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ABSTRACT

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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 identification approach relies on the fact that forward-looking agents react to anticipated changes in exogenous fundamentals before such changes materialize. It further allows us to distinguish changes in fundamentals by their anticipation horizon. We find that anticipated shocks account for about half of predicted aggregate fluctuations in output, consumption, investment, and employment.

JEL Classification: C11, C51, E13 and E32
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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. This proliferation of states makes it less likely that the dynamics of the observables possess 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, variable 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, 2011).

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 $t-4$.

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, in the context of our model, anticipated shocks are an important source of uncertainty. Specifically, our model predicts that anticipated shocks explain about one half of the variances of output, hours, consumption, and investment. This result is of interest in light of the fact that the existing DSGE econometric literature on the sources of business cycles implicitly attributes one hundred percent of aggregate fluctuations to unanticipated variations in economic fundamentals.

The fact that the DSGE 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 here.

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 in the context of a small artificial economy. Section 3 presents the DSGE model. Section 4 explains how to introduce anticipated disturbances into the DSGE model. 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. It also performs a number of identification tests. Section 6 presents our estimates of the contribution of anticipated shocks to business-cycle

[1] Our 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.

fluctuations. Section 7 concludes.

2 Identification of Anticipated Shocks: An 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]

The model is given by

$$x_t = \rho_x x_{t-1} + \epsilon_t^0 + \epsilon_{t-1}^1 + \epsilon_{t-2}^2,$$

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

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 parameters ρ_x and ρ_y govern the persistence of x_t and y_t and lie in the interval $(-1, 1)$. 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 true impulse responses of the observable x_t to unit innovations in each of the three

[2]We thank Harald Uhlig for suggesting this example.

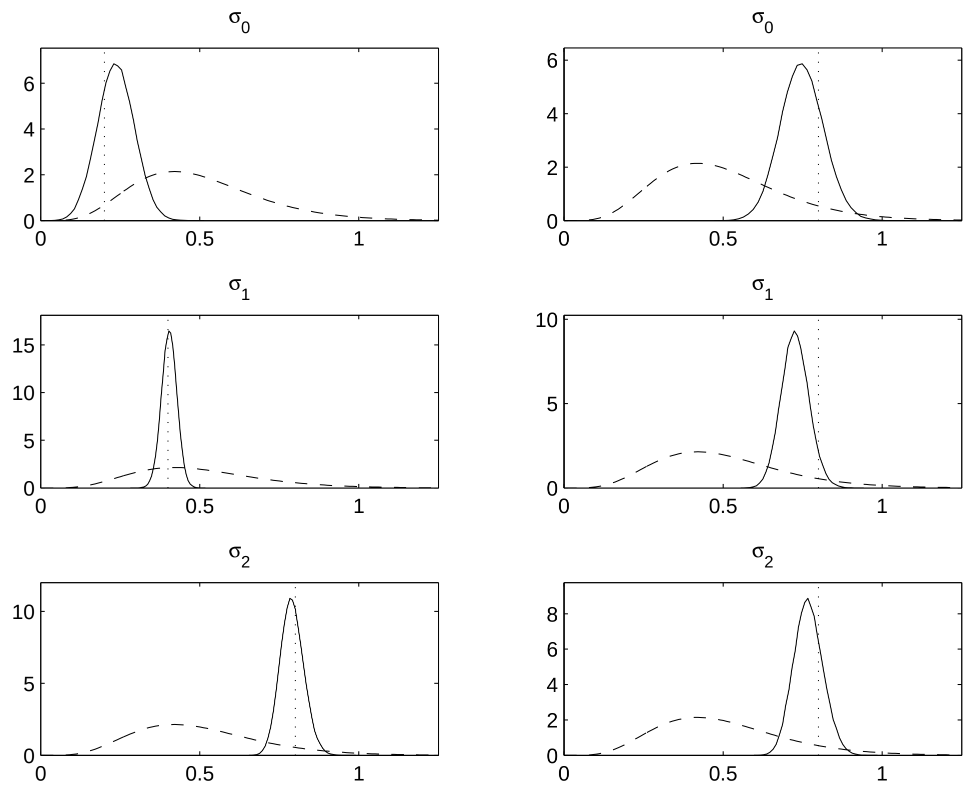
shocks, ϵ_t^0, ϵ_t^1, and ϵ_t^2 are copies of each other, simply shifted one period to the right (see Schmitt-Grohé and Uribe, 2011b, section 1). This feature of the model may raise the question of whether an econometrician would be able to correctly identify the parameters of interest with a sample of observations on x_t and v_t. The answer to this question is yes. The intuition for why identification is 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 covariance between v_t and x_{t+1} depends only on σ_1. So this moment identifies σ_1. Second, the variance of v_t depends only on σ_1 and σ_2 and therefore identifies σ_2, given σ_1. And third, the variance of x_t depends on σ_0, σ_1, and σ_2, so it identifies σ_0, given σ_1 and σ_2. 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, this case assumes 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. Figure 1

displays 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 uncovers 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 left column of figure 1, the posterior means are, respectively, $(0.24, 0.40, 0.79)$, 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 right column 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 corresponding posterior means.)

