55
$\sigma_{g^y}^{me}$	Uniform	0.15	0.09	0.30	0.00	0.30	0.30	0.30	0.00

Note: For the Bayesian Estimation, results are based on 500,000 draws from the posterior distribution. A star indicates that a linear transformation of the associated parameter has the indicated prior distribution.

of priors gives rise to prior probability densities for the share of anticipated shocks in the variance of key macroeconomic variables that are quite dispersed. See figure 2.

The prior distributions for the remaining estimated structural parameters of the model follow broadly those used in the related literature. An exception is the preference parameter γ , controlling the income elasticity of labor supply, which, to our knowledge has not been previously estimated. We adopt a uniform prior distribution for γ , with a support spanning the interval $(0,1]$. Our MLE and Bayesian estimates of γ are consistent with each other and both point to a value close to zero. This estimate implies that in the absence of habit formation, the model would display a labor supply schedule with a near-zero wealth elasticity, providing support for the preference specification proposed by Greenwood, Hercowitz, and Huffman (1988).

Finally, we choose a uniform prior distribution for the standard deviation of measurement error in output growth. We restrict the measurement error to account for at most 10 percent of the variance of output growth.

Rather than discussing the ML or Bayesian posterior estimates of each of the parameters defining the stochastic processes of the anticipated and unanticipated disturbances included in the model, we believe it will prove more insightful to discuss the implication of these estimates for the importance of anticipation as a source of business cycles. Before turning to this issue, however, we will discuss the model's ability to fit actual data.

5.2 Model Fit

Table 3 presents the model's predictions regarding standard deviations, correlations with output growth, and serial correlations of the seven time series included as observables in the estimation. Predicted second moments are computed unconditionally. When the model is estimated using maximum likelihood, the population second moments are computed using the point estimates of the structural parameters. When the model is estimated using Bayesian methods, the table reports the median of the posterior distribution of the population second moments. For comparison, the table also shows the corresponding empirical second moments calculated over the sample 1955:Q1 to 2006:Q4.

The second moments predicted by the estimated model are quite similar under maximum likelihood and Bayesian estimation. Overall, the estimated model matches remarkably well the empirical second moments. In particular, it replicates the observed levels of volatility in consumption, investment, hours, government spending, total factor productivity, and the relative price of investment, and slightly underpredicts the volatility of output. The model also captures well the autocorrelations and contemporaneous correlations with output growth

Table 3: Model Predictions

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

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

of consumption, investment, government spending, total factor productivity, and the relative price of investment. The most notable discrepancies between model predictions and data can be found in the serial correlation of the growth rate of hours and, to a lesser extent, in the correlation of hours and output.

5.3 Estimated Sources of Uncertainty

Table 4 addresses a standard question in business-cycle analysis. Namely, what is the contribution of the different sources of uncertainty considered in this study to explaining business-cycle fluctuations. We group the sources of uncertainty into three categories: technology shocks, aggregate demand shocks, and wage-markup shocks. Technology shocks consist of stationary neutral productivity shocks, z_t , permanent neutral productivity shocks, X_t , stationary investment-specific productivity shocks, z_t^I , and permanent investment-specific productivity shocks, A_t . Aggregate demand shocks consist of government spending shocks, g_t , and preference shocks, ζ_t . Table 4 presents the share of the overall predicted variance of the variables of interest attributed to each of the three categories of shocks. It shows that the majority of the variances of output and investment is accounted for by technology shocks. Consumption is explained mostly by aggregate demand shocks, and hours are driven to a large extent by wage-markup shocks. These findings are in line with variance decompositions reported in related studies. For instance, Justiniano, Primiceri, and Tambalotti (2008, table 4) report that technology shocks account for 71 percent of variations in output and 92 per-

Table 4: Share of Variance Explained by Technology, Demand, and Wage-Markup Shocks

	g^Y	g^C	g^I	g^h
Technology Shocks				
Median Share	0.58	0.17	0.86	0.25
5 Percent	0.52	0.11	0.83	0.19
95 Percent	0.64	0.24	0.90	0.30
Demand Shocks				
Median Share	0.25	0.65	0.02	0.07
5 Percent	0.21	0.56	0.01	0.06
95 Percent	0.29	0.73	0.03	0.09
Wage-Markup Shocks				
Median Share	0.17	0.18	0.12	0.68
5 Percent	0.14	0.13	0.09	0.62
95 Percent	0.22	0.24	0.15	0.75

Note: Estimates are based on 500,000 draws from the posterior distribution. Technology shocks are ϵ_t^i for $i = 0, 4, 8$ and $j = z, x, z^I, a$. Demand shocks are ϵ_j^i , for $i = 0, 4, 8$ and $j = g, \zeta$. Wage-markup shocks are ϵ_μ^i , for $i = 0, 4, 8$.

cent of variations in investment. At the same time, these authors find that the majority of fluctuations in consumption and hours are accounted for by, respectively, aggregate demand shocks (57 percent), and markup shocks (70 percent).

