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Firm-specific capital, inflation persistence and the sources of business cycles

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Abstract

This paper estimates a firm-specific capital DSGE model. Firm-specific capital improves the fit of DSGE models to the data (as shown by a large increase in the value of the log marginal likelihood). This results from a lower implied estimate of the NKPC slope for a given degree of price stickiness. Firm-specific capital leads to a better fit to the volatilities of macro variables and a greater persistence of inflation. It is also shown that firm-specific capital reduces the dependence of New Keynesian models on price markup shocks and that it increases the persistence of output to monetary shocks.

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1 Introduction

Despite being a more appealing choice of modelling capital (standard business cycle models assume that capital can be instantly and costlessly transferred across firms which is empirically unrealistic) there are still few examples of dynamic stochastic general equilibrium (DSGE) models with firm-specific capital and very little empirical work on the topic.[1]

Altig, Christiano, Eichenbaum and Linde (hence ACEL, 2011) estimate the firm-specific and homogeneous capital DSGE models in terms of the reduced form New Keynesian Phillips curve (NKPC) and show how the assumption of firm-specific capital reduces the frequency of price re-optimization at the firm level.[2] This approach implies the two models to be observationally equivalent with respect to aggregate prices and quantities (and to differ only in terms of price frequency adjustment at the micro level). This is because only the mapping between the structural parameters and the slope of the NKPC is affected by the introduction of firm-specific capital.

In this paper I take the reverse approach. I fix the frequency of price adjustment at the firm level with values based on micro studies (such as Klenow and Kryvtsov, 2008). I then study the differences at the aggregate level of modelling capital as firm-specific rather than the more conventional homogeneous capital case. That is, in this paper, the parameter priors between the two models are assumed to be identical at the micro rather than at the macro level (and the models will differ in terms of the implied prior of the NKPC slope).

The estimated model in this paper is similar to that in ACEL (2011) but rather than using a limited information strategy I adopt a Bayesian estimation approach (which has become very popular in macroeconomics with Smets and Wouters, 2003, 2007, as prominent references). This too is an important difference because the posterior distribution obtained from Bayesian estimation offers a particularly natural method of comparing models which

[1] One possible reason for this is that when capital is firm-specific it is no longer possible to solve the price setting problem without considering the firm's optimal investment behavior. This makes the model considerably less tractable but it turns out to still be possible to derive an aggregate-supply relation following the method developed in Woodford (2005).

[2] Other relevant empirical papers that have done this are Eichenbaum and Fisher (2007) and Matheron (2006).

enables me to show that firm-specific-capital is important for DSGE models to achieve a better fit to U.S. macro time series data (as shown by a large increase in the value of the log marginal data density).[3] This paper also extends the knowledge in the literature by looking at a wider range of shocks than those considered in previous studies of firm-specific capital models. Besides total factor productivity and monetary shocks the model includes discount rate, labor supply, government spending, capital-embodied technology and price markup shocks too.

My analysis suggests that the improved fit to the data of the New Keynesian model seems to be behind a better fit to the volatilities of macro variables observed in the data. Of particular interest is the finding that firm-specific capital substantially increases the persistence of inflation. This represents an important result since a major limitation of micro-founded models of dynamic price adjustment is that they do not imply inflation inertia (Romer, 2011). Previous approaches adopted to bringing inflation inertia into New Keynesian models have not been fully satisfying.[4] The models, for the benchmark case, presented here are purely forward-looking, having no "intrinsic" inflation persistence (that is, all persistence is "inherited" from the driving variable in the NKPC). This shows that it is possible for price staggering models to account for the high reduced form persistence seen in the data without the presence of a lagged inflation term (as done in Galí and Gertler, 1999, and Christiano,

[3] As I do, de Walque, Smets and Wouters (2006) and Nolan and Thoenissen (2008) analyze how firm-specific capital affects the aggregate behavior of economic variables. However, de Walque, Smets and Wouters (2006) assume Taylor contracts whereas I assume Calvo contracts (which is more conventional in the business cycle literature). Nolan and Thoenissen (2008) adopt a calibration methodology which makes it hard to assess which model fits the data better. With calibration the marginal likelihood is not computed, so in order to discriminate between models one would need to specify: (i) a distance to measure the difference between estimated and model moments, and (ii) a loss function that would determine which moments are the most important to match.

[4] The most prominent approaches are: rule-of thumb behavior (Galí and Gertler, 1999), indexation of price contracts (Christiano, Eichenbaum and Evans, 2005) and sticky information (Mankiw and Reis, 2002). Galí and Gertler (1999) introduce inertia by assuming that a fraction of firms raises prices mechanically in line with past inflation rates. This is unrealistic, since we do not observe micro prices that change automatically with lagged inflation (see the evidence shown in Bils and Klenow, 2004, and Nakamura and Steinsson, 2008). Christiano, Eichenbaum and Evans (2005) and Mankiw and Reis (2002) assume some adjustment of prices between reviews. Again, this does not match the observations at the micro level (see Bils and Klenow, 2004, and Nakamura and Steinsson, 2008). Many prices are fixed for extended periods and there is little support that firms set price paths like those predicted by models of price indexation of contracts or sticky information.

Eichenbaum and Evans, 2005) in their aggregate supply relation (intrinsic persistence). This has important implications for monetary policy (see Fuhrer, 2010).

The firm-specific capital specification is able to fit the data better because it implies a lower implied slope of the NKPC for a given degree of price stickiness. If in the homogeneous capital model one chooses a degree of price stickiness so that its implied prior NKPC slope is about the same as that of the firm-specific capital model, then the differences in fit between the models become negligible. The firm-specific capital, however, fits the evidence better for a plausible degree of price stickiness at the micro level. Empirical macro researchers who follow a Bayesian approach choose parameter priors mostly to be in line with micro studies. For those using this method, the results in this paper suggest it is beneficial to model capital as firm-specific. Researchers that prefer the more conventional homogeneous capital assumption may opt instead to allow the degree of price stickiness to be determined from macro estimates of the NKPC slope. The main difficulty with such an approach is that identification of the NKPC slope has been shown to be weak (see Mavroeidis, Plagborg-Møller and Stock, 2014).

Another relevant result is the significant reduction of the size of the volatility of price markup shocks, when firm-specific capital is assumed. This is of importance since it helps address the criticism of Chari, Kehoe, and McGrattan (2009) on the usefulness of New Keynesian models for policy analysis due to their reliance on these shocks in order to explain the data..

I also study how the model's responses to exogenous shocks are changed by the introduction of firm-specific capital. I find that the introduction of firm-specific capital has important dynamic implications. The impulse response functions show that firm-specific capital, by making firms change prices by less, aids considerably in propagating the responses of output, while dampening movements in inflation, to exogenous "demand" shocks (since these tend to move output and prices in the same direction) such as fiscal and monetary policy shocks. This is an important point since Chari, Kehoe and McGrattan (2000) found the standard New Keynesian model to have difficulty in generating output persistence in response to monetary shocks.

Other related empirical papers in the literature include those on sectoral heterogeneity in price stickiness. Like firm-specific capital, heterogeneous price stickiness leads to more persistent effects on aggregate output of monetary shocks (see for example Carvalho, 2006, and Dixon and Kara, 2011) and affects the relative importance of exogenous shocks to cyclical fluctuations (see Bouakez, Cardia and Ruge-Murcia, 2014). It is also worth mentioning other promising explanations for inflation persistence. Sargent, Williams and Zha (2006) explain the historical movements in US inflation as the result of the monetary authority's learning about the state or structure of the economy. Cogley and Sbordonne (2008) show how the introduction of a time-varying inflation trend allows for a purely forward-looking NKPC to fit the data well. In recent work, Bianchi and Ilut (2014) show that the dynamics of inflation depend crucially on the monetary/fiscal policy mix and that high inflation persistence disappears when fiscal discipline is restored.

