INVESTMENT SHOCKS AND BUSINESS CYCLES

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Abstract. Shocks to the marginal efficiency of investment are the most important drivers of business cycle fluctuations in US output and hours. Moreover, these disturbances drive prices higher in expansions, like a textbook demand shock. We reach these conclusions by estimating a DSGE model with several shocks and frictions. We also find that neutral technology shocks are not negligible, but their share in the variance of output is only around 25 percent, and even lower for hours. Labor supply shocks explain a large fraction of the variation of hours at very low frequencies, but not over the business cycle. Finally, we show that imperfect competition and, to a lesser extent, technological frictions are the key to the transmission of investment shocks in the model.

1. Introduction

What is the source of economic fluctuations? This is one of the defining questions of modern dynamic macroeconomics, at least since Sims (1980) and Kydland and Prescott (1982). Yet, the literature is far from a consensus on the right answer. On the one hand, the work that approaches the question from the perspective of general equilibrium models tends to attribute a dominant role in business cycles to neutral technology shocks (see King and Rebelo (1999) for a comprehensive assessment). On the other hand, the structural VAR literature usually points at other disturbances as the main sources of business cycles, and rarely finds that technology shocks explain more than one quarter of output fluctuations (Shapiro and Watson (1988), King, Plosser, Stock, and Watson (1991), Cochrane (1994), Gali (1999), Christiano, Eichenbaum, and Vigfusson (2004) and Fisher (2006)).

This paper confirms the SVAR evidence, but it does so from the perspective of a fully articulated dynamic stochastic general equilibrium (DSGE) model. Our main finding is that shocks to the marginal efficiency of investment are the key drivers of macroeconomic

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fluctuations. These shocks affect the yield of a foregone unit of consumption in terms of tomorrow's capital input. In the literature, they are often referred to as investment specific technology shocks, since they are equivalent to productivity shocks specific to the capital goods producing sector in a simple two-sector economy (Greenwood, Hercowitz, and Krusell (1997)). For simplicity, we label them *investment shocks*.

Our finding regarding the importance of investment shocks for business cycles is based on the Bayesian estimation of a New Neoclassical Synthesis model (Goodfriend and King (1997)) of the US economy, which includes a rich set of nominal and real rigidities, along the lines of Christiano, Eichenbaum, and Evans (2005). As in Smets and Wouters (2007), the model features several shocks that can potentially play a role in fluctuations. Among them, a neutral technology shock, as in the RBC literature, an investment shock, as in Greenwood, Hercowitz, and Huffman (1988) and Greenwood, Hercowitz, and Krusell (2000), and a shock to labor supply, as in Hall (1997).

According to our estimates, *investment shocks* account for between 50 and 60 percent of the variance of output and hours at business cycle frequencies and for more than 80 percent of that of investment. The contribution of the *neutral technology shock* is also non-negligible. It explains about a quarter of the movements in output and consumption, although only about 10 percent of those in hours. Moreover, this shock generates most of the comovement between consumption and output, a feature of business cycles that the investment shock has some trouble replicating.

In this respect, the neutral technology and the investment shock play a complementary role in our model. The former contributes a significant share of the comovement between output and consumption, while the latter is mainly responsible for generating the overall volatility and comovement of output, investment and hours. Another aspect of this complementarity is that the two shocks can be characterized as a supply and a demand shock respectively. In fact, investment shocks generate a positive comovement between prices and quantities, while technology shocks move the two in opposite directions.

As for the *labor supply shock*, we find that it is the dominant source of fluctuations in hours at very low frequencies, although not over the business cycle.

Investment shocks are unlikely candidates to generate business cycles in standard neoclassical models, as emphasized for example by Barro and King (1984) and Greenwood, Hercowitz, and Huffman (1988). In this framework, a positive shock to the marginal efficiency of investment increases the rate of return on capital, which induces households to work harder, but also to consume less. Moreover, with capital fixed in the short run, labor productivity falls and so does the competitive real wage. This is clearly not a recognizable business cycle.

Our results contradict this conventional view because our model adds to its neoclassical core a number of real and nominal rigidities, such as habit formation in consumption, variable capital utilization, investment adjustment costs and imperfect competition with price stickiness in goods and labor markets. These frictions were originally proposed in the literature as a way to improve the empirical performance of monetary models (Christiano, Eichenbaum, and Evans (2005)). We show that they also play a crucial role in turning investment shocks into a viable source of business cycle fluctuations.

For example, variable capital utilization acts as an endogenous shifter of the marginal product of labor. In response to a positive shock to the efficiency of new capital, utilization of existing capital rises. When capital and labor are complements, higher utilization increases labor productivity and therefore shifts labor demand. As a result, consumption, hours, productivity and the competitive real wage can all be procyclical in response to investment shocks, as first emphasized by Greenwood, Hercowitz, and Huffman (1988).

Monopolistic competition with sticky prices and wages plays a similar role, since it drives an endogenous wedge between the marginal product of labor and the marginal rate of substitution between leisure and consumption.[1] As a result, the relative movements of consumption and hours are not as tightly restricted as in a perfectly competitive economy, in which the intra-temporal efficiency condition must hold. So, for example, in our estimated model, price mark-ups decrease in response to a positive investment shock, thus shifting labor demand to the right. This mechanism therefore reinforces the effect of endogenous capital utilization on labor demand. We find that the endogeneity of markups generated by the presence of sticky prices and wages is crucial for the propagation of the investment shock, even more so than the technological frictions.

The prominent role of investment shocks in business cycles that we find in our model is consistent with the SVAR evidence of Fisher (2006) and Canova, Lopez-Salido, and Michelacci

[1] This wedge is the sum of two components: the mark-up of price over marginal cost and the mark-up of wages over the marginal rate of substitution. Changes in these two mark-ups shift labor demand and labor supply respectively.

(2006), and broadly in line with the general equilibrium analysis of Greenwood, Hercowitz, and Krusell (2000). However, we do no use direct observations on the relative price of investment as a proxy for investment specific technological progress. Instead, we treat the investment shock as an unobservable process, and identify it through its dynamic effects on the variables included in the estimation, according to the restrictions implied by the DSGE model.[2] This empirical strategy might be better suited to capture sources of variation in the marginal efficiency of investment that are not fully reflected in the variability of the relative price of investment to consumption. This would be the case, for example, in an economy in which the price of investment were sticky, or in which the process of capital accumulation were subject to more frictions than those we have modeled here, as in Bernanke, Gertler, and Gilchrist (1999) or Christiano, Motto, and Rostagno (2007).

This paper is also related to a recent literature on the estimation of medium and large scale DSGE models (Altig, Christiano, Eichenbaum, and Linde (2005), Del Negro, Schorfheide, Smets, and Wouters (2007), Gertler, Sala, and Trigari (2007), Justiniano and Primiceri (2007) and Smets and Wouters (2007)). We share with this literature the basic structure of the theoretical framework, but we differ from it in two important respects. First, we focus the analysis on the origins of business cycle fluctuations, which leads us to emphasize the key role of investment shocks. Second, we investigate how the departures of our model from the neoclassical benchmark contribute to this result.

The rest of the paper is organized as follows. Section 2 provides some details of the theoretical model. Section 3 describes the approach to inference and discusses the fit of the estimated model. Sections 4 and 5 highlight the role of investment shocks in fluctuations and the effect of frictions on their transmission. Section 6 compares our estimates of the investment shock to the data on the relative price of investment. Section 7 conducts a series of robustness checks, including a detailed comparison with the results of Smets and Wouters (2007). Section 8 concludes.

2. The Model Economy

This section outlines our baseline model of the U.S. business cycle. This is a medium-scale DSGE model, with a host of nominal and real frictions, along the lines of Christiano, Eichenbaum, and Evans (2005). The model fits the data well, which is not surprising in light

[2] In this respect, our strategy is similar to that followed by Fisher (1997), who infers the properties of technological progress in the investment sector through a GMM strategy applied to macroeconomic quantities.

of the evidence presented in Del Negro, Schorfheide, Smets, and Wouters (2007) and Smets and Wouters (2007).[3]

The model economy is populated by five classes of agents. Producers of final goods, which "assemble" a continuum of intermediate goods produced by monopolistic intermediate goods producers. Households, who consume the final good, accumulate capital, and supply differentiated labor services to competitive "employment agencies". A Government. We present their optimization problems in turn.

2.1. **Final goods producers.** At every point in time t, perfectly competitive firms produce the final consumption good Y_t, combining a continuum of intermediate goods $Y_t(i)$, $i \in [0,1]$ according to the technology

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{1}{1+\lambda_{p,t}}} di\right]^{1+\lambda_{p,t}}.$$

$\lambda_{p,t}$, follows the exogenous stochastic process

$$\log \lambda_{p,t} = (1-\rho_p)\log \lambda_p + \rho_p \log \lambda_{p,t-1} + \varepsilon_{p,t} - \theta_p \varepsilon_{p,t-1},$$

where $\varepsilon_{p,t}$ is $i.i.d.N(0,\sigma_p^2)$. This process represents a disturbance to the desired mark-up of prices over marginal costs for intermediate firms. For simplicity, we label this shock as *price mark-up shock*. As in Smets and Wouters (2007), the ARMA(1,1) structure helps capturing the moving average, high frequency component of inflation. Profit maximization and the zero profit condition imply the following relationship between the price of the final good, P_t, and the prices of the intermediate goods, $P_t(i)$

$$P_t = \left[\int_0^1 P_t(i)^{\frac{1}{\lambda_{p,t}}} di\right]^{\lambda_{p,t}},$$

and the demand function for the intermediate good i

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\frac{1+\lambda_{p,t}}{\lambda_{p,t}}} Y_t.$$

[3] We experimented with a number of variants of the baseline model. These robustness checks are reported in section 7.

2.2. **Intermediate goods producers.** A monopolist produces the intermediate good i according to the production function

$$Y_t(i) = \max\left\{A_t^{1-\alpha} K_t(i)^{\alpha} L_t(i)^{1-\alpha} - A_t F; 0\right\},$$

where $K_t(i)$ and $L_t(i)$ denote the capital and labor inputs for the production of good i and F represents a fixed cost of production. A_t is an exogenous stochastic process capturing the effects of technology, whose growth rate ($z_t \equiv \Delta \log A_t$) evolves according to

$$z_t = (1-\rho_z)\gamma + \rho_z z_{t-1} + \varepsilon_{z,t},$$

where $\varepsilon_{z,t}$ is $i.i.d.N(0,\sigma_z^2)$. Therefore, the level of technology is non stationary.