Table 5 produces a finer variance decomposition. It shows that neutral and investment specific productivity shocks contribute in equal parts to explaining the variance of output growth, about 28 percent each. The estimated contribution of neutral productivity shocks is in line with that reported by Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2008). In turn, of the 29 percent of the variance of output explained by investment-specific productivity shocks, the share explained by movements in A_t , the shock to the technical rate of transformation of consumption goods into investment goods, is virtually nil. This finding stands in sharp contrast with that reported in Justiniano, Primiceri, and Tambalotti (2008). These authors find that A_t plays a central role in explaining movements in output. The main reason for this discrepancy is that we include the relative price of investment in the set of observables used in the estimation of the model, whereas Justiniano, Primiceri, and Tambalotti do not. To see why the estimated importance of A_t depends on whether or not the price of investment is included in the set of observables, note first that in a decentralized version of our economy, A_t would be identical to the relative price of investment goods in terms of consumption goods. Hence, including the price of investment in the set of observables introduces restrictions upon the estimated stochastic process

Table 5: Variance Decomposition

Innovation	g^Y	g^C	g^I	g^h	g^g	g^{TFP}	g^A
Stationary Neutral Technology Shock (z_t)							
Total	0.12	0.03	0.14	0.16	0.00	0.78	0.00
ϵ_z^0	0.11	0.03	0.13	0.13	0.00	0.71	0.00
ϵ_z^4	0.01	0.00	0.01	0.01	0.00	0.04	0.00
ϵ_z^8	0.00	0.00	0.00	0.01	0.00	0.03	0.00
Nonstationary Neutral Technology Shock (μ_t^x)							
Total	0.16	0.11	0.08	0.03	0.05	0.22	0.00
ϵ_x^0	0.14	0.09	0.07	0.02	0.04	0.17	0.00
ϵ_x^4	0.01	0.01	0.00	0.01	0.00	0.02	0.00
ϵ_x^8	0.01	0.01	0.00	0.01	0.01	0.02	0.00
Stationary Investment-Specific Technology Shock (z_t^I)							
Total	0.28	0.02	0.63	0.05	0.00	0.00	0.00
$\epsilon_{z^I}^0$	0.21	0.01	0.44	0.03	0.00	0.00	0.00
$\epsilon_{z^I}^4$	0.01	0.00	0.04	0.00	0.00	0.00	0.00
$\epsilon_{z^I}^8$	0.06	0.01	0.15	0.02	0.00	0.00	0.00
Nonstationary Investment-Specific Technology Shock (μ_t^a)							
Total	0.01	0.00	0.01	0.00	0.00	0.00	1.00
ϵ_a^0	0.00	0.00	0.00	0.00	0.00	0.00	0.40
ϵ_a^4	0.00	0.00	0.00	0.00	0.00	0.00	0.30
ϵ_a^8	0.00	0.00	0.00	0.00	0.00	0.00	0.30
Government Spending Shock (g_t)							
Total	0.09	0.01	0.01	0.02	0.95	0.00	0.00
ϵ_g^0	0.03	0.00	0.00	0.01	0.37	0.00	0.00
ϵ_g^4	0.04	0.00	0.00	0.01	0.35	0.00	0.00
ϵ_g^8	0.02	0.00	0.00	0.01	0.23	0.00	0.00
Preference Shock (ζ_t)							
Total	0.16	0.64	0.01	0.05	0.00	0.00	0.00
ϵ_ζ^0	0.08	0.34	0.01	0.02	0.00	0.00	0.00
ϵ_ζ^4	0.04	0.14	0.00	0.01	0.00	0.00	0.00
ϵ_ζ^8	0.04	0.17	0.00	0.01	0.00	0.00	0.00
Wage-Markup Shock (μ_t)							
Total	0.18	0.18	0.12	0.68	0.00	0.00	0.00
ϵ_μ^0	0.00	0.00	0.00	0.02	0.00	0.00	0.00
ϵ_μ^4	0.16	0.17	0.11	0.62	0.00	0.00	0.00
ϵ_μ^8	0.01	0.01	0.01	0.05	0.00	0.00	0.00

Note: Figures correspond to the mean of 500,000 draws from the posterior distribution of the variance decomposition.

of the investment-specific technology shock A_t as the estimation procedure tries to match the sample properties of its empirical counterpart. By contrast, when the relative price of investment is not included in the set of observables, the estimated process of A_t can more freely contribute to explaining the observed statistical properties of other variables included as observables. But this extra freedom comes at a cost. For instance, Justiniano, Primiceri, and Tambalotti report that the standard deviation of their estimated investment-specific shock process is four times as large as that of its empirical counterpart. As is clear from table 3, our estimated model matches closely the standard deviation of the relative price of investment. Again, we ascribe the success of the estimated model along this dimension to the fact that we include the relative price of investment in the set of observables used in the econometric estimation.