We apply two additional identification tests to this example model. One consists in examining the rank of the information matrix. We compute this matrix applying the methodology proposed by Chernozhukov and Hong (2003). We find that for both parameterizations of the data generating process, the information matrix is full rank. The second test we apply is

Figure 1: Identification in the Example Economy



Note. Posterior densities are shown with solid lines, prior densities with broken lines, and the true value of σ_i for $i = 0, 1, 2$ with vertical dotted lines. Posterior densities are calculated using 500,000 draws from the posterior distribution of the respective parameter. The left column of the figure corresponds to the case in which the true parameter values are $\sigma_2 = 2\sigma_1 = 4\sigma_0 = 0.8$. The right column corresponds to the case in which the true parameter values are $\sigma_2 = \sigma_1 = \sigma_0 = 0.8$.

Iskrev's (2010) test of identifiability. In essence the Iskrev test checks whether the derivatives of the predicted autocovariogram of the observables with respect to the vector of estimated parameters has rank equal to the length of the vector of estimated parameters. For the example model developed in this section, the rank condition can be shown analytically to hold globally. This result obtains even in the special cases in which either ρ_x or ρ_y or both are nil. See Schmitt-Grohé and Uribe (2011b) section 2 for a derivation of this result.

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

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

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

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

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

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

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 is due to 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 $\gamma \to 0$, 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

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

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 (2011).

The sequential budget constraint of the household is given by

$$C_t + A_t I_t + T_t = W_t^* h_t + r_t u_t K_t + P_t. \tag{5}$$

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 (linear) 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.[3] We assume that the growth rate of A_t, denoted

$$\mu_t^a \equiv \frac{A_t}{A_{t-1}},$$

follows a stationary process and has a steady-state value of μ^a. 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},

[3]The linear relationship between the relative price of investment and A_t and the implied exogeneity of the relative price of investment could be broken by assuming that the technology for transforming consumption goods into investment goods is nonlinear. In Schmitt-Grohé and Uribe (2011a), we estimate the curvature of the technology for producing investment goods and find that the data strongly favors a linear specification like the one maintained here.

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, with a steady-state value $\mu > 1$. 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

$$Y_t = z_t F(u_t K_t, X_t h_t, X_t L), \tag{6}$$

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 growth rate of the permanent productivity shock, denoted

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

is assumed to be an exogenous, stationary stochastic process with a steady-state value equal to μ^x.

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. 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 $X_t^G = \left(X_{t-1}^G\right)^{\rho_{xg}} \left(X_{t-1}^Y\right)^{1-\rho_{xg}}$, 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 $X_t^Y = X_t A_t^{\alpha_k/(\alpha_k-1)}$. Notice that X_t^G resides in the information set of period $t-1$. This fact together 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.

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

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

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

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

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

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

$$\left[\zeta_t U'(V_t) - \Pi_t \gamma \frac{S_t}{C_t - bC_{t-1}}\right] - \beta b E_t \left[\zeta_{t+1} U'(V_{t+1}) - \Pi_{t+1} \gamma \frac{S_{t+1}}{C_{t+1} - bC_t}\right] = \Lambda_t$$

$$\theta \psi \zeta_t U'(V_t) h_t^{\theta-1} S_t = \Lambda_t \frac{z_t X_t F_2(u_t K_t, X_t h_t, X_t L)}{1 + \mu_t}$$

$$\Pi_t = \psi \zeta_t U'(V_t) h_t^{\theta} + \beta(1-\gamma) E_t \Pi_{t+1} \frac{S_{t+1}}{S_t}$$

$$Q_t \Lambda_t = \beta E_t \Lambda_{t+1} \left[z_{t+1} u_{t+1} F_1(u_{t+1} K_{t+1}, X_{t+1} h_{t+1}, X_{t+1} L) + Q_{t+1}(1 - \delta(u_{t+1}))\right]$$

$$z_t F_1(u_t K_t, X_t h_t, X_t L) = Q_t \delta'(u_t)$$

$$A_t \Lambda_t = Q_t \Lambda_t z_t^I \left[1 - S\left(\frac{I_t}{I_{t-1}}\right) - \frac{I_t}{I_{t-1}} S'\left(\frac{I_t}{I_{t-1}}\right)\right] + \beta E_t Q_{t+1} \Lambda_{t+1} z_{t+1}^I \left(\frac{I_{t+1}}{I_t}\right)^2 S'\left(\frac{I_{t+1}}{I_t}\right),$$

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: $V_t^F = Y_t - W_t h_t - A_t I_t + \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t} V_{t+1}^F$. This expression states that the value of the firm equals the present discounted value of current and future expected dividends.

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, we wish to avoid the proliferation of estimated parameters. Each anticipation horizon adds one parameter per driving force, namely, the standard deviation of the innovation at that particular anticipation horizon. Under the current specification we are estimating 21 standard deviations. This is 14 parameters more than in a specification without anticipation. It would be of interest to study the robustness of our results regarding the importance of anticipation to making the anticipation structure longer and denser.