As in Calvo (1983), a fraction ξ_p of firms cannot re-optimize their prices and, therefore, set their prices following the indexation rule

$$P_t(i) = P_{t-1}(i)\pi_{t-1}^{\iota_p}\pi^{1-\iota_p},$$

where $\pi_t \equiv \frac{P_t}{P_{t-1}}$ and π denotes the steady state value of π_t. On the other hand, re-optimizing firms choose their price, $\tilde{P}_t(i)$, by maximizing the present value of future profits, subject to the usual cost minimization condition,

$$E_t \sum_{s=0}^{\infty} \xi_p^s \beta^s \lambda_{t+s} \left\{ \left[\tilde{P}_t(i) \left(\Pi_{j=0}^{s} \pi_{t-1+j}^{\iota_p} \pi^{1-\iota_p} \right) \right] Y_{t+s}(i) - \left[W_t L_t(i) + r_t^k K_t(i) \right] \right\},$$

where λ_{t+s} is the marginal utility of consumption, and W_t and r_t^k denote the nominal wage and the rental rate of capital.

2.3. **Employment agencies.** Firms are owned by a continuum of households, indexed by $j \in [0,1]$. As in Erceg, Henderson, and Levin (2000), each household is a monopolistic supplier of specialized labor, $L_t(j)$. A large number of "employment agencies" combines this specialized labor into labor services available to the intermediate firms, according to

$$L_t = \left[\int_0^1 L_t(j)^{\frac{1}{1+\lambda_{w,t}}} dj\right]^{1+\lambda_{w,t}}.$$

$\lambda_{w,t}$ follows the exogenous stochastic process

$$\log \lambda_{w,t} = (1-\rho_w)\log \lambda_w + \rho_w \log \lambda_{w,t-1} + \varepsilon_{w,t} - \theta_w \varepsilon_{w,t-1},$$

where $\varepsilon_{w,t}$ is $i.i.d.N(0,\sigma_w^2)$. This shock is a disturbance to the desired mark-up of the wage over the marginal rate of substitution for wage setters. For simplicity, we label this shock as *wage mark-up shock*. It plays the same economic role of the "labor supply" shock present in the analysis of Hall (1997), Del Negro, Schorfheide, Smets, and Wouters (2007) or Justiniano and Primiceri (2007).[4] Profit maximization and the zero profit condition for the perfectly competitive employment agencies imply the following relationship between the wage paid by the intermediate firms and the wage received by the supplier of labor of type j, $W_t(j)$

$$W_t = \left[\int_0^1 W_t(j)^{\frac{1}{\lambda_{w,t}}} dj\right]^{\lambda_{w,t}},$$

and the labor demand function

$$L_t(j) = \left(\frac{W_t(j)}{W_t}\right)^{-\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} L_t.$$

2.4. **Households.** Each household maximizes the utility function

$$E_t \sum_{s=0}^{\infty} \beta^s b_{t+s} \left[\log\left(C_{t+s} - hC_{t+s-1}\right) - \varphi \frac{L_{t+s}(j)^{1+\nu}}{1+\nu}\right],$$

where C_t is consumption, h is the "degree" of habit formation and b_t is a "discount factor" shock affecting both the marginal utility of consumption and the marginal disutility of labor.[5] This shock follows the stochastic processes

$$\log b_t = \rho_b \log b_{t-1} + \varepsilon_{b,t},$$

with $\varepsilon_{b,t} \sim i.i.d.N(0, \sigma_b^2)$. Note that we work with log utility to ensure the existence of a balanced growth path, as in the real business cycle tradition. Moreover, consumption is not indexed by j because the existence of state contingent securities ensures that in equilibrium consumption and asset holdings are the same for all households.

The household's budget constraint is

$$P_tC_t + P_tI_t + T_t + B_t \leq R_{t-1}B_{t-1} + Q_{t-1}(j) + \Pi_t + W_t(j)L_t(j) + r_t^k u_t \bar{K}_{t-1} - P_t a(u_t)\bar{K}_{t-1},$$

where I_t is investment, T_t are lump-sum taxes, B_t is holdings of government bonds, R_t is the gross nominal interest rate, $Q_t(j)$ is the net cash flow from participating in state contingent securities, and Π_t is the per-capita profit accruing to households from ownership of the firms.

Households own capital and choose the capital utilization rate, u_t, which transforms physical capital into effective capital according to

$$K_t = u_t \bar{K}_{t-1}.$$

[4] The two shocks would be observationally equivalent if we did not have the output gap in the policy rule.

[5] We assume a cashless limit economy as described in Woodford (2003).

Effective capital is then rented to firms at the rate r_t^k. The cost of capital utilization is $a(u_t)$ per unit of physical capital. As in Altig, Christiano, Eichenbaum, and Linde (2005), we assume that $u_t = 1$ and $a(u_t) = 0$ in steady state. In our log-linear approximation of the model solution, we only need to specify the curvature of the function a in steady state, $\chi \equiv \frac{a''(1)}{a'(1)}$. The physical capital accumulation equation is

$$\bar{K}_t = (1-\delta)\bar{K}_{t-1} + \mu_t \left(1 - S\left(\frac{I_t}{I_{t-1}}\right)\right) I_t,$$

where δ denotes the depreciation rate. The function S captures the presence of adjustment costs in investment, as in Christiano, Eichenbaum, and Evans (2005) and Altig, Christiano, Eichenbaum, and Linde (2005). We assume that S and $S' = 0$, and $S'' > 0$ in steady state.[6] Following Greenwood, Hercowitz, and Krusell (1997) and Fisher (2006), μ_t can be interpreted as an investment specific technology shock affecting the efficiency with which consumption goods are transformed into capital. For simplicity, we label this shock as the *investment shock.* We assume that it follows the exogenous process

$$\log \mu_t = \rho_\mu \log \mu_{t-1} + \varepsilon_{\mu,t},$$

where $\varepsilon_{\mu,t}$ is $i.i.d.N(0, \sigma_\mu^2)$.

As in Erceg, Henderson, and Levin (2000), a fraction ξ_w of households cannot re-optimize their wages and, therefore, set them according to the indexation rule

$$W_t(j) = W_{t-1}(j) \left(\pi_{t-1} e^{z_{t-1}}\right)^{\iota_w} \left(\pi e^{\gamma}\right)^{1-\iota_w}.$$

The remaining fraction of re-optimizing households maximizes instead

$$E_t \sum_{s=0}^{\infty} \xi_w^s \beta^s b_{t+s} \left\{ -\varphi \frac{L_{t+s}(j)^{1+\nu}}{1+\nu} \right\},$$

subject to the labor demand function.

2.5. **Government.** Monetary policy sets short term nominal interest rates following a Taylor type rule of the form

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y_t^*}\right)^{\phi_Y} \right]^{1-\rho_R} \left[\frac{Y_t / Y_{t-1}}{Y_t^* / Y_{t-1}^*} \right]^{\phi_{dY}} \eta_{mp,t},$$

where R is the steady state for the nominal interest rate. Following Smets and Wouters (2007), monetary policy is assumed to respond to deviations of inflation from the steady

[6] Lucca (2005) shows that this formulation of the adjustment cost function is equivalent (up to first order) to a generalization of the time to build assumption.

state, and to the level and the growth rate of the output gap (Y_t/Y_t^*).[7] The monetary policy rule is also perturbed by a monetary policy shock, $\eta_{mp,t}$, which evolves according to

$$\log \eta_{mp,t} = \rho_{mp} \log \eta_{mp,t-1} + \varepsilon_{mp,t},$$

where $\varepsilon_{mp,t}$ is $i.i.d.N(0, \sigma_{mp}^2)$.

Fiscal policy is fully Ricardian: the Government finances its budget deficit by issuing short term bonds. Public spending is determined exogenously as a time-varying fraction of GDP

$$G_t = \left(1 - \frac{1}{g_t}\right) Y_t,$$

where g_t is a disturbance following the stochastic process

$$\log g_t = (1 - \rho_g) \log g + \rho_g \log g_{t-1} + \varepsilon_{g,t},$$

with $\varepsilon_{g,t} \sim i.i.d.N(0, \sigma_g^2)$.

2.6. **Market clearing.** The aggregate resource constraint,

$$C_t + I_t + G_t + a(u_t)\bar{K}_{t-1} = Y_t,$$

can be derived by combining the Government and the households' budget constraints with the zero profit condition of the final goods producers and the employment agencies.

2.7. **Model solution.** In this model, consumption, investment, capital, real wages and output evolve along a stochastic balanced growth path, since the technology process A_t has a unit root. Therefore, in order to solve the model, we first rewrite it in terms of detrended variables, compute the non-stochastic steady state of the transformed model, and then log-linearly approximate it around this steady state.

3. Bayesian Inference

3.1. **Data and priors.** We estimate the model using

$$[\Delta \log Y_t, \Delta \log C_t, \Delta \log I_t, \log L_t, \Delta \log \frac{W_t}{P_t}, \pi_t, R_t] \tag{3.1}$$

as the vector of observable variables, where Δ denotes the temporal difference operator. We use quarterly data and our dataset covers the period from 1954QIII to 2004QIV. A precise description of the data series used in the estimation can be found in appendix A.

[7] The output gap is defined as the difference between output and flexible price output (Woodford (2003)).

We use Bayesian methods to characterize the posterior distribution of the structural parameters of the model (see An and Schorfheide (2007) for a survey). The posterior distribution combines the likelihood function with prior information.[8] In the rest of this section we briefly discuss the assumptions about the prior.

We fix a small number of parameters to values commonly used in the literature. In particular, we set the quarterly depreciation rate of capital (δ) to 0.025 and the steady state government spending to GDP ratio ($1-1/g$) to 0.22, which corresponds to the average value of G_t/Y_t in our sample. Table 1 reports the priors for the remaining parameters of the model. While these priors are relatively disperse and broadly in line with those adopted in previous studies (Del Negro, Schorfheide, Smets, and Wouters (2007) or Justiniano and Primiceri (2007)), some of them deserve a brief discussion.

For all but two persistence parameters we use a Beta prior, with mean 0.6 and standard deviation 0.2. One of the two exceptions is neutral technology, which already includes a unit root. For this reason, the prior for the autocorrelation of its growth rate (ρ_z) is centered at 0.4 instead. We use 0.4 also to center the prior for the persistence of the monetary policy shocks, because the policy rule already allows for interest rates inertia. The covariance matrix of the innovations is assumed to be diagonal. The inter-temporal preference, price and wage mark-up shocks are normalized to enter with a unity coefficients in the consumption, price inflation and wage equations respectively (see Smets and Wouters (2007) and appendix B). The priors on the innovations' standard deviations are quite disperse and chosen in order to generate volatilities for the endogenous variables broadly in line with the data.

As opposed to commenting on the prior for specific coefficients, we evaluate all the priors on the exogenous processes and the structural parameters indirectly, by analyzing their implications for the unconditional variance decomposition of the observable variables of the model. Table 2 makes clear that our prior beliefs are in line with the traditional RBC view: the variability of output, consumption, investment and hours is due for the most part to neutral technological disturbances. According to our prior-based variance decomposition, the investment shock is the least important shock.

3.2. **Parameter estimates.** In table 1, we report the estimates of the model's parameters. We present posterior medians, standard deviations and 90 percent posterior intervals. In line with previous studies, we estimate a substantial degree of price and wage stickiness,

[8] In section 7 we show that results are robust to estimating the model by maximum likelihood (flat priors).

habit formation in consumption and adjustment costs in investment (see, for instance, Altig, Christiano, Eichenbaum, and Linde (2005), Del Negro, Schorfheide, Smets, and Wouters (2007) or Smets and Wouters (2007)).