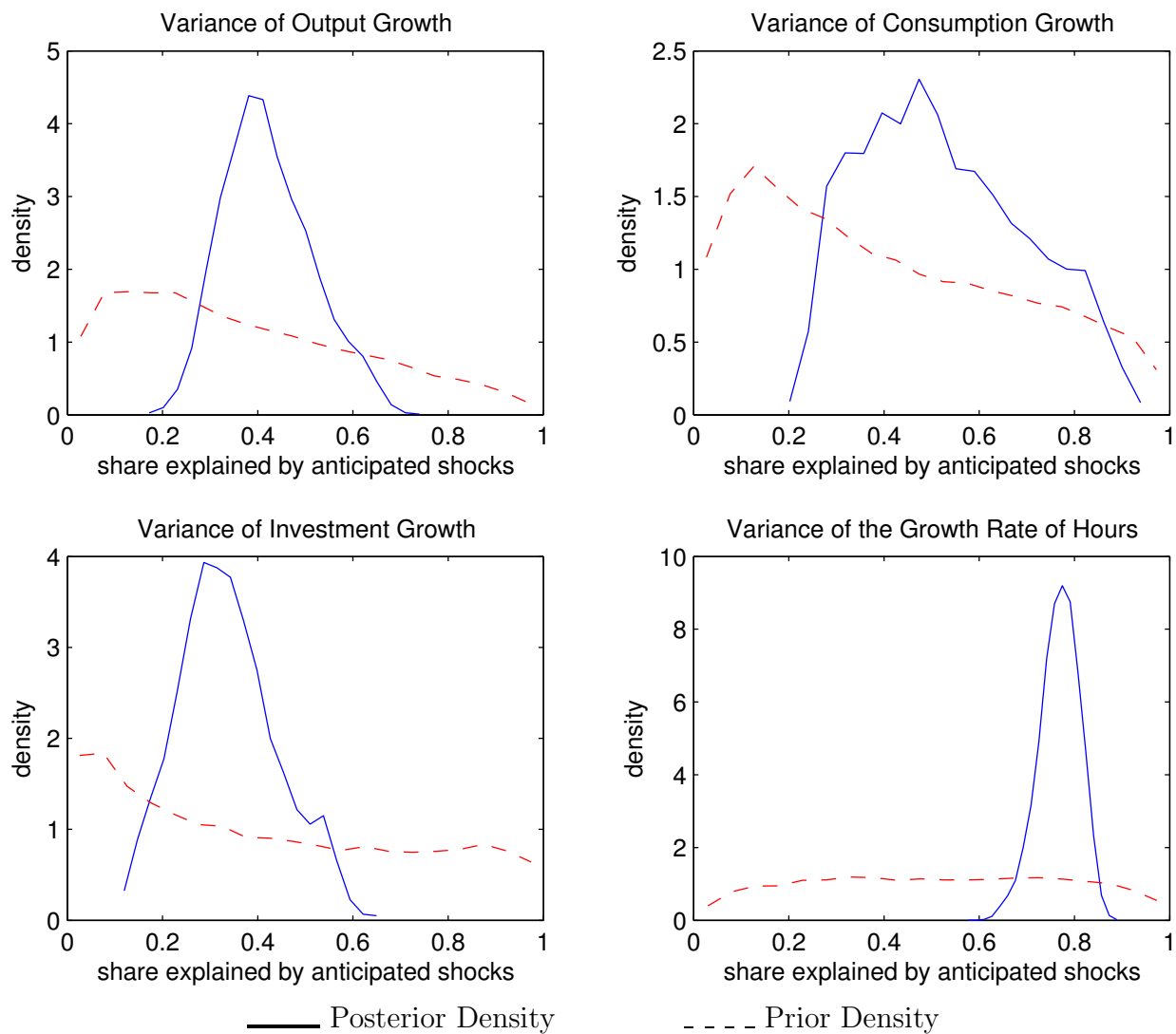
6 The Importance of Anticipated Shocks

In this section, we present model-based evidence on the importance of anticipated shocks as sources of business-cycle fluctuations. We convey this evidence from five alternative perspectives: (1) unconditional variance decompositions based on the Bayesian estimate of our model; (2) unconditional variance decompositions based on the maximum-likelihood estimate of our model; (3) comparison of prior and posterior densities of the shares of the variances of macroeconomic variables of interest explained by anticipated shocks; (4) variance decompositions based on HP-filtered simulated data; (5) spectral analysis.

Table 6 displays the share of the unconditional variances of output growth, consumption growth, investment growth, and hours growth that according to our estimation can be accounted for by anticipated shocks. For the Bayesian estimation of the model (line 1) the table displays the median posterior share computed from 500,000 draws from the posterior distribution of the vector of estimated structural parameters. The table shows that anticipated shocks account for 41 percent of the variance of output growth and for 77 percent of movements in hours. This is a remarkable finding in light of the fact that the long existing literature on business cycles has implicitly attributed one hundred percent of the variance of output and hours growth to unanticipated shocks. Our results indicate that once one allows for unanticipated and anticipated disturbances to play separate roles, the latter source of business cycles emerges as an important driving force.

Figure 2 displays the prior and posterior probability density functions of the share of the variance of output growth, consumption growth, investment growth, and hours growth accounted for by anticipated shocks in our estimated model. It is evident from this figure that our choice of prior distributions for the standard deviations of the underlying anticipated

Figure 2: Prior and Posterior Probability Densities of the Share of the Variance of Selected Variables Attributable to Anticipated Shocks



Note. The prior and posterior probability density functions were computed using 500,000 draws from the prior and posterior distributions of the corresponding shares, respectively.

