What's News In Business Cycles*

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Abstract

In this paper, we perform a structural Bayesian estimation 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 four real rigidities: investment adjustment costs, variable capacity utilization, habit formation in consumption, and habit formation in leisure. Business cycles are assumed to be driven by permanent and stationary neutral productivity shocks, permanent investment-specific shocks, and government spending shocks. Each of these shocks is buffeted by four types of structural innovations: unanticipated innovations and innovations anticipated one, two, and three quarters in advance. We find that anticipated shocks account for more than two thirds of predicted aggregate fluctuations. This result is robust to estimating a variant of the model featuring a parametric wealth elasticity of labor supply. (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 central goal of this paper is to present a model-based econometric answer to these questions.

Specifically, we formulate a dynamic, stochastic, general equilibrium (DSGE) model of the U.S. economy driven by a large number of unanticipated and anticipated shocks. We then apply Bayesian methods to estimate the parameters defining the stochastic processes of these 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.

Our assumed theoretical environment is a real-business-cycle model augmented with four real rigidities: internal habit formation in consumption, internal habit formation in leisure, investment adjustment costs, and variable capacity utilization. In incorporating these frictions into our equilibrium business-cycle model, we are guided by a large existing literature showing that these frictions improve the model's empirical fit. Our model is assumed to be driven by four structural shocks. Namely, stationary neutral productivity shocks, nonstationary neutral productivity shocks, nonstationary investment-specific productivity shocks, and government spending shocks.

The novel element in our theoretical formulation is the assumption that each of the four structural shocks features an anticipated component and an unanticipated component. The anticipated component is, in turn, driven by innovations announced one, two, or three quarters in advance. We estimate the model using Bayesian methods on U.S. postwar quarterly data.

We find that anticipated shocks are the most important source of uncertainty: They explain about two thirds of the variance of output, consumption, investment, and hours worked. Moreover, our results suggest that what matters most are anticipated changes in the future path of total factor productivity (TFP). Indeed, anticipated shocks to the permanent and stationary components of total factor productivity jointly explain more than two thirds of the variance of output growth. By contrast anticipated movements in investment-specific productivity or government spending play virtually no role in driving business cycles.

We find that in response to the most important estimated anticipated shock, namely, anticipated stationary changes in productivity, output, consumption, investment, and hours all increase. The increase in hours is driven by a sharp increase in capacity utilization, which drives up the marginal product of labor, thereby boosting labor demand. In response to the second most important anticipated shock, namely anticipated changes in the permanent component of TFP, we find that output, investment, and consumption comove, which is in line with the empirical evidence presented in Beaudry and Portier (2006). However, contrary to the empirical evidence presented by these authors, our estimated model predicts a contraction in hours worked in response to an anticipated permanent increase in TFP.

The predicted contraction in hours is the consequence of a positive wealth effect induced by the expected future increase in TFP, which elevates the demand for leisure. In a recent theoretical paper, Jaimovich and Rebelo (2008) emphasize that one way to produce positive comovement of output, consumption, investment, and hours in response to permanent expected future changes in TFP is to assume a preference specification that minimizes the wealth elasticity of labor supply as in Greenwood, Hercowitz, and Huffman (1988). Jaimovich and Rebelo generalize the Greenwood et al. preference specification by introducing a parameter that controls the strength of the wealth elasticity of labor supply. We estimate a variant of our model that incorporates preferences of the type suggested by Jaimovich and Rebelo and find a near-zero wealth elasticity of labor supply. Also, our estimates indicate that under this preference specification anticipated shocks explain the majority of aggregate fluctuations at business-cycle frequency. This result is in accordance with those obtained under our baseline preference specification. Furthermore, our estimate of the model with Jaimovich-Rebelo preferences improves over the baseline model in that it predicts an increase in hours in response to an anticipated permanent change in total factor productivity.

The idea that changes in expectations about the future path of exogenous economic fundamentals may represent an important source of aggregate fluctuations has a long history in economics, going back at least to Pigou (1927). Recently, these ideas have been revived in an important paper by Beaudry and Portier (2006). These authors propose an identification scheme for uncovering anticipated shocks in the context of a vector error correction model for total factor productivity and stock prices. Beaudry and Portier's findings suggest that innovations in the growth rate of total factor productivity are to a large extent anticipated. Moreover, the anticipated shock they identify explains more than 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 in two important dimensions: first our estimation is based on a formal dynamic, stochastic, optimizing, rational expectations model. Second, we employ a full information econometric approach to estimation. This strategy allows us to identify a larger set of anticipated disturbances than does the VECM approach of Beaudry and Portier. In particular, it allows us to identify not only anticipated changes in the growth rate of total factor productivity, but also other anticipated sources of economic fluctuations, such as anticipated changes in the stationary component of total factor productivity, in government spending, and in the growth rate of the relative price of investment. This turns out to be an important distinction. For we find that, although news about the nonstationary component of total factor productivity are a significant source of business cycles, as suggested by the work of Beaudry and Portier, so are news about future expected changes in the stationary component of total factor productivity. An additional advantage of our estimation strategy is that it allows us to identify the length of anticipation for each source of disturbance. For example, we find that stationary changes in productivity are for the most part anticipated three quarters in advance, whereas nonstationary changes in productivity are estimated to be learned only one quarter in advance.

In this paper, we draw an important distinction between the effect of anticipated shocks and the pure anticipation effect. This distinction is in order because anticipated shocks eventually materialize in actual changes in exogenous economic fundamentals. In computing aggregate volatilities in an economy buffeted by anticipated shocks, one necessarily puts in the same bag the economic effects triggered by anticipation and the economic effects triggered by the eventual realization of the anticipated shocks. To disentangle these two effects, we define the pure anticipation effect as the difference between the volatilities of two economies that differ only in the information set available to economic agents. In one economy agents are able to anticipate some components of future changes in exogenous economic fundamentals, whereas in the other economy agents are unable to do so. We find that at short horizons the pure anticipation effect is significant. In particular, we show that the variance of forecasting errors at horizons below 8 quarters can be remarkably different in the economies with and without anticipation. We also find that in the long run, the pure anticipation effect is small.

The present paper is related to Davis (2007) who in independent and contemporaneous work estimates the effect of anticipated shocks in a model with nominal rigidities. He finds that anticipated shocks explain about half of the volatility of output growth, which is consistent with the results reported in this paper. However, contrary to our results and those reported in Beaudry and Portier (2006), Davis finds a negligible role for anticipated shocks to TFP. Instead, he finds that the most important source of news shocks are anticipated changes in the relative price of investment.[1]

The remainder of the paper is organized in nine sections. Section 2 presents the theoretical model. Section 3 explains how to introduce anticipated disturbances into the model and derives the autoregressive representation of the exogenous stochastic state variables.

[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.

This section also demonstrates that our model of anticipated shocks nests as a special case a model of technological diffusion. In addition, this section shows that our framework can accommodate revisions in expectations, such as anticipated increases in productivity that fail to materialize. Section 4 presents a Bayesian estimation of the deep structural parameters of the model, including those defining the stochastic processes of the anticipated and unanticipated components of the four assumed sources of business cycles. Section 5 contains the central result of the paper. It performs a variance decomposition of output growth and other macroeconomic indicators of interest into anticipated and unanticipated sources of uncertainty. Section 6 defines and estimates the pure anticipation effect. Section 7 relates the findings of our paper to those obtained using a structural VECM approach. Section 8 discusses the dynamic effects of anticipated shocks. Section 9 estimates a variant of the model in which agents have preferences of the type developed by Jaimovich and Rebelo (2008). Finally, section 10 concludes.

2 The Model

Consider an economy populated by a large number of identical, infinitely lived agents with habit-forming preferences defined over consumption, C_t, and leisure, ℓ_t, and described by the utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t - \theta_c C_{t-1}, \ell_t - \theta_\ell \ell_{t-1}), \tag{1}$$

where β denotes the subjective discount factor and θ_c and θ_ℓ govern the degree of internal habit formation in consumption and leisure, respectively. It is well known that habit formation helps explain the smooth observed behavior of consumption. Habits in leisure are less frequently introduced in business-cycle models. We motivate this feature as a natural way to introduce adjustment costs in hours worked. In a recent paper, Jaimovich and Rebelo (2008) suggest that adjustment costs in labor effort helps prevent a decline in equilibrium employment in response to anticipated productivity shocks. In effect, an anticipated increase in productivity produces a wealth effect that induces households to work less. However, it also makes households anticipate an increase in labor effort at the time the productivity shock actually materializes. With labor adjustment costs, the prospect of having to increase hours in the future provides an incentive for households to start adjusting labor supply upward already at the moment they receive the news.

We note that the introduction of habit formation implies adjustment costs in the supply of labor. Alternatively, one could model adjustment costs in labor demand, as in Cogley and Nason (1995). These authors model adjustment costs in labor as a direct resource cost that is proportional to the level of output. This proportionality ensures that labor adjustment costs do not vanish along the growth path of the economy. In the habit formation formulation presented here the condition that adjustment costs not fade over time is satisfied when preferences are consistent with long-run balanced growth. In turn, this latter condition is satisfied by the following assumed functional form for the period utility function:

$$U(x,y) = \frac{(xy^{\chi})^{1-\sigma} - 1}{1-\sigma},$$

with $\chi > 0$ and $\sigma > 1$.

We normalize the total time endowment per period to unity. Then hours worked, denoted h_t, are given by

$$h_t = 1 - \ell_t. \tag{2}$$

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

$$K_{t+1} = (1 - \delta(u_t))K_t + I_t \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right], \tag{3}$$

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 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.

Output, denoted Y_t, is produced with a homogeneous-of-degree-one production function that takes as inputs capital and labor services. This 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

$$Y_t = z_t F(u_t K_t, X_t h_t), \tag{4}$$

where F is taken to be of the Cobb-Douglas form:

$$F(x, y) = x^{\alpha} y^{1-\alpha},$$

where $\alpha \in (0, 1)$ is a parameter.

The government is assumed to consume an exogenous and stochastic amount of goods G_t each period. The resource constraint of the economy is given by

$$C_t + A_t I_t + G_t = Y_t. \tag{5}$$

The variable A_t denotes the technical rate of transformation between consumption and investment goods. It is assumed to be exogenous and stochastic. In a decentralized equilibrium A_t represents the relative price of investment goods in terms of consumption goods.

Because this economy is free of distortions, the competitive equilibrium allocation coincides with the solution to a social planner problem consisting in choosing nonnegative processes C_t, h_t, ℓ_t, K_{t+1}, u_t, Y_t, and I_t to maximize (1) subject to (2)-(5), given K_0 and exogenous processes for G_t, X_t, A_t, and z_t. Letting $\Lambda_t Q_t$ and Λ_t denote the Lagrange multipliers on (3) and (5), respectively, the first-order conditions associated with this problem are (2)-(5), and

$$U_1(C_t - \theta_c C_{t-1}, \ell_t - \theta_\ell \ell_{t-1}) - \theta_c^i \beta E_t U_1(C_{t+1} - \theta_c C_t, \ell_{t+1} - \theta_\ell \ell_t) = \Lambda_t$$

$$U_2(C_t - \theta_c C_{t-1}, \ell_t - \theta_\ell \ell_{t-1}) - \theta_\ell^i \beta E_t U_2(C_{t+1} - \theta_c C_t, \ell_{t+1} - \theta_\ell \ell_t) = \Lambda_t z_t X_t F_2(u_t K_t, X_t h_t)$$

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

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

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

Here, 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 average Tobin's Q, which refers to the value of the firm per unit of installed capital. Let V_t denote the value of the firm at the beginning of period t. Then one can write V_t recursively as:

$$V_t = Y_t - W_t h_t - A_t I_t + \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t} V_{t+1},$$

where $W_t \equiv X_t F_2(u_t K_t, X_t h_t)$ denotes the real wage rate that would result in a decentralized version of our neoclassical economy and is given by the marginal product of labor. This 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, because households are assumed to be the owners of the firms. Using the particular Cobb-Douglas form assumed for the production function, we can then rewrite the above expression as

$$V_t = \alpha Y_t - A_t I_t + \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t} V_{t+1}.$$

Average Tobin's Q is defined as V_t/K_t, which we denote by Q_t^a. Using the above expression we can write Q_t^a recursively as

$$Q_t^a = \alpha \frac{Y_t}{K_t} - \frac{A_t I_t}{K_t} + \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t} \frac{K_{t+1}}{K_t} Q_{t+1}^a.$$

As we will discuss later on, marginal and average Q have very similar dynamic properties in our estimated model.

3 Introducing Anticipated Shocks

The model is driven by four exogenous forces: the stationary neutral productivity shock z_t, the nonstationary neutral productivity shock X_t, the investment-specific productivity shock A_t, and the government spending shock G_t. We assume that all of these forces are subject to anticipated as well as unanticipated innovations.