As in Del Negro, Schorfheide, Smets, and Wouters (2007) and Justiniano and Primiceri (2007), capital utilization is not very elastic: in response to a 1 percent positive change in the rental rate of capital, utilization increases by slightly less than 0.2 percent.

Similar to Smets and Wouters (2007), our estimates of the share of capital income (α) and the Frisch elasticity of labor supply ($1/\nu$) are both lower than the values typically adopted in the RBC literature. However, as we show in section 7, none of our results depend crucially on these estimates of α and ν. We investigate the empirical performance of the model in the next subsection.

3.3. **Model fit.** Given our posterior estimates, how well does the model fit the data? In this section, we address this question by comparing a set of statistics implied by the model to those measured in the data. In particular, we study the standard deviation and the complete correlation structure of the observable variables included in the estimation.

Table 3 reports the model-implied standard deviation of our seven observable variables, as well as the standard deviation of these variables relative to output growth. We also report 90 percent probability intervals that account for both parameter uncertainty and small sample uncertainty. Relative to the data, the model overpredicts a bit the volatility of output growth, but approximately matches the relative standard deviations of consumption, investment growth and hours. There is also a tendency to underpredict the volatility of nominal interest rates and inflation, which might be due to the fact that the model captures only part of the very high correlation between these two variables.

Why does not the model capture perfectly the standard deviation of the observable variables? This is due to the discipline imposed by the likelihood-based estimation procedure, that strikes a balance between matching standard deviations and other moments in the data like, for instance, autocorrelations and cross-correlations. Following Gertler, Sala, and Trigari (2007), figure 1 displays the full matrix of cross-correlations of the observable variables in the data (grey line) and in the model (back line). We also report the 90 percent posterior intervals implied by parameter uncertainty and small sample uncertainty.

Focus first on the upper-left 4-by-4 block of the matrix, which includes all the quantities in the model. On the diagonal, we see that the model captures the decaying autocorrelation structure of these four variables very well. The success is particularly impressive for hours, for which the model-implied and data autocorrelations lay virtually on top of each other. In terms of cross-correlations, the model does extremely well for output (the first row and column) and for hours (the fourth row and column), but fails to capture the contemporaneous correlation between consumption and investment growth. This correlation is slightly positive in the data, but essentially zero in the model.[9]

In sum, relative to smaller scale RBC models (e.g. Cooley and Prescott (1995) or King and Rebelo (1999)), we probably do less well in matching the properties of consumption. However, our model performs considerably better in terms of hours worked. This is important because one of our main objectives is investigating the sources of business cycle fluctuations in hours.

With respect to prices, the model is overall quite successful in reproducing the main stylized facts. We emphasize two issues: first, the model struggles to capture the full extent of the persistence of inflation and the nominal interest rate, even in the presence of inflation indexation and of a fairly high smoothing parameter in the interest rate rule. Second, we match very closely the correlation between output and inflation, which is highlighted for example by Smets and Wouters (2007) as an important measure of the model's empirical success.

4. Shocks and Business Cycles

In this section, we present the central result of the paper: investment shocks are the most important source of business cycle fluctuations. First, we document this finding quantitatively, by looking at the variance decomposition implied by the estimated model. We focus in particular on output and hours. Second, we provide some intuition for the result by studying the impulse responses of some key variables to the main shocks in the model. This exercise also allows us to informally discuss how those shocks are identified by our empirical procedure.

4.1. **Variance decomposition.** Table 4 reports the contribution of each shock to the unconditional variance of the *observable* variables included in the estimation. From the first row of the table, we see that investment shocks account for more than 50 percent of the fluctuations in the growth rate of output, by far the largest share. The role of investment shocks as drivers of fluctuations in output is even more striking in figure 2, where we plot GDP

[9] The cross-correlation between consumption and investment improves when we use a non-separable utility function in consumption and leisure. We will return to this point in section 7.

growth in the data (the grey line) and in the model, conditional on the estimated sequence of the investment shocks alone (the black line). In particular, investment shocks appear largely responsible for "dragging" GDP growth down in correspondence with business cycle troughs. This is especially evident for the last two downturns, as well as for the recessions of the sixties. The main exceptions are the "twin" recessions of the early eighties, in which monetary factors are widely believed to have played a fundamental role.

Looking at the other shocks and variables, two results stand out. First, the neutral technology shock remains fairly important in our estimates, explaining around one quarter of the volatility of output, consumption and real wages. Second, the wage mark-up shock, which in this model is indistinguishable from Hall's (1997) labor supply shock, has a very important role in the fluctuations of wages, inflation and especially hours. It explains between one half and two thirds of their volatility.

The variance decomposition of hours in table 4 is puzzling. The investment shock explains only 20 percent of the volatility of hours, less than half its contribution to output. Yet, the close comovement of hours and output is perhaps the most notable feature of business cycles. Table 5 sheds some light on this apparent contradiction, by focusing on fluctuations in the *level* of all variables at business cycle frequencies.[10]

At business cycle frequencies, investment shocks explain approximately 60 percent of the fluctuations in hours, 50 percent of those in output and more than 80 percent of those in investment. We conclude that investment shocks are the leading source of business cycle fluctuation. The main caveat to this result comes from consumption. Investment shocks explain only a small fraction of its variability, which is mainly driven by the inter-temporal preference shock. This is a symptom of the well-known failure of standard consumption Euler equations to capture the empirical relationship between consumption and interest rates, as argued in Primiceri, Schaumburg, and Tambalotti (2005).

Another interesting result emerging from the comparison of tables 4 and 5 is that the role of wage mark-up shocks virtually disappears when we restrict attention to business cycle frequencies. This is particularly noticeable for hours, with a drop in the share of variance attributed to wage mark-up shocks from 65 percent overall to only 6 percent at business cycle

[10] We compute the spectral density implied by the DSGE model, appropriately transformed to obtain the spectrum of the *level* of output, consumption, investment and wages. We define the business cycle frequencies as those corresponding to periodic components with cycles between 6 and 32 quarters, as in Stock and Watson (1999).

frequencies. Figure 3 clarifies this point by plotting the share of the variance of hours explained by the wage mark-up shock, as a function of the spectrum frequencies. Our definition of business cycles corresponds to a frequency range between 0.19 and 1, as pointed out by the dotted vertical lines in the picture. The steep decline of this "conditional spectrum" in the low frequency band demonstrates that the importance of wage mark-up shocks for hours is primarily concentrated at very low frequencies. This result is roughly consistent with Hall's (1997) finding of an important role for labor supply shocks in the fluctuation of hours, although his cyclical decomposition attributes a key role to those shocks also at business cycle frequencies.

4.2. **Model dynamics and shock identification.** Our results so far suggest that to understand business cycles, we must understand investment shocks, since these shocks are the largest contributors to fluctuations in several key macroeconomic variables. But what properties of this and the other shocks allow us to separately identify their contributions? This section provides some intuition for how this identification is achieved, by studying the impulse responses of several key variables to some of the shocks. In particular, we focus on the three shocks that are responsible for the bulk of fluctuations according to our estimates. They are the investment shock, the neutral technology shock and the wage mark-up (or labor supply) shock.

Figure 4 reports the impulse responses to the investment shock. Following a positive impulse, output, hours, investment, real wages and labor productivity all rise persistently and in a hump-shaped pattern. The reaction in investment is contemporaneous and roughly proportional to that in output, but larger by a factor of almost five. This factor is close to the ratio of the unconditional volatilities of the two series.

The response of hours is very similar to that of output, in terms of dynamic profile and scale. This accounts for the very similar shares of business cycle fluctuations in output and hours explained by investment shocks, given that the cyclical components of the two series have very similar volatilities. The increase in hours is not associated with a drop in average labor productivity, as would be the case in a standard neoclassical model. The procyclicality of labor productivity in response to investment shocks is the combined result of the endogeneity of capital utilization (Greenwood, Hercowitz, and Huffman (1988)) and of the increasing returns implied by the presence of fixed costs in production.

As for consumption, its response is flat initially and rises only with a delay of a few quarters. This failure of consumption to co-move on impact with the other macroeconomic variables is the main reason why the investment shock accounts for less then 10 percent of the movements in consumption, and thus for a smaller share of the variance of output, compared to investment. Moreover, this lack of comovement, which is especially pronounced for the consumption-investment pair, explains why the model has some difficulty in capturing the correlation between these two variables, as we pointed out in section 3.3

Finally, looking at inflation and the nominal interest rate, we see that they both rise in response to a positive investment shock. In this respect, the investment shock displays the typical features of a textbook “demand” shock: quantities and prices move in the same direction, leading to a tightening of monetary policy. In fact, the positive comovement of prices and quantities is one of the distinguishing characteristics of the investment shock, when compared to wage mark-up and neutral technology shocks, whose impulse responses are depicted in figures 5 and 6.

For example, an increase in the desired wage mark-up depresses all quantities, but leads to a fairly persistent increase in real wages and marginal costs. As a consequence, inflation rises, followed by the nominal interest rate. Moreover, the response in hours, and in all other quantities, is extremely persistent. This persistence is the source of the large contribution of the wage mark-up shock to the low frequency fluctuations in the labor input highlighted in the previous section.

Similarly, output, consumption and investment all rise in response to a positive neutral technology shock. Real wages are also procyclical, but their increase lags behind the rise in the marginal product of labor, so that marginal costs and therefore inflation fall. In fact, the increase in markups–the reciprocal of real marginal costs–is enough to counteract the positive effect of higher productivity on labor demand. so that hours fall. This finding is sharply at odds with the implications of a standard RBC model, but consistent with most of the recent SVAR and DSGE literature (Gali (1999), Francis and Ramey (2006), Canova, Lopez-Salido, and Michelacci (2006), Fernald (2007), Basu, Fernald, and Kimball (2007); Gali and Rabanal (2004) and Smets and Wouters (2007), but see Christiano, Eichenbaum, and Vigfusson (2004) for an exception.). The lack of comovement between output and hours accounts to a large extent for the limited role of neutral technology shocks as sources of fluctuations in our model. On the other hand, these disturbances generate the right comovement between output and consumption. As a result, neutral technology shocks retain a non-negligible role in the fluctuations of these two variables.

In conclusion, our analysis proposes a fairly nuanced view of the sources of business cycles. Investment shocks impart the main impetus to fluctuations, which spread from investment to output and hours. Consumption, however, is largely isolated from these disturbances and its comovement with the rest of the economy is mainly driven by neutral technology shocks. Finally, labor supply shocks account for a large fraction of the movements in hours, but these are concentrated at very low frequencies.

As for wages and prices, their movement is mainly driven by exogenous changes in desired markups, as it should be in an economy in which monetary policy is not too far from optimal. In this respect, it is especially remarkable that inflation and wages are almost completely isolated from investment shocks. The fact that this shock explains close to half of the movements in nominal interest rates suggests that achieving this nominal stabilization required a fair amount of activism on the part of monetary policy.