Table 6: Share of Variance Explained by Anticipated Shocks

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

Note: Line 1: Bayesian estimates are medians of 500,000 draws from the posterior distributions of the corresponding shares. Line 2: Maximum-likelihood estimates are computed at the point estimate of the vector of structural parameters. Line 3: Bayesian estimate of the model with stock prices included in the set of observables. Line 4: shares of the variances of predicted HP filtered logarithms of output, consumption, investment, and hours explained by anticipated shocks, computed as described in the body of the text. Line 5: Bayesian estimation of a special case of the baseline model with $\sigma_j^i = 0$ for $i = 0, 4, 8$, and $j = \zeta, \mu, z^I$, and TFP unobservable.

and unanticipated disturbances delivers highly dispersed prior distributions for the share of variance accounted for by anticipated shocks. By contrast, the corresponding posterior distributions are concentrated around their respective means. This is particularly the case for the growth rates of hours worked, output, and investment. The figure demonstrates that our finding of a significant fraction of aggregate volatility being explained by anticipated shocks is not an artifact of the assumed priors.

To further convey the notion that our findings on the importance of anticipated shocks are not driven by the assumed underlying prior distributions, we present in line 2 of table 6 variance decompositions based on a classical maximum likelihood estimation of the model. The MLE estimates of the fraction of variations in output, consumption, investment, and hours explained by anticipated shocks are indeed slightly higher than the corresponding Bayesian estimates. This result suggests that our choice of priors is conservative in the sense that it results in a smaller estimated role of anticipated shocks than implied by the maximum likelihood estimate.

6.1 Incorporating Data on Stock Prices

The empirical literature on anticipated shocks has emphasized the role of stock prices in capturing information about future expected changes in economic fundamentals. Beaudry and Portier (2006), for instance, use observations on stock prices to identify anticipated permanent changes in total factor productivity. The reason why stock prices are believed to be informative about anticipated changes in fundamentals is that they are typically con-

sidered more flexible than other nominal and real aggregate variables often included in the econometric estimation of macroeconomic models. Real variables such as consumption, investment, and employment are believed to be costly to adjust in the short run due to the presence of habit formation, time to build, and hiring and firing costs. At the same time, the adjustment of product and factor prices is assumed to be hindered by the presence of price rigidities. With this motivation in mind, we reestimate the model including in the set of observables the growth rate of the real per capita value of the stock market as measured by the S&P500 index. Line 3 of table 6 displays the result of this estimation regarding the importance of anticipated shocks. As expected, when stock prices are included in the set of observables, the model attributes a larger fraction of business-cycle fluctuations to anticipated shocks. For the four variables considered in the table, on average the share of unconditional variances explained by anticipated shocks is 68 percent when stock prices are included in the estimation versus 50 percent when they are not included. The reason why we decided not to include stock prices in our baseline estimation is twofold. First, the existing related model-based literature on the sources of business cycles typically does not include observations on stock prices in estimation (e.g., Smets and Wouters, 2007; and Justiniano, Primiceri, and Tambalotti, 2009). Excluding stock prices from the baseline estimation facilitates comparison with this literature. Second, and perhaps more importantly, as is well known, the neoclassical model does not provide a fully adequate explanation of asset price movements.

6.2 The Anticipated Component of Hodrick-Prescott-Filtered Business Cycles

Line 4 of table 6 shows that the role of anticipated shocks is also estimated to be prominent if one measures the business-cycle component of a time series by using the Hodrick-Prescott filter. We perform this exercise as follows. (1) We draw a realization of the vector of estimated parameters Θ from its posterior distribution. (2) Then allowing only one innovation to be active at a time, we generate artificial time series of the logarithmic levels of output, consumption, investment, and hours of length 500 quarters. (Log-levels are obtained by accumulating growth rates.) At this point, our procedure has decomposed each observable into 21 independent time series corresponding to the 21 innovations included in our model. (3) We apply the Hodrick-Prescott filter to the last 207 observations—the length of our actual data sample—of each of the 21 independent components using a smoothing parameter value of 1,600. (4) For each variable of interest (output, consumption, investment, and hours), we compute the ratio of the sum of the variances of its 14 components associated with anticipated