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

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

We impose the following structure on the error term μ_t:

$$\mu_t = \epsilon_{x,t}^0 + \epsilon_{x,t-1}^1 + \epsilon_{x,t-2}^2 + \epsilon_{x,t-3}^3,$$

where $\epsilon^j_{x,t}$ for $j = 0, 1, 2$, and 3 denotes j-period anticipated changes in the level of x_t. For example, $\epsilon^2_{x,t-2}$ is an innovation to the level of x_t that materializes in period t, but that agents learn about in period $t-2$. Therefore, $\epsilon^2_{x,t-2}$ is in the period $t-2$ information set of economic agents but results in an actual change in the variable x_t only in period t. We thus say that $\epsilon^2_{x,t-2}$ is a 2-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 horizon. That is, $E\epsilon^j_{x,t}\epsilon^k_{x,t-m} = 0$ for $k, j = 0, 1, 2, 3$ 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 μ_t is unconditionally mean zero and serially uncorrelated, that is, $E\mu_t = 0$ and $E\mu_t\mu_{t-m} = 0$ for $m > 0$. Moreover, the error term μ_t is unforecastable given only past realizations of itself. That is, $E(\mu_{t+m}|\mu_t, \mu_{t-1}, \dots) = 0$, for $m > 0$.

The key departure of this paper from standard business-cycle analysis is the assumption that economic agents have an information set much larger than one simply containing current and past realizations of μ_t. In particular, agents are assumed to observe in period t current and past values of the innovations $\epsilon^0_{x,t}$, $\epsilon^1_{x,t}$, $\epsilon^2_{x,t}$, and $\epsilon^3_{x,t}$. That is, agents can forecast future values of μ_t as follows:

$$E_t\mu_{t+1} = \epsilon^1_{x,t} + \epsilon^2_{x,t-1} + \epsilon^3_{x,t-2}$$

$$E_t\mu_{t+2} = \epsilon^2_{x,t} + \epsilon^3_{x,t-1}$$

$$E_t\mu_{t+3} = \epsilon^3_{x,t}$$

$$E_t\mu_{t+m} = 0; \quad m \geq 4.$$

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, leisure, 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.

3.1 Autoregressive Representation of Anticipated Shocks

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

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

where

$$\tilde{x}_t = \begin{bmatrix} x_t \\ \epsilon^1_{x,t} \\ \epsilon^2_{x,t} \\ \epsilon^3_{x,t} \\ \epsilon^2_{x,t-1} \\ \epsilon^3_{x,t-1} \\ \epsilon^3_{x,t-2} \end{bmatrix}; \quad M = \begin{bmatrix} \rho & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}; \quad \eta = \begin{bmatrix} \sigma^0_x & 0 & 0 & 0 \\ 0 & \sigma^1_x & 0 & 0 \\ 0 & 0 & \sigma^2_x & 0 \\ 0 & 0 & 0 & \sigma^3_x \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}; \quad \nu_t = \begin{bmatrix} \nu^0_t \\ \nu^1_t \\ \nu^2_t \\ \nu^3_t \end{bmatrix}.$$

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 four driving forces in our model. Specifically, the stationary neutral productivity shock is assumed to obey the following law of motion

$$\ln z_t = \rho_z \ln z_{t-1} + \epsilon^0_{z,t} + \epsilon^1_{z,t-1} + \epsilon^2_{z,t-2} + \epsilon^3_{z,t-3},$$

where $\epsilon^i_{z,t}$ is an i.i.d. normal innovation with mean 0 and standard deviation σ^i_z for $i = 0, 1, 2, 3$. The disturbance $\epsilon^0_{z,t}$ is an unanticipated shock to z_t. This is the standard type of shock assumed in most existing business-cycle models. The disturbance $\epsilon^1_{z,t}$ represents an innovation to z_{t+1}, which is announced in period t but materializes only in period $t+1$. Note that $\epsilon^1_{z,t}$ does not appear in the expression for z_t given above. Rather, the above expression features $\epsilon^1_{z,t-1}$, the one-period-ahead announcement in period $t-1$. Similarly, $\epsilon^2_{z,t}$, and $\epsilon^3_{z,t}$ represent two- and three-period-ahead announcements of future changes in the level of technology.

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

$$\ln X_t = \ln X_{t-1} + \ln \mu^x_t,$$

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

$$\ln(\mu^x_t/\mu^x) = \rho_x \ln(\mu^x_{t-1}/\mu^x) + \epsilon^0_{x,t} + \epsilon^1_{x,t-1} + \epsilon^2_{x,t-2} + \epsilon^3_{x,t-3}, \tag{6}$$

where $\epsilon^i_{x,t}$ is an i.i.d. process distributed normally with mean zero and standard deviation σ^i_x, for $i = 0, 1, 2, 3$. Here $\epsilon^0_{x,t}$ represents the unanticipated component of the innovation to the growth rate of the permanent neutral productivity shock, and $\epsilon^1_{x,t}$, $\epsilon^2_{x,t}$, and $\epsilon^3_{x,t}$, represent productivity changes anticipated one, two, and three quarters, respectively. 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

$$\ln A_t = \ln A_{t-1} + \ln \mu^a_t,$$

with the gross growth rate of A_t, denoted μ^a_t, following the stationary autoregressive process

$$\ln(\mu^a_t/\mu^a) = \rho_a \ln(\mu^a_{t-1}/\mu^a) + \epsilon^0_{a,t} + \epsilon^1_{a,t-1} + \epsilon^2_{a,t-2} + \epsilon^3_{a,t-3}.$$

The innovations $\epsilon^i_{a,t}$ are assumed to be i.i.d. normal with mean zero and standard deviation σ^i_a for $i = 0, 1, 2, 3$. Here again, $\epsilon^0_{a,t}$ denotes the unanticipated innovation in the growth rate of the relative price of investment, and $\epsilon^1_{a,t}$, $\epsilon^2_{a,t}$, and $\epsilon^3_{a,t}$ represent anticipated changes in the growth rate of the relative price of investment. The parameter μ^a represents the drift in the price of investment.

We assume that government spending, G_t, displays a stochastic trend given by X^G_t. We let $g_t \equiv G_t/X^G_t$ denote detrended government spending. The trend in government spending is assumed to be cointegrated with the trend in output, denoted X^Y_t. 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

$$X^G_t = \left(X^G_{t-1}\right)^{\rho_{xg}} \left(X^Y_{t-1}\right)^{1-\rho_{xg}},$$

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 $X^Y_t = X_t A_t^{\alpha/(\alpha-1)}$. Log deviations of government spending from trend are assumed to follow the autoregressive process

$$\ln(g_t/g) = \rho_g \ln(g_{t-1}/g) + \epsilon^0_{g,t} + \epsilon^1_{g,t-1} + \epsilon^2_{g,t-2} + \epsilon^3_{g,t-3},$$

where $\epsilon^i_{g,t}$ is assumed to be an i.i.d. normal innovation with mean 0 and standard deviation σ^i_g, for $i = 0, 1, 2, 3$. This specification implies that innovations in government spending have a unanticipated component, given by $\epsilon^0_{g,t}$, and anticipated components given by $\epsilon^1_{g,t}$, $\epsilon^2_{g,t}$, and

$\epsilon^3_{g,t}$. Notice that X^G_t resides in the information set of period $t-1$. This fact together with 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.

3.2 A Special Case: Technological Diffusion

The stochastic and informational structure assumed above encompasses as a special case the model of technological diffusion presented in Beaudry and Portier (2006). Specifically, these authors assume that the nonstationary component of TFP, X_t, evolves over time according to the following law of motion:

$$\ln X_t = \sum_{i=0}^{\infty} d_i \eta_{t-i},$$

where η_t is white noise with standard deviation σ_η, and d_i is given by

$$d_i = 1 - \phi^i; \quad \phi \in [0, 1).$$

Notice that $d_0 = 0$ and that d_i increases monotonically with i, reaching a maximum value of one. This means that in this model technological innovations are incorporated gradually into the production process.

We wish to show that this diffusion process is a special case of the informational structure described above. To see this, apply the temporal difference operator to $\ln X_t$ to obtain

$$\ln X_t - \ln X_{t-1} = (1-\phi) \sum_{i=1}^{\infty} \phi^{i-1} \eta_{t-i}.$$

This expression can be written recursively as

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

Comparing this expression with equation (6), and recalling the notation $\mu^x_t \equiv \ln X_t - \ln X_{t-1}$, we have that the diffusion model is a special case of our assumed stochastic structure with $\sigma^1_x = (1-\phi)\sigma_\eta$, $\sigma^0_x = \sigma^2_x = \sigma^3_x = 0$, $\rho_x = \phi$, and $\mu^x = 1$.

3.3 Accommodating Revisions

The structure given above to anticipated and unanticipated innovations is flexible enough to accommodate revisions in announcements. The innovation $\epsilon^0_{z,t}$, for instance, can be thought of as incorporating period t revisions to announcements made in period $t-1$ or earlier regarding the level of productivity in period t.

Similarly, the innovation $\epsilon^1_{z,t}$ can be thought of as incorporating period t revisions to announcements made in period $t-1$ or earlier regarding the level of productivity in period $t+1$. More generally, $\epsilon^i_{z,t}$ can be interpreted as containing period-t revisions to announcements made in period $t-1$ or earlier regarding the level of productivity in period $t+i$.

A similar interpretation can be assigned to innovations to the growth rate of nonstationary neutral productivity, the growth rate of investment specific productivity, and deviations of government spending from trend.

3.4 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. Appendix A describes this transformation and presents the complete set of equilibrium conditions in stationary form.

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

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

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

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 μ_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.

Table 1: Calibrated Parameters

Parameter	Value	Description
β	0.973	Subjective discount factor
σ	2	Intertemporal elasticity of substitution
α	0.3	Capital share
δ_0	0.025	Steady-state depreciation rate
u	1	Steady-state capacity utilization rate
μ^y	1.0045	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

Note: The time unit is one quarter.

4 Estimating Anticipated Shocks

We use Bayesian 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 unanticipated and anticipated innovations. The parameters that are not estimated are calibrated in a standard fashion.

4.1 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 2 to σ, the parameter defining the curvature of the period utility function. This value is standard in the business-cycle literature. We set α equal to 0.3, which implies a labor share of 70 percent. We assume that the annual depreciation rate is 10 percent. We calibrate the parameter δ_1 to ensure that capacity utilization, u, equals unity in the steady state. We follow Campbell and Cochrane (1999) and set the discount factor equal to 0.973 per quarter. This value of β matches the mean risk-free rate in their habit-formation model with the average real return on Treasury bills. It delivers a relatively high deterministic-steady-state interest rate of about 11 percent. Note that the exercise in Campbell and Cochrane consists in matching the average risk-free rate that emerges in a stochastic environment rather than the interest rate associated with the nonstochastic steady state. Our results are robust to assuming higher values of β that are more conventional in the RBC literature.

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. 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.

4.2 Estimated Parameters

We perform a Bayesian estimation of the noncalibrated structural parameters of the model. We follow the methodology described in the survey by An and Schorfheide (2007). 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. Then, 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 $L(Y|\Theta)P(\Theta)$. We use the Metropolis-Hastings algorithm to obtain draws from the posterior distribution of Θ.

The vector of estimated parameters, Θ, is given by the parameters defining the stochastic process for anticipated and unanticipated innovations, namely, σ_j^i for $i = 0, 1, 2, 3$ and $j = z, x, a, g$. In addition, the parameter vector Θ includes the parameters governing the persistence of the four structural shocks in the model, ρ_j for $j = z, x, a, g$, the parameter governing the smoothness in the trend component of government spending, ρ_{xg}, the parameters defining habits in consumption and leisure, θ_c and θ_ℓ, respectively, the preference parameter χ linked to the Frisch elasticity of labor supply, the parameter governing the convexity of the cost of adjusting capacity utilization, δ_2, 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 includes six time series: the per capita growth rates of real GDP, real consumption, real investment, and real government expenditure, the growth rate of the relative price of investment, and the logarithm of the level of per capita hours worked. We assume that all six time series contain measurement error. Formally, the vector of observable variables is given by

$$\begin{bmatrix} \Delta \ln(Y_t) \\ \Delta \ln(C_t) \\ \Delta \ln(A_t I_t) \\ \ln(h_t) \\ \Delta \ln(G_t) \\ \Delta \ln(A_t) \end{bmatrix} \times 100 + \begin{bmatrix} \epsilon_{y,t}^{me} \\ \epsilon_{c,t}^{me} \\ \epsilon_{i,t}^{me} \\ \epsilon_{h,t}^{me} \\ \epsilon_{g,t}^{me} \\ \epsilon_{a,t}^{me} \end{bmatrix},$$

Table 2: Prior Distributions

Parameter	Distribution	Mean	Std. Dev.	Lower Bound	Upper Bound
σ_j^0	Uniform			0	$5\sqrt{3}$
σ_j^i	Uniform			0	5
σ_k^{me}	Uniform			0	$\frac{1}{4}\widehat{\sigma}_k$
δ_2	Uniform			0.01	10
θ_c, θ_ℓ	Beta*	0.5	0.1	0	0.99
$\rho_z, \rho_g, \rho_{xg}$	Beta*	0.7	0.2	0	0.99
ρ_x	Beta*	0	0.1	-0.5	0.5
ρ_a	Beta*	0.5	0.1	0	0.7
κ, χ	Gamma	4.0	1.0	0	∞

Note. $i = 1, 2, 3$, $j = z, x, a, g$, me=measurement error, $k = y, c, i, h, g, a$. The symbol $\widehat{\sigma}_k$ denotes the sample standard deviation of the empirical measure of variable k. Beta* indicates that a linear transformation of the parameter has a beta prior distribution.

where Δ denotes the temporal difference operator and $\epsilon_{k,t}^{me}$ is an i.i.d. innovation with mean zero and standard deviation σ_k^{me}, denoting the error made in period t in measuring variable k, for $k = y, c, i, h, g$, and a. The appendix provides more detailed information about the data used in the estimation of the model.