5. Inspecting the Mechanism: How Investment Shocks Become Important

In a standard neoclassical environment, neutral technology shocks are the most natural source of business cycles, since they can easily produce comovement of output, consumption, investment, hours and labor productivity. In fact, Barro and King (1984) show that generating this kind of comovement in response to most other shocks is problematic. In particular, they explicitly identify investment shocks as unlikely candidates to generate recognizable business cycles. Their reasoning can be outlined as follows: a positive shock to the marginal efficiency of investment increases the rate of return on current resources, inducing agents to postpone consumption. With lower consumption, the marginal utility of income increases, shifting labor supply to the right, along an unchanged labor demand schedule.[11] As a result, hours and output increase, but consumption, wages and labor productivity are all countercyclical.

This is not what happens in our estimated model, though, in which investment shocks trigger procyclical movements in all the key macroeconomic variables discussed above (see

[11] Labor demand is unchanged on impact because the investment shock does not directly affect the marginal product of labor.

figure 4.)[12] As a consequence of this significant change in the transmission mechanism with respect to the neoclassical benchmark, investment shocks emerge from our analysis as the single most important source of business cycle fluctuations. In this section, we study more closely how the frictions included in our baseline model contribute to this result.

In principle, most of these frictions have the potential to make the transmission of investment shocks more conformable with the typical pattern of business cycles. Some of them, such as endogenous capital utilization and investment adjustment costs, have been analyzed before with this objective in mind, most prominently by Greenwood, Hercowitz, and Huffman (1988) and Greenwood, Hercowitz, and Krusell (2000). Some others, such as monopolistic competition with sticky prices and wages, have not.[13]

For instance, habit formation makes households reluctant to sharply adjust their consumption, reducing their willingness to substitute over time. As a consequence, consumption is less likely to fall significantly in response to a positive investment shock. Similarly, investment adjustment costs smooth the reaction of investment, thus limiting the extent of its negative comovement with consumption.

Endogenous capital utilization is another channel through which consumption might become procyclical, as first highlighted by Greenwood, Hercowitz, and Huffman (1988). In fact, an improvement in the efficiency of new investment gives firms the incentive to increase the utilization of existing capital, due to the drop in its relative value. Higher capital utilization in turn implies a higher marginal product of labor, so that labor demand shifts to the right. For a given labor supply schedule, this shift implies an increase in hours and wages, as well as in consumption. Moreover, the increase in the marginal product of labor with constant returns to scale implies that average productivity also rises.

Finally, monopolistic competition in goods and labor markets drives a wedge between the marginal rate of substitution between consumption and leisure, and the marginal product of labor. Sticky prices and wages make this wedge endogenous. As a result of this inefficiency, the restriction on the relative movement of consumption and hours emphasized by Barro and King (1984) fails to hold. More specifically, a positive investment shock produces a drop in the equilibrium mark-up in product markets, as we can see from the fact that the real

[12] Consumption is the only possible exception, since it only increases with a delay of about one year, as we pointed out in section 4.2.

[13] Rotemberg and Woodford (1995) make the point that endogenous markup variation is an additional channel through which aggregate shocks might affect fluctuations, especially in employment. However, they do not consider investment shocks in their analysis.

marginal cost rises in figure 4. This fall in markups induces a positive shift in labor demand, similar to that associated with changes in utilization.

A symmetric argument holds for the wage markup, which acts as a shifter of labor supply. According to our estimates, the wage markup increases following an investment shock. Therefore, labor supply contracts, thus counteracting the inter-temporal substitution effect brought about by the higher rate of return. In this respect, the effects of an endogenous wage markup on the transmission of shocks are not too dissimilar from those of utility functions that weaken the inter-temporal substitution effect on labor supply, as for example in Greenwood, Hercowitz, and Huffman (1988).or Jaimovich and Rebelo (2006).

In the rest of this section, we investigate the quantitative role of all these frictions in turning investment shocks into the dominant source of fluctuations. To this end, we study the variance decomposition of several restricted versions of the baseline model, in which we shut down one category of frictions at-a-time. We consider the following groups of frictions. First, we estimate a model with no habit in consumption, which corresponds to $h = 0$. Second, we fix capital utilization and eliminate investment adjustment costs by setting $1/\chi = 0.0001$ and $S'' = 0$. Third, we consider models with (nearly) competitive labor and goods markets, by calibrating $\xi_w = 0.01$, $\iota_w = 0$, $\lambda_w = 1.01$ and $\xi_p = 0.01$, $\iota_p = 0$, $\lambda_p = 1.01$. Finally, we reduce our model all the way to its standard neoclassical core, by shutting down all the frictions simultaneously.

The results of this exercise are reported in table 6. The table focuses on the contributions of investment shocks to the volatility of output and hours at business cycle frequencies, since this is where the importance of these shocks is most evident. First, we observe that removing any of the frictions reduces the contribution of investment shocks to fluctuations. This is as expected, given our preceding discussion of the effects of the frictions on the transmission mechanism.

In terms of relative contributions, imperfect competition has the most significant marginal impact. In the perfectly competitive model, the contribution of investment shocks to fluctuations in output and hours drops to 4 and 8 percent respectively. This decline is due almost equally the role of endogenous mark-ups in goods and labor markets. Endogenous utilization and adjustment costs come next. Their exclusion reduces the contribution of investment shocks to fluctuations in both hours and output by more than half. The friction that plays the smallest role at the margin is time non-separability.

Finally, the last column in table 6 shows that the contribution of the investment shock disappears entirely in the frictionless model. This result suggests that our estimation procedure is not unduly affecting our findings on the role of investment shocks. When we restrict ourselves to the standard neoclassical model, we recover what we would expect in light of the theoretical analysis of Barro and King (1984) and Greenwood, Hercowitz, and Huffman (1988): investment shocks do not play any role in fluctuations.[14]

We conclude this section by pointing out that the effect of the frictions included in our model is not only to amplify the contribution of investment shocks in fluctuations. Removing any of the frictions considered in table 6 from the baseline model significantly deteriorates its overall empirical performance. This is illustrated in table 7, where we report the log-marginal data density of the restricted versions of the model described above.[15] Since differences in log-marginal data densities across models correspond to log-posterior odds, it is clear that the fit of all the restricted models is substantially worse than the baseline.

6. Investment Shocks and the Relative Price of Investment

In our empirical investigation, we have assumed that the marginal efficiency of investment follows an exogenous stochastic process. Consequently, we have treated the investment shock as a latent variable, in line with some recent prominent papers in the literature (see, for instance, Smets and Wouters (2007) or Del Negro, Schorfheide, Smets, and Wouters (2007)). Another branch of literature, however, has pointed out that the investment shock corresponds to the relative price of consumption to investment goods in a two-sector version of our model (Greenwood, Hercowitz, and Krusell (1997), Greenwood, Hercowitz, and Krusell (2000), Fisher (2006)). For the purpose of comparing more closely our results to this strand of work, this section estimates a version of the model in which this correspondence between the investment shock and the relative price is considered more explicitly.

First, this requires allowing for non-stationarity in the process for the investment shock, because the relative price of consumption exhibits an upward trend in the postwar period.

[14] In the estimated frictionless model, we find that the neutral technology and labor supply shock explains 43 and 47 percent of the variance of output and 4 and 78 percent of that of hours at business cycle frequencies.

[15] The marginal data density (or marginal likelihood) is the expected value of the likelihood function with respect to the prior density and is the appropriate way of comparing models from a Bayesian perspective (Gelman, Carlin, Stern, and Rubin (1995)).

In this respect, we follow Greenwood, Hercowitz, and Krusell (1997) and assume that the investment shock follows a trend stationary process. However, consistent with the relative price data, we allow for a break in the trend in 1982:II. We calibrate the slope of this broken trend to match the average growth rate of the relative price of consumption before and after 1982:II.

In addition, we make a few small modifications to the baseline model, along the lines of Altig, Christiano, Eichenbaum, and Linde (2005). For example, we assume that the cost of adjusting investment depends on the quantity of investment installed, rather than on its value in terms of consumption. Therefore, $S(I_t/I_{t-1})$ becomes $S\left((\mu_t I_t) / \left(\mu_{t-1} I_{t-1}\right)\right)$, where I_t is now the real value of investment in terms of consumption.[16] Consistent with this definition, we also deflate all nominal variables for the estimation by the consumption deflator, on which we also base our measure of price inflation.

The second column of table 8 reports the share of variance of output and hours explained by the investment shock at business cycle frequencies. These numbers are in line with the variance decomposition of the baseline model, although they are slightly lower. We conclude that our results are robust to a specification of the model which is consistent with the common interpretation of investment shocks as the reciprocal of the relative price of investment.[17]

Next, we compare the smoothed estimate of the investment shock to the relative price of consumption in the data, both expressed in deviation from the broken linear trend.[18] The two series exhibit a similar degree of autocorrelation, although our measure of the investment shock is considerably more volatile, with a standard deviation approximately four times larger than the relative price. This might be related to the well known measurement problems concerning the price of investment and durable consumption goods (see, for example, Gordon (1990) or Cummins and Violante (2002)). Another possible interpretation of this finding is that our estimated investment shock is hiding unmodeled frictions in the capital accumulation process, of the kind considered for example by Christiano, Motto, and Rostagno (2007).

[16] We make three additional small changes to the model, which are required to ensure the existence of a balanced growth path. We scale the fixed cost of production and index wages to the deterministic trend in the investment shock and scale the cost of capital utilization by the inverse of the investment shock.

[17] We have also experimented with a stochastic trend. In that case, the shares of variance of output and hours are even higher (third column of table 8), although the estimated persistence of the growth rate of the investment shock is very high as well.

[18] We construct this relative price using the chain-weighted deflators for our components of consumption (non-durables and services) and investment (durables and total private investment).

7. Robustness Analysis

In this section we demonstrate the robustness of our result to a number of alternative specifications of the model. The results of these robustness checks are presented in table 8, which, to save space, only reports the share of the variance of output and hours explained by the investment shock at business cycle frequencies.

7.1. **The model of Smets and Wouters (2007).** Our results on the role of investment shocks might seem at odds with those of Smets and Wouters (2007, SW hereafter). In particular, they recover a dominant role for the wage mark-up shock at long horizons, while their investment shock accounts for less than 25 percent of fluctuations in GDP at any horizon.

This apparent discrepancy arises from two sources. First, SW look at forecast-error variance decompositions at various horizons, while we focus on business cycle frequencies from a spectral decomposition. Given the predominance of wage mark-up shocks in the spectrum of hours at low frequencies, it is not surprising that these shocks dominate the variations in output and hours at long forecast horizons, as reported by SW.