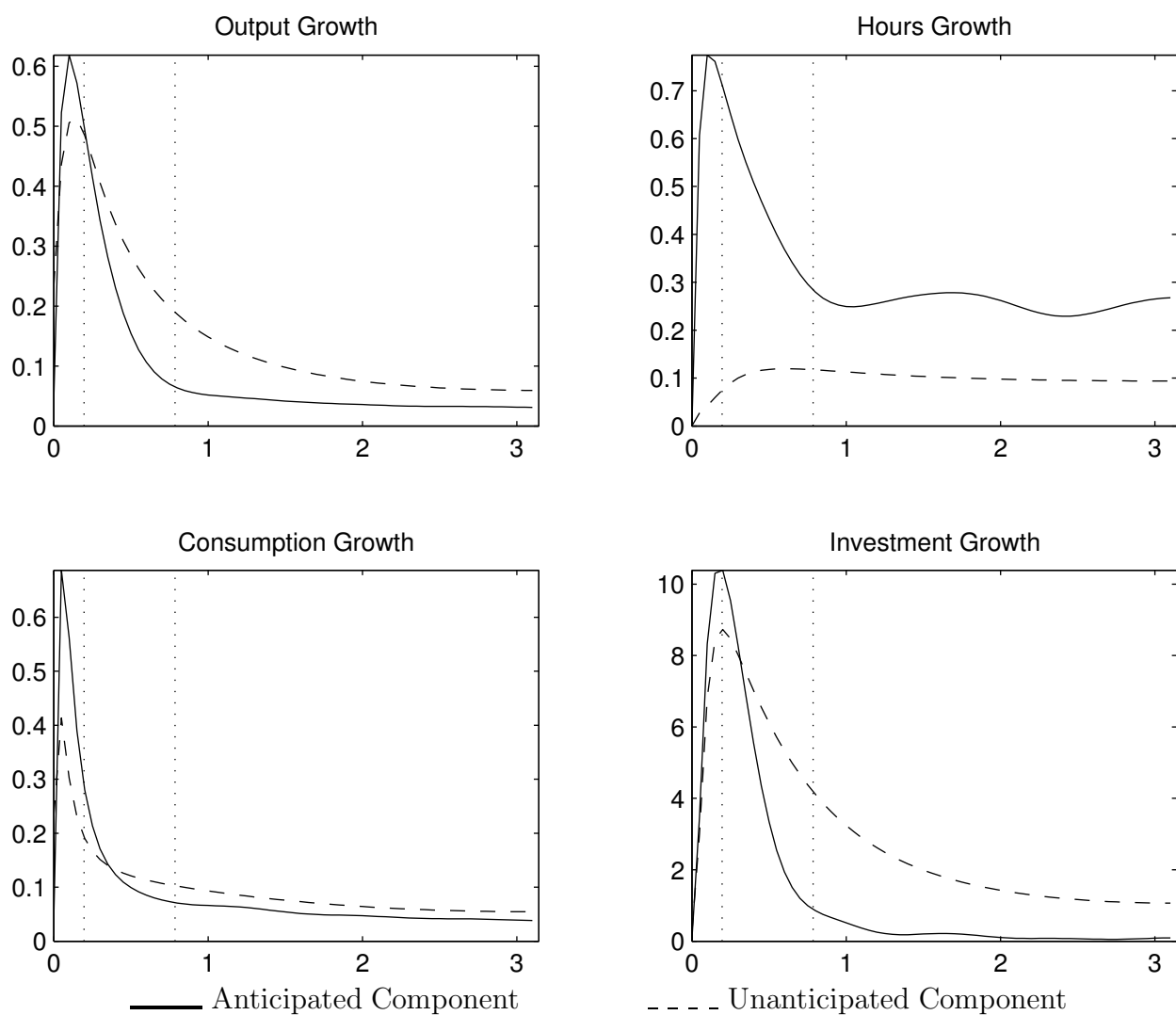
shocks to the sum of the variances of all of its 21 components. This ratio provides the share of the variance attributable to anticipated shocks for each observable. (5) We repeat steps (1)-(4) 500,000 times and report the median shares. This procedure takes into account both parameter and finite-sample uncertainty.

We find that the median share of predicted variances explained by anticipated shocks at business cycle frequencies, as defined by the HP filter, are higher than those obtained using growth rates. This is particularly the case for investment, for which the share explained by anticipated shocks rises from 33 percent when the cycle is described by unconditional second moments of first-differenced variables to 49 percent when the cycle is measured using simulated, HP-filtered time series. Overall, anticipated shocks explain between 48 and 84 percent of the variances of the four macroeconomic indicators considered. These results suggest that the importance of anticipated shocks in accounting for variations in business fluctuations is robust to detrending the predicted time series using growth rates or using the Hodrick-Prescott filter.

6.3 Anticipated Shocks in the Frequency Domain

Thus far, we have limited our attention to analyzing the role of anticipated shocks using the time domain. Here, we conduct a brief exploration of the significance of anticipated shocks from the perspective of the frequency domain. Figure 3 displays the population spectrums of the anticipated component (solid lines) and the unanticipated components (broken lines) of output growth, hours growth, consumption growth, and investment growth. The population spectrums were computed at the posterior mean of the vector of estimated parameters. Business-cycle frequencies, defined as 8 to 32 quarters, are marked by two dotted vertical lines. The fact that the spectra associated with the anticipated and the unanticipated components have different shapes suggests that these two components play distinct roles in explaining business cycles. For instance, for hours worked the spectrum of the anticipated component is downward sloping whereas the spectrum of the unanticipated component is upward sloping. This means that anticipated shocks are estimated to be relatively more important at the lower range of business-cycle frequencies. In the case of output and investment even though the spectra of both the anticipated and the unanticipated components are downward sloping, the one associated with the anticipated component has more density around the lower end of the business cycle spectrum, indicating again that anticipated shocks are relatively more important in explaining lower frequency business-cycle movements. Finally, the consumption spectrum shows that movements in consumption at business-cycle frequencies are accounted for by anticipated and unanticipated shocks in equal

Figure 3: The Population Spectrum



Note. Computed at the mean of the posterior distribution. The two vertical dotted lines mark frequencies between 8 and 32 quarters.

parts.

6.4 A Parsimonious Shock Specification

In this subsection we address two potential issues regarding the shock structure and observability assumptions maintained thus far. In regard to the shock structure of the model analyzed in previous sections, a potential concern is that it contains a number of nonstructural and ad-hoc sources of uncertainty. Among these are the preference shock, ζ_t , the wage markup shock, μ_t , and the shock shifting the law of motion of the capital stock, z_t^I . Although these shocks are customarily included in estimated medium-scale DSGE models, it is of interest to ascertain whether the importance of anticipated shocks is robust to omitting them. For this reason, in this section we estimate a special case of our model in which we set

$$\sigma_k^i = 0,$$

for $k = z^I, \zeta, \mu$ and $i = 0, 4, 8$.