4.2.1 Prior Distributions

Table 2 displays the assumed prior distribution $P(\Theta)$ of the estimated structural parameters contained in the vector Θ. Because we could find no studies that helped us form priors on the importance of the various anticipated disturbances modeled in this paper, we deliberately choose flat and quite disperse priors. Specifically, we assign a common uniform prior distribution to the standard deviation of the twelve anticipated shocks, σ_j^i, for $i = 1, 2, 3$ and $j = z, x, a, g$, with a lower bound of 0 and an upper bound of 5 percent. We also assign a common uniform prior distribution to the standard deviations of the four unanticipated innovations, σ_j^0, for $j = z, x, a, g$, with a lower bound of 0 and an upper bound of $5\sqrt{3}$ percent. The larger upper bound in the prior distribution of the unanticipated shocks guarantees that at the mean of the prior distribution, the variance of the unanticipated component of each shock equals the sum of the variances of the associated anticipated components. Our choice of priors, which makes all unanticipated shocks taken together as important as all anticipated shocks taken together, is guided by the work of Beaudry and Portier (2006) who find that at least 50 percent of the variance of output growth is explained by anticipated shocks.

We also choose uniform prior distributions for the standard deviation of measurement errors. We restrict the standard deviation of measurement errors in the observable variables to be at most 25 percent of the standard deviations of the corresponding empirical variables. Our results are robust to choosing upper bounds for these uniform distributions equal to 50 or 75 percent of the standard deviations of the underlying observable variables.

We also give a uniform prior distribution to the parameter δ_2, which measures the convexity of the function relating the rate of capacity utilization to the depreciation rate. We bound δ_2 away from zero by setting the lower bound of the prior distribution to 0.01. Such a lower bound is necessary because capacity utilization is indeterminate up to first order when the depreciation rate increases linearly with the rate of capacity utilization.

We assign beta distributions to linear transformations of the parameters defining the strength of habit formation in consumption and leisure, θ_c and θ_ℓ, the autoregressive coefficients of the four exogenous shocks, ρ_z, ρ_g, ρ_x, ρ_a, and the smoothing parameter of the trend component of government purchases, ρ_{xg}. We assume that the parameters ρ_z, ρ_g, ρ_{xg}, θ_c, and θ_ℓ divided by 0.99 have a beta prior distribution, so that the maximum value that these parameters can take is 0.99. We introduce this linear transformation to avoid numerical instability when evaluating the likelihood at near-unity values for these parameters.

The prior mean for the consumption habit formation parameter θ_c is 0.5, a value that is within the range of values used in the related literature. There is little independent econometric evidence on the degree of habit formation in leisure. Calibrated models with habits in leisure are also rare. An exception is Lettau and Uhlig (2000) who study the asset pricing implications of a real-business-model with habits in leisure and consumption. They consider two extreme calibrations of the habit parameter for leisure, 0 and 0.95. The mean of our prior for θ_ℓ falls between these two values.

Stationary neutral productivity shocks as well as government spending shocks are typically estimated to be highly persistent. Based on this fact, we choose a relatively high mean value of 0.7 for the prior distributions of the serial correlations ρ_z and ρ_g as well as for the smoothness parameter in the trend component of government spending, ρ_{xg}. By contrast, the growth rate of the nonstationary component of total factor productivity is typically estimated to have a near-zero serial correlation (e.g., Cogley and Nason, 1995). Accordingly, we set the mean of the prior distribution of ρ_x at a value of 0, and assume that $\rho_x + 0.5$ follows a beta prior distribution.

Our time series for the relative price of investment has a serial correlation of 0.5. We therefore set the mean of the prior distribution of ρ_a equal to 0.5. We assume that $\rho_a/0.7$ has a beta prior distribution, which allows for a maximum value of 0.7 for ρ_a itself.

Finally, we adopt gamma prior distributions with mean equal to 4 for the parameters χ

and κ governing the elasticity of labor supply and the cost of adjusting investment. This assumption implies that at the mean of the prior the Frisch elasticity of labor supply is 1.3 in the absence of habit formation in leisure. The mean of the prior distribution of κ is in line with existing priors of this parameters (e.g., Justiniano, Primiceri, and Tambalotti, 2008).

4.2.2 Posterior Distributions

Table 3 displays salient aspects of the posterior distribution of the parameter vector Θ. It displays the mean of the posterior distribution and 90-percent posterior intervals. These statistics were computed from a chain of 10 million draws generated using a random walk Metropolis-Hastings algorithm discarding the first 6 million draws.

The estimated process for the stationary neutral productivity shock, z_t, is highly persistent and driven mostly by unanticipated innovations, $\epsilon^0_{z,t}$ and three-quarter-ahead anticipated innovations, $\epsilon^3_{z,t}$. Both of these disturbances have a standard deviation of about 3 percent per quarter and are tightly estimated. One- and two-quarter-ahead anticipated innovations are estimated to have a significantly smaller standard deviation of about 0.6 and display much more dispersed distributions.

The posterior distributions of the parameters defining the process for the growth rate of the nonstationary neutral productivity shock, μ^x_t, are shown in the second panel of table 3. The persistence parameter, ρ_x, is centered at a value of 0.14, implying virtually no serial correlation in the growth rate of the permanent component of TFP. The most important component of the innovation to μ^x_t is estimated to be $\epsilon^1_{x,t}$, the one-quarter-ahead anticipated disturbance. Its standard deviation, σ^1_x, has a large posterior mean of 2.3 percent. All other disturbances to this process have smaller posterior means and relatively flatter distributions.

The estimated mean of the standard deviations of the innovations to the remaining two exogenous processes, namely, the growth rate of investment-specific technological change, μ^a_t, and deviations of government spending from trend, g_t, are relatively small in magnitude.

We obtain relatively tight posterior distributions for the structural parameters defining preferences and technology. Our estimates indicate a significant amount of habit formation in consumption, with a posterior mean of θ_c equal to 0.85. This value is in consistent with a large number of existing estimates. The degree of habit formation in leisure is also estimated to be substantial, with a 90-percent posterior interval of θ_ℓ equal to $(0.50, 0.63)$. The estimated posterior mean of the preference parameter χ is 6.1. It suggests a relatively low Frisch elasticity of labor supply of about unity, a value consistent with a number of calibrated and estimated real-business-cycle studies. Our estimate of κ, the parameter governing investment adjustment costs, is 5.0. This value is somewhat higher than those estimated in related studies. These studies, however, generally include nominal frictions in the form of sticky

Table 3: Posterior Distributions

Parameter	Prior distribution			Posterior distribution		
	Distribution	Mean	Std. Dev.	Mean	5 percent	95 percent
	Stationary Neutral Productivity Shock					
ρ_z	Beta*	0.7	0.2	0.89	0.87	0.91
σ_z^0	Uniform	4.3	2.5	2.7	2.4	3.1
σ_z^1	Uniform	2.5	1.4	0.56	0.05	1.3
σ_z^2	Uniform	2.5	1.4	0.56	0.05	1.3
σ_z^3	Uniform	2.5	1.4	3.0	2.5	3.6
	Nonstationary Productivity Shock					
ρ_x	Beta*	0	0.1	0.14	0.0	0.27
σ_x^0	Uniform	4.3	2.5	0.59	0.05	1.4
σ_x^1	Uniform	2.5	1.4	2.3	1.6	3.0
σ_x^2	Uniform	2.5	1.4	1.3	0.2	2.4
σ_x^3	Uniform	2.5	1.4	1.1	0.1	2.0
	Investment-Specific Productivity Shock					
ρ_a	Beta*	0.5	0.1	0.52	0.43	0.61
σ_a^0	Uniform	4.3	2.5	0.13	0.01	0.29
σ_a^1	Uniform	2.5	1.4	0.14	0.01	0.3
σ_a^2	Uniform	2.5	1.4	0.16	0.02	0.31
σ_a^3	Uniform	2.5	1.4	0.16	0.02	0.31
	Government Spending Shock					
ρ_g	Beta*	0.7	0.2	0.98	0.97	0.99
ρ_{xg}	Beta*	0.7	0.2	0.99	0.99	0.99
σ_g^0	Uniform	4.3	2.5	0.40	0.03	0.89
σ_g^1	Uniform	2.5	1.4	0.51	0.05	1.0
σ_g^2	Uniform	2.5	1.4	0.63	0.08	1.1
σ_g^3	Uniform	2.5	1.4	0.38	0.03	0.86
	Preference and Technology Parameters					
θ_c	Beta*	0.5	0.1	0.85	0.83	0.88
θ_ℓ	Beta*	0.5	0.1	0.56	0.49	0.62
κ	Gamma	4.0	1.0	5.0	4.1	6.0
δ_2	Uniform	5.0	2.9	0.11	0.08	0.15
χ	Gamma	4.0	1.0	6.1	4.5	8.0
	Measurement Errors					
$\sigma_{g^Y}^{me}$	Uniform	0.11	0.065	0.23	0.23	0.23
$\sigma_{g^C}^{me}$	Uniform	0.064	0.036	0.13	0.12	0.13
$\sigma_{g^I}^{me}$	Uniform	0.29	0.16	0.56	0.55	0.57
$\sigma_{g^g}^{me}$	Uniform	0.14	0.082	0.28	0.27	0.28
σ_h^{me}	Uniform	0.51	0.29	0.80	0.60	0.98
$\sigma_{\mu^a}^{me}$	Uniform	0.051	0.029	0.07	0.01	0.10

Note: Results are based on the last 4 million elements of a 10-million MCMC chain of draws from the posterior distribution. Beta* indicates that a linear transformation of the parameter has a beta prior distribution.

Table 4: Share of Variance Explained by Anticipated Shocks

	g^Y	g^C	g^I	h
Mean Share	0.70	0.85	0.58	0.68
90-percent interval				
5 Percent	0.63	0.76	0.50	0.58
95 Percent	0.77	0.90	0.66	0.76

Note: Results are based on the last 4 million elements of a 10-million MCMC chain of draws from the posterior distribution.

prices and wages, which are absent in the present model. The mean posterior of δ_2, the parameter measuring the convexity of the function relating the rate of capacity utilization to the depreciation rate is 0.11. This value implies an elasticity of capacity utilization with respect to the rental rate of capital of 0.6. This elasticity is larger than the one found in related Bayesian estimations of DSGE models with nominal rigidities and no anticipated shocks. (Justiniano et al. (2007), for instance, estimate an elasticity of about 0.2.)

The bottom panel of table 3 presents descriptive statistics of the posterior distributions of measurement errors. As is common in estimated DSGE models, measurement errors tend to be significant. In this case, the estimated mean of most of this shocks are close to the upper bound of their prior distributions.

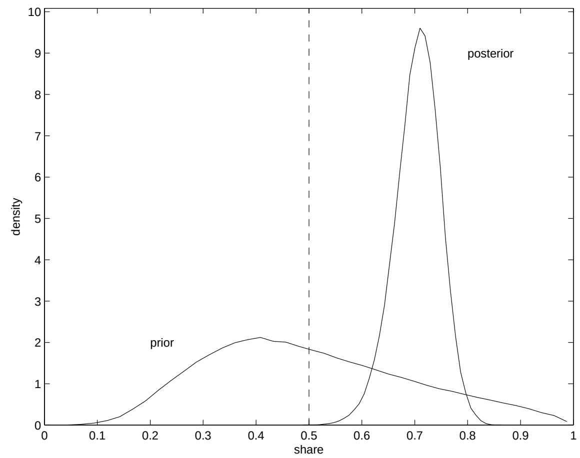
5 The Importance of Anticipated Shocks

Table 4 presents the main result of this paper. It displays the share of the unconditional variances of output growth, consumption growth, investment growth, and the logarithm of hours worked accounted for by anticipated shocks. The table displays the mean posterior share and the associated 90 percent posterior interval computed from 4 million draws from the posterior distribution of the vector of estimated structural parameters.

The table shows that news shocks account for 70 percent of the variance of output growth. 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 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 the dominant driving force.