The remainder of the paper is organized as follows. Section 2 outlines the DSGE model. Section 3 describes the estimation methodology and results. In section 4 I look at the implications for business cycle dynamics. Section 5 summarizes the paper's findings.

2 The Models

In this section I describe the homogeneous and firm-specific capital models. The models are very similar to those presented in ACEL (2011). The main differences to ACEL (2011) consist in the introduction of four stochastic shocks (to price markup, discount rate, labor supply and exogenous spending). In order to analyze better the role of firm-specific capital in increasing the persistence of inflation I will consider both the case in which firms that do not re-optimize keep prices unchanged (this is the more common formulation for Calvo price setting, see for example Galí, 2008) and the case in which they follow a lagged inflation indexation rule (as in ACEL, 2011). In the last subsection I compare both models with respect to inflation dynamics. In the interest of conserving space the exposition is kept brief and readers interested in more details can refer to ACEL (2011) and its technical appendix (ACEL, 2004).

2.1 The Homogeneous Capital Model

2.1.1 Firms

Final Good Firm The final consumption good, Y_t, is produced by a representative firm that operates in a perfectly competitive market. The production function that transforms intermediate goods, $y_t(i)$, into final output is given by:

$$Y_t = [\int_0^1 y_t(i)^{1/\lambda_{f,t}} di]^{\lambda_{f,t}}, \tag{1}$$

where $\lambda_{f,t} = \lambda_f + \varepsilon_{f,t}$ is a stochastic parameter that determines the time-varying markup in the goods market and $\varepsilon_{f,t}$ is the price markup shock which is assumed to follow a first-order autoregressive, $AR(1)$, process, : $\hat{\varepsilon}_{f,t} = \rho_f \hat{\varepsilon}_{f,t-1} + e_{f,t}$. The use of '$\hat{}$' is done to denote from now on variables in log deviation from the steady state and $e_{n,t}$ will denote IID-Normal error terms. Cost minimization implies the following demand for the i^{th} intermediate good:

$$y_t(i) = (P_t/P_t(i))^{\lambda_{f,t}/(\lambda_{f,t}-1)} Y_t, \tag{2}$$

where P_t is an index cost of buying a unit of Y_t:

$$P_t = [\int_0^1 P_t(i)^{1/(1-\lambda_{f,t})} di]^{1-\lambda_{f,t}}. \tag{3}$$

Intermediate Good Firms The i^{th} intermediate good firm production function is:

$$y_t(i) = \begin{cases} K_t(i)^\alpha (z_t h_t(i))^{1-\alpha} - \phi z_t^* & \text{if } K_t(i)^\alpha (z_t h_t(i))^{1-\alpha} \geqslant \phi z_t^*, \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where α is the capital share and ϕ captures fixed production costs. The variables $K_t(i)$ and $h_t(i)$ represent respectively capital and labor services used as inputs in the production of the i^{th} intermediate good. The above function includes an aggregate neutral technology process denoted as z_t having as growth rate $\mu_{z,t}$. The variable z_t^* is given by:

$$z_t^* = \Upsilon_t^{\alpha/(1-\alpha)} z_t, \tag{5}$$

where Υ_t denotes a shock to capital-embodied technology and has growth rate $\mu_{\Upsilon,t}$. Both technological shocks are assumed to follow an $AR(1)$ process: $\hat{\mu}_{z,t} = \rho_z \hat{\mu}_{z,t-1} + e_{z,t}$ and $\hat{\mu}_{\Upsilon,t} = \rho_\Upsilon \hat{\mu}_{\Upsilon,t-1} + e_{\Upsilon,t}$.

Intermediate good producers are subject to Calvo price staggering: a fraction ξ_p of firms does not re-optimize prices. In the benchmark case I will assume that firms that are unable to re-optimize keep prices unchanged ($P_t(i) = P_{t-1}$). However, I will also consider the case in which such firms adopt a lagged inflation indexation rule ($P_t(i) = \pi_{t-1} P_{t-1}(i)$ where π_t stands for aggregate inflation $\pi_t = P_t/P_{t-1}$).

The i^{th} intermediate good firm chooses $P_t(i)$, $K_{t+j}(i)$ and $h_t(i)$ to maximize the following profit function subject to (2), (4) and its price setting constraints:

$$E_t \sum_{j=0}^{\infty} \beta^j \Lambda_{t+j} \{ P_{t+j}(i) y_{t+j}(i) - P_{t+j} [w_{t+j} R_{t+j}(\nu) h_{t+j}(i) + r_{t+j}^k K_{t+j}(i)] \}, \tag{6}$$

where $0 < \beta < 1$ is the household's discount factor, Λ_{t+j} is the Lagrange multiplier on the households's budget constraint, ν is the fraction of the wage bill that must be financed in advance, finally, $w_t = W_t/P_t$, R_t and r_t^k are respectively the real wage, interest rate and rental rate of capital.

2.1.2 Households

Consider an economy with a continuum of infinitely lived agents on the interval [0,1] who have preferences over consumption of a single non-durable good C_t. The preferences of the

j^{th} household are given by:

$$E_t^j \sum_{s=0}^{\infty} \beta^s \varepsilon_{b,t+s}[\log(C_{t+s} - bC_{t+s-1}) - \varepsilon_{l,t+s}\psi_L \frac{{h_{j,t+s}}^{1+\sigma_L}}{1+\sigma_L}], \tag{7}$$

where $b > 0$ indicates the existence of habit formation, ψ_L measures disutility from working and σ_L is the inverse of the labor supply elasticity. There are two preference shocks. A discount rate ($\hat{\varepsilon}_{b,t} = \rho_b \hat{\varepsilon}_{b,t-1} + e_{b,t}$) and a labor supply shock ($\hat{\varepsilon}_{l,t} = \rho_l \hat{\varepsilon}_{l,t-1} + e_{l,t}$).

The budget constraint is given by:

$$\begin{aligned} M_{t+1} &= R_t[M_t - Q_t + (x_t - 1)M_t^a] + A_{j,t} + Q_t + W_{j,t}h_{j,t} - P_t T_t \\ &\quad + P_t r_t^k u_t \bar{K}_t + D_t - (1+\eta(V_t))P_t C_t - P_t \Upsilon_t^{-1}(I_t + a(u_t)\bar{K}_t), \end{aligned} \tag{8}$$

where M_t and Q_t are respectively the household's money stock and cash balances, x_t is the gross growth rate of the economy-wide per capita stock of money M_t^a (which equals M_t in equilibrium), $A_{j,t}$ is the net cash inflow from state-contingent securities, T_t are government taxes, u_t is the utilization rate of capital which household's rent to firms ($K_t = u_t \bar{K}_t$), D_t are firm profits and V_t is the velocity of the household's cash balances ($V_t = P_t C_t / Q_t$). The capital-embodied technology process Υ_t is used here as the price of investment goods (I_t) relative to consumption goods.

The function $\eta(\cdot)$ is an increasing and convex function that captures the role of cash balances in facilitating transactions. To solve the model it is necessary to specify the steady state values of the function's level (η), first (η') and second derivatives (η''). To do this, one first defines the interest semi-elasticity of money demand (ϵ_t):

$$\epsilon_t \equiv -\frac{100 \times d(\log Q_t/P_t)}{400 \times dR_t}.$$

Evaluating ϵ_t at the steady state gives the following expression:

$$\epsilon = \frac{1}{4}(\frac{1}{R-1})(\frac{1}{2+\sigma_\eta}),$$

where σ_η is the curvature of $\eta(\cdot)$ at the steady state ($\sigma_\eta = \eta'' V/\eta'$). Finally the first order condition for Q_t at the steady state results in:

$$R = 1 + \eta' V^2.$$

Because R is obtained from estimated parameters, the function $\eta(\cdot)$ can then be parameterized by choosing values for η, ϵ and V.