A second potential concern with our baseline estimation is the inclusion of total factor productivity as an observable variable. In particular, the construction of an empirical measure of TFP requires the use of data on the capital stock, which, as is well known, is difficult to measure accurately. Consequently, in this section we omit TFP from the set of observables.

We estimate the resulting parsimonious version of the model using Bayesian methods. For the parameters that are estimated, we impose identical priors as those used in the baseline estimation. In line with the findings of the extensive literature devoted to fitting DSGE models to quarterly postwar data, the exclusion of the nonstructural shocks results in a weakening of the model's ability to fit the data. The central question for our purposes, however, concerns the predictions of the estimated model regarding the importance of anticipated disturbances. Line 5 of table 6 presents the estimated shares of unconditional variances accounted for by anticipated shocks. These shares are calculated at the posterior mean of the vector of estimated parameters. The estimated parsimonious model predicts that about two thirds of the variances of output, consumption, investment, and hours is accounted for by anticipated shocks. It follows that our central result, namely that anticipated shocks are important drivers of business cycles, is robust to doing away with the set of nonstructural or ad-hoc shocks that are customarily used to fit medium-scale macroeconomic models to the data. The facts that the model allows for fewer sources of uncertainty and that the set of observables excludes TFP naturally results in a significant increase in the importance of TFP shocks. Indeed, more than 90 percent of the volatility of output growth is now

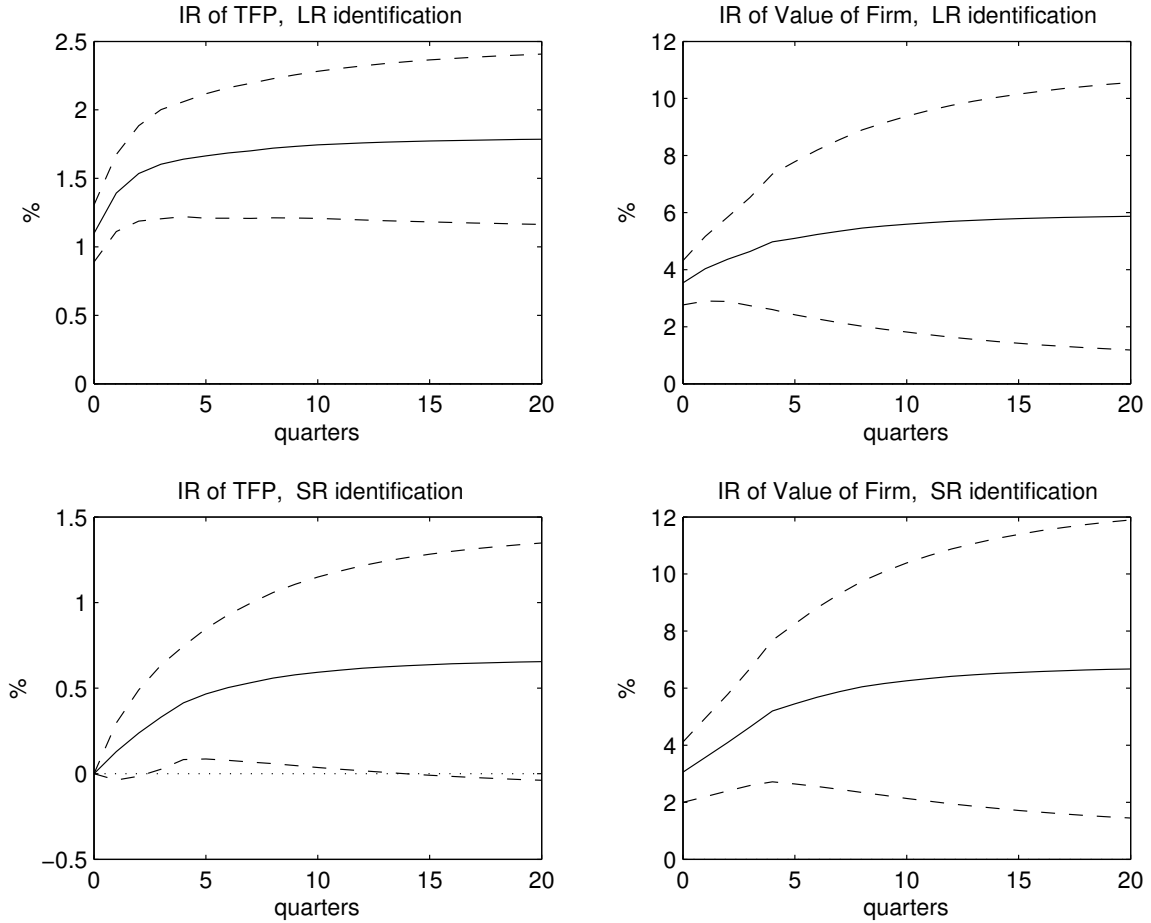
explained by stationary and nonstationary neutral productivity shocks. Of the two types of TFP shocks, nonstationary neutral TFP shocks are the single most important source of fluctuations explaining about 70 percent of the volatility of output growth. Further, the single most important component of nonstationary TFP shocks are eight-quarter anticipated innovations, which alone explain almost 50 percent of movements in output, consumption, investment, and hours. This result is in line with the findings of Beaudry and Portier (2006) obtained in the context of an empirical VAR model. In the next section we explore further the connection between the predictions of our estimated parsimonious DSGE model and those stemming from empirical VAR models.