Figure 1 displays the prior and posterior probability density functions of the share of the variance of output growth accounted for by anticipated shocks. It is evident from this figure that the posterior probability that the share of the variance accounted for by anticipated

Figure 1: Prior and Posterior Probability Densities of the Share of the Variance of Output Growth Attributable to Anticipated Shocks



Note. The prior and posterior probability density functions were computed using the last 4 million elements of a 10-million MCMC chain of draws from the prior and posterior distributions of the parameters, respectively.

shocks is less than 50 percent is virtually nil. This probability is given by the area below the posterior density function and to the left of the vertical dashed line. By contrast, the prior probability that the share of the variance of output growth explained by anticipated shocks is less than 50 percent is 54 percent. This number results from computing the area below the prior density function and to the left of the dashed vertical line. We interpret the results displayed in figure 1 as suggesting that the data speaks clearly in favor of a significant role for anticipated shocks in driving output fluctuations.

Anticipated disturbances play a similarly central role in explaining the volatility of consumption, investment, and hours. As shown in table 4, for each of these three variables, anticipated shocks explain more than fifty percent of their variances with more than 95 percent probability.

Table 5 addresses a standard question in business-cycle analysis. Namely, what is the contribution of each of the sources of uncertainty considered in this study to explaining business-cycle fluctuations. It presents the share of the overall predicted variance of the variables of interest attributed to each of the sixteen shocks considered. Table 5 shows that two thirds of the unconditional variance of output growth is explained by the stationary productivity shock z_t. That is, about two thirds of the variance of output growth is explained jointly by the innovations $\epsilon^0_{z,t}$, $\epsilon^1_{z,t}$, $\epsilon^2_{z,t}$, and $\epsilon^3_{z,t}$. The remaining one third of the variance of output growth can be attributed to μ^x_t, the nonstationary neutral technology shock. That is, $\epsilon^0_{x,t}$, $\epsilon^1_{x,t}$, $\epsilon^2_{x,t}$, and $\epsilon^3_{x,t}$ together are responsible for about one third of the variance of

Table 5: Variance Decomposition by Type of Shock

Innovation	g^Y	g^C	g^I	h
Stationary Neutral Tech. Shock, z_t				
$\epsilon^0_{z,t}$	0.28	0.13	0.42	0.30
$\epsilon^1_{z,t}$	0.01	0.01	0.02	0.01
$\epsilon^2_{z,t}$	0.01	0.01	0.02	0.01
$\epsilon^3_{z,t}$	0.35	0.25	0.41	0.18
$\sum_{i=0}^3 \epsilon^i_{z,t}$	0.66	0.40	0.86	0.49
Nonstationary Neutral Tech. Shock, μ^x_t				
$\epsilon^0_{x,t}$	0.02	0.03	0.01	0.03
$\epsilon^1_{x,t}$	0.20	0.37	0.08	0.30
$\epsilon^2_{x,t}$	0.07	0.14	0.03	0.10
$\epsilon^3_{x,t}$	0.03	0.07	0.02	0.05
$\sum_{i=0}^3 \epsilon^i_{x,t}$	0.32	0.60	0.13	0.47
Government Spending Shock, g_t				
$\epsilon^0_{g,t}$	0.00	0.00	0.00	0.01
$\epsilon^1_{g,t}$	0.00	0.00	0.00	0.01
$\epsilon^2_{g,t}$	0.01	0.00	0.00	0.01
$\epsilon^3_{g,t}$	0.00	0.00	0.00	0.00
$\sum_{i=0}^3 \epsilon^i_{g,t}$	0.02	0.00	0.00	0.03
Investment Specific Productivity Shock, μ^a_t				
$\epsilon^0_{a,t}$	0.00	0.00	0.00	0.00
$\epsilon^0_{a,t}$	0.00	0.00	0.00	0.00
$\epsilon^0_{a,t}$	0.00	0.00	0.00	0.00
$\epsilon^0_{a,t}$	0.00	0.00	0.00	0.00
$\sum_{i=0}^3 \epsilon^i_{a,t}$	0.00	0.00	0.00	0.00

Note: Variance decompositions are performed at the mean of the posterior distribution of the estimated structural parameters.

output growth. Government spending shocks and investment-specific productivity shocks explain jointly a negligible fraction of the variance of output growth. A similar conclusion emerges when one examines the variance decomposition of consumption growth, investment growth, and hours. Here, also, stationary and nonstationary neutral technology shocks explain virtually all of the variation predicted by the model.

The insignificant role played by investment-specific productivity shocks may seem at odds with some existing related studies. A recent example is the work by Justiniano, Primiceri, and Tambalotti (2008), who estimate that investment-specific shocks are responsible for more than fifty percent of output fluctuations in the postwar United States. An important difference between our estimation strategy and that of Justiniano, Primiceri, and Tambalotti is that we include the relative price of investment in the set of observable variables, whereas they do not. Indeed, when we estimate our model excluding the relative price of investment from the set of observables, we find that investment-specific shocks account for about one third of the variation of output. The intuition for this finding is that including the price of investment in the set of observables introduces restrictions upon the estimated stochastic process of the relative price of investment as it must match the sample properties of its empirical counterpart. When the relative price of investment is not included in the set of observables, the estimated process of the investment-specific shock 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.

It is worth noting that the central results of the present paper stand even when we estimate the model excluding the relative price of investment from the set of observable variables. For anticipated shocks continue to play a dominant role in driving business cycles. Specifically, we estimate that they continue to explain more than two thirds of predicted output variations. Also in line with our baseline estimation results, virtually all anticipated disturbances take the form of variations in total factor productivity.

The finding that government spending and investment-specific shocks play no role in explaining the variance of the four macroeconomic variables we study, implies that the anticipated component of these two sources of uncertainty must be virtually nil as well. We therefore concentrate for the remainder of this paper on the dynamics induced by stationary and nonstationary neutral productivity shocks.

Inspecting the estimated contribution of disturbances anticipated zero, one, two, and three quarters in advance to the overall variance of output, consumption, investment, and hours reals that virtually all of the variance of output growth is explained by only three innovations: $\epsilon^3_{z,t}$, $\epsilon^0_{z,t}$, and $\epsilon^1_{x,t}$. Specifically, 35 percent of the variance of output is due to three-quarter anticipated changes in the level of the stationary neutral technology shock, $\epsilon^3_{z,t}$. Another 20 percent of the variance of output is attributable to one-quarter anticipated changes in the growth rate of the nonstationary productivity shock, $\epsilon^1_{x,t}$. And 28 percent of the variance of output is due to unanticipated movements in the stationary neutral productivity shock. The same pattern emerges from examining the sources of fluctuations in consumption, investment, and hours.

Notably, we find that all permanent changes in total factor productivity are anticipated. This is because the contribution of $\epsilon^0_{x,t}$ to explaining the variance of output growth is almost nil. This result is in line with the empirical findings of Beaudry and Portier (2006). These authors document a near perfect correlation between shocks that change TFP permanently and shocks that fail to change TFP on impact. In section 7, we relate our findings to those of Beaudry and Portier in more detail.

5.1 Marginal Data Densities

To further ascertain the significance of anticipated shocks as a source of business cycles, we estimate a version of the model in which we restrict the variances of all anticipated shocks to be zero ($\sigma^i_k = 0$, for $i = 1, 2, 3$ and $k = z, x, g, a$). That is, by construction, all sources of uncertainty are unanticipated, which is the case typically considered in the related literature on the sources of economic fluctuations. Table 6 reports marginal data densities for the baseline model and for the model with no anticipation. The marginal data densities are computed using Geweke's modified harmonic mean estimator for various truncation values and a Markov chain of 4 million draws for each specification. The table shows that the data favors the model with anticipated shocks over the model without anticipated shocks. The log Bayes factor, given by the difference between the two log marginal data densities, is about 310 and stable across truncation values.

5.2 The Role of Anticipated Shocks at Different Time Horizons

Thus far, we have analyzed the contribution of anticipated shocks to explaining the unconditional variance of variables of interest. Table 7 shows that the importance of anticipated shocks is not limited to long horizons. It displays the share of the variance of forecasting errors explained by anticipated shocks at different forecasting horizons. For horizons between 8 and 32 quarters—the range typically associated with business-cycle frequencies—anticipated shocks again account for the majority of the forecasting error variance of all four macroeconomic indicators considered in the table.

Table 6: Log Marginal Data Densities

	Log Marginal Data Density		
Truncation Parameter	Baseline Model	No Anticipation	Jaimovich-Rebelo Preferences
0.1	-2131	-2441.1	-1950.2
0.2	-2130.3	-2441	-1950
0.3	-2130	-2440.9	-1949.8
0.4	-2129.7	-2440.8	-1949.7
0.5	-2129.5	-2440.8	-1949.6
0.6	-2129.3	-2440.7	-1949.5
0.7	-2129.2	-2440.7	-1949.4
0.8	-2129.1	-2440.7	-1949.4
0.9	-2129	-2440.7	-1949.3

Notes: The log marginal data densities are computed based on Geweke's modified harmonic mean estimator for Markov chains of 4 million draws.

Table 7: Share of Variance of Forecasting Error Due to Anticipated Shocks

Horizon (quarters)	g^Y	g^C	g^I	h
1	0.41	0.98	0.096	0.021
2	0.52	0.91	0.24	0.19
3	0.61	0.88	0.37	0.31
4	0.66	0.86	0.53	0.43
8	0.7	0.85	0.56	0.55
16	0.7	0.86	0.56	0.58
32	0.7	0.85	0.57	0.59
∞	0.7	0.85	0.57	0.67

Note: Variance decompositions are performed at the mean of the posterior distribution of the estimated structural parameters.

5.3 Two Alternative Prior Distributions

Our baseline priors imply that at the mean of the prior distribution of the structural parameters, the share of the variance of output growth explained by anticipated shocks is about 50 percent. Also, under the baseline prior the standard deviations of all exogenous sources of uncertainty are assumed to be uniformly distributed. We now study the robustness of our results to reducing the importance of anticipated shocks under the prior distribution, and to moving away from uniform distributions for the standard deviations of the exogenous driving forces.

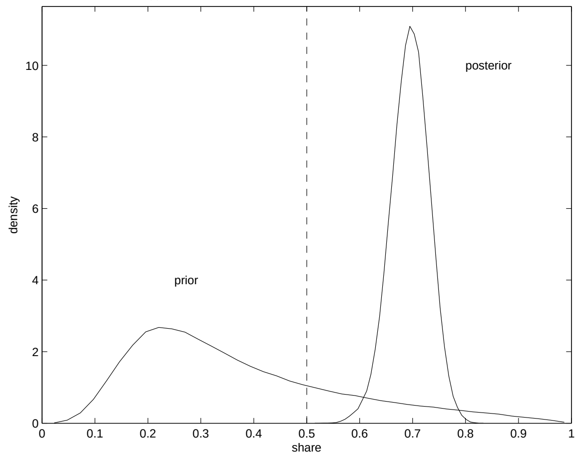
5.3.1 Alternative Uniform Prior Distribution

Our first robustness exercise assumes that the under the prior the variance of the unanticipated component of each of the four sources of uncertainty is twice as large as the variance of the three associated anticipated components taken together. That is, we consider a prior distribution in which the mean of the standard deviations satisfies $(\sigma_k^0)^2 = 2\sum_{j=1}^3(\sigma_k^j)^2$ for $k = z, x, g, a$. Specifically, we assume that the prior distribution of the standard deviation of each anticipated component is uniform with lower bound equal to 0 and upper bound equal to 3. At the same time, we assume that the standard deviation of each unanticipated shock follows a uniform distribution with lower bound 0 and upper bound equal to $3\sqrt{6}$. The prior distributions assumed for all remaining estimated parameters are as in the baseline case (see table 2). After reestimating the model under this new prior distribution, we find that the posterior distribution of the estimated parameter vector is little changed vis-a-vis the one estimated under the baseline prior distribution. Figure 2 displays the prior and posterior distributions of the share of output growth explained by anticipated shocks. We note that the posterior distribution is virtually identical to the one obtained under the baseline estimation strategy. However, the prior distribution of the share of output growth explained by anticipated shocks shifted markedly to the left compared to the baseline case. Under the current assumptions, the posterior probability that the share of output growth explained by anticipated shocks is below 50 percent is, as in the baseline case, near zero. By contrast the corresponding prior probability is 77 percent. We conclude that our central finding that the majority of the estimated aggregate volatility is explained by anticipated shocks is robust to significantly increasing the prior importance of the unanticipated sources of uncertainty.