The function $a(\cdot)$ measures adjustment costs to changing the utilization rate of capital (u_t) and is assumed to be increasing and convex. In the steady state $u = 1$ and $a(1) = 0$. To solve the model, one needs only the elasticity of the capital utilization cost function: $\sigma_a = a''(1)/a'(1) = \Psi_k/(1 - \Psi_k)$. Following Smets and Wouters (2007) I estimate the model in terms of the parameter Ψ_k rather than σ_a.

The capital accumulation equation is given by:

$$\bar{K}_{t+1} = (1-\delta)\bar{K}_t + (1 - S(\frac{I_t}{I_{t-1}}))I_t, \tag{9}$$

where δ is the depreciation rate and $S(\cdot)$ is the investment adjustment cost function which is assumed to be increasing and convex. In the steady state $S = S' = 0$ and S'' is a positive constant which affects only model dynamics.

2.1.3 Wage Setting Decision

As in ACEL (2011) and Nolan and Thoenissen (2008) I assume a continuum of monopolistically competitive households (indexed on the unit interval), each of which supplies a differentiated labor service to the production sector. Labor hours are aggregated with a Dixit-Stiglitz technology:

$$H_t = [\int_0^1 h_{j,t}^{1/\lambda_w} dj]^{\lambda_w}, \tag{10}$$

where λ_w defines the steady state wage markup over the marginal rate of substitution of leisure for consumption. Labor demand for household j's labor is:

$$h_{j,t} = \left[\frac{W_t}{W_{j,t}}\right]^{\lambda_w/(\lambda_w-1)} H_t, \tag{11}$$

where $\tilde{W}_t$ is the price index cost of H_t:

$$W_t = [\int_0^1 W_{j,t}^{1/(1-\lambda_w)} dj]^{(1-\lambda_w)}, \tag{12}$$

where λ_w defines the steady state wage markup over the marginal rate of substitution of leisure for consumption. The household union takes into account the labor demand curve when setting wages which are set in staggered contracts (ξ_w gives the probability that a household will not be able to renegotiate wages at any given period). If a household cannot re-optimize its wage at time t, it sets $W_{j,t}$ according to

$$W_{j,t} = \pi_{t-1}\mu_{z*}W_{j,t-1}.$$

2.1.4 Monetary and Fiscal Policy

The growth of money supply (x_t) is as in ACEL (2011):

$$\hat{x}_t = \hat{x}_{M,t} + \hat{x}_{z,t} + \hat{x}_{\Upsilon,t}. \tag{13}$$

The stochastic processes $\hat{x}_{M,t}$, $\hat{x}_{z,t}$, and $\hat{x}_{\Upsilon,t}$ are defined as follows:

$$\begin{aligned}
\hat{x}_{M,t} &= \rho_{xM}\hat{x}_{M,t-1} + e_{M,t}, \\
\hat{x}_{z,t} &= \rho_{xz}\hat{x}_{z,t-1} + c_z e_{z,t} + c_z^p e_{z,t-1}, \\
\hat{x}_{\Upsilon,t} &= \rho_{x\Upsilon}\hat{x}_{z,t-1} + c_\Upsilon e_{\Upsilon,t} + c_\Upsilon^p e_{\Upsilon,t-1},
\end{aligned}$$

where $e_{M,t}$ is a monetary policy shock. As in ACEL (2011) the terms capturing the response of monetary policy to innovations in neutral ($\hat{x}_{z,t}$) and capital-embodied ($\hat{x}_{\Upsilon,t}$) technology have both an autoregressive component and a moving average, MA, component.

The government adjusts lump sum taxes to ensure that its intertemporal budget constraint holds ($G_t = T_t$) . Government expenses are assumed exogenous and to follow a first order autoregressive process: $\hat{g}_t = \rho_g \hat{g}_{t-1} + e_{g,t}$ where $g_t = G_t / z_t^*$.

2.1.5 Market Clearing

Loan market clearing requires that:

$$W_t H_t = x_t M_t - Q_t. \tag{14}$$

The economy's resource constraint is given by:

$$(1 + \eta(V_t))C_t + \Upsilon_t^{-1}(I_t + a(u_t)\bar{K}_t) + G_t \leqslant Y_t. \tag{15}$$

2.2 The Firm-Specific Capital Model

The firm-specific capital model differs in very little from the homogeneous capital model. In this model, firms own their capital (which cannot be instantly and costlessly reallocated across firms) rather than renting it from households as in the homogenous capital model case. In the firm-specific capital model the capital accumulation equation is given by:

$$\bar{K}_{t+1}(i) = (1 - \delta)\bar{K}_t(i) + (1 - S(\frac{I_t(i)}{I_{t-1}(i)}))I_t(i). \tag{16}$$

The i^{th} intermediate good firm chooses $P_t(i)$, $\bar{K}_{t+j}(i)$, $u_{t+j}(i)$ and $h_t(i)$ to maximize the following profit function subject to (2), (4), (16) and its price setting constraints:

$$E_t \sum_{j=0}^{\infty} \beta^j \Lambda_{t+j} \{ P_{t+j}(i) y_{t+j}(i) - P_{t+j} w_{t+j} R_{t+j}(\nu) h_{t+j}(i) - P_{t+j} \Upsilon_{t+j}^{-1} [I_{t+j}(i) + a(u_{t+j}(i)) \bar{K}_{t+j}(i)] \}. \tag{17}$$

The models are identical in every other aspect.

2.3 Inflation Dynamics

The economy's price inflation equation, often referred to as the NKPC, in the benchmark case (firms that are unable to re-optimize keep prices unchanged) in both the homogeneous and the firm-specific capital model, takes the following form:

$$\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} + \gamma(\hat{s}_t + \hat{\varepsilon}_{f,t}), \tag{18}$$

where γ is a function of the model's structural parameters and $\hat{s}_t$ is the average real marginal cost in log deviation from the steady state. I also consider the case in which firms that are unable to re-optimize adopt a lagged inflation indexation rule as in ACEL (2011), in which case, the NKPC takes for both models (homogeneous and firm-specific capital) the form:

$$\Delta\hat{\pi}_t = \beta E_t \Delta\hat{\pi}_{t+1} + \gamma(\hat{s}_t + \hat{\varepsilon}_{f,t}). \tag{19}$$

The dynamic relationship between inflation and aggregate economic activity may be identical for the homogeneous and firm-specific capital models but they differ with respect to the magnitude of γ:

$$\gamma = \frac{(1-\xi_p)(1-\xi_p\beta)}{\xi_p}\zeta.$$

In the homogeneous capital model $\zeta = 1$. As shown in ACEL (2004) in the firm-specific capital model $\zeta \leqslant 1$ is a non-linear function of the parameters of the model. The assumption of firm-specific capital changes the predicted slope of the Phillips curve trade-off to an extent that can be quantitatively significant; in particular, for a given degree of price stickiness (ξ_p) the firm-specific capital implies a smaller γ relative to the homogeneous capital model (see Woodford, 2005).

3 Model Estimation

3.1 Estimation Methodology

I use Bayesian techniques to estimate the models presented in section 2.[5] As in Smets and Wouters (2007), I estimate the mode and standard deviation of the posterior distribution by maximizing the log posterior function (that combines the parameter priors with the likelihood of the data). The mean and log data density (computed by modified harmonic mean estimation) were obtained after the Metropolis-Hastings algorithm was used to get a complete picture of the posterior distribution.[6]

The dataset used consists of the following quarterly US aggregate time series: 100 times the log difference of the GDP deflator (dlP_t), real consumption (dlC_t), real investment (dlI_t), real wages (dlW_t) and real GDP(dlY_t), 100 times the log of average hours (lH_t) worked (for the non-farm business sector for all persons) and the federal funds rate (FF_t). These are the same time series as in Smets and Wouters (2007) but updated to include more recent observations as well. I will therefore estimate the models for the period 1966Q1 to 2012Q4 (whereas Smets and Wouters, 2007, estimated their model with data from 1966Q1 to 2004Q4).