Second, following most of the literature, our measure of investment includes consumer durables, which SW include instead in consumption, along with non-durables and services. When we re-estimate our model with the SW's dataset, the variance share of investment shocks at business cycle frequencies falls to about 20 percent for both output and hours. However, the discrepancy with our baseline results is explained by a rise in the role of the inter-temporal preference shock (b_t), which now accounts for roughly one quarter of the variation of output and one third of that of hours. As a result, the combined variance share of the inter-temporal and investment shocks is in line with what reported in our baseline specification.[19]

There is a third potential source of discrepancy between our results and those of SW, and that is in some details of the model. As it turns out, however, this discrepancy is quantitatively irrelevant. To verify it, we estimate their model on our dataset. The shares of output and hours variability attributed to the investment shocks are reported in table 8. They are very close to those in our baseline model. We conclude that most of the discrepancy between our results and theirs is attributable to a different definition of investment. At the same time, even with their definition of investment, our results remain essentially robust,

[19] The correlation between a filtered estimate of the inter-temporal preference shock recovered from this estimation and the investment shock estimated with our dataset is 0.67.

once we recognize that their inter-temporal preference shock and our investment shock play very similar economic roles across the two models.

7.2. $\alpha = 0.3$ **and** $\nu = 1$**.** Our baseline estimates of the share of capital income (α) and the Frisch elasticity of labor supply ($1/\nu$) differ from the standard values used in the RBC literature. To verify that our estimates of α and ν do not play an important role for the results, we re-estimate the model calibrating $\alpha = 0.3$ and $\nu = 1$, which are more typical values. Table 8 reports the results of this experiment: the investment shocks still explains most of the variation of hours and output at business cycle frequencies.

7.3. **No ARMA shocks.** Following Smets and Wouters (2007), in the baseline model we have assumed that wage and price mark-up shocks follow ARMA(1,1) processes. While the ARMA assumption improves the fit of the model, we want to make sure that our main results do not depend on this assumption. Therefore, we re-estimate the model under the assumption that mark-up shocks follow simpler AR(1) processes instead (Del Negro, Schorfheide, Smets, and Wouters (2007) and Justiniano and Primiceri (2007)). As table 8 makes clear, this modification does not undermine our main results.

7.4. **Output growth in the policy rule.** In our baseline model, the monetary authorities set short term nominal interest rates as a function of inflation and the output gap, defined as the deviation of output from its flexible price level. Since the literature has not reached an agreement on the right measure of real activity that should be included in the policy rule, we re-estimate the model specifying the Taylor rule in terms of output growth, as opposed to the output gap. Table 8 shows that this change is not important for our main result.

7.5. **Maximum Likelihood.** In our baseline exercise, we follow the recent literature on Bayesian estimation of DSGE models and use the prior information reported in table 1. To verify that our priors do not drive our main results, we re-estimate the model by maximum likelihood. Maximizing the likelihood is numerically much more challenging than maximizing the posterior. The use of weakly informative priors, in fact, ameliorates problems related to flatness of the likelihood function and multiple local modes. Nevertheless, we were able to compute the maximum likelihood estimates.[20] As illustrated in table 8, these estimates

[20] To be precise, in order to maximize the likelihood we need to calibrate $\varkappa$, because the likelihood is not very informative about this parameter and this creates convergence problems in the maximization routine. Therefore, we have calibrated $\varkappa = 5$, which is our prior mean. Notice that this value of $\varkappa$ implies a low elasticity of capital utilization which, if anything, makes the propagation of investment shocks more challenging.

provide a similar picture of the results: the investment shock still drives most of the business cycle fluctuations in output and hours.

8. Concluding Remarks

What is the source of business cycle fluctuations? We revisited this fundamental question of macroeconomics from the perspective of an estimated New Neoclassical Synthesis model. We found that shocks to the marginal efficiency of investment are the main drivers of movements in hours, output and investment over the cycle. Neutral technology shocks also retain a non negligible role in the fluctuations of consumption and output and are mainly responsible for their comovement. Finally, shocks to labor supply account for a large share of the variance of hours at very low frequencies, but their contribution over the business cycle is negligible.

One important qualification of our results is that the volatility of the investment shock we estimate is much larger than the volatility of the price of investment relative to consumption measured in the data. In a two-sector representation of our model in which the sector producing capital goods is perfectly competitive, the two would be the same. There are several possible reasons for this discrepancy. First, measuring the price of durable goods in a manner consistent with theory is notoriously problematic. Second, a serious effort at modeling a two-sector economy would probably include sticky prices also in the capital goods sector. In such a model, we would expect investment prices to be smoother than marginal costs. Third, the estimated investment shock might hide frictions in the capital accumulation process that we abstracted from. Models that explicitly include these type of frictions, such as that in Christiano, Motto, and Rostagno (2007), therefore represent a promising avenue for future research.

Appendix A. The Data

Our dataset spans a sample from 1954QIII to 2004QIV. All data are extracted from the Haver Analytics database (series mnemonics in parenthesis). Following Del Negro, Schorfheide, Smets, and Wouters (2007), we construct real GDP by diving the nominal series (GDP) by population (LF and LH) and the GDP Deflator (JGDP). Real series for consumption and investment are obtained in the same manner, although consumption corresponds only to personal consumption expenditures of non-durables (CN) and services (CS), while investment is the sum of personal consumption expenditures of durables (CD) and gross private domestic investment (I). Real wages correspond to nominal compensation per hour in the non-farm business sector (LXNFC), divided by the GDP deflator. We measure the labor input by the log of hours of all persons in the non-farm business sector (HNFBN), divided by population. The quarterly log difference in the GDP deflator is our measure of inflation, while for nominal interest rates we use the effective Federal Funds rate. We do not demean or detrend any series.

Appendix B. Normalization of the Shocks

As in Smets and Wouters (2007), we re-normalize some of the exogenous shocks by dividing them by a constant term. For instance, one of our log-linearized equilibrium conditions is the following Phillips curve:

$$\hat{\pi}_t = \frac{\beta}{1+\beta\iota_p} E_t \hat{\pi}_{t+1} + \frac{1}{1+\beta\iota_p}\hat{\pi}_{t-1} + \kappa\hat{s}_t + \kappa\hat{\lambda}_{p,t},$$

where $\kappa \equiv \frac{(1-\beta\xi_p)(1-\xi_p)}{(1+\iota_p\beta)\xi_p}$, s_t is the model-implied real marginal cost and the "hat" denotes log deviations from the non-stochastic steady state. The normalization consists of defining a new exogenous variable, $\hat{\lambda}^*_{p,t} \equiv \kappa\hat{\lambda}_{p,t}$, and estimating the standard deviation of the innovation to $\hat{\lambda}^*_{p,t}$ instead of $\hat{\lambda}_{p,t}$. We do the same for the wage mark-up and the inter-temporal preference shock, for which we use the following normalizations:

$$\begin{aligned}
\hat{\lambda}^*_{w,t} &= \left(\frac{(1-\beta\xi_w)(1-\xi_w)}{\left(1+\nu\frac{\lambda_w}{\lambda_w-1}\right)(1+\beta)\xi_w}\right)\hat{\lambda}_{w,t} \\
\hat{b}^*_t &= \left(\frac{(1-\rho_b)(e^\gamma - h\beta\rho_b)(e^\gamma - h)}{e^\gamma h + e^{2\gamma} + \beta h^2}\right)\hat{b}_t
\end{aligned}$$

These normalizations are chosen in such a way that these shocks enter the wage and consumption equations (respectively) with a unity coefficient. In this way it is easier to choose a reasonable prior for their standard deviation. Moreover, the normalization is a practical way to impose correlated priors across coefficients, which is desirable in some cases. For instance, imposing a prior on the standard deviation of the innovation to $\hat{\lambda}^*_{p,t}$ corresponds to imposing prior that allow for correlation between κ and the standard deviation of the innovations to $\hat{\lambda}_{p,t}$. Often, these normalizations improve the convergence properties of the MCMC algorithm.

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Table 1: Prior densities and posterior estimates for baseline model with all frictions

		Prior			Posterior [2]		
Coefficient	Description	Prior Density [1]	Mean	Std	Median	Std	[5 , 95]
α	Capital Share	N	0.30	0.05	0.17	0.006	[0.16 0.18]
ι_p	Price indexation	B	0.50	0.15	0.24	0.073	[0.14 , 0.39]
ι_w	Wage indexation	B	0.50	0.15	0.11	0.029	[0.06 , 0.16]
γ	SS technology growth rate	N	0.50	0.03	0.48	0.023	[0.44 , 0.52]
h	Consumption habit	B	0.50	0.10	0.79	0.023	[0.76 , 0.83]
λ_p	SS mark-up goods prices	N	0.15	0.05	0.25	0.032	[0.19 , 0.30]
λ_w	SS mark-up wages	N	0.15	0.05	0.15	0.033	[0.07 , 0.19]
$logL^{ss}$	SS leisure	N	396.83	0.50	397.16	0.480	[396.4 , 398.0]
$100(\pi-1)$	SS quarterly inflation	N	0.50	0.10	0.71	0.078	[0.56 , 0.82]
$100(\beta^{-1}-1)$	Discount factor	G	0.25	0.10	0.14	0.045	[0.07 0.22]
ν	Inverse Frisch elasticity	G	2.00	0.75	3.59	0.674	[2.63 , 4.84]
ξ_p	Calvo prices	B	0.66	0.10	0.84	0.016	[0.82 , 0.87]
ξ_w	Calvo wages	B	0.66	0.10	0.71	0.019	[0.68 , 0.74]
χ	Elasticity capital utilization costs	G	5.00	1.00	5.80	1.001	[4.38 , 7.58]
S''	Investment adjustment costs	G	4.00	1.00	2.95	0.301	[2.43 , 3.39]
Φ_p	Taylor rule inflation	N	1.70	0.30	1.97	0.144	[1.71 , 2.20]
Φ_y	Taylor rule output	N	0.13	0.05	0.05	0.012	[0.03 , 0.07]
Φ_{dy}	Taylor rule output growth	N	0.13	0.05	0.23	0.016	[0.21 0.26]
ρ_R	Taylor rule smoothing	B	0.60	0.20	0.81	0.016	[0.79 0.84]

(Continued on the next page)

Table 1: Prior densities and posterior estimates for baseline model with all frictions

Coefficient	Description	Prior			Posterior [2]			
		Prior Density [1]	Mean	Std	Median	Std	[5	, 95]
ρ_{mp}	Monetary Policy	B	0.40	0.20	0.16	0.048	[0.07	0.22]
ρ_z	Neutral Technology growth	B	0.60	0.20	0.23	0.043	[0.15	0.30]
ρ_g	Government spending	B	0.60	0.20	0.99	0.001	[0.99	0.99]
ρ_μ	Investment	B	0.60	0.20	0.73	0.031	[0.68	0.78]
ρ_p	Price mark-up	B	0.60	0.20	0.94	0.017	[0.91	0.96]
ρ_w	Wage mark-up	B	0.60	0.20	0.98	0.003	[0.98	0.99]
ρ_b	Intertemporal preference	B	0.60	0.20	0.65	0.027	[0.60	0.68]
θ_p	Price mark-up MA	B	0.50	0.20	0.78	0.010	[0.76	0.79]
θ_w	Wage mark-up MA	B	0.50	0.20	0.95	0.002	[0.94	0.95]
σ_{mp}	Monetary policy	I	0.10	1.00	0.22	0.012	[0.21	0.25]
σ_z	Neutral Technology growth	I	0.50	1.00	0.89	0.049	[0.81	0.98]
σ_g	Government spending	I	0.50	1.00	0.35	0.017	[0.32	0.38]
σ_μ	Investment	I	0.50	1.00	6.01	0.505	[5.02	6.79]
σ_p	Price mark-up	I	0.10	1.00	0.14	0.002	[0.14	0.15]
σ_w	Wage mark-up	I	0.10	1.00	0.24	0.003	[0.23	0.24]
σ_b	Intertemporal preference	I	0.10	1.00	0.04	0.001	[0.04	0.04]
(log) Likelihood at median						-1094.7		

Calibrated coefficients: depreciation rate (δ) is 0.025, g implies a SS government share of 0.22

Relative to the text, the standard deviations of the innovations are scaled by 100 for the estimation, which is reflected in the prior and posterior estimates.