We assume that all exogenous shocks x_t, for $x = z, \mu^x, \mu^a, g, z^I, \zeta, \mu$, evolve over time according to the following law of motion:

$$\ln(x_t/x) = \rho_x \ln(x_{t-1}/x) + \epsilon_{x,t},$$

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

where $\epsilon^j_{x,t}$ for $j = 0, 4$, and 8 is assumed to be an i.i.d. normal disturbance with mean zero and standard deviation σ^j_x.

The innovation $\epsilon^j_{x,t}$ denotes j-period anticipated changes in the logarithm of x_t. For example, $\epsilon^4_{x,t-4}$ is an innovation to the level of x_t that materializes in period t, but that agents learn about in period $t-4$. Therefore, $\epsilon^4_{x,t-4}$ 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 $\epsilon^4_{x,t-4}$ is a 4-period anticipated innovation in x_t. The disturbance $\epsilon^j_{x,t}$ has mean zero, standard deviation σ^j_x, and is uncorrelated across time and across anticipation horizons. That is, $E\epsilon^j_{x,t}\epsilon^k_{x,t-m} = 0$ for $k, j = 0, 4, 8$ and $m > 0$, and $E\epsilon^j_{x,t}\epsilon^k_{x,t} = 0$ for any $k \neq j$. These assumptions imply that the error term $\epsilon_{x,t}$ is unconditionally mean zero and serially uncorrelated, that is, $E\epsilon_{x,t} = 0$ and $E\epsilon_{x,t}\epsilon_{x,t-m} = 0$ for $m > 0$. Moreover, the error term $\epsilon_{x,t}$ is unforecastable given only past realizations of itself. That is, $E(\epsilon_{x,t+m}|\epsilon_{x,t}, \epsilon_{x,t-1}, \dots) = 0$, for $m > 0$. Note that the proposed process for $\epsilon_{x,t}$ 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 $\epsilon_{x,t}$. In particular, agents are assumed to observe in period t current and past values of the innovations $\epsilon^0_{x,t}$, $\epsilon^4_{x,t}$, and $\epsilon^8_{x,t}$. That is, agents can forecast future values of $\epsilon_{x,t}$ as follows:

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

Because agents are forward looking, they use the information contained in the realizations of the various innovations $\epsilon^j_{x,t}$ 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 $\epsilon^j_{x,t}$, 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 a first-order linear stochastic difference equation of the form

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

where $\nu_{x,t} = [\ \nu^0_{x,t} \quad \nu^4_{x,t} \quad \nu^8_{x,t}\ ]'$ distributes normal i.i.d. with mean zero and variance-covariance matrix equal to the identity matrix. The vector $\tilde{x}_t$ and the matrices M and η are given in Schmitt-Grohé and Uribe (2011b) section 4.

The central goal of our investigation is to econometrically estimate the nonzero elements of η, which are given by the standard deviations of the anticipated and unanticipated components of each of the seven exogenous shocks, σ^0_j, σ^4_j and σ^8_j, for $j = z, \mu^x, \mu^a, z^I, g, \zeta, \mu$.

4.2 Accommodating Revisions

We view the structure given above to anticipated and unanticipated innovations as just one of potentially many ways to model information diffusion. Our approach 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 $\epsilon^8_{z,t}$. 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 $\epsilon^4_{z,t+4}$ is negative. This is equivalent to the announcement that the productivity improvement announced in period t will not materialize as expected. At this point, the economy may enter into a recession even though none 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 $\epsilon^0_{z,t+8}$ is negative and offsets the prior two announcements $\epsilon^8_{z,t} + \epsilon^4_{z,t+4}$. This is a situation in which agents learn that the earlier optimistic outlook for productivity did not pan out at all. The economy may 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. This interpretation suggests an equivalent but more parsimonious representation of anticipation in which state variables collect all prior innovations that will materialize in a given horizon. One advantage of this formulation is that it reduces the number of exogenous state variables in the system. We present this formulation, which was suggested to us by an anonymous referee, in Schmitt-Grohé and Uribe (2011b) section 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.

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

$$x_{t+1} = h_x x_t + \eta \nu_{t+1}, \tag{7}$$

$$y_t = g_x x_t + \xi m_t, \tag{8}$$

where x_t is a vector of endogenous and exogenous state variables, y_t is the vector of observables, ν_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 and classical maximum likelihood (ML) methods 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 anticipated and unanticipated innovations. The parameters that are not estimated are calibrated in a standard fashion.

5.1 Calibrated Parameters

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 degree of decreasing returns to scale of 10 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,

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.

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 -0.43 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:Q2 to 2006:Q4. Following Justiniano, Primiceri, and Tambalotti (2008), 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.