[5] This was done with Dynare. The Matlab codes were based on those developed by ACEL (2011), which can be obtained from Christiano's website (http://faculty.wcas.northwestern.edu/~lchrist/research/ACEL/acelweb.htm), and Wieland et al. (2012).

[6] A sample of 250 000 draws was created. The value of the scale used for the jumping distribution in Metropolis-Hastings algorithm was adjusted to yield an acceptance rate of approximately 23%, the optimal rate proposed by Gelman et al. (1996). The MCMC univariate and multivariate diagnostics indicate convergence and stability in all measures of the parameter moments.

The corresponding measurement equations are:

$$\begin{bmatrix} dlY_t \\ dlC_t \\ dlI_t \\ dlW_t \\ lH_t \\ dlP_t \\ FF_t \end{bmatrix} = \begin{bmatrix} \bar{\gamma}_y \\ \bar{\gamma}_y \\ \bar{\gamma}_y + \bar{\gamma}_k \\ \bar{\gamma}_y \\ \bar{h} \\ \overline{\pi} \\ \bar{r} \end{bmatrix} + \begin{bmatrix} \widehat{\tilde{y}}_t - \widehat{\tilde{y}}_{t-1} \\ \hat{c}_t - \hat{c}_{t-1} \\ \hat{\imath}_t - \hat{\imath}_{t-1} \\ \widehat{\tilde{w}}_t - \widehat{\tilde{w}}_{t-1} \\ \hat{h}_t \\ \hat{\pi}_t \\ \hat{R}_t \end{bmatrix}, \tag{20}$$

where $\tilde{y}_t = y_t/z_t^*$, $\tilde{w}_t = w_t/z_t^*$ and $\bar{h}$ is normalized to be equal to zero. The parameters $\bar{\gamma}_y$, $\bar{\gamma}_k$, $\overline{\pi}$ and $\bar{r}$ relate to the model's steady state as follows: $\mu_{z^*} = 1 + \bar{\gamma}_y/100$, $\mu_\Upsilon = 1 + \bar{\gamma}_k/100$, $\pi = 1+\overline{\pi}/100$ and $R = 1+\bar{r}/100$.

The Bayesian approach has several advantages over other methods. The calibration approach does not attach any probabilistic measures of uncertainty to the quantitative statements that it generates. Unlike generalized method of moments (GMM) or the minimum distance method, Bayesian estimates are based on the likelihood function generated by the DSGE model (the Bayesian approach therefore satisfies by construction the Likelihood Principle that states that all of the information existing in a sample is contained in the likelihood function). Bayesian methods also have several advantages over maximum likelihood estimation (MLE). Fernández-Villaverde and Rubio-Ramírez (2004) find Bayesian estimates to outperform MLE results in small samples. In addition, the Bayesian approach uses priors to incorporate additional information into the parameter estimation, thus avoiding the "dilemma of absurd parameter estimates" common when maximum likelihood is applied in DSGE estimation, and helps in identifying parameters.[7]

[7]Likelihoods of DSGE models are full of local maxima and minima and of nearly flat surfaces. As Fernández-Villaverde (2009) points out this is due both to the "sparsity of the data (quarterly data do not give us the luxury of many observations that micro panels provide) and to the flexibility of DSGE models in generating similar behavior with relatively different combination of parameter values."

3.2 Prior Distribution of the Parameters

I fixed some of the parameters in the estimation procedure. The depreciation rate δ is fixed at 0.025, the exogenous spending-GDP ratio is set at 18% and the steady-state markup of the labor union (λ_w) at 1.5. These are the same values as in Smets and Wouters (2007). The steady-state markup of the intermediate firm (λ_f) is set at 1.05 (the intermediate value considered by ACEL, 2011). The Calvo price stickiness parameter ξ_p is set at 0.5, a value chosen to be consistent with the evidence on prices reported by Bils and Klenow (2004) and Klenow and Kryvtsov (2008). As mentioned in the introduction estimates of ξ_p from macro data do not provide any information on the degree of price stickiness (since the estimates depend on modelling assumptions, as shown in the previous section). The remaining fixed parameters are set as in ACEL (2011). I assume the inverse elasticity of labor supply with respect to real wages σ_L and the labor disutility parameter ψ_L to be 1. The fraction of the wage bill that must be financed in advance ν is also set to 1. V and η are set to 0.45 and 0.036 respectively. Finally, ϕ is chosen to ensure that firm profits are zero in the steady state.

I now proceed to discuss the choice of prior distribution for the remaining model's parameters. I start by discussing the prior of the parameters which were not estimated in Smets and Wouters (2007). The quarterly trend growth rate of capital-embodied technology ($\bar{\gamma}_k$) is assumed to be normal distributed of mean 0.4 and standard deviation 0.1. This is the same prior as that I adopted for $\bar{\gamma}_y$, which was chosen to be the same as in Smets and Wouters (2007). This seemed a reasonable choice given that ACEL (2011) choose fixed parameter values which would be the equivalent of 0.42 and 0.45 for $\bar{\gamma}_k$ and $\bar{\gamma}_y$ respectively. The prior for the steady state interest semi-elasticity of money demand (ϵ) was chosen to be a normal distribution of mean 0.6 and standard deviation of 0.25. This was based on the estimates of ACEL (2011) whose benchmark model estimate of ϵ was 0.61 (with standard error of 0.23). The remaining structural parameters are common to the Smets and Wouters (2007) model and identical priors were adopted.

The priors for the exogenous processes are also the same as in Smets and Wouters (2007).

The standard errors of the shocks are assumed to follow an inverse-gamma distribution with a mean of 0.1 and standard deviation of 2. The AR and MA parameters are assumed to be beta distributed with mean 0.5 and standard deviation 0.2.

The first three columns of Tables 1 and 2 give an overview of the assumptions made regarding the prior distribution (shape, mean and standard deviation) of the estimated parameters.

I now look at how mean prior assumptions affect differently the slope of the NKPC between the two models. These differences are captured by the parameter ζ which measures how much less steep the NKPC slope is in the firm-specific capital (FSC) model relative to the homogeneous capital (HC) model. In the homogenous capital model $\zeta = 1$ whereas in the firm-specific capital model $\zeta \leqslant 1$ and depends on the value of several structural parameters. I focus on the parameters that one would consider more relevant for capital dynamics: the parameter that determines the elasticity of the capital utilization cost function (Ψ_k), the parameter that determines investment adjustment costs (S'') and the capital share (α). Table 3 shows the sensitivity of ζ in the FSC model to changes in the values of Ψ_k, S'', and α while keeping the remaining parameters fixed at the respective prior means values. The table shows that for the prior mean values considered, the NKPC slope (γ) in the FSC model is only 22% as steep as that of the HC model. Let's start by looking at how changes in Ψ_k affect the steepness of the NKPC slope. For values of Ψ_k close to zero the elasticity of capital utilization is high, for values of Ψ_k close to 1 the elasticity of capital utilization is low. Table 3 shows that low values of Ψ_k increase the steepness of the NKPC slope while high values decrease it. This makes sense, the more variable capital utilization is the less constrained firms are in adjusting the capital input and therefore the assumption of firm-specific capital becomes less relevant. Table 3 also shows that the steepness of the NKPC slope is not very sensitive to the value of investment adjustment costs. Finally, the higher the capital share the stronger the effect on the NKPC slope from the assumption of firm-specific capital. Similar findings to those in this table were also reported by Madeira (2014) in the context of a model where employment is firm-specific.