[1] N stands for Normal, B Beta, G Gamma and I Inverted-Gamma1 distribution

[2] Median and posterior percentiles from 2 chains of 120,000 draws generated using a Random walk Metropolis algorithm, where we discard the initial 20,000 and retain one in every 20 subsequent draws. Additional longer chains produced almost identical posterior moments.

Table 2: Prior variance decomposition for observable variables in the baseline model

Medians and [5,95] prior percentiles

Series \ Shock	**Policy**	**Neutral**	**Government**	**Investment**	**Price mark-up**	**Wage mark-up**	**Preference**
Output growth	0.01	0.26	0.23	0.00	0.00	0.01	0.08
	[0.00,0.33]	[0.02,0.88]	[0.02,0.85]	[0.00,0.04]	[0.00,0.14]	[0.00,0.39]	[0.00,0.74]
Consumption growth	0.01	0.31	0.00	0.00	0.00	0.00	0.42
	[0.00,0.34]	[0.01,0.93]	[0.00,0.11]	[0.00,0.03]	[0.00,0.09]	[0.00,0.27]	[0.02,0.98]
Investment growth	0.01	0.38	0.00	0.03	0.00	0.01	0.04
	[0.00,0.45]	[0.01,0.95]	[0.00,0.13]	[0.00,0.43]	[0.00,0.25]	[0.00,0.69]	[0.00,0.93]
Hours	0.02	0.17	0.07	0.01	0.00	0.04	0.05
	[0.00,0.54]	[0.00,0.90]	[0.00,0.68]	[0.00,0.13]	[0.00,0.29]	[0.00,0.92]	[0.00,0.81]
Wage growth	0.00	0.73	0.00	0.00	0.04	0.09	0.00
	[0.00,0.03]	[0.10,0.99]	[0.00,0.03]	[0.00,0.01]	[0.00,0.50]	[0.01,0.71]	[0.00,0.17]
Inflation	0.01	0.11	0.01	0.00	0.08	0.08	0.03
	[0.00,0.66]	[0.00,0.86]	[0.00,0.19]	[0.00,0.08]	[0.00,0.79]	[0.00,0.95]	[0.00,0.81]
Interest Rates	0.02	0.15	0.02	0.00	0.02	0.03	0.11
	[0.00,0.43]	[0.00,0.92]	[0.00,0.34]	[0.00,0.14]	[0.00,0.50]	[0.00,0.88]	[0.00,0.94]

Since reporting median shares, these need not add up to one, although mean shares do.

Obtained by generating random draws from the prior distributions of the parameters given in table 1.

Table 3: Standard deviations and relative standard deviations in the data and in the baseline model with all frictions [1]

	Standard deviation			Relative standard deviation [2]		
		Baseline Model			Baseline Model	
Series	Data	Median	[5 , 95]	Data	Median	[5 , 95]
Output growth	0.94	1.14	[1.00 , 1.31]	1.00	1.00	
Consumption growth	0.51	0.72	[0.62 , 0.82]	0.54	0.63	[0.53 , 0.74]
Investment growth	3.59	4.59	[3.95 , 5.36]	3.83	4.03	[3.61 , 4.50]
Hours	4.11	4.47	[3.09 , 6.75]	4.39	3.91	[2.79 , 5.81]
Wage growth	0.55	0.66	[0.59 , 0.75]	0.59	0.58	[0.50 , 0.67]
Inflation	0.60	0.49	[0.39 , 0.63]	0.64	0.43	[0.34 , 0.56]
Interest Rates	0.84	0.66	[0.52 , 0.83]	0.90	0.58	[0.45 , 0.74]

[1] For each parameter draw, we generate 1000 samples of the observable series implied by the model with same length as our dataset (202 observations) after discarding 50 initial observations. For the relative standard deviations, for each replication and parameter draw we take the ratio of the standard deviation of each series to that of output. Table reports median and 5th and 95th percentile together with the corresponding moments in the data.

[2] Standard deviation relative to the standard deviation of output growth

Table 4: Posterior variance decomposition for observable variables in the baseline model

Medians and [5,95] posterior percentiles

Series \ Shock	**Policy**	**Neutral**	**Government**	**Investment**	**Price mark-up**	**Wage mark-up**	**Preference**
Output growth	0.04	0.20	0.07	0.51	0.04	0.05	0.09
	[0.03, 0.06]	[0.15, 0.25]	[0.06, 0.08]	[0.45, 0.57]	[0.03, 0.05]	[0.03, 0.07]	[0.07, 0.11]
Consumption growth	0.02	0.26	0.02	0.07	0.01	0.09	0.53
	[0.01, 0.03]	[0.21, 0.32]	[0.02, 0.03]	[0.04, 0.11]	[0.00, 0.01]	[0.06, 0.13]	[0.46, 0.60]
Investment growth	0.03	0.05	0.00	0.87	0.03	0.01	0.01
	[0.02, 0.04]	[0.04, 0.07]	[0.00, 0.00]	[0.84, 0.89]	[0.02, 0.04]	[0.01, 0.01]	[0.01, 0.02]
Hours	0.02	0.03	0.02	0.20	0.05	0.65	0.02
	[0.02, 0.04]	[0.02, 0.04]	[0.01, 0.03]	[0.12, 0.30]	[0.03, 0.07]	[0.52, 0.77]	[0.01, 0.03]
Wage growth	0.00	0.29	0.00	0.03	0.22	0.46	0.00
	[0.00, 0.00]	[0.23, 0.34]	[0.00, 0.00]	[0.02, 0.04]	[0.18, 0.27]	[0.42, 0.50]	[0.00, 0.00]
Inflation	0.03	0.07	0.00	0.06	0.24	0.56	0.02
	[0.02, 0.06]	[0.05, 0.11]	[0.00, 0.00]	[0.03, 0.11]	[0.17, 0.32]	[0.44, 0.68]	[0.01, 0.03]
Interest Rates	0.10	0.05	0.01	0.45	0.02	0.24	0.11
	[0.08, 0.14]	[0.04, 0.08]	[0.01, 0.01]	[0.34, 0.57]	[0.02, 0.04]	[0.13, 0.37]	[0.08, 0.15]

Since reporting median shares, these need not add up to one, although mean shares do.

Table 5: Variance decomposition at business cycle frequencies[1] in the baseline model with all frictions

Medians and [5,95] posterior percentiles

Series \ Shock	**Policy**	**Neutral**	**Government**	**Investment**	**Price mark-up**	**Wage mark-up**	**Preference**
Output	0.05	0.24	0.02	0.53	0.05	0.04	0.07
	[0.04, 0.07]	[0.18, 0.30]	[0.01, 0.02]	[0.45, 0.61]	[0.03, 0.07]	[0.03, 0.06]	[0.05, 0.09]
Consumption	0.02	0.27	0.02	0.08	0.01	0.08	0.51
	[0.01, 0.03]	[0.21, 0.33]	[0.02, 0.03]	[0.05, 0.14]	[0.00, 0.01]	[0.05, 0.12]	[0.42, 0.59]
Investment	0.03	0.06	0.00	0.85	0.04	0.01	0.01
	[0.02, 0.04]	[0.04, 0.09]	[0.00, 0.00]	[0.81, 0.89]	[0.02, 0.05]	[0.01, 0.01]	[0.01, 0.02]
Hours	0.06	0.10	0.02	0.61	0.06	0.06	0.08
	[0.05, 0.09]	[0.08, 0.13]	[0.02, 0.03]	[0.54, 0.67]	[0.04, 0.08]	[0.03, 0.08]	[0.06, 0.11]
Wages	0.00	0.39	0.00	0.04	0.31	0.25	0.00
	[0.00, 0.01]	[0.30, 0.47]	[0.00, 0.00]	[0.02, 0.07]	[0.24, 0.38]	[0.21, 0.31]	[0.00, 0.01]
Inflation	0.03	0.14	0.00	0.07	0.40	0.31	0.02
	[0.02, 0.05]	[0.10, 0.19]	[0.00, 0.00]	[0.04, 0.13]	[0.32, 0.49]	[0.25, 0.38]	[0.01, 0.03]
Interest Rates	0.18	0.09	0.01	0.48	0.04	0.04	0.15
	[0.14, 0.23]	[0.07, 0.12]	[0.00, 0.01]	[0.41, 0.56]	[0.03, 0.06]	[0.03, 0.06]	[0.11, 0.19]

Since reporting median shares, these need not add up to one, although mean shares do.

[1] Decomposition of the variance corresponding to periodic components with cycles of between 6 and 32 quarters, obtained using the spectrum of the DSGE model and an inverse first difference filter for output, consumption, investment and wages to obtain the levels. The spectral density is computed from the state space representation of the model and 500 bins for frequencies covering that range of periodicities. Results are identical to those that would result from repeatedly simulating the observables, obtaining the levels and then applying a Band-Pass filter. Variance shares for periods of 2 to 32 quarters obtained with the spectrum implied by the DSGE, or by HP filtering the model observables (transformed to levels where appropriate) deliver a very similar decomposition.

Table 6: Variance share for output and hours at business cycle frequencies[1] explained by investment shocks for alternative specifications without some frictions

Series	Baseline	No habits [2]	No investment costs and variable capital utilization [3]	Perfectly competitive goods and labor markets [4]	Perfectly competitive goods markets[5]	Perfectly competitive labor market [6]	Frictionless model [7]
Output	0.53	0.38	0.23	0.04	0.30	0.31	0.02
Hours	0.61	0.50	0.30	0.08	0.50	0.41	0.03

[1] Share of the variance of output (level) and hours, corresponding to periodic components of cycles between 6 and 32 quarters explained by investment shocks alone. Obtained using the spectrum from the state-space representation of the DSGE. Variance decompositions are performed at the mode of each specification.