5.3.2 Inverse Gamma Prior Distribution

One feature common to both the baseline and the alternative uniform prior distributions is that they assign relatively little probability to the event that the share of the variance of

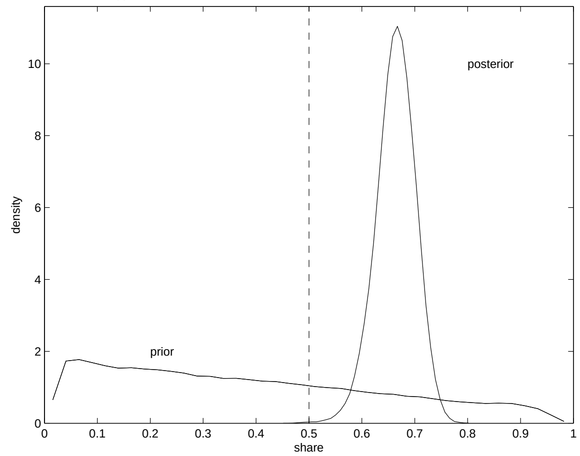
Figure 2: Alternative Uniform Prior Distribution: Prior and Posterior Probability Densities of the Share of the Variance of Output Growth Attributable to Anticipated Shocks



Note. The underlying prior distributions for the standard deviations of the unanticipated components, σ_k^0, are uniform over $[0, 3\sqrt{6}]$, and for the standard deviations of the anticipated components, σ_k^j, are uniform over $[0, 3]$, for $k = z, x, a, g$ and $j = 1, 2, 3$. The prior and posterior probability density functions were computed using the last 4 million elements of a 10-million MCMC chain of draws from the prior and posterior distributions of the parameters, respectively.

output growth explained by anticipated shocks be very small, say less than 10 percent. For instance, in figure 2 the probability that the share of the variance of output explained by anticipated shocks is less than 10 percent is only 2 percent. To address this issue, our second robustness test replaces the uniform prior distributions for the standard deviations of the exogenous shocks with inverse gamma distributions. We parameterize these distributions as follows: (a) we impose that at the mean of the prior distribution the variance of each unanticipated component is twice as large as the sum of the variance of all three of its associated anticipated components. That is, we impose $(\sigma_k^0)^2 = 2\sum_{j=1}^{3}(\sigma_k^j)^2$ for $k = z, x, g, a$. (b) We impose that at the mean of the prior distribution, the share of the variance of output growth explained by stationary neutral productivity shocks, nonstationary neutral productivity shocks, permanent investment-specific technology shocks, and government spending shocks is about 30 percent, 30 percent, 30 percent, and 10 percent, respectively. (c) The coefficient of variation of the prior distribution of the standard deviations of all 16 innovations is 3. (d) The volatility of output growth predicted by the model when the structural parameters are evaluated at the mean of the prior is about 1 percent per quarter, as observed in our sample. And (e) for each type of shock (z, x, a, or g), the prior distribution of the standard deviations is common across anticipated innovations. These restrictions uniquely pin down

Figure 3: Inverse Gamma Prior Distribution: Prior and Posterior Probability Densities of the Share of the Variance of Output Growth Attributable to Anticipated Shocks



Note. The prior and posterior probability density functions were computed using the last 4 million elements of a 10-million MCMC chain of draws from the prior and posterior distributions of the parameters, respectively.

the 32 parameters defining the inverse gamma prior distributions of the standard deviations of the 16 structural innovations of the model. The prior distributions of all remaining estimated parameters are as in the baseline case (see table 2). We reestimate the model under this new prior and, as in the first robustness test, find that the posterior distribution of the estimated parameter vector is little affected by the change in the prior distribution.

Figure 3 displays the prior and posterior probability densities of the share of the variance of output growth attributable to anticipated shocks. The posterior density is virtually identical to the one we obtained under the baseline prior specification. In particular the probability that the share of the variance of output growth explained by anticipated shocks is less than 50 percent is practically zero. On the other hand, the prior density now assigns a non negligible probability to the event that anticipated shocks explain a small fraction of the variance of output growth. For example the area under the prior density and to the left of 0.1 is 15 percent, compared with a corresponding value of 2 percent under the baseline prior. We take this result to mean that the data strongly favors parameter specifications in which anticipated shocks play a major role in generating business cycles.

6 The Pure Anticipation Effect

Our estimation results suggest that more than two thirds of business-cycle fluctuations are caused by anticipated shocks. However, anticipated shocks have two components: One is the pure anticipation effect, resulting from the change in behavior triggered by the announcement of future changes in exogenous fundamentals. The second component is a realization effect. It takes place when the pre-announced shock materializes into an actual change in fundamentals. Consider, for instance, a situation in which agents learn in period 0 that in period three total factor productivity will increase permanently by one percent. This announcement generates a wealth effect that induces households to increase consumption and leisure. In turn, the change in labor supply causes movements in wages, employment, and output. All of these effects begin to take place in period zero, three quarters before the actual increase in total factor productivity. Compare this situation with one in which agents are surprised in period three with a permanent, one-percent increase in TFP. In periods 0, 1, and 2 all endogenous variables are unaffected by the upcoming TFP shock. We note that even from period 3 onward the behavior of endogenous variables will in principle be different with and without anticipation. The reason is that the two economies will enter period three with different values for the endogenous state variables, such as the capital stock, the stocks of habit in consumption and leisure, and past investment. Note further that the entire path of the exogenous state variables (in particular TFP) is identical in both situations described here. The pure anticipation effect captures the difference between the time paths of endogenous variables with and without anticipation.

The use of an optimizing, rational expectations, DSGE model allows us to decompose the total contribution of anticipated shocks into the pure anticipation effect and the realization effect. To this end, we compare the variance of the forecast error induced by the baseline economy, which we denote by VFE (and present in table 7), with the variance of the forecast error induced by an economy without anticipation, which we denote by VFE^{na}. To construct VFE^{na}, we change the information set of households as follows: Consider, for example, the stochastic process for the stationary component of TFP, z_t. The law of motion of this exogenous variable is given by

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

This process is identical to the one assumed in the baseline economy. That is, $\nu_{z,t}$ is a Gaussian white noise process with unconditional mean zero and unconditional variance $\sigma^2_{\nu_z}$ given by

$$\sigma^2_{\nu_z} = \left(\sigma_z^0\right)^2 + \left(\sigma_z^1\right)^2 + \left(\sigma_z^2\right)^2 + \left(\sigma_z^3\right)^2,$$

where all the parameters on the right-hand side of this expression take the values estimated for the baseline economy (table 3). The key difference between the economy without anticipation and the baseline economy is that in the economy without anticipation agents can

Table 8: Relative Variance of Forecasting Errors in the Economies With and Without Anticipation

Horizon	VFE/VFE^{na}			
(quarters)	g^Y	g^C	g^I	h
1	0.55	2.9	0.42	0.34
2	0.66	1.7	0.49	0.39
3	0.77	1.4	0.59	0.44
4	0.87	1.2	0.78	0.52
8	0.94	1.1	0.84	0.62
16	0.95	1.1	0.86	0.64
32	0.97	1.1	0.88	0.66
∞	0.97	1.1	0.88	0.74

Note. All structural parameters take values corresponding to the mean of their posterior distributions as reported in table 3, except when altered in accordance with the counterfactual exercise displayed in the table.

only observe realizations of $\nu_{z,t}$ and not realizations of its individual components, $\epsilon^0_{z,t}$, $\epsilon^1_{z,t-1}$, $\epsilon^2_{z,t-2}$, and $\epsilon^3_{z,t-3}$. Therefore, in the economy without anticipation $\nu_{z,t}$ is unforecastable by economic agents, that is,

$$E_{t-j}\nu_{z,t} = 0,$$

for all $j > 0$. By contrast, in the baseline economy, in which agents are assumed to observe the individual components of $\nu_{z,t}$ given by $\epsilon^0_{z,t}$, $\epsilon^1_{z,t-1}$, $\epsilon^2_{z,t-2}$, and $\epsilon^3_{z,t-3}$, $\nu_{z,t}$ is indeed forecastable by economic agents. Specifically, in the baseline economy we have that

$$E_{t-1}\nu_{z_t} = \epsilon^1_{z,t-1} + \epsilon^2_{z,t-2} + \epsilon^3_{z,t-3},$$

$$E_{t-2}\nu_{z_t} = \epsilon^2_{z,t-2} + \epsilon^3_{z,t-3},$$

$$E_{t-3}\nu_{z_t} = \epsilon^3_{z,t-3},$$

and

$$E_{t-j}\nu_{z_t} = 0$$

for $j \geq 4$. In modeling the economy without anticipation, we impose the same change in information structure just discussed for the stationary productivity shock, z_t, to the three other exogenous driving forces, μ^x_t, μ^a_t, and g_t.

Table 8 displays the ratio

$$\frac{VFE}{VFE^{na}}$$

for various forecasting horizons and four endogenous variables of interest. Values of this ratio below unity indicate that the baseline economy (the economy with anticipation) has a smaller forecasting error variance than the counterfactual economy without anticipation. That is, a value of the ratio below one means that anticipation has a stabilizing effect on the variable in question. The table shows that anticipation greatly dampens short-term volatility in output, investment, and hours. In the case of output, the variance of the one-step ahead forecasting error falls by about half when anticipation is taken into account. On the other hand, consumption is much more unpredictable in the short run in the economy in which agents obtain advanced notice of future changes in economic fundamentals. We note that for output and consumption, the pure anticipation effect vanishes at long horizons. For hours and investment, on the other hand, the dampening effect of anticipation is significant even at very long horizons. For instance, unconditionally, hours worked are about 25 percent less volatile in the economy with anticipation than in the economy without it.

7 Relation To VECM Estimates of Anticipated Shocks

In a recent paper, Beaudry and Portier (2006) estimate the importance of anticipated 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 a news shock: first, the shock affects TFP in the long run (we refer to this restriction as identification scheme I). And second, the shock cannot affect TFP contemporaneously (we refer to this restriction as identification scheme II). Applying the Beaudry-Portier definition of news shocks to our DSGE model, would uncover some combination of the anticipated components of the nonstationary neutral productivity shock. That is, a combination of $\epsilon^1_{x,t}$, $\epsilon^2_{x,t}$, and $\epsilon^3_{x,t}$.

Table 9 reports the share of business-cycle fluctuations explained jointly by $\epsilon^1_{x,t}$, $\epsilon^2_{x,t}$, and $\epsilon^3_{x,t}$ in our estimated DSGE model. For comparison, the table also shows the contribution of the news shock estimated by Beaudry and Portier (2006), as reported in their figure 10. The VECM of Beaudry and Portier identifies a larger contribution of anticipated shocks to TFP growth to aggregate fluctuations than does our estimated DSGE model. Our estimates fall closer to the ones obtained by Beaudry and Portier when applying the second identification scheme (i.e., when the news shock is imposed to have no contemporaneous effect on TFP).

An advantage of performing the estimation of news shocks in the context of a DSGE model is that it allows for the identification of news shocks other that anticipated permanent changes in TFP. Indeed, we find that news shocks explain 70 percent of the predicted variance of output (see table 4). Of this figure only about half (30 percent) is attributable to anticipated

Table 9: Estimated Contribution of Beaudry-Portier-Style News Shocks

	g^Y	g^C	g^I	h
Estimated DSGE Model				
– Baseline Model	0.31	0.58	0.13	0.44
– Jaimovich-Rebelo Preferences	0.48	0.51	0.47	0.77
Beaudry-Portier Estimated VECM				
– Identification Scheme I	0.75	0.90	0.45	0.70
– Identification Scheme II	0.55	0.65	0.25	0.75

Note: The numbers reported in the rows below the one entitled 'Beaudry-Portier Estimated VECM' Estimate' correspond to the share of the forecast error variance at horizon 30 quarters. Identification scheme I identifies an innovation that has a long-run effect on TFP, and identification scheme II identifies an innovation that has no contemporaneous effect on TFP. The numbers reported here are approximations, as they represent our reading of the bottom panels of figure 10 in Beaudry and Portier (2006).

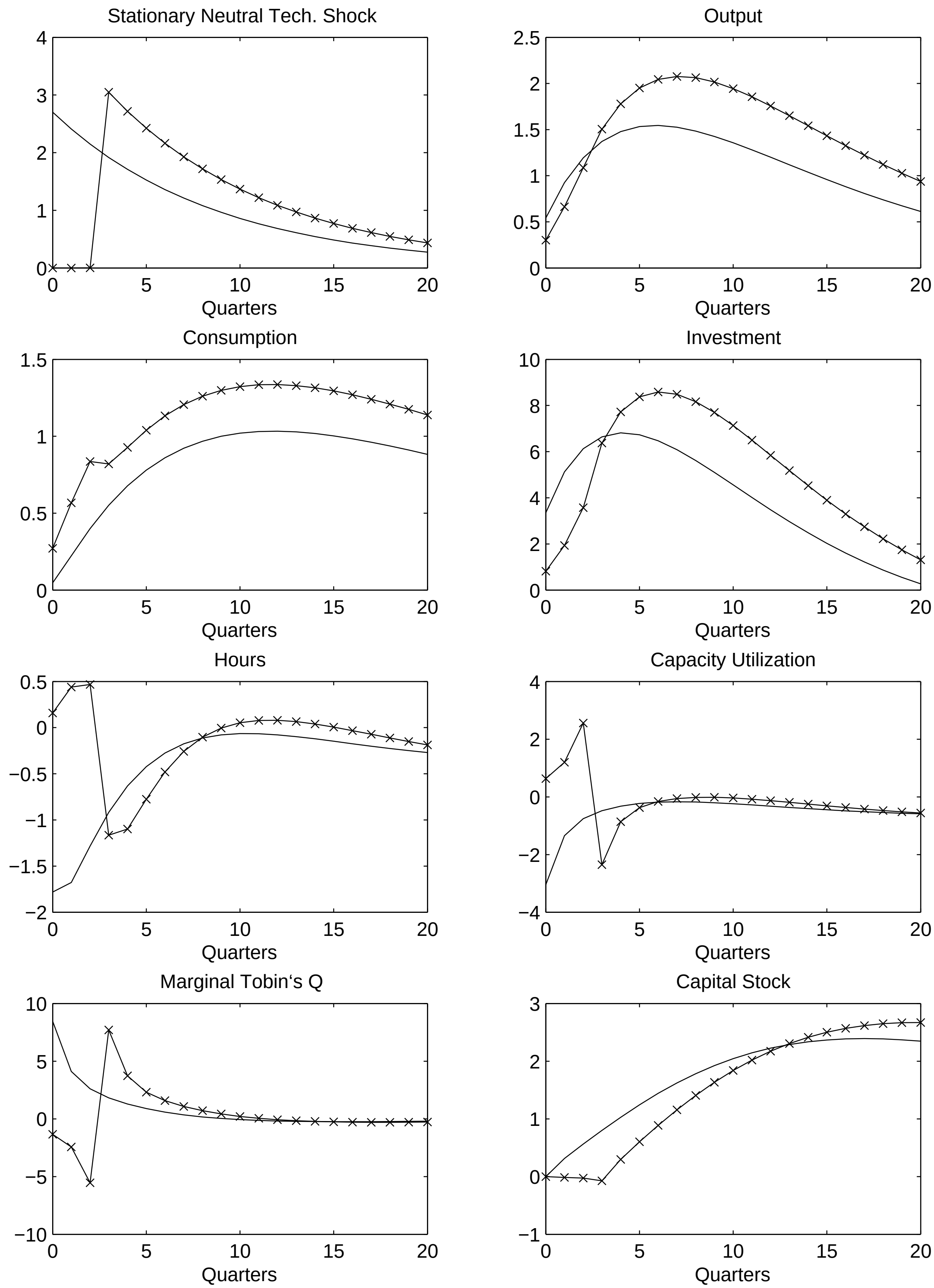
permanent changes in TFP. The other half is attributable to anticipated temporary changes in TFP.