3.3 Parameter Estimates

For summary purposes I follow Rabanal and Rubio-Ramírez (2005) and present only the mean and the standard deviation of the posterior distributions for the parameters of both models. The numbers for the benchmark case are reported in Tables 1 (structural parameters) and 2 (exogenous shock parameters). To conserve space, parameter estimates for the case when firms that are unable to re-optimize adopt a lagged inflation indexation rule and other robustness exercises are shown in a "web appendix" to this paper.

The estimates of most parameters turn out to be relatively similar for both models and in line with those found in other studies such as Rabanal and Rubio-Ramírez (2005) and Smets and Wouters (2003, 2007). For this reason I highlight only the parameters where there are marked differences between the firm-specific capital (FSC) and homogeneous capital (HC) models. Few of the structural parameters are significantly altered. One of those is the quarterly trend growth rate of output ($\bar{\gamma}_y$). This is estimated to be 0.35 in the FSC model while in the HC model an estimate of 0.4 is obtained. The habit formation parameter (b) also appears to differ between models. The respective estimate for the FSC and HC models is 0.39 and 0.47. Another parameter significantly altered is Ψ_k which determines the elasticity of the capital utilization cost function. The mean estimate of Ψ_k is 0.71 in the FSC model but only 0.59 in the HC model. This implies that capital utilization is estimated to be less responsive to the rental rate of capital under the firm-specific capital assumption. The other remaining structural parameter substantially affected is the capital share, α. This parameter is estimated to be 0.26 when capital is assumed to be firm-specific but only 0.21 under the more conventional homogeneous capital assumption. The analysis in the previous subsection of Table 3 suggests that the higher values of Ψ_k and α estimated in the FSC model indicate that the data favors a lower value of the NKPC slope γ.

In the case of the exogenous shocks parameters there are more marked differences between models. The estimates of the mean volatility of both capital-embodied technology (σ_Υ) and price markup shocks (σ_f) are reduced with the assumption of firm-specific capital. In the FSC model the estimated mean of σ_Υ is 1.99 while in the HC model a value of 2.54 is obtained. For the volatility of the price markup shock the estimated mean of the FSC model is 0.28 which is substantially lower than the 0.58 value obtained in the HC model. Turning attention to the autoregressive coefficients, one observes that the estimates of the government spending (0.94 under the FSC assumption and 0.84 under the HC assumption) and labor supply (0.49 under the FSC assumption and 0.38 under the HC assumption) shocks are higher in the FSC model than in the HC model, whereas the opposite happens with price markup (0.68 under the FSC assumption and 0.93 under the HC assumption) and monetary shocks (0.17 under the FSC assumption and 0.36 under the HC assumption).

These differences between model estimates extend to the case when firms that are unable to re-optimize adopt a lagged inflation indexation rule.

4 Implications for Business Cycle Fluctuations

4.1 Data Fit

The marginal likelihood of the model gives an indication of the overall empirical performance of the model given the data and reflects its prediction ability. It therefore forms a natural benchmark for comparing the overall fit of the two DSGE models considered here. I computed the marginal likelihood by modified harmonic mean estimation for both the firm-specific capital and homogeneous capital models. The values are displayed in the last line of Table 2. The log marginal likelihood of the model with firm-specific capital is -1653.89 which is considerably higher than that of the homogeneous capital model (-1762.32). Calculation of the Bayes factor (BF) indicates this to be a large improvement in fit to the data. The BF of model 1 against model 2 is the ratio of their marginal likelihoods. Kass and Raftery (1995) suggest that values of 2 logBF above 10 can be considered very strong evidence in favor of model 1. When I consider the firm-specific capital model (model 1) against the homogeneous capital model (model 2) the value of 2 logBF is 216.86. This strongly supports the hypothesis that introducing firm-specific capital in DSGE models is highly relevant for the understanding of business cycle fluctuations.

What is driving the improvement in the fit to the data? Table 4 presents the key business cycle statistics (standard deviation, contemporaneous correlation with GDP growth and degree of first order autocorrelation, AC) for the US aggregate time series data used to estimate the models and the corresponding values obtained by simulating the models under their respective estimated mean parameter values. The FSC model matches better the standard deviation observed in the data of all variables apart for consumption growth, average hours worked and the nominal interest rate. With respect to the contemporaneous correlation with output growth, the FSC model only does better with respect to the cyclicality of the real wage growth. The difference between the two models with respect to persistence is largest for inflation. The FSC model generates a 0.75 degree of first order autocorrelation which is considerably more than the 0.63 of the HC model and much closer to what is observed in the data (0.87). This constitutes an important finding since a major limitation of micro-founded models of dynamic price adjustment is that they do not imply inflation inertia (Romer, 2011). It is somewhat surprising to find that the firm-specific capital model leads to increased persistence in inflation, despite the fact that its assumption leads to a flatter Phillips curve (Fuhrer, 2006, 2010, shows that a smaller γ reduces inflation persistence in the purely forward-looking NKPC). The reason lies in the lower mean estimated volatility of the price markup shock. Fuhrer (2006, 2010) shows that inflation is more autocorrelated, in the purely forward-looking NKPC, the smaller the volatility of the shock that perturbs the driving process. However, with respect to the persistence of the remaining variables none of the models seems to outperform the other. The FSC model matches better the first order autocorrelation observed in the data of real consumption growth and real wage growth. However, the HC model matches better the autocorrelation of output, investment and interest rates.

Overall these findings are robust to assuming that firms which are unable to re-optimize adopt a lagged inflation indexation rule. In this case too the FSC model is found to: fit the data substantially better (the 2logBF is 122.98), match better the standard deviation of aggregate US time series and generate higher persistence in inflation (0.9 and 0.85 respective values for the first order autocorrelation of the FSC and HC models). Assuming the Phillips curve to have lagged inflation therefore allows the HC model to generate higher persistence in inflation and allows it to have a fit to the data closer to that of the FSC model. Both the FSC and the HC models have a better fit to the data in the case when firms that are unable to re-optimize adopt a lagged inflation indexation rule than in the benchmark case (in which firms that do not re-optimize keep prices unchanged). This confirms the importance of introducing sources of higher persistence in inflation to permit DSGE models a better fit to the macro data. The finding that the FSC model fits the data better than the HC model is also robust to having α fixed at 0.36 as in ACEL (2011) and using a sample of the data restricted from 1966Q1 to 2007Q4 in order to exclude the zero lower bound period.[8]

4.2 Price Frequency Adjustment, NKPC Slope and Data Fit

Table 5 shows the implied average price duration (APD) in months, the implied NKPC slope (γ) and the resulting log marginal likelihood by modified harmonic mean estimation for different values of the Calvo price stickiness parameter (ξ_p) in the benchmark case. In the benchmark case $APD = 3/(1-\xi_p)$.[9] In the first line ξ_p is set at 0.5 which implies that average price duration is 6 months. This is in line with the micro evidence in Klenow and Kryvtsov (2008) who estimated price frequency adjustment to be between 4 and 7 months. The third column shows that for this value the implied NKPC slope for the mean estimates

[8] The DSGE model equations are linearized before estimation. Therefore, parameter estimates could have been distorted because the models do not take into account non-linearities such as the zero lower bound on central bank interest rates and downward wage rigidity (which appear to have been binding in the period after 2007Q4). The finding that the estimates were not much affected is consistent with the DSGE estimation results in Galí, Smets, and Wouters (2012) who also did not find large differences in parameter values of adding observations from 2007 onwards (the main differences consisted only of a higher estimated degree of wage stickiness and persistence in shocks). The non-linearities could have represented a greater issue if the goal were to be the estimation of a single reduced form equation. Galí (2011) shows that estimates of the New Keynesian Wage Phillips curve are significant when using a sample of the data ending in 2007Q4 but not when including data on the recent recession (despite falling during the 2007-2009 recession, wage inflation has remained positive, while the model predicts wage deflation).