[2] h calibrated at 0.01

[3] S'' calibrated at 0.01, $1/\chi$ calibrated at 0.001

[4] λ_{w}, ξ_{w}, ι_{w}, λ_{p}, ξ_{p} *and* ι_{p} calibrated at 0.01

[5] λ_{w}, ξ_{w} and ι_{w} calibrated at 0.01

[6] λ_{p}, ξ_{p} and ι_{p} calibrated at 0.01

[7] combines the calibration for all specifications above, except baseline

Table 7: Log-Marginal Data Densities for baseline and alternative specifications without some frictions

Specification	Log Marginal [1]
Baseline	-1215.10
No habits	-1316.75
No investment costs and variable capital utilization	-1298.04
Perfectly competitive goods and labor markets	-1466.52
Perfectly competitive goods markets	-1433.42
Perfectly competitive labor market	-1283.19
Frictionless model	-1521.88

[1] Except for the baseline, the log marginal data density is computed using the Metropolis-Laplace approximation at the posterior mode. The specification favored by the data attains the highest marginal density.

Full set of parameter estimates is available from the authors upon request

Table 8: Robustness check for the variance share of output and hours at business cycle frequencies[1] explained by investment shocks

Series	Baseline	Trend stationary investment shock [2]	Stochastic trend investment shock [3]	Smets and Wouters (2007) [4]	$\nu = 1$ and $\alpha = 0.3$	No MA components [5]	Taylor rule with output growth [6]	MLE [7]
Output	0.53	0.40	0.56	0.56	0.66	0.52	0.49	0.60
Hours	0.61	0.45	0.70	0.56	0.77	0.56	0.54	0.64

[1] Share of the variance of output (level) and hours, corresponding to periodic components of cycles between 6 and 32 quarters explained by investment shocks alone. Obtained using the spectrum from the state-space representation of the DSGE. Variance decompositions are performed at the mode of each specification.

[2] Model with broken linear trend in investment shocks (break occurs in 1982q2)

[3] Model with stochastic trend in investment shocks

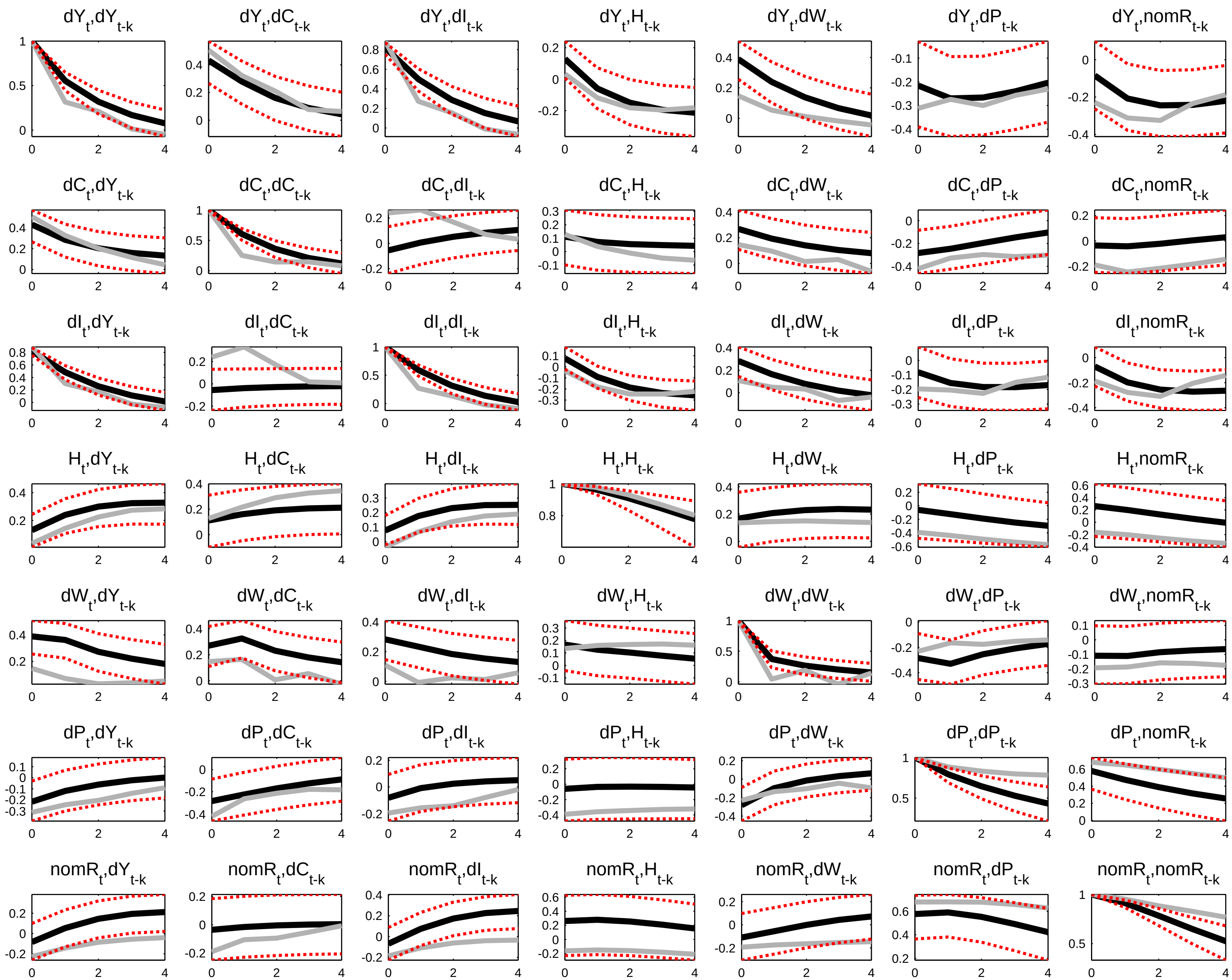
[4] Smets and Wouters' (2007) model estimated by Bayesian methods with their priors, using our dataset and sample.

[5] Moving average component for price and wage mark-up shocks calibrated to zero.

[6] Taylor rule responds to observable output growth instead of the output gap.

[7] Baseline specification estimated by maximum likelihood.

Fig 1: Autocorrelation for baseline specification, dsge median (dark), dsge 5-95 (dotted) & data (grey)



legend: dY=output growth, dC=consumption growth, dI=investment growth, H=hours, dW=wages growth, dP=inflation, nomR=nominal interest rate

Figure 2: Year−to−year output growth, actual data and counterfactual explained by investment shocks