6.5 Relation To VAR Estimates of Anticipated Shocks

Beaudry and Portier (2006) estimate the importance of anticipated permanent TFP shocks using an empirical vector error correction model (VECM). Their identification strategy is designed to uncover anticipated permanent changes in total factor productivity. Specifically, these authors impose two conditions for an innovation in TFP growth to be an anticipated shock: first, the shock must affect TFP in the long run (we refer to this restriction as the long-run identification scheme). And second, the shock cannot affect TFP contemporaneously (we refer to this restriction as the short-run identification scheme). The shocks that satisfy both BP identification schemes in our model are the anticipated components of the nonstationary neutral productivity shock, that is, $\epsilon_{x,t}^4$ and $\epsilon_{x,t}^8$. We note, however, that our DSGE model does not have a VAR representation of the type considered in BP. One reason for the lack of a BP-style VAR representation is that the number of innovations we consider is larger than the number of observables included in the VARs considered by BP. It follows that the shocks identified by the BP methodology cannot be interpreted as $\epsilon_{x,t}^4$, or $\epsilon_{x,t}^8$, or a combination thereof. We therefore interpret the BP empirical results as a particular filtering of the data that can be compared to a similar filtering performed on artificial data generated by our theoretical model.

Figure 4 displays impulse responses of adjusted TFP—i.e., $z_t X_t^{1-\alpha_k}$ —and the value of the firm applying the Beaudry-Portier long- and short-run identification schemes to a VAR in the growth rates of TFP and the value of the firm estimated on artificial data generated using the parsimonious specification of the model. We use this version of the model because it assigns a relatively large role to anticipated permanent TFP shocks. We generate artificial data of length 1212 quarters and discard the first 1000 elements. The remaining time series are of equal length as those used in the empirical work of BP. We repeat the estimation of the VAR 1000 times and report the mean and standard deviation of the BP-style impulse

Figure 4: Beaudry-Portier-Style Impulse Response Functions Model Generated Data



Note. Solid lines correspond to mean point estimates and broken lines to point estimates \pm two standard-deviation bands. Impulse responses are computed from a bivariate VAR in the growth rates of TFP and the value of the firm. Artificial data are generated from the parsimonious specification of the model. The VAR is estimated 1000 times. Each time, an artificial time series of length 1212 is created, but only the last 212 observations are used in the estimation of the VAR.

responses. The figure shows that in response to a BP-style innovation, TFP and the value of the firm display a significant increase. In this sense, the predictions of our estimated model are consistent with the empirical results of BP. We reiterate our hesitation to interpret the shocks identified in this exercise as being anticipated TFP shocks because, as explained above, our theoretical model does not imply a bi-variate VAR representation.

7 Conclusion

In this paper, we perform classical maximum likelihood and Bayesian estimation of a dynamic general equilibrium model to assess the importance of anticipated and unanticipated shocks as sources of macroeconomic fluctuations. Our theoretical environment is a neoclassical growth model augmented with three real rigidities: habit formation in consumption, investment adjustment costs, and variable capacity utilization.

We consider seven different sources of uncertainty: stationary and nonstationary neutral productivity shocks, nonstationary shocks to the relative price of investment, stationary shocks to the marginal efficiency of investment, government spending shocks, preference shocks, and wage-markup shocks. Each of these sources of uncertainty is assumed to feature an unanticipated component and components anticipated four and eight quarters. We estimate the model on quarterly U.S. data on output, consumption, investment, hours, government spending, total factor productivity, the relative price of investment, and stock prices over the postwar period.

Our central finding is that about half of the variance of the growth rates of output, consumption, investment, and hours is attributable to anticipated disturbances. This result stands in sharp contrast to the existing literature on the sources of business cycles, which, implicitly, assumes that the totality of aggregate fluctuations is due to unanticipated changes in economic fundamentals. We find that anticipated variations in wage markups are a major source of fluctuations in hours worked. A possible interpretation of these anticipated shocks is that they represent expected outcomes of wage and benefit negotiations between employers and workers, and that the uncertainty about the eventual form of the compensation packages that will emerge from these negotiations represent a source of fluctuations in hours. Anticipated preference shocks are estimated to account for a sizeable fraction of the variance of consumption growth. This type of anticipated shock affects the consumption Euler equation differently at different horizons. For example, a four-quarter anticipated preference shock affects the consumption Euler equation for assets with a maturity of four quarters, and an eight-quarter anticipated preference shock affects the term premium on an asset with a maturity of eight quarters. One might therefore interpret the importance of

anticipated preference shocks as evidence of maturity specific shocks to the term structure of interest rates. We estimate that an important source of fluctuations in investment spending are anticipated changes in the marginal efficiency of investment. These changes affect the marginal rate of transformation of new capital goods into installed capital, and can be interpreted, in the context of a financial accelerator model, as reflecting anticipated variations in financial frictions faced by firms. Unlike consumption, investment, and hours, each of whose anticipated component is explained primarily by one type of anticipated shock, the anticipated component of output is explained by various anticipated disturbances, including anticipated wage-markup shocks, anticipated preference shocks, anticipated movements in the marginal efficiency of investment, and anticipated government spending shocks.