[9] In the case when one assumes that firms that are unable to re-optimize adopt a lagged inflation indexation rule the average price duration in both models is 3 months independent of the value of ξ_p. In this case, $3/(1-\xi_p)$ is the average period between price re-optimization and no longer corresponds to the average price duration (in the benchmark case these are the same, since firms that do not re-optimize keep prices unchanged).

(shown in Table 1) is 0.09 for the FSC model and 0.5 for the HC model. The GMM estimates of γ by Galí and Gertler (1999) for the period 1960Q1 until 1997Q4 vary between 0.01 and 0.05. Therefore while under both the FSC and HC assumptions the implied NKPC slope is very high, it is considerably less so for the FSC model. As shown in the prior subsection the FSC model fits the aggregate data considerably better than the HC model (2 logBF=216.86).

The second line of Table 5 shows what happens when the models are re-estimated with the probability of non-adjustment of prices increased to 2/3, which implies that prices on average remain unchanged for a period of 9 months. This is a value which exceeds those reported by Klenow and Kryvtsov (2008) but is broadly in line with the price frequency adjustment "between 7 and 9 months" found by Nakamura and Steinsson (2008) in the micro data. For this value of ξ_p the implied NKPC slope is 0.03 and 0.17 for the FSC and HC models respectively. The NKPC slope γ in the FSC model is therefore consistent with the estimates obtained by Galí and Gertler (1999). In the HC model the NKPC becomes substantially "flatter" but is still at a value of γ much higher than those obtained in the literature. For $\xi_p = 2/3$ the FSC model also fits the data significantly better, but the "gap" between models is reduced (2 logBF is 168.82). The fit of both models to the data improved with the increase in the degree of price stickiness.

The bottom line of Table 5 shows the models' data fit and NKPC slope when the average price duration is set at 12 months ($\xi_p = 0.75$). Again, the NKPC becomes flatter for both models but in the HC model it is still at quite a high value (0.08). This means that the HC model has at the same time an average price duration which is too high relative to that found in the micro studies and a NKPC which is too steep relative to the macro estimates in the literature. Again, the data fit of both models improves with a higher degree of price stickiness and a lower γ.[10] The gap in data fit (2 logBF is 61.86) between the FSC and HC models remains significant but is further reduced.

The question remains if the differences in fit between the models are solely due to a

[10]The finding of improved data fit at lower values of γ is consistent with the results of Rudd and Whelan (2007) and Madeira (2014) who using updated datasets obtained insignificant estimates of γ using the labor share marginal cost measure proposed by Galí and Gertler (1999). Mavroeidis, Plagborg-Møller and Stock (2014) also obtained insignificant estimates of γ for the Galí and Gertler (1999) sample with revised data.

different implied slope of the NKPC. If all model parameters were estimated with MLE then the fit between the models would be identical. However, due to the Bayesian estimation approach the posterior likelihood of the FSC and HC models is also determined by priors on the models' parameters. It may therefore be the case that the differences between the fit of the two models are not solely restricted to differences in the implied prior of the NKPC slope (γ). To answer this question I fixed the parameter ξ_p in the HC model in such a way as to make the prior of γ the same as that of the FSC model. Table 6 shows the respective values of ξ_p, average price duration (APD) in months and the resulting log marginal likelihood for different prior mean values of γ. The table shows that for the same mean implied prior value of γ, the HC model requires about twice the duration in average price duration (values much higher than those reported in the micro studies). The differences in fit between the two models, however, are negligible (except when $\gamma = 0.11$ in which the differences could be viewed as evidence that the HC model is strongly preferred to the FSC model). This suggests that the empirical differences in fit between the FSC and HC model are mostly due to different implied values of γ for a given degree of price stickiness.

4.3 Variance Decomposition

Table 7 shows the contribution of each of the exogenous shocks to the 20 quarter (the midpoint of the interval of the periodicities which correspond to business cycles) forecast error variance of output, inflation and the nominal interest rate, for the mean parameter estimates. The models differ substantially in terms of the driving forces of business cycle fluctuations. Monetary policy shocks ($e_{M,t}$) explain a larger share of output, inflation and interest rate movements under firm-specific capital, whereas price markup ($e_{f,t}$) shocks explain less.

The results in Table 7 indicate that FSC is useful in reducing the dependence of New Keynesian models on what Chari, Kehoe, and McGrattan (2009) refer as "dubiously structural shocks" which correspond to $e_{l,t}$, $e_{f,t}$, $e_{g,t}$ and $e_{b,t}$. In the FSC model the "dubious" shocks account for a total of 59.09%, 32.85% and 6.12% of the business cycle fluctuations of output, inflation and the nominal interest rate respectively. In the HC model however these shocks play a significantly larger role, accounting for a total of 76.29%, 42.13% and 5.35% of the business cycle fluctuations of output, inflation and the nominal interest rate respectively. Therefore we see that in the FSC model dubious shocks represent a smaller share of output and inflation fluctuations (due mostly to a reduction in the importance of price markup shocks) while in interest rates dubious shocks represent a similar fraction in both models.

These differences are also present if it is assumed that firms that do not re-optimize adopt a lagged inflation indexation rule.

4.4 Impulse Response Functions

In this section I compare the dynamic responses to 1% exogenous shocks of the FSC and HC models. To conserve space, I present only the responses to monetary policy, neutral technology, capital-embodied technology and price markup shocks (figures for the remaining shocks are included in the "web appendix"). That is, the shocks considered by ACEL (2011) and the price markup shock (to gain intuition for the substantial differences between the FSC and HC models with respect to this shock shown previously). In order to understand better the role of firm-specific capital both models are simulated under the estimated mean parameter values obtained for the FSC model. Figures 1-4 display the impulse response functions of both models key endogenous variables (output, consumption, investment, capital, capital utilization, interest rate, inflation, hours and real wages) for the benchmark case.

I find the model's impulse response functions to exogenous shocks to be significantly altered by the introduction of firm-specific capital. Firm-specific capital makes firms adjust prices by less, thus drawing out the period of above-normal output to "demand" shocks (since these tend to move output and prices in the same direction). The impulse response functions show that firm-specific capital does indeed aid considerably in propagating the responses of output not just to some exogenous "demand" shocks such as monetary policy shocks, but also to some "supply" shocks such as disturbances to neutral technology and price markups.

Figure 1 displays the impulse response functions of both models to monetary policy shocks. The figure shows that the firm-specific capital model leads to a larger short run increase in output to a money supply shock. This happens because firms-specific capital is a real rigidity in the sense of Ball and Romer (1990). As such it strengthens the strategic complementarity of firms and mitigates price changes to aggregate economic shocks. For this reason, prices increase by less in the FSC model in response to a money supply shock and therefore the increase in output is larger relative to the HC model. This highlights the role of firm-specific capital as a useful mechanism in helping to address Chari, Kehoe and McGrattan (2000) criticism of the lack of output persistence of New Keynesian models to monetary shocks. The impulse response functions help understand why the FSC model implies that monetary shocks account for a larger share of business cycle fluctuations.

Figure 2 shows that firm-specific capital also amplifies the effects on output from a neutral technology shock. This happens because the FSC assumption mitigates the initial increase in prices resulting from this shock.[11] This helps explain why neutral technology shocks explain a greater fraction of output fluctuations in the FSC model (see Table 7).

Figure 3 shows the impulse response function to a capital-embodied technology shock. As with the previous shocks the FSC assumption mitigates movements in inflation. For this reason the increase in inflation from the shock is smaller in the FSC model relative to the HC model and therefore the fall in output is smaller as well. The impulse response functions show that. in the FSC model. hours and investment move in a different direction to output (more so than in the HC model). Because these variables are procyclical in the data (see Table 4) this can help account for the reduced estimated volatility of this shock in the FSC model.