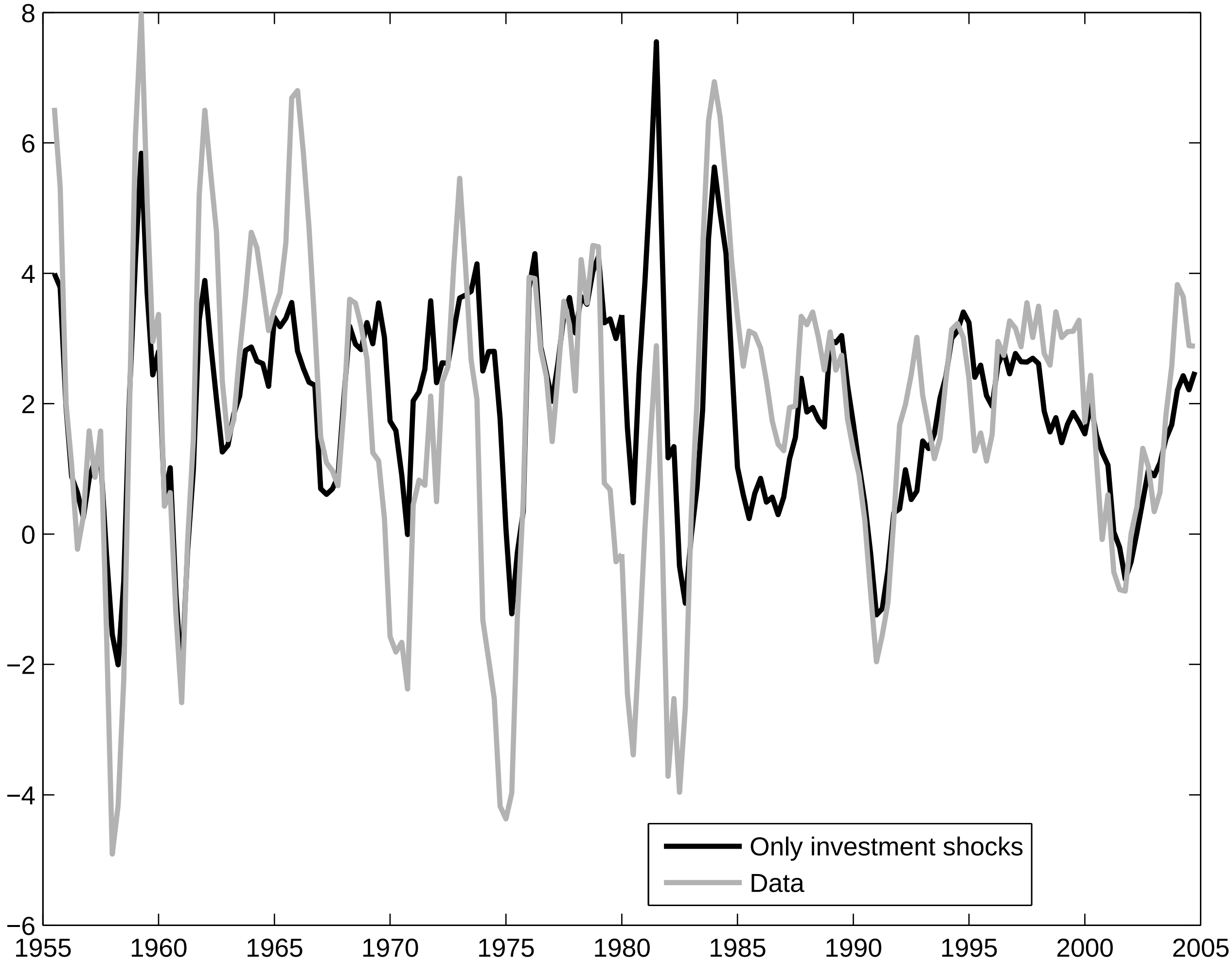
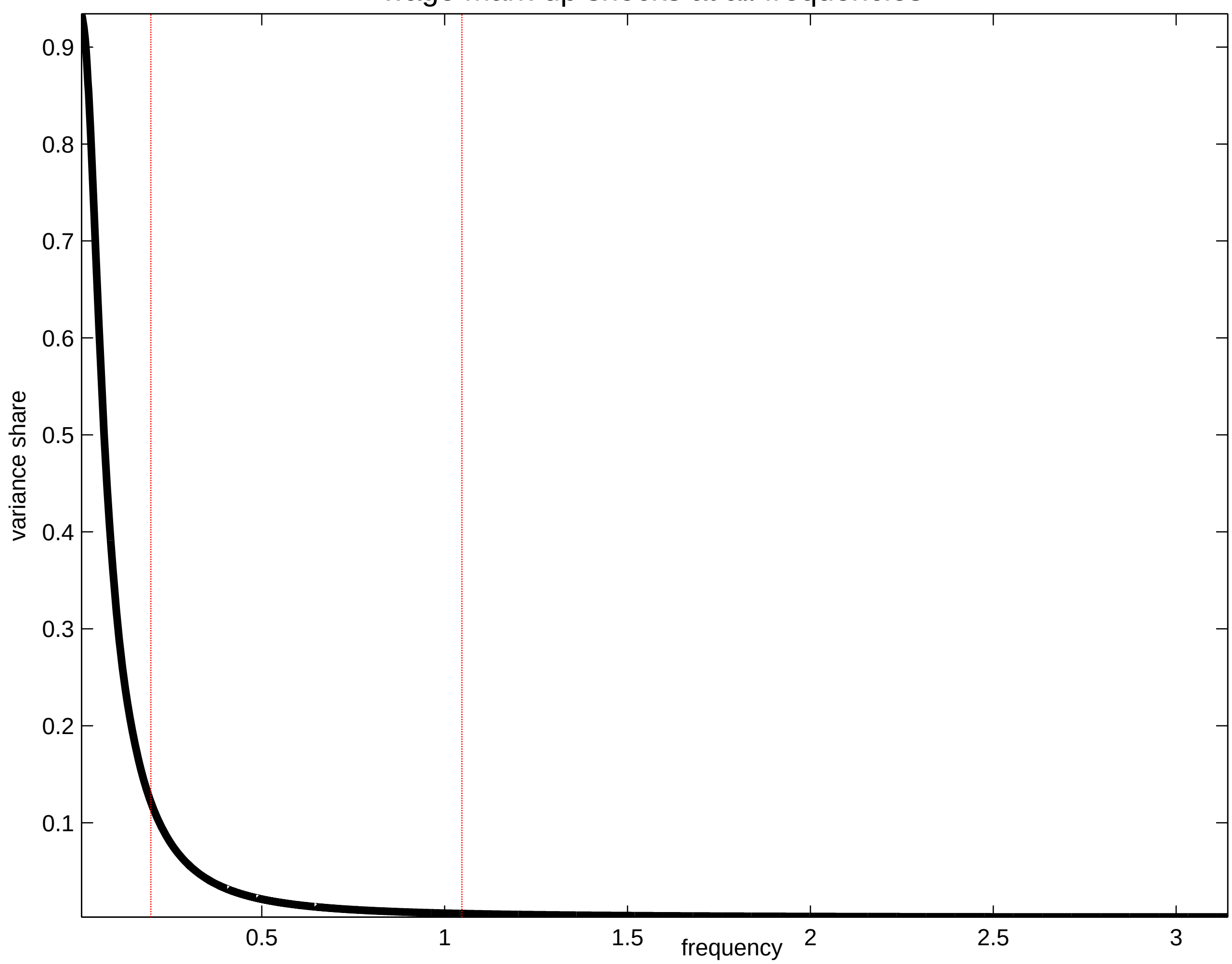
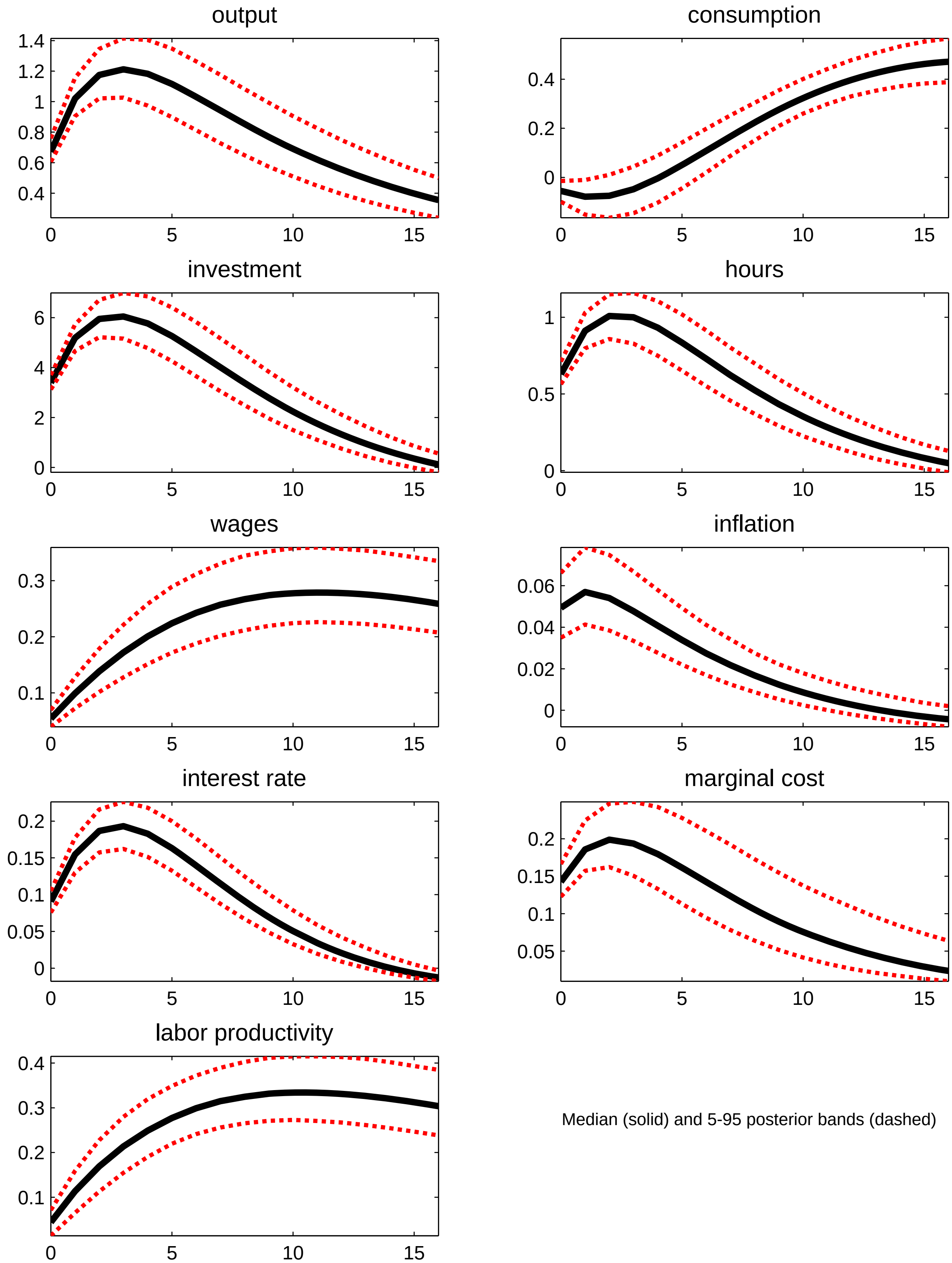


Figure 3: Variance share of Hours explained by wage mark-up shocks at all frequencies



Computed at the median of the paremeter estimates.
Vertical dashed lines mark the frequency band associated with business cycles of 6 to 32 quarters.

Figure 4: Impulse responses to an investment shock



Median (solid) and 5-95 posterior bands (dashed)

Figure 5: Impulse responses to a wage mark-up shock

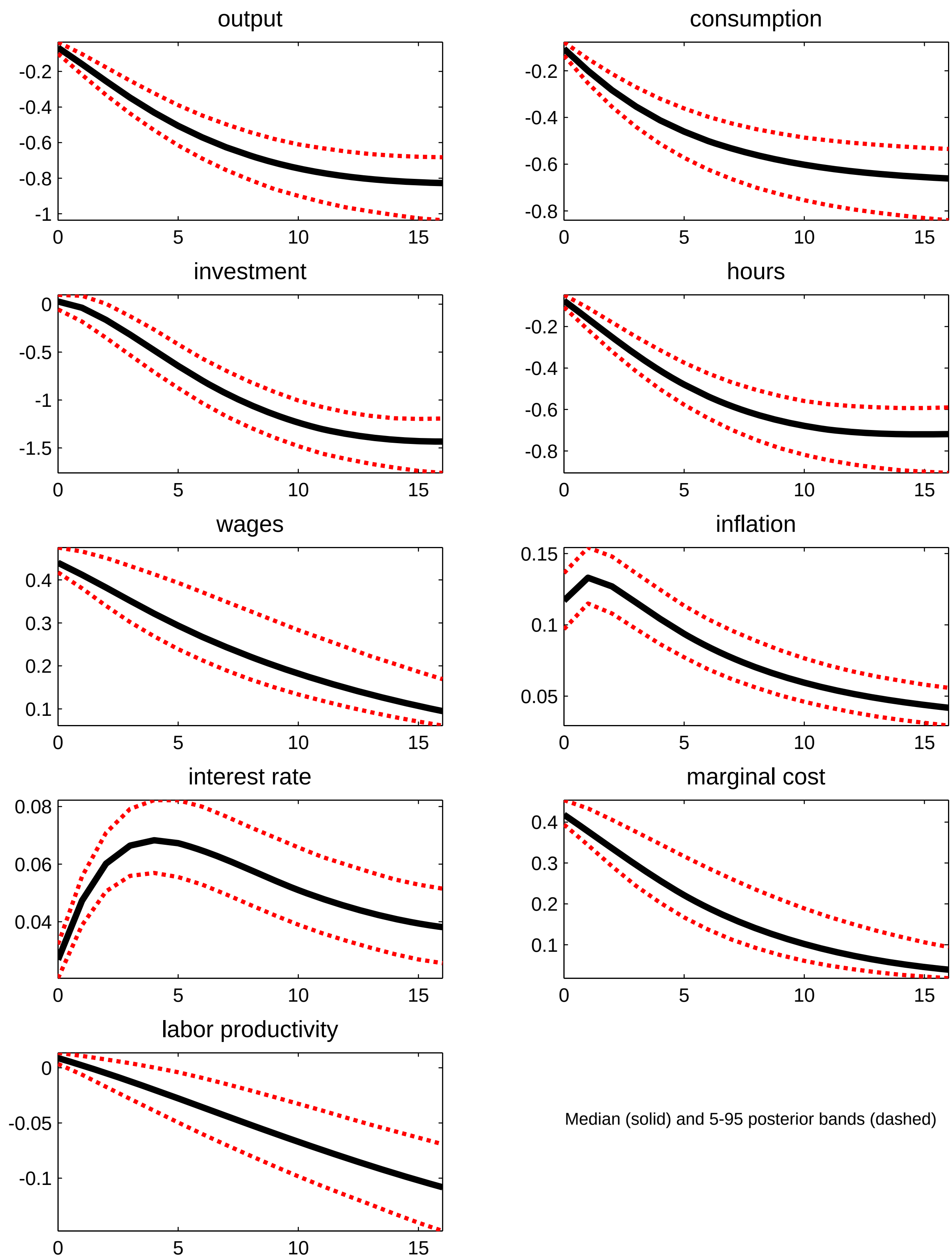


Figure 6: Impulse responses to a neutral technology shock