Our investigation contributes to an ongoing debate on the extent to which government spending shocks are anticipated. Most of the existing literature on this topic has employed structural vector autoregression analysis. A branch of this literature emphasizes the importance of augmenting VARs with information stemming from a narrative approach to the identification of public spending shocks. This branch finds that a large fraction of government spending shocks are indeed anticipated, whereas, by construction, the pure SVAR-based literature identifies only unanticipated innovations in government spending. Unlike this literature, our identification approach is based on an optimizing model populated by forward-looking agents who in general respond differently to anticipated and unanticipated disturbances. For this reason, our empirical approach is particularly well suited to uncover the relative importance of anticipated government spending shocks. We find that two thirds of government spending shocks are anticipated. This result falls in between those reported in the narrative and purely SVAR literatures.

An important outcome of our investigation is that shocks to the price of investment, whether anticipated or unanticipated, are unimportant in driving business cycles. This result is at odds with a number of related full-information DSGE-model-based empirical studies that find that the majority of fluctuations in output and hours are caused by disturbances in the relative price of investment. We identify the source of this discrepancy as being related to whether the relative price of investment is or is not included in the set of observables. In our econometric estimation we include the price of investment as an observable time series, whereas the literature that emphasizes the importance of this type of shocks does not.

This study represents the first effort to estimate a general equilibrium model with a parametric specification of the wealth elasticity of labor supply. Our findings suggest a wealth elasticity of labor supply close to zero. This result suggests that wealth effects are not important for explaining movements in hours in response to aggregate shocks.

We conclude by relating our work to the early contributions on quantitative equilib-

rium business cycle theory. The seminal work of Prescott (1986) argued that the majority of business-cycle fluctuations in the postwar U.S. economy is attributable to exogenous stochastic variations in technology. Our results are in line with this conclusion in a narrow sense. For we find that two thirds of observed fluctuations in output and investment growth are explained by technology shocks. However, our results depart from those of the early RBC literature along a number of dimensions. First, that literature restricts attention to one type of technology shock, namely neutral technology shocks. It attributes to this type of shock about two thirds of observed output fluctuations. We find a smaller role for neutral productivity shocks and a significant role for shocks to the marginal efficiency of investment. Specifically, we estimate that neutral productivity shocks and shocks to the efficiency of investment each explain 28 percent of the unconditional variance of output growth. In the case of investment, the importance of neutral productivity shocks relative to shocks to the marginal efficiency of investment is even smaller (22 versus 63 percent). Second, we find that all productivity shocks taken together play a small role in explaining movements in consumption and hours. Our estimates indicate that consumption is to a large extent explained by preference shocks, and hours worked mostly by variations in wage-markup shocks. Finally, the RBC literature attributes all business-cycle variations to unanticipated shocks. The main contribution of the present study is to open the door for the possibility that innovations in exogenous economic fundamentals are anticipated at least in part by economic agents. The central finding of our investigation is that allowing for this possibility uncovers a dominant source of business-cycle fluctuations.

Appendix: Data Sources

The time series used to construct the six observable variables used in the estimation are:

1. Real Gross Domestic Product, BEA, NIPA table 1.1.6., line 1, billions of chained 2000 dollars seasonally adjusted at annual rate. Downloaded from www.bea.gov.
2. Gross Domestic Product, BEA NIPA table 1.1.5., line 1, billions of dollars, seasonally adjusted at annual rates.
3. Personal Consumption Expenditure on Nondurable Goods, BEA, NIPA table 1.1.5., line 4, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.
4. Personal Consumption Expenditure on Services, BEA NIPA table 1.1.5., line 5, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.
5. Gross Private Domestic Investment, Fixed Investment, Nonresidential, BEA NIPA table 1.1.5., line 8, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

6. Gross Private Domestic Investment, Fixed Investment, Residential, BEA NIPA table 1.1.5., line 11, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

7. Government Consumption Expenditure, BEA NIPA table 3.9.5., line 2, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

8. Government Gross Investment, BEA NIPA table 3.9.5., line 3, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

9. Civilian Noninstitutional Population Over 16, BLS LNU00000000Q. Downloaded from www.bls.gov.

10. Nonfarm Business Hours Worked, BLS, PRS85006033, seasonally adjusted, index 1992=100. Downloaded from www.bls.gov.

11. GDP Deflator = (2) / (1).

12. Real Per Capita GDP = (1) / (9).

13. Real Per Capita Consumption = [(3) + (4)] / (11) / (9).

14. Real Per Capita Investment = [(5) + (6)] / (9) / (11).

15. Real Per Capita Government Expenditure = [(7) + (8)] / (9) / (11).

16. Per Capita Hours = (10) / (9).

17. Relative Price of Investment: Authors' calculation following the methodology proposed in Fisher (2006). An appendix detailing the procedure used in the construction of this series is available from the authors upon request.

18. Total factor productivity in the non-farm business sector adjusted for capital capacity utilization. This series is taken from Beaudry and Lucke (2009).

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