The impulse response functions of the price markup shock (Figure 4) are also interesting. This is the only shock for which one observes larger changes in inflation in the FSC model

[11] An increase in inflation occurs because positive neutral and capital-embodied technology shocks lead to a fall in capital in the ACEL (2011) model. This can be verified by inspecting the linearized capital evolution equation in ACEL (2004: 41). Hours increase in response to the shock which implies that marginal costs increase (because labor and capital are complementary). Higher marginal costs in turn lead to an increase in inflation.

relative to the HC model. Despite the fact that it is not a demand shock the FSC model generates larger fluctuations in all variables represented relative to the HC model. Why is this the case? The price markup increase leads to an increase in inflation and consequently a fall in output. The fall in output implies a fall in marginal costs. All else equal, the reduction in marginal costs would lead to a reduction in inflation which would partially offset the initial direct increase from the markup shock. However, due to stronger strategic complementarities, the reduction in marginal costs has a smaller effect on prices under firm-specific capital. For this reason the total increase in inflation is higher in the FSC model than in the HC model resulting in amplified reactions of the other macro variables to the price markup increase. This helps understand why the FSC model does not require such a large volatility (σ_f) and autocorrelation (ρ_f) of price markup shocks in order to match the data.

An analysis of the impulse response functions for the case in which firms that do not re-optimize adopt a lagged inflation indexation rule would yield similar conclusions to those reported here (again, to conserve space, these results are shown only in the "web appendix").

5 Conclusion

In this paper I estimate a firm-specific capital DSGE model with Bayesian techniques using US time series data. I find that firm-specific capital is empirically important in order for the model to match aggregate US data, even in the presence of more than one source of nominal rigidity (the model includes both sticky prices and wages). By comparing the firm-specific capital and homogeneous capital models, for a given degree of price stickiness, I find that the New Keynesian model with firm-specific capital fits better the volatility of aggregate economic variables seen in the data. Of significant interest is the fact that firm-specific capital leads to greater persistence of inflation.

I also extend the analysis of the effects of firms-specific capital to other exogenous shocks besides the more conventional monetary and productivity shocks. In particular, I find that firm-specific capital reduces the reliance of New Keynesian models on price markup shocks and that it increases the persistence of output to monetary shocks.

References

[1] Altig, D., Christiano L. J., Eichenbaum, M., and Linde, J., 2004. Technical appendix to 'Firm-Specific Capital, Nominal Rigidities and the Business Cycle'.

[2] Altig, D., Christiano L. J., Eichenbaum, M. and Linde, J., 2011. Firm-Specific Capital, Nominal Rigidities and the Business Cycle. *Review of Economic Dynamics* 14 (2), 225-247.

[3] Ball, L., and Romer, D., 1990. Real rigidities and the non-neutrality of money. *Review of Economic Studies* 57, 183-203.

[4] Bianchi, F., and Ilut, C., 2014. Monetary/Fiscal Policy Mix and Agents' Beliefs. NBER Working Papers 20194, National Bureau of Economic Research, Inc.

[5] Bils, M., and Klenow, P., 2004. Some evidence on the importance of sticky prices. *Journal of Political Economy* 112 (5), 947–985.

[6] Bouakez, H., Cardia, E., and Ruge-Murcia, F., 2014. Sectoral Price Rigidity and Aggregate Dynamics. *European Economic Review* 65, 1–22.

[7] Carvalho, C., 2006. Heterogeneity in Price Stickiness and the Real Effects of Monetary Shocks. *The B.E. Journal of Macroeconomics* 6 (3), 1-58.

[8] Chari, V., Kehoe, P. and McGrattan, E., 2000. Sticky Price Models of the Business Cycle: Can the Contract Multiplier Solve the Persistence Problem?. *Econometrica* 68 (5), 1151-1180.

[9] Chari, V., Kehoe, P., and McGrattan, E., 2009. New Keynesian Models: Not Yet Useful for Policy Analysis. *American Economic Journal: Macroeconomics* 1 (1), 242-66.

[10] Christiano, L., Eichenbaum, M., and Evans, C., 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy* 113 (1), 1-45.

[11] Cogley, T., and Sbordone, A., 2008. Trend Inflation, Indexation, and Inflation Persistence in the New Keynesian Phillips Curve. *American Economic Review* 98 (5), 2101-26.

[12] de Walque, G., Smets, F., and Wouters, R., 2006. Firm-Specific Production Factors in a DSGE Model with Taylor Price Setting. *International Journal of Central Banking* 2 (3), 107-154.

[13] Dixon, H., and Kara, E., 2011. Contract length heterogeneity and the persistence of monetary shocks in a dynamic generalized Taylor economy. *European Economic Review* 55 (2), 280-292.

[14] Eichenbaum, M., and Fisher, J., 2007. Estimating the frequency of price re-optimization in Calvo-style models. *Journal of Monetary Economics* 54 (7), 2032-2047.

[15] Fernández-Villaverde, J., and Rubio-Ramírez, J. F., 2004. Comparing dynamic equilibrium models to data: a Bayesian approach. *Journal of Econometrics* 123 (1), 153-187.

[16] Fernández-Villaverde, J., 2009. The Econometrics of DSGE Models. NBER Working Papers 14677.

[17] Fuhrer, J., 2006. Intrinsic and Inherited Inflation Persistence. *International Journal of Central Banking* 2 (3), 49-86.

[18] Fuhrer, J., 2010. Inflation Persistence. In: Benjamin M. Friedman & Michael Woodford (Eds.). *Handbook of Monetary Economics* 1 (3), 423-486. Elsevier.

[19] Galí, J., and Gertler, M., 1999. Inflation dynamics: A structural econometric analysis. *Journal of Monetary Economics* 44 (2), 195-222.

[20] Galí, J., 2008. *Monetary Policy, Inflation and the Business Cycle: An Introduction to the New Keynesian Framework*. Princeton University Press.

[21] Galí, J., 2011. The Return Of The Wage Phillips Curve. J*ournal of the European Economic Association* 9 (3), 436-461.

[22] Galí, J., Smets, F., and Wouters, R., 2012. Unemployment in an Estimated New Keynesian Model. In *NBER Macroeconomics Annual*, edited by D. Acemoglu, J.Parker, and M. Woodford. University of Chicago Press.

[23] Gelman, A., Roberts, G., and Gilks, W., 1996. Efficient Metropolis jumping rules. In: Bernardo, J., Berger, J., David, A. and Smith, A. (Eds.). *Bayesian Statistics V*, 599-608. Oxford University Press.

[24] Kass, Robert E., and Raftery, A., 1995. Bayes Factors. *Journal of the American Statistical Association* 90, 773-795.

[25] Klenow, P., and Kryvtsov, O., 2008. "State-Dependent or Time-Dependent Pricing: Does it Matter for Recent U.S. Inflation?," *The Quarterly Journal of Economics* 123, 863-904.

[26] Madeira, J., 2014. Overtime Labor, Employment Frictions, and the New Keynesian Phillips Curve. *Review of Economics and Statistics* 96 (4), 767-778.

[27] Mankiw, N., and Reis, R., 2002. Sticky Information Versus Sticky Prices: A Proposal To Replace The New Keynesian Phillips Curve. *The Quarterly Journal of Economics* 117 (4), 1295-1328.

[28] Matheron, J., 2006. Firm-Specific Labor and Firm-Specific Capital: Implications for the Euro-Data New Phillips Curve. *International Journal of Central Banking* 2 (4), 33-64.

[29] Mavroeidis, S., Plagborg-Møller, M., and Stock, J. H., 2014. Empirical Evidence on Inflation Expectations in the New Keynesian Phillips Curve. *Journal of Economic Literature* 52 (1),124-88.