5.2 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 (7) and (8) 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 sample 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 $j = z, \mu^x, z^I, \mu^a, g, \mu, \zeta$. 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:Q2 to 2006:Q4. The data include seven time series: the growth rates of per capita 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 their respective observable counterparts, namely, 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

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

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, $\epsilon^{me}_{y,t}$, is assumed to be an i.i.d. innovation with mean zero and standard deviation $\sigma^{me}_{g^y}$. 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, $\sigma^{me}_{g^y}$.

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

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

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 of priors gives rise to prior probability densities for the share of anticipated shocks in the variance of key macroeconomic variables

Table 2: Parameter Estimation on U.S. Data

Parameter	Bayesian Estimation							ML Estimation	
	Prior Distribution				Posterior Distribution				
	Distribution	Median	5%	95%	Median	5%	95%	Point Est.	Std.
θ	Gamma*	3.89	2.57	5.81	4.74	3.88	5.83	5.39	0.85
γ	Uniform	0.50	0.05	0.95	0.00	0.00	0.01	0.00	0.00
κ	Gamma	3.92	2.51	5.77	9.11	7.41	10.91	25.07	2.25
δ_2/δ_1	Igamma	0.75	0.32	2.45	0.34	0.23	0.50	0.44	0.15
b	Beta	0.50	0.17	0.83	0.91	0.89	0.93	0.94	0.01
ρ_{xg}	Beta	0.73	0.32	0.96	0.72	0.44	0.88	0.74	0.17
ρ_z	Beta	0.73	0.32	0.96	0.92	0.85	0.96	0.96	0.03
σ_z^0	Gamma	1.04	0.08	4.51	0.65	0.54	0.74	0.62	0.09
σ_z^4	Gamma	0.43	0.03	1.84	0.11	0.01	0.31	0.11	0.08
σ_z^8	Gamma	0.43	0.03	1.84	0.09	0.01	0.27	0.11	0.08
ρ_{μ^a}	Beta	0.50	0.17	0.83	0.48	0.38	0.58	0.48	0.06
$\sigma_{\mu^a}^0$	Gamma	0.22	0.02	0.94	0.21	0.02	0.35	0.16	0.09
$\sigma_{\mu^a}^4$	Gamma	0.09	0.01	0.39	0.16	0.01	0.34	0.20	0.10
$\sigma_{\mu^a}^8$	Gamma	0.09	0.01	0.39	0.16	0.01	0.33	0.19	0.10
ρ_g	Beta	0.73	0.32	0.96	0.96	0.93	0.99	0.96	0.02
σ_g^0	Gamma	0.73	0.05	3.14	0.62	0.06	1.07	0.53	0.31
σ_g^4	Gamma	0.30	0.02	1.28	0.57	0.04	1.07	0.69	0.31
σ_g^8	Gamma	0.30	0.02	1.28	0.37	0.03	1.00	0.43	0.29
ρ_{μ^x}	Beta*	0.23	-0.18	0.46	0.38	0.12	0.49	0.27	0.16
$\sigma_{\mu^x}^0$	Gamma	0.32	0.02	1.36	0.38	0.22	0.57	0.45	0.16
$\sigma_{\mu^x}^4$	Gamma	0.13	0.01	0.56	0.08	0.01	0.28	0.12	0.09
$\sigma_{\mu^x}^8$	Gamma	0.13	0.01	0.56	0.10	0.01	0.27	0.12	0.09
ρ_μ	Beta	0.73	0.32	0.96	0.98	0.95	1.00	0.98	0.01
σ_μ^0	Gamma	0.82	0.06	3.56	0.50	0.04	1.24	1.51	1.00
σ_μ^4	Gamma	0.34	0.02	1.46	4.79	3.18	5.70	3.93	1.12
σ_μ^8	Gamma	0.34	0.02	1.46	0.51	0.04	2.85	3.20	1.26
ρ_ζ	Beta	0.50	0.17	0.83	0.17	0.07	0.30	0.10	0.07
σ_ζ^0	Gamma	4.37	0.32	18.87	4.03	1.20	6.02	2.83	1.79
σ_ζ^4	Gamma	1.78	0.13	7.70	1.89	0.17	4.84	2.76	1.99
σ_ζ^8	Gamma	1.78	0.13	7.70	2.21	0.14	4.85	5.34	1.51
ρ_{z^I}	Beta	0.50	0.17	0.83	0.47	0.22	0.64	0.21	0.10
σ_{z^I}	Gamma	11.88	0.88	51.36	11.72	8.90	14.94	34.81	4.03
$\sigma_{z^I}^4$	Gamma	4.85	0.36	20.97	1.93	0.16	6.15	11.99	4.47
$\sigma_{z^I}^8$	Gamma	4.85	0.36	20.97	5.50	1.71	10.58	14.91	2.55
$\sigma_{g^y}^{me}$	Uniform	0.15	0.02	0.29	0.30	0.30	0.30	0.30	0.00

Note. Bayesian estimates 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.

that are quite dispersed (see figure 2 and table 5).

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 maximum likelihood 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.

5.3 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:Q2 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 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 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.

Table 3: Model Predictions

Statistic	Y	C	I	h	G	TFP	A
	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. The columns labeled Y, C, I, h, G, TFP, and A refer, respectively, to the growth rates of output, private consumption, investment, hours, government consumption, total factor productivity, and the relative price of investment.

5.4 Identifiability and Identification

To gauge the ability of our empirical strategy to identify the parameter vector Θ, we perform three identification tests. First, we check for the identifiability of the estimated parameter vector Θ by applying the test proposed by Iskrev (2010). See Schmitt-Grohé and Uribe (2011b) section 3 for details on the implementation of this test. We find that the derivative of the vectorized predicted autocovariogram of the vector of observables with respect to Θ has full column rank when evaluated at the maximum-likelihood estimate or at the posterior mean or median of the Bayesian estimate. Full column rank obtains starting with the inclusion of covariances of order 0 and 1. According to this test, therefore, the parameter vector Θ is identifiable in the neighborhood of our estimate. Specifically, the test result indicates that in the neighborhood of our estimate of Θ, all values of Θ different from our estimate give rise to autocovariograms that are different from the one associated with our estimate of Θ.

Our second identification test consists in examining the rank of the information matrix. We compute this matrix following the methodology proposed by Chernozhukov and Hong (2003). We find that the information matrix is full rank, which suggests that, given our data sample, the parameter vector Θ is indeed identified.

Our third identification test consists in applying our estimation strategy to artificial data stemming from the DSGE model to show that our proposed empirical approach can recover the underlying parameters. Specifically, we calibrate our baseline DSGE model using the posterior mean of the estimated parameters. Then we generate artificial data for the seven observables. The artificial data set contains 207 observations, which is the length of the actual data set used in our study. We add measurement error to the time series of output growth of the size implied by our calibration. Then we estimate the model using ML and Bayesian methods following exactly the same procedures and code as we do in our estimation using real data. The Bayesian estimates are based on the same prior distributions as those used in our estimation of the model on actual data. At no point does the estimation procedure make use of our knowledge of the true parameter values. Table 4 displays the results of this identification test. The table reports the true value of the parameter vector, the maximum-likelihood estimate, and the posterior median, 5th percentile, and 95th percentile computed from 500,000 draws from the posterior distribution. In our view, given the size of the artificial data sample, both the ML and Bayesian estimation procedure capture the true parameter values reasonably well.

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 through a number of perspectives.

6.1 Bayesian Estimate

Table 5 displays the share of the unconditional variances of output growth, consumption growth, investment growth, and hours growth that according to our Bayesian estimation can be accounted for by anticipated shocks. Panel 2 of the table displays the median posterior share as well as the fifth and ninety fifth percentiles 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 finding is of interest 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 represent an example of a model economy in which when one allows for unanticipated and anticipated disturbances to play separate roles, the latter emerge as an important driving force.

Figure 2 displays the prior and posterior probability density functions of the share of

Table 4: Estimation On Artificial Data

Parameter	True Value	ML Point Estimate	Bayesian Estimation						
			Prior Distribution				Posterior Distribution		
			Distribution	Median	5%	95%	Median	5%	95%
θ	4.78	6.25	Gamma*	3.89	2.57	5.81	4.82	3.92	4.90
γ	0.00	0.00	Uniform	0.50	0.05	0.95	0.00	0.00	0.01
κ	9.12	9.49	Gamma	3.92	2.51	5.77	5.44	4.09	6.97
δ_2/δ_1	0.35	0.67	Igamma	0.75	0.32	2.45	0.39	0.25	0.58
b	0.91	0.96	Beta	0.50	0.17	0.83	0.91	0.88	0.93
ρ_{xg}	0.70	0.76	Beta	0.73	0.32	0.96	0.65	0.37	0.82
ρ_z	0.91	0.91	Beta	0.73	0.32	0.96	0.87	0.78	0.93
σ_z^0	0.65	0.49	Gamma	1.04	0.08	4.51	0.63	0.40	0.76
σ_z^4	0.13	0.20	Gamma	0.43	0.03	1.84	0.17	0.01	0.45
σ_z^8	0.11	0.32	Gamma	0.43	0.03	1.84	0.21	0.02	0.48
ρ_{μ^a}	0.48	0.43	Beta	0.50	0.17	0.83	0.44	0.33	0.55
$\sigma_{\mu^a}^0$	0.20	0.17	Gamma	0.22	0.02	0.94	0.26	0.06	0.33
$\sigma_{\mu^a}^4$	0.16	0.17	Gamma	0.09	0.01	0.39	0.10	0.01	0.28
$\sigma_{\mu^a}^8$	0.16	0.21	Gamma	0.09	0.01	0.39	0.09	0.01	0.26
ρ_g	0.96	0.94	Beta	0.73	0.32	0.96	0.92	0.85	0.97
σ_g^0	0.59	0.00	Gamma	0.73	0.05	3.14	0.53	0.04	0.90
σ_g^4	0.56	0.31	Gamma	0.30	0.02	1.28	0.35	0.02	0.86
σ_g^8	0.43	0.86	Gamma	0.30	0.02	1.28	0.41	0.03	0.89
ρ_{μ^x}	0.35	0.20	Beta*	0.23	-0.18	0.46	0.28	0.02	0.97
$\sigma_{\mu^x}^0$	0.39	0.68	Gamma	0.32	0.02	1.36	0.43	0.19	0.65
$\sigma_{\mu^x}^4$	0.10	0.00	Gamma	0.13	0.01	0.56	0.11	0.01	0.37
$\sigma_{\mu^x}^8$	0.11	0.04	Gamma	0.13	0.01	0.56	0.11	0.01	0.35
ρ_μ	0.97	0.97	Beta	0.73	0.32	0.96	0.95	0.91	0.99
σ_μ^0	0.55	0.00	Gamma	0.82	0.06	3.56	1.15	0.08	2.88
σ_μ^4	4.65	5.00	Gamma	0.34	0.02	1.46	3.72	0.60	4.69
σ_μ^8	0.81	1.97	Gamma	0.34	0.02	1.46	0.41	0.02	3.95
ρ_ζ	0.18	0.13	Beta	0.50	0.17	0.83	0.17	0.07	0.29
σ_ζ^0	3.85	6.11	Gamma	4.37	0.32	18.87	3.58	0.35	5.59
σ_ζ^4	2.15	4.88	Gamma	1.78	0.13	7.70	1.51	0.10	4.19
σ_ζ^8	2.28	5.71	Gamma	1.78	0.13	7.70	2.09	0.16	5.27
ρ_{z^I}	0.45	0.17	Beta	0.50	0.17	0.83	0.52	0.19	0.75
$\sigma_{z^I}^0$	11.73	13.16	Gamma	11.88	0.88	51.36	6.89	4.71	9.62
$\sigma_{z^I}^4$	2.45	8.48	Gamma	4.85	0.36	20.97	2.35	0.16	8.35
$\sigma_{z^I}^8$	5.69	9.05	Gamma	4.85	0.36	20.97	2.20	0.19	6.96
$\sigma_{g^y}^{me}$	0.30	0.28	Uniform	0.15	0.02	0.29	0.28	0.26	0.30

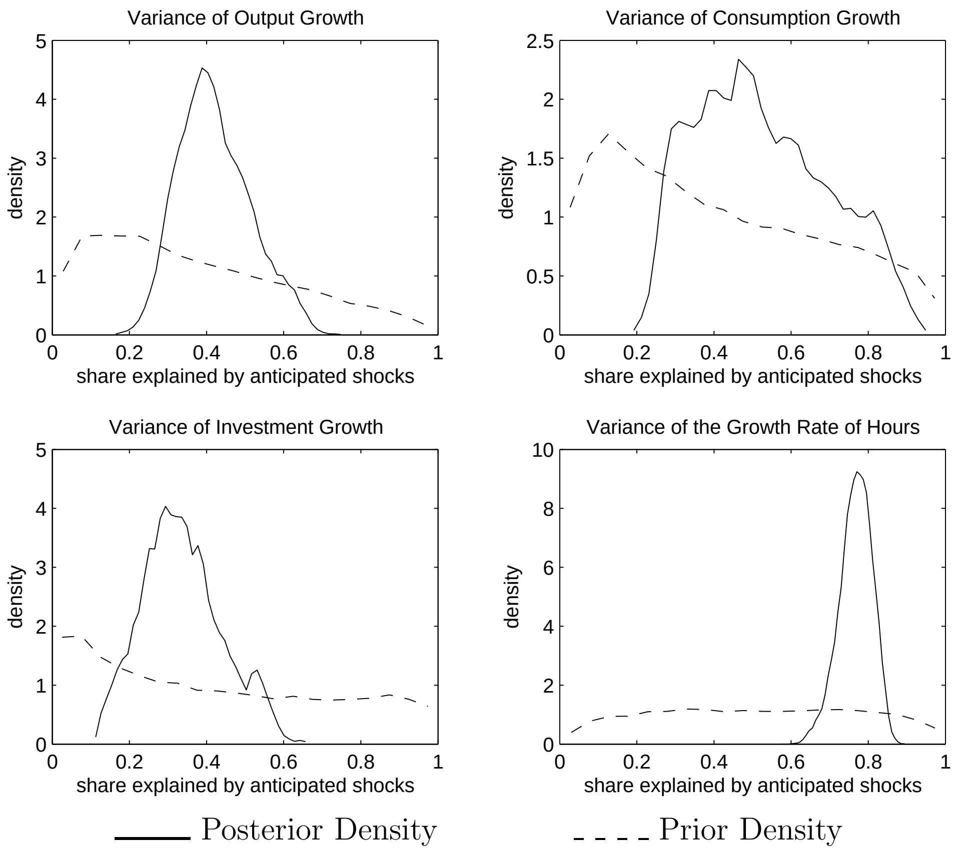
Note. The true parameter value is the posterior mean of the Bayesian estimation on actual data. The posterior median, 5th percentile, and 95th percentile estimated on artificial data were computed over 500,000 draws from the posterior distribution of the estimated parameter vector.

Table 5: Share of Unconditional Variance Explained by Anticipated Shocks

Percentile	Y	C	I	h
1. Prior				
5th	5	5	3	9
50th	33	36	37	51
95th	83	88	92	92
2. Posterior				
5th	28	28	17	69
50th	41	50	33	77
95th	60	83	53	83
3. Maximum Likelihood Estimation				
Point Estimate	49	70	41	72
4. Stock Prices Observable				
5th	61	77	62	45
50th	67	82	68	55
95th	73	85	73	66
5. HP Filtered Predictions				
5th	30	34	24	74
50th	46	56	47	84
95th	64	81	68	90

Note. Shares are in percent. For panels 1 through 4, Y, C, I, and h denote the growth rates of output, consumption, investment, and hours, respectively. For panel 5, Y, C, I, and h denote the HP-filtered log-levels of output, consumption, investment, and hours, respectively, with a smoothing parameter of 1600. The prior and posterior percentiles were computed using 500,000 draws from the prior and posterior distributions of the corresponding shares.

Figure 2: Prior and Posterior Probability Densities of the Share of the Unconditional Variance of the Growth Rates 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.

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 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 sizable fraction of aggregate volatility being explained by anticipated shocks is not an artifact of the assumed priors.

6.2 Maximum Likelihood Estimate

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 panel 3 of table 5 variance decompositions based on a classical maximum likelihood estimation of the model. The maximum likelihood 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.

6.3 Anticipated Wage Markup Shocks

Table 6 presents a variance decomposition of the seven observables into the 21 sources of uncertainty present in our DSGE model. Among the anticipated sources of uncertainty, the most relevant one is ϵ_{μ}^{4}, the four-quarter anticipated innovation in wage markups. A number of existing studies have found that wage markups are an important source of aggregate fluctuations, especially in hours worked. For instance, Justiniano et al. (2008) report that 65 percent of the variance of hours is explained by this type of disturbance and Smets and Wouters (2007) estimate that it explains about half of the forty-quarter ahead forecasting error variance of output. Our findings are consistent with these results. Wage-markup shocks explain 69 percent of the unconditional variance of hours growth and 17 percent of the unconditional variance of output growth. However, our results depart from the existing literature in that we find that virtually the totality of movements in hours and output due to wage markup shocks is attributable to its anticipated component. Specifically, we estimate that four-quarter-anticipated markup shocks explain 62 percent of the variance of employment growth and 16 percent of the variance of output growth. By contrast, unanticipated

Table 6: Variance Decomposition

Innovation	Y	C	I	h	G	TFP	A
Stationary Neutral Tech. Shock (z_t)							
ϵ_z^0	11	3	13	13	0	71	0
ϵ_z^4	1	0	1	1	0	4	0
ϵ_z^8	0	0	0	1	0	3	0
Nonstationary Neutral Tech. Shock (μ_t^x)							
$\epsilon_{\mu^x}^0$	14	9	7	2	4	17	0
$\epsilon_{\mu^x}^4$	1	1	0	1	0	2	0
$\epsilon_{\mu^x}^8$	1	1	0	1	1	2	0
Stationary Investment-Specific Tech. Shock (z_t^I)							
$\epsilon_{z^I}^0$	21	1	44	3	0	0	0
$\epsilon_{z^I}^4$	1	0	4	0	0	0	0
$\epsilon_{z^I}^8$	6	1	15	2	0	0	0
Nonstationary Investment-Specific Tech. Shock (μ_t^a)							
$\epsilon_{\mu^a}^0$	0	0	0	0	0	0	40
$\epsilon_{\mu^a}^4$	0	0	0	0	0	0	30
$\epsilon_{\mu^a}^8$	0	0	0	0	0	0	30
Government Spending Shock (g_t)							
ϵ_g^0	3	0	0	1	37	0	0
ϵ_g^4	4	0	0	1	35	0	0
ϵ_g^8	2	0	0	1	23	0	0
Preference Shock (ζ_t)							
ϵ_ζ^0	8	34	1	2	0	0	0
ϵ_ζ^4	4	14	0	1	0	0	0
ϵ_ζ^8	4	17	0	1	0	0	0
Wage-Markup Shock (μ_t)							
ϵ_μ^0	0	0	0	2	0	0	0
ϵ_μ^4	16	17	11	62	0	0	0
ϵ_μ^8	1	1	1	5	0	0	0

Note. Figures are in percent and correspond to the mean of 500,000 draws from the posterior distribution of the variance decomposition. The columns labeled Y, C, I, h, G, TFP, and A refer, respectively, to the growth rates of output, private consumption, investment, hours, government consumption, total factor productivity, and the relative price of investment.

variations in wage markups are estimated to have a negligible role in generating movements in hours and other indicators of aggregate activity. A possible interpretation of anticipated wage-markup shocks is that they represent expected outcomes of wage and benefit negotiations between employers and workers that are decided in the present but implemented with a lag.

The reason why anticipated wage-markup shocks are favored by our data sample is that they help account for the observed regularity that output and the main components of aggregate demand (consumption and investment spending) all lead employment. We document this pattern in Schmitt-Grohé and Uribe (2011b) section 5. There, we also show that the DSGE model's ability to capture this pattern diminishes when we shut off the four-period anticipated markup shock. The intuition behind this result is that an increase in expected wage markups represents an anticipated adverse cost-push shock to the economy. It induces firms to immediately cut spending in investment goods and to lower capacity utilization. It also induces households to adjust consumption downward upon the news, as they anticipate a decline in income. By contrast, labor supply does not adjust much on impact. This is because our estimated wealth elasticity of labor supply, governed by the parameter γ, is close to zero. Instead, the response of hours is delayed and takes place mostly once the markup shock is realized. In this way, the model captures the observed lagging behavior of employment relative to output and the components of aggregate demand.

6.4 Anticipated Government Spending Shocks

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 four or eight quarters. In the VAR 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. Mountford and Uhlig (2009) apply the sign restriction methodology due to Uhlig (2005) to identify anticipated and unanticipated fiscal shocks in vector autoregressions. Our proposed model-based methodology allows us to jointly evaluate the relative importance of both types of government spending shocks. Table 6 shows that 60 percent of the variance of government spending is due to anticipated shocks and 40 percent is to due to unanticipated shocks. Furthermore, the table shows that government spending shocks account for close to ten percent of the variance of output growth. This magnitude is standard in the literature. A 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. This result suggests that the VAR and narrative approaches to estimating the effects of government spending shocks are not mutually exclusive but complementary.

6.5 Investment-Specific Shocks

A growing literature is concerned with the macroeconomic effects of investment-specific shocks. Our economic environment embeds two such disturbances: A_t and z_t^I. The shock A_t affects the rate of transformation of consumption goods into investment goods, whereas z_t^I affects the rate of transformation of investment goods into installed capital. Table 6 shows that A_t is estimated to play no role in generating economic fluctuations. This result is in sharp contrast with that obtained by Justiniano et al. (2008) whose estimation assigns a central role to this disturbance. The reason for this discrepancy is that our estimation includes the relative price of investment as an observable, whereas the estimation in Justiniano et al. does not. As mentioned earlier, the relative price of investment is linearly linked to A_t. The negligible role of A_t in our estimation reflects the fact that the observed volatility of the relative price of investment is low. If we were to eliminate the price of investment from the set of observables, A_t would emerge as an important driver of aggregate fluctuations, but at the cost of an implied volatility of the relative price of investment several times larger than its observed counterpart.

On the other hand, the investment-specific shock z_t^I is estimated to explain a significant fraction of variation in output (28 percent) and investment (63 percent). This result is consistent with those reported in Justiniano et al. (2011). A novel result emerging from our investigation is that a substantial fraction of the contribution of z_t^I to aggregate volatility (about 30 percent) is due to its anticipated components.

6.6 No Anticipation in TFP Shocks

Finally, in line with many existing studies, we find that neutral technology shocks explain a sizable fraction of the variance of output growth, about 30 percent. However, we find that all of this contribution stems from the unanticipated component of TFP. The minor role assigned to anticipated neutral productivity shocks is a consequence of the fact that in our formulation this type of shock competes with a variety of other shocks. In Schmitt-Grohé and Uribe (2011b) section 7, we show that in the context of a more parsimonious shock specification that allows only for productivity and government spending shocks, the anticipated component of neutral technology shocks plays a major role in driving business cycles.

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

Panel 5 of table 5 shows that the role of anticipated shocks is also estimated to be prominent when 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 or prior distribution, depending on whether we are computing posterior or prior share densities. (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 endogenous variable of interest (i.e., output, consumption, investment, and hours) 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 endogenous variable considered. (5) We repeat steps (1)-(4) 500,000 times and report the median shares as well as the fifth and ninety fifth percentiles. 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 47 percent when the cycle is measured using simulated, HP-filtered time series. Overall, anticipated shocks explain between 46 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.

6.8 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 considered 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. In the theoretical model, we associate this variable with the value of the firm at the beginning of the period, V_t^F, defined in section 3. Panel 4 of table 5 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, the median share of their unconditional variance explained by anticipated shocks ranges from 55 to 82 percent when stock prices are included in the estimation. Moreover, the posterior distributions of the shares of variances explained by anticipated shocks are more concentrated around their medians pointing more clearly to their importance. 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, 2011). 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.

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 identification methodology represents a fundamental departure from VAR-based approaches to the identification of anticipated shocks. For it exploits the fact that in theoretical environments in which agents are forward looking, endogenous variables, such as output, consumption, investment, and employment, react to anticipated changes in fundamentals, whereas the fundamentals themselves do not. Moreover, the fact that economic agents' responses to future changes in economic fundamentals depend on how far into the future the change is expected to occur, allows our empirical strategy to identify horizon-specific anticipated shocks.

Our central finding is that, in the context of our model, 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 those in 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.

Appendix: Data Sources

The time series used to construct the seven 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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