Finally, Beaudry and Portier document a near perfect correlation between the news shocks identified under their schemes I and II, suggesting that both schemes identify essentially the same news innovation. This turns out not to be the case in the context of our estimated DSGE model. In effect, applying Beaudry and Portier identification scheme I (i.e., permanent effect on TFP) to our DSGE model would uncover a combination of $\epsilon^1_{x,t}$, $\epsilon^2_{x,t}$, and $\epsilon^3_{x,t}$. At the same time, applying the Beaudry and Portier identification scheme II (i.e., no contemporaneous effect on TFP) to our estimated DSGE model would recover some combination of $\epsilon^1_{x,t}$, $\epsilon^2_{x,t}$, $\epsilon^3_{x,t}$, $\epsilon^1_{z,t}$, $\epsilon^2_{z,t}$, $\epsilon^3_{z,t}$, $\epsilon^0_{g,t}$, $\epsilon^1_{g,t}$, $\epsilon^2_{g,t}$, $\epsilon^3_{g,t}$, $\epsilon^0_{a,t}$, $\epsilon^1_{a,t}$, $\epsilon^2_{a,t}$, and $\epsilon^3_{a,t}$. These two combinations of shocks account for different fractions of business-cycle fluctuations in our model. The difference is accounted for to a large extent by anticipated changes in the stationary component of TFP (i.e., $\epsilon^i_{z,t}$ for $i = 1, 2, 3$). For instance, $\epsilon^3_{z,t}$ alone explains about one third of the predicted volatility of output growth.

8 The Dynamic Effects of Anticipated Shocks

Figure 4 displays impulse response functions to the two most important disturbances impinging on our model economy. Namely, three-quarter anticipated stationary changes in total factor productivity, $\epsilon^3_{z,t}$, and unanticipated stationary changes in total factor productivity, $\epsilon^0_{z,t}$. Combined, these two innovations explain 64 percent of the predicted variance of output

Figure 4: Impulse Response to One-Standard-Error Anticipated and Unanticipated Innovations in the Stationary Technology Shock ($\epsilon_{z,t}^{3}$ and $\epsilon_{z,t}^{0}$)



Crossed line: 3-qrt Anticipated Shock, $\epsilon_{z,t}^{3}$. Solid line: Unanticipated Shock, $\epsilon_{z,t}^{0}$.

growth (see table ??). In each case, the size of the shock is one standard deviation of the respective innovation. All variables are measured in percent deviations of levels from trend.

The equilibrium response to the three-quarter ahead anticipated stationary innovation in TFP is shown with a crossed line in figure 4. TFP remains at its steady-state level in periods 0, 1, and 2, and rises by about 3 percent in period 3. Households learn about this upcoming increase in TFP already in period 0. Output, consumption, and investment all display a hump-shaped boom in response to this innovation, starting in period zero, when the future increase in TFP is announced. The expansion in consumption is driven by a positive wealth effect associated with the expected future increase in TFP. The hump shape of the consumption boom is governed by the presence of internal habit formation. Because investment adjustment costs depend on the growth rate of investment, firms wish to arrive in period 3, when the shock materializes in an actual increase in TFP, with a high level of past investment. In order to achieve this goal, firms begin investing immediately upon learning about the future increase in TFP.

The increase in the supply of goods necessary to meet demand is brought about through a rise in capacity utilization. In turn, the increase in capacity utilization during the early transition raises the marginal product of labor, leading to an equilibrium increase in employment. The increase in hours worked occurs in spite of the fact that the anticipated increase in productivity creates a positive wealth effect that tends to depress labor supply. The increase in both hours worked and capacity utilization induces an expansion in output, which inherits the smooth and hump-shaped characteristic of the responses of investment and consumption.

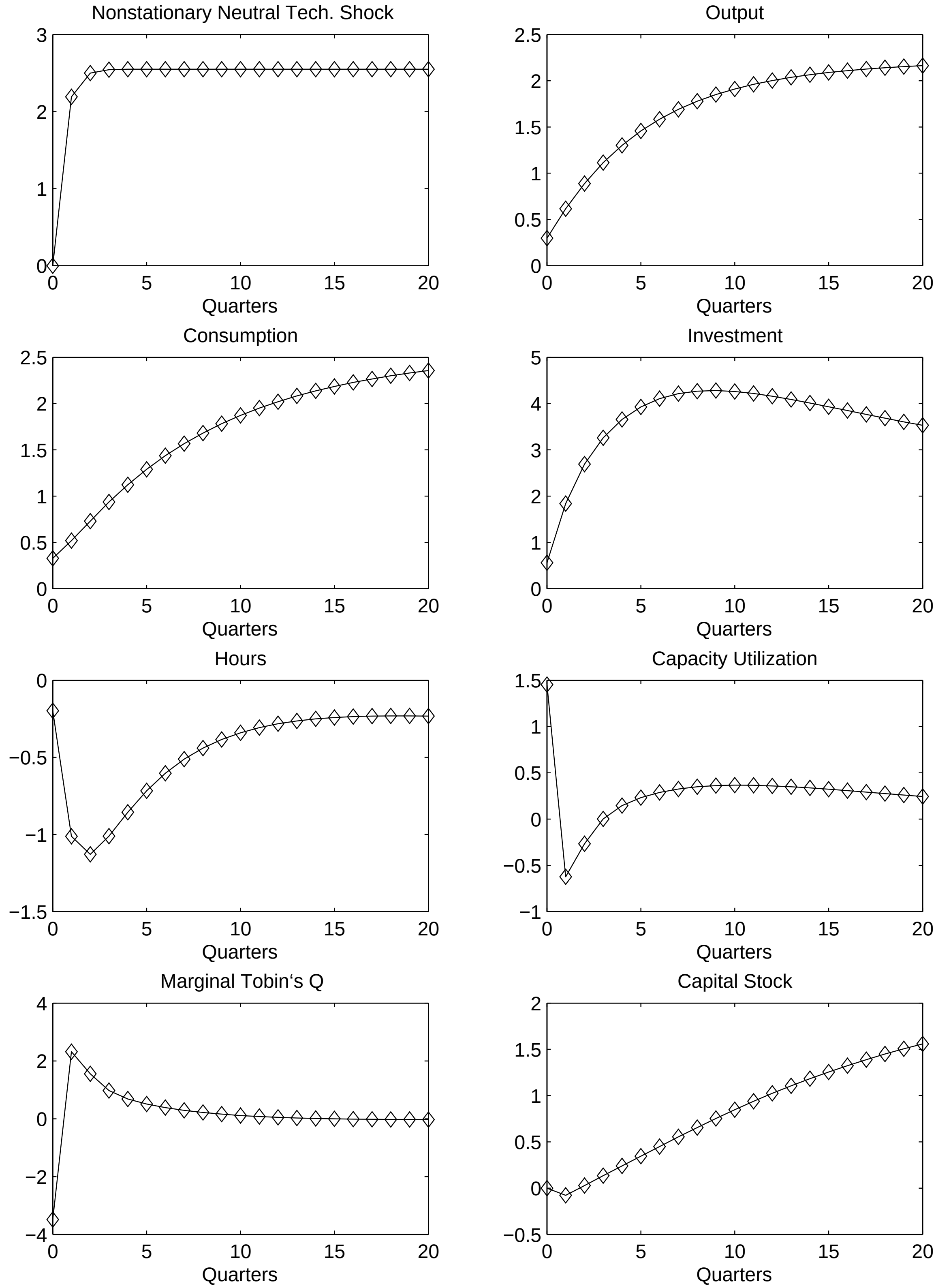
Using capacity utilization more intensively upon the announcement of the future increase in TFP entails a cost in the form of an elevated depreciation rate. This effect is so strong in this economy that in spite of the higher rate of investment the capital stock fails to increase in the early transition. The flat path of capital in periods zero to three appears counterintuitive in the sense that one would expect capital to increase when firms are engaged in above-average levels of investment. These peculiar dynamics are the consequence of modeling adjustment costs as depending on the growth rate of investment rather than on the growth rate of the capital stock. In the present setup, firms are attempting to get rid of part of the capital stock to free up resources for investment and consumption. As a result, the price of installed capital, given by marginal Tobin's Q, falls with the announcement of the future increase in TFP. However, once the increase in TFP materializes in period 3, the marginal product of capital rises, boosting the price of installed capital, or marginal Tobin's Q. With a higher price of capital, firms find it too costly to continue to operate with high rates of capacity utilization—recall that the cost of higher capacity utilization is a higher rate of capital depreciation. Consequently, capacity utilization falls markedly in quarter 3. We also find that average Tobin's Q, not shown in figure 4, mimics the behavior of marginal Tobin's Q, falling on impact and rising sharply in period 3 with the increase in TFP.

The economy's response to an unanticipated, trend reverting increase in productivity ($\epsilon^0_{z,t}$), is shown with solid lines in figure 4. This shock generates hump-shaped booms in output, consumption, and investment. The expansion in economic activity takes place in the context of a contraction in employment. The reason why employment falls is that the increase in TFP entails a positive wealth effect, which induces households to contract labor supply. In addition to the wealth effect, the increase in TFP gives rise to a substitution effect toward labor and consumption. In the case of the labor supply, the wealth effect appears to dominate the substitution effect. This wealth effect is exacerbated by the presence of habit formation in consumption. Indeed, eliminating habit formation in consumption by setting $\theta_c = 0$ and holding all other structural parameters fixed, results in a positive and hump-shaped response of hours.

Figure 5 displays the response of the model to a one-quarter anticipated increase in the nonstationary component of total factor productivity, $\epsilon^1_{x,t}$. This innovation is the third most important source of business cycles in our estimated model, accounting for 18 percent of the predicted volatility of output growth (see table **??**). In period zero, TFP is unchanged. Nevertheless, output, consumption, and investment all increase in anticipation of the permanent increase in TFP that is expected to occur in period 1. By contrast, hours worked contract upon the release of news in period 0. The contraction in hours is driven by a positive wealth effect that induces households to demand more leisure and consumption. Capacity utilization rises in period zero as a way to increase output. Higher capacity utilization raises the marginal product of hours, thus creating an increased demand for labor, which ameliorates the wealth-effect-induced decline in hours. As in the case of the stationary productivity shock, households are willing to get rid of their holdings of physical capital in order to generate resources for consumption and investment purposes. As a result, the price of installed capital, or marginal Tobin's Q, falls in period 0. A similar fall occurs in average Q (not shown). Indeed, in a competitive equilibrium it is the fall in the price of capital that induces households to utilize capital more intensively.

From the analysis of the impulse response functions implied by our estimated model, we find that the model is capable of generating positive comovement in output, consumption, and investment in response to anticipated productivity shocks. Moreover, in response to the estimated single most important source of economic fluctuations, namely three-quarter anticipated changes in the stationary component of TFP, or $\epsilon^3_{z,t}$, hours positively comove on impact with output, consumption, and investment. While most studies in the literature on

Figure 5: Impulse Response to a One-Quarter Anticipated One-Standard-Error Innovation in the Non-Stationary Neutral Technology Shock ($\epsilon^1_{x,t}$)



news make positive comovement in response to news shock a desired prediction of any theoretical model of business cycles, we wish to emphasize that the available empirical evidence is silent in regard to the response of macroeconomic aggregates of interest to news about future changes in the level of the stationary component of TFP.