[30] Nakamura, E., and Steinsson, J., 2008. "Five Facts about Prices: A Reevaluation of Menu Cost Models," *The Quarterly Journal of Economics* 123, 1415-1464.

[31] Nolan, C., and Thoenissen, C., 2008. Labour markets and firm-specific capital in New Keynesian general equilibrium models. *Journal of Macroeconomics* 30 (3), 817-843.

[32] Rabanal, P., and Rubio-Ramírez, J., 2005. Comparing New Keynesian models of the business cycle: A Bayesian approach. *Journal of Monetary Economics* 52 (6), 1151-1166.

[33] Romer, D., 2011. *Advanced Macroeconomics*. McGraw-Hill.

[34] Rudd, J., and Whelan, K., 2007. Modeling Inflation Dynamics: A Critical Review of Recent Research. *Journal of Money, Credit and Banking* 39 (s1), 155-170.

[35] Sargent, T., Williams, N., and Zha, T., 2006. Shocks and Government Beliefs: The Rise and Fall of American Inflation. *American Economic Review* 96 (4), 1193-1224.

[36] Smets, F., and Wouters, R., 2003. An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area. *Journal of the European Economic Association* 1 (5), 1123-1175.

[37] Smets, F., and Wouters, R., 2007. Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic Review* 97 (3), 586-606.

[38] Wieland, V., Cwik, T., Müller, G. J., Schmidt, S., and Wolters, M., 2012. A New comparative approach to macroeconomic modeling and policy analysis. J*ournal of Economic Behavior and Organization* 83, 523-541.

[39] Woodford, M., 2005. Firm-Specific Capital and the New-Keynesian Phillips Curve. *International Journal of Central Banking* 1 (2), 1–46.

6 Tables

Table 1: Bayesian Estimation of Structural Parameters (benchmark case)

	Prior Distribution			Estimated Maximum Posterior			
				FSC		HC	
	Type	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
$\bar{\gamma}_y$	Normal	0.40	0.10	0.35	0.02	0.40	0.01
$\bar{\gamma}_k$	Normal	0.40	0.10	0.27	0.05	0.24	0.04
$100(\beta^{-1}-1)$	Gamma	0.25	0.10	0.61	0.10	0.56	0.10
$\overline{\pi}$	Gamma	0.63	0.10	0.80	0.10	0.70	0.10
$\bar{h}$	Normal	0.00	1.00	1.43	0.94	0.84	0.92
b	Beta	0.70	0.10	0.39	0.04	0.47	0.04
ϵ	Normal	0.60	0.25	1.67	0.13	1.72	0.14
Ψ_k	Beta	0.50	0.15	0.71	0.07	0.59	0.05
S''	Normal	4.00	1.50	0.17	0.03	0.19	0.02
α	Normal	0.30	0.05	0.26	0.01	0.21	0.01
ξ_w	Beta	0.50	0.10	0.63	0.03	0.63	0.02

Table 2: Bayesian Estimation of Exogenous Shock Parameters (benchmark case)

	Prior Distribution			Estimated Maximum Posterior			
				FSC		HC	
	Type	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
σ_z	Inv. Gamma	0.10	2.00	0.94	0.12	0.96	0.12
σ_Υ	Inv. Gamma	0.10	2.00	1.99	0.16	2.54	0.19
σ_b	Inv. Gamma	0.10	2.00	2.11	0.19	2.36	0.21
σ_g	Inv. Gamma	0.10	2.00	1.01	0.06	0.96	0.05
σ_f	Inv. Gamma	0.10	2.00	0.28	0.02	0.58	0.03
σ_l	Inv. Gamma	0.10	2.00	4.20	0.26	4.59	0.28
σ_M	Inv. Gamma	0.10	2.00	0.73	0.05	0.72	0.07
ρ_z	Beta	0.50	0.20	0.77	0.02	0.78	0.02
ρ_Υ	Beta	0.50	0.20	0.45	0.02	0.42	0.02
ρ_b	Beta	0.50	0.20	0.99	0.01	0.99	0.005
ρ_g	Beta	0.50	0.20	0.94	0.02	0.84	0.06
ρ_f	Beta	0.50	0.20	0.68	0.05	0.93	0.01
ρ_l	Beta	0.50	0.20	0.49	0.04	0.38	0.03
ρ_{xM}	Beta	0.50	0.20	0.17	0.08	0.36	0.09
ρ_{xz}	Beta	0.50	0.20	0.85	0.01	0.86	0.02
c_z	Beta	0.50	0.20	0.29	0.12	0.25	0.12
c_z^p	Beta	0.50	0.20	0.61	0.15	0.68	0.13
$\rho_{x\Upsilon}$	Beta	0.50	0.20	0.06	0.03	0.09	0.05
c_Υ	Beta	0.50	0.20	0.43	0.04	0.36	0.03
c_Υ^p	Beta	0.50	0.20	0.03	0.02	0.04	0.02
Log data density (modified harmonic mean)				-1653.89		-1762.32	

Table 3: Sensivity of steepeness of the NKPC slope in the FSC model

	Ψ_k			S''			α		
	0.10	0.50	0.90	0.50	4.00	7.50	0.20	0.30	0.40
ζ	0.62	0.22	0.12	0.22	0.22	0.22	0.31	0.22	0.17

Table 4: Business Cycle Statistics (benchmark case)

	US data			FSC Model			HC Model		
	St. D.	Corr(dlY_t)	AC (1)	St. D.	Corr(dlY_t)	AC (1)	St. D.	Corr(dlY_t)	AC (1)
dlY_t	0.85	1.00	0.30	1.82	1.00	0.25	1.92	1.00	0.27
dlC_t	0.72	0.69	0.29	1.35	-0.20	0.48	1.25	0.09	0.49
dlI_t	2.41	0.66	0.60	6.05	0.58	0.76	6.91	0.59	0.72
dlW_t	0.63	0.02	0.05	1.15	-0.01	-0.14	1.36	-0.02	-0.20
lH_t	3.50	0.15	0.98	8.30	0.12	0.95	8.02	0.14	0.95
dlP_t	0.60	-0.20	0.87	1.28	0.05	0.75	2.08	-0.05	0.63
FF_t	0.90	-0.08	0.96	0.84	-0.003	0.91	0.85	-0.05	0.92

Table 5: Average price duration (APD), γ and data fit for a given ξ_p (benchmark case)

ξ_p	APD	γ		Log data density (modified harmonic mean)		
		FSC	HC	FSC	HC	2 logBF
0.5	6 months	0.09	0.50	-1653.89	-1762.32	216.86
2/3	9 months	0.03	0.17	-1593.69	-1678.10	168.82
0.75	12 months	0.02	0.08	-1571.78	-1633.64	61.86

Table 6: Average price duration (APD), ξ_p and data fit for a given γ (benchmark case)

γ	ξ_p		APD		Log data density (modified harmonic mean)		
	FSC	HC	FSC	HC	FSC	HC	2 logBF
0.11	0.5	0.72	6 months	11 months	-1653.89	-1650.69	-6.40
0.04	2/3	0.83	9 months	17 months	-1593.69	-1592.40	-2.58
0.02	0.75	0.87	12 months	24 months	-1571.78	-1569.78	-4.00

Table 7: Variance Decomposition 20 Quarter Horizon (benchmark case)

	$e_{z,t}$	$e_{\Upsilon,t}$	$e_{b,t}$	$e_{g,t}$	$e_{f,t}$	$e_{l,t}$	$e_{M,t}$
$\widehat{\widetilde{y}}_t$(FSC)	10.30	12.50	22.40	15.35	11.57	9.77	18.11
$\hat{\pi}_t$ (FSC)	36.26	21.80	6.38	1.54	22.49	2.44	9.09
$\hat{R}_t$ (FSC)	83.65	4.20	1.48	2.98	1.22	0.44	6.04
$\widehat{\widetilde{y}}_t$(HC)	3