By contrast, there exists some evidence on the macroeconomic effects of news about future changes in the nonstationary component of total factor productivity. In effect, the empirical findings of Beaudry and Portier (2006) suggest that output, investment, consumption, employment, and stock price all rise in response to an anticipated permanent increase in TFP. In accordance with the data, our estimated model predicts an increase in output, consumption, and investment in response to a one-quarter anticipated permanent increase in TFP. But the estimated model fails to generate the observed increases in hours and stock prices. The success of the model in predicting an increase in output as well as its failure to predict an increase in stock prices in response to an anticipated permanent increase in TFP are closely linked through movements in capacity utilization. The predicted rise in capacity utilization raises the number of effective units of capital employed thereby allowing output to expand on impact. But at the same time, the higher intensity of capacity utilization comes at the cost of lost physical capital, which can be supported in equilibrium only via depressed prices for installed capital, i.e., via a decline in (marginal and average) Tobin's Q.

9 Estimating Anticipated Shocks Under Jaimovich-Rebelo Preferences

In our estimated baseline model, an anticipated permanent increase in productivity generates a wealth effect that causes households to reduce labor supply. The wealth effect on labor supply is estimated to be sufficiently strong to dominate the substitution effect induced by the increase in the marginal product of labor stemming from the higher equilibrium rates of capital capacity utilization. This intuition suggests that a potential way to overturn the counterfactual predictions of the baseline model regarding the response of hours to anticipated permanent productivity shocks is to adopt a preference specification that attenuates the wealth elasticity of labor supply. Such a preference specification has been proposed by Greenwood et al. (1988) and has recently been generalized and applied to explaining the dynamic response to anticipated permanent changes in TFP by Jaimovich and Rebelo (2008). In the this section, we therefore estimate a variant of our model that features this type of preferences.

Consider an economy populated by a large number of identical agents with preferences

Table 10: Jaimovich and Rebelo Preferences: Calibration Restrictions

Parameter	Value	Description
β	0.985	Subjective discount factor
σ	1	Intertemporal elasticity of substitution
α	0.36	Capital 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 worked

Note: The time unit is one quarter.

described the utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t - \psi h_t^{\theta} S_t), \tag{9}$$

where β denotes the subjective discount factor, and S_t is a geometric average of current and past consumption levels, which can be written recursively as

$$S_t = C_t^{\gamma} S_{t-1}^{1-\gamma}.$$

We impose $\gamma \in (0, 1]$ and $\theta > 1$. Note that as $\gamma \to 0$, the argument of the period utility function becomes linear in consumption and a function of hours worked, which is the 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 is small, anticipated increases in productivity will not depress labor supply, contrary to what happens in the baseline model. As γ increases, the wealth elasticity of labor supply rises. Because no econometric evidence exists on the value of the parameter γ, a central goal of this section is to obtain an estimate of this key parameter. We assume that the period utility function is of the CRRA family. That is, $U(x) = (x^{1-\sigma} - 1)/(1 - \sigma)$. The remaining elements of the model are as in the baseline model described in the previous sections.

As in the baseline case, we calibrate some structural parameters and estimate others. The calibration follows Jaimovich and Rebelo and is shown in table 10.

We perform a Bayesian estimation of the model employing the same set of observables as in the baseline model. We assume the same prior distributions for all estimated structural parameters that are common to our baseline model. There are two new estimated parameters in the present model. One of these parameters is γ, which governs the wealth elasticity of labor supply. The prior distribution for this parameter is a uniform defined on the interval $(0, 1]$. The second new parameter is θ, which determines the Frisch elasticity of labor supply in the special case in which γ equals zero. We impose a uniform prior distribution for this parameter over the interval $(1.1, 11)$, which implies a wide range of wage elasticities between 10 and 0.1 when γ is close to zero.

Table 11 displays the prior and posterior means and the 90-percent posterior intervals for the 31 estimated structural parameters. These summary statistics were computed from the last 4 million elements of a 10 million MCMC chain of draws from the posterior distribution. Of particular interest is the estimate of the preference parameter γ. The estimated posterior distribution has a mean of 0.007 and is highly concentrated, with a 90-percent posterior interval ranging from 0.006 to 0.009. The near zero value for γ implies that preferences are close to those proposed by Greenwood, Hercowitz, and Huffman (1988). It follows that in our estimated model, the wealth elasticity of labor supply is near zero. To our knowledge, this is the first estimate of this parameter using aggregate data and taking into account all cross equation restrictions imposed by a fully-fledged DSGE model. With respect to the remaining structural parameters of the model, we note that the estimated volatilities of the innovations to TFP, σ_k^i, for $i = 0, 1, 2, 3$ and $k = x, z$, fall sharply relative to those obtained under the baseline preference specification. At the same time, the serial correlation of the growth rate of the nonstationary component of TFP, ρ_x, is estimated to be significantly larger under Jaimovich-Rebelo preferences.

Table 12 displays the share of the variance of endogenous variables of interest explained by anticipated shocks. It shows that anticipated shocks explain about 80 percent of the variance of output growth, consumption growth, investment growth, and hours worked. The associated 90-percent posterior intervals all lie above 50 percent. These estimates are consistent with those obtained under the baseline preference specification. Figure 6 displays the posterior probability density function of the share of the variance of output growth accounted for by anticipated shocks. The posterior probability that the share of the variance accounted for by anticipated shocks is less than 50 percent is nil. This probability is given by the area below the density function and to the left of the vertical dashed line.

Table 13 displays the unconditional variance decomposition of output growth, consumption growth, investment growth, and hours worked. In line with the results obtained under the baseline preference specification, under Jaimovich-Rebelo preferences neutral technology shocks explain virtually the totality of the unconditional variation of the four macroeconomic

Table 11: Prior and Posterior Distributions: Jaimovich and Rebelo Preferences

Parameter	Prior distribution			Posterior distribution		
	Distribution	Mean	Std. Dev.	Mean	5 percent	95 percent
	Stationary Neutral Productivity Shock					
ρ_z	Beta*	0.7	0.2	0.92	0.90	0.94
σ_z^0	Uniform	4.3	2.5	0.82	0.68	0.97
σ_z^1	Uniform	2.5	1.4	0.27	0.03	0.53
σ_z^2	Uniform	2.5	1.4	0.14	0.01	0.34
σ_z^3	Uniform	2.5	1.4	1.06	0.90	1.22
	Nonstationary Productivity Shock					
ρ_x	Beta*	0	0.1	0.33	0.23	0.41
σ_x^0	Uniform	4.3	2.5	0.11	0.01	0.27
σ_x^1	Uniform	2.5	1.4	0.14	0.01	0.33
σ_x^2	Uniform	2.5	1.4	0.28	0.02	0.64
σ_x^3	Uniform	2.5	1.4	1.51	1.25	1.79
	Investment-Specific Productivity Shocks					
ρ_a	Beta*	0.5	0.1	0.50	0.41	0.58
σ_a^0	Uniform	4.3	2.5	0.12	0.01	0.25
σ_a^1	Uniform	2.5	1.4	0.24	0.11	0.33
σ_a^2	Uniform	2.5	1.4	0.12	0.01	0.24
σ_a^3	Uniform	2.5	1.4	0.11	0.01	0.22
	Government Spending Shocks					
ρ_g	Beta*	0.7	0.2	0.99	0.99	0.99
ρ_{xg}	Beta*	0.7	0.2	0.99	0.99	0.99
σ_g^0	Uniform	4.3	2.5	1.02	0.91	1.14
σ_g^1	Uniform	2.5	1.4	0.08	0.01	0.19
σ_g^2	Uniform	2.5	1.4	0.09	0.01	0.23
σ_g^3	Uniform	2.5	1.4	0.52	0.33	0.68
	Preference and Technology Parameters					
θ	Uniform	6	2.9	1.16	1.14	1.18
γ	Uniform	0.5	0.29	0.01	0.01	0.01
κ	Gamma	4	1	3.08	2.58	3.67
δ_2	Uniform	5	2.9	0.02	0.02	0.03
	Measurement Errors					
$\sigma_{g^Y}^{me}$	Uniform	0.11	0.065	0.23	0.23	0.23
$\sigma_{g^C}^{me}$	Uniform	0.064	0.036	0.12	0.12	0.13
$\sigma_{g^I}^{me}$	Uniform	0.29	0.16	0.57	0.56	0.57
$\sigma_{g^g}^{me}$	Uniform	0.14	0.082	0.28	0.26	0.28
σ_h^{me}	Uniform	0.51	0.29	0.08	0.01	0.18
$\sigma_{\mu^a}^{me}$	Uniform	0.051	0.029	0.08	0.02	0.10

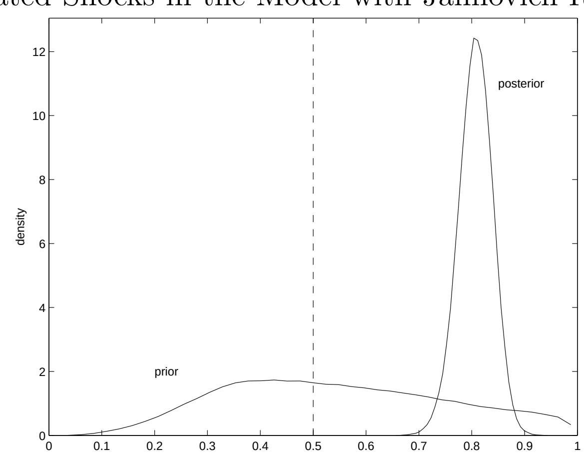
Note: See notes to table 3.

Table 12: Share of Variance Explained by Anticipated Shocks in the Model with Jaimovich-Rebelo Preferences

	g^Y	g^C	g^I	h
Mean share	0.81	0.82	0.80	0.92
90-percent interval				
5-percent	0.75	0.76	0.75	0.89
95-percent	0.86	0.87	0.85	0.95

Note: Results are based on the last 4 million elements of a 10-million MCMC chain of draws from the posterior distribution.

Figure 6: Posterior Probability Density of the Share of the Variance of Output Growth Attributable to Anticipated Shocks in the Model with Jaimovich-Rebelo Preferences



Note. The posterior probability density is constructed from the last 4 million elements of a 10-million MCMC chain of draws from the posterior distribution of the estimated parameters.

Table 13: Variance Decomposition Under Jaimovich-Rebelo Preferences

	g^Y	g^C	g^I	h
	Stationary Neutral Technology Shock, z_t			
$\epsilon^0_{z,t}$	0.19	0.18	0.20	0.07
$\epsilon^1_{z,t}$	0.02	0.02	0.02	0.01
$\epsilon^2_{z,t}$	0.01	0.00	0.01	0.00
$\epsilon^3_{z,t}$	0.28	0.27	0.30	0.14
$\sum_{i=0}^3 \epsilon^i_{z,t}$	0.50	0.47	0.52	0.21
	Nonstationary Neutral Technology Shock, μ^x_t			
$\epsilon^0_{x,t}$	0.00	0.00	0.00	0.00
$\epsilon^1_{x,t}$	0.00	0.01	0.00	0.01
$\epsilon^2_{x,t}$	0.02	0.02	0.02	0.03
$\epsilon^3_{x,t}$	0.46	0.49	0.45	0.74
$\sum_{i=0}^3 \epsilon^i_{x,t}$	0.49	0.52	0.47	0.77
	Investment-Specific Technology Shock, μ^a_t			
$\epsilon^0_{a,t}$	0.00	0.00	0.00	0.00
$\epsilon^1_{a,t}$	0.00	0.00	0.00	0.01
$\epsilon^2_{a,t}$	0.00	0.00	0.00	0.00
$\epsilon^3_{a,t}$	0.00	0.00	0.00	0.00
$\sum_{i=0}^3 \epsilon^i_{a,t}$	0.01	0.01	0.01	0.01
	Government Spending Shock, g_t			
$\epsilon^0_{g,t}$	0.00	0.00	0.00	0.00
$\epsilon^1_{g,t}$	0.00	0.00	0.00	0.00
$\epsilon^2_{g,t}$	0.00	0.00	0.00	0.00
$\epsilon^3_{g,t}$	0.00	0.01	0.00	0.00
$\sum_{i=0}^3 \epsilon^i_{g,t}$	0.01	0.01	0.00	0.00

Note: Variance decompositions are performed at the mean of the posterior distribution of the estimated structural parameters.

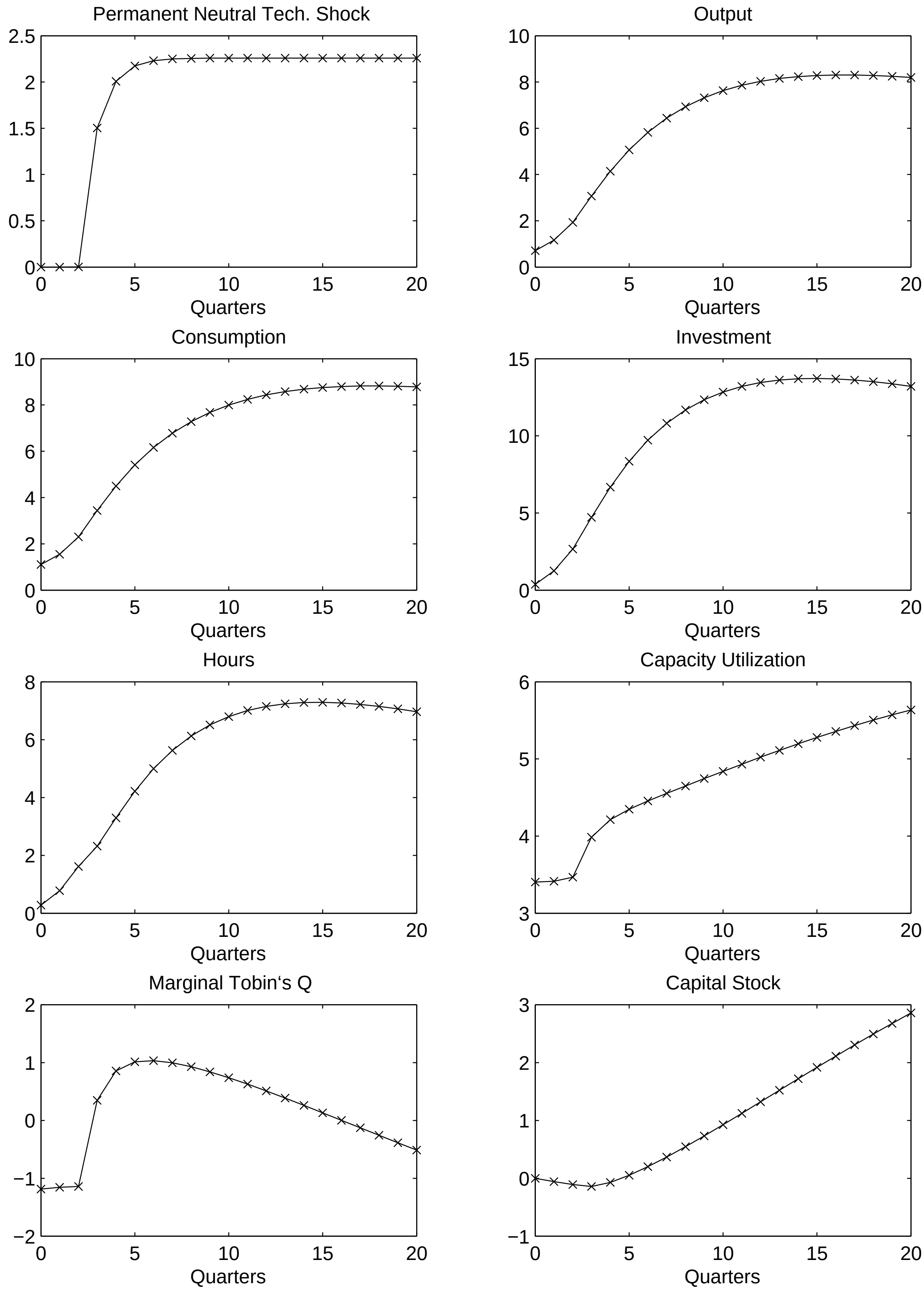
variables considered. It follows that in this model, as in the baseline case, all of the variance attributable to anticipated shocks stems from anticipated changes in neutral productivity. Three innovations, namely, $\epsilon^3_{x,t}$, $\epsilon^3_{z,t}$ and $\epsilon^0_{z,t}$, explain more than 93 percent of business cycles in this model economy.

Our estimation of the model specification with Jaimovich-Rebelo preferences assigns a prominent role to news about future changes in the nonstationary component of TFP. For instance, three-quarter-anticipated permanent changes in TFP ($\epsilon^3_{x,t}$) alone explain about half of the predicted volatility of output, hours, consumption, and investment. This finding is in line with the VECM evidence reported in Beaudry and Portier (2006). Table 9 compares the share of volatilities of macroeconomic variables of interest explained by news about changes in the permanent component of TFP in the baseline specification, in the Jaimovich-Rebelo-preference specification, and in the Beaudry-Portier VECM model.

Figure 7 displays impulse responses to a one-standard-deviation increase in $\epsilon^3_{x,t}$, the three-quarter-anticipated, nonstationary, neutral productivity shock. This is the single most important source of business fluctuations in the present model (see table 13). The figure shows that output, consumption, investment, and hours all experience hump-shaped booms in response to the anticipated increase in TFP growth. The rise in hours worked contrasts with the contraction in this variable implied by the baseline model (see figure 5). It is driven by two factors: the absence of a wealth effect on labor supply (recall that γ is estimated to be close to zero), and the initial increase in capital capacity utilization, which boosts the marginal productivity of labor. The positive comovement of output, consumption, investment, and hours in response to anticipated changes in the permanent component of TFP is in line with the empirical evidence presented in Beaudry and Portier (2006). In this respect, therefore, the model with Jaimovich-Rebelo preferences improves upon the predictions of the baseline model. However, like the baseline model, the current specification continues to predict counter factually a decline in the price of installed capital in response to the announcement of future permanent increases in TFP.

Table 6 reports marginal data densities for the models with baseline preferences and Jaimovich-Rebelo preferences. The marginal data densities are computed using Geweke's modified harmonic mean estimations for various truncation values and a Markov chain of 4 million draws for each specification. The table shows that the data favors the model with Jaimovich-Rebelo preferences. The log Bayes factor, given by the difference between the two log marginal data densities, is about 180 and stable across truncation values.

Figure 7: Jaimovich-Rebelo Preferences: Impulse Response to a Three-Quarter Anticipated One-Standard-Error Innovation in the Non-Stationary Neutral Technology Shock ($\epsilon^3_{x,t}$)



10 Conclusion

In this paper, we perform a 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 four real rigidities: habit formation in consumption, habit formation in leisure, investment adjustment costs, and variable capacity utilization.

We consider four different sources of uncertainty, stationary neutral productivity shocks, non-stationary neutral productivity shocks, permanent investment-specific technology shocks, and government spending shocks. Each of these four sources of uncertainty features an unanticipated component and components anticipated one, two, and three quarters.

Our central finding is that at least two thirds of the variance of output growth and other key macroeconomic variables is attributable to anticipated disturbances. Our results are robust to assuming preferences that feature a low wealth elasticity of labor supply like those suggested in a recent paper by Jaimovich and Rebelo (2008). Specifically, we find that in the context of a model with this type of preferences anticipated shocks explain about 80 percent of the predicted variance of macroeconomic aggregates. An important byproduct of the present study is to provide a Bayesian estimate of the parameter governing the wealth elasticity of labor supply within this family of preferences. We find that the data favor a preference specification displaying a near zero wealth elasticity of labor supply.

To conclude, we relate our work to the early contributions on quantitative equilibrium 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 total factor productivity. Our results are in line with this assessment. Indeed, we find that neutral productivity shocks explain the vast majority of fluctuations at business cycle frequency. Specifically, we estimate that stationary and non-stationary neutral productivity shocks explain about two thirds and one third of business-cycle fluctuations, respectively. On the other hand, we estimate that investment specific and government spending shocks play a negligible role. However, by construction, Prescott allocated all innovations in total factor productivity to unanticiapted components. The contribution of the present study can be interpreted as opening the door for the possibility that innovations in total factor productivity be anticipated at least in part by economic agents. The central finding of our investigation is that allowing for this possibility is not only relevant but uncovers the dominant source of business-cycle fluctuations.

Appendix A: Equilibrium Conditions in Stationary Form

The stochastic trend components of output, capital, and government spending are given, respectively, by $X_t^Y = A_t^{\alpha/(\alpha-1)} X_t$, $X_t^K = A_t^{1/(\alpha-1)} X_t$, and $X_t^G = (X_{t-1}^G)^{\rho_{xg}} (X_{t-1}^Y)^{1-\rho_{xg}}$. Define the following stationary variables: $y_t = \frac{Y_t}{X_t^Y}$, $k_t = \frac{K_t}{X_{t-1}^K}$, $g_t = \frac{G_t}{X_t^G}$, $c_t = \frac{C_t}{X_t^Y}$, $i_t = \frac{I_t}{X_t^K}$, $q_t = \frac{Q_t}{A_t}$, $q_t^a = \frac{Q_t^a}{A_t \mu_t^k}$, $\lambda_t = (X_t^Y)^\sigma \Lambda_t$, and $x_t^g = \frac{X_t^G}{X_t^Y}$. Define the growth rates of the trends in output and capital as $\mu_t^y = \frac{X_t^Y}{X_{t-1}^Y}$ and $\mu_t^k = \frac{X_t^K}{X_{t-1}^K}$. Then, the equilibrium conditions in stationary form are:

$$1 = h_t + \ell_t$$

$$k_{t+1} = (1 - \delta(u_t)) \frac{k_t}{\mu_t^k} + i_t \left[1 - S\left(\frac{i_t \mu_t^k}{i_{t-1}} \right) \right]$$

$$c_t + i_t + g_t x_t^g = y_t$$

$$y_t = z_t F\left(\frac{u_t k_t}{\mu_t^k}, h_t \right)$$

$$U_1\left(c_t - \theta_c \frac{c_{t-1}}{\mu_t^y}, \ell_t - \theta_\ell \ell_{t-1} \right) - \theta_c^i \beta E_t U_1\left(c_{t+1}\mu_{t+1}^y - \theta_c c_t, \ell_{t+1} - \theta_\ell \ell_t \right) = \lambda_t$$

$$U_2\left(c_t - \theta_c \frac{c_{t-1}}{\mu_t^y}, \ell_t - \theta_\ell \ell_{t-1} \right) - \theta_\ell^i \beta E_t U_2\left(c_{t+1}\mu_{t+1}^y - \theta_c c_t, \ell_{t+1} - \theta_\ell \ell_t \right) = \lambda_t z_t F_2\left(u_t \frac{k_t}{\mu_t^k}, h_t \right)$$

$$q_t \lambda_t = \beta E_t \mu_{t+1}^a (\mu_{t+1}^y)^{-\sigma} \lambda_{t+1} \left[z_{t+1} u_{t+1} F_1\left(u_{t+1} \frac{k_{t+1}}{\mu_{t+1}^k}, h_{t+1} \right) + q_{t+1}(1 - \delta(u_{t+1})) \right]$$

$$z_t F_1\left(u_t \frac{k_t}{\mu_t^k}, h_t \right) = q_t \delta'(u_t)$$

$$\lambda_t = q_t \lambda_t \left[1 - S\left(\frac{i_t \mu_t^k}{i_{t-1}} \right) - \frac{i_t \mu_t^k}{i_{t-1}} S'\left(\frac{i_t \mu_t^k}{i_{t-1}} \right) \right] + \beta E_t \mu_{t+1}^a (\mu_{t+1}^y)^{-\sigma} q_{t+1} \lambda_{t+1} \left(\frac{i_{t+1}\mu_{t+1}^k}{i_t} \right)^2 S'\left(\frac{i_{t+1}\mu_{t+1}^k}{i_t} \right)$$

$$\mu_t^y = (\mu_t^a)^{\alpha/(\alpha-1)} \mu_t^x$$

$$\mu_t^k = (\mu_t^a)^{1/(\alpha-1)} \mu_t^x$$

$$x_t^g = \frac{(x_{t-1}^g)^{\rho_{xg}}}{\mu_t^y}$$

$$\ln(\mu_t^x/\mu^x) = \rho_x \ln(\mu_{t-1}^x/\mu^x) + \epsilon_{x,t}^0 + \epsilon_{x,t-1}^1 + \epsilon_{x,t-2}^2 + \epsilon_{x,t-3}^3$$

$$\ln(\mu_t^a/\mu^a) = \rho_a \ln(\mu_{t-1}^a/\mu^a) + \epsilon_{a,t}^0 + \epsilon_{a,t-1}^1 + \epsilon_{a,t-2}^2 + \epsilon_{a,t-3}^3$$

$$\ln z_t = \rho_z \ln z_{t-1} + \epsilon_{z,t}^0 + \epsilon_{z,t-1}^1 + \epsilon_{z,t-2}^2 + \epsilon_{z,t-3}^3$$

$$\ln(g_t/g) = \rho_{gg} \ln(g_{t-1}/g) + \epsilon_{g,t}^0 + \epsilon_{g,t-1}^1 + \epsilon_{g,t-2}^2 + \epsilon_{g,t-3}^3.$$

To obtain the dynamics of average Tobin's Q, add the stationary variable q_t^a and the following equation to the above set of equilibrium conditions:

$$q_t^a = \alpha \frac{y_t}{k_t} - \frac{i_t}{k_t} + \beta E_t \frac{\lambda_{t+1}}{\lambda_t} (\mu_{t+1}^y)^{1-\sigma} \frac{k_{t+1}}{k_t} q_{t+1}^a.$$

Appendix B: 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 (2005). An appendix detailing the procedure used in the construction of this series is available from the authors upon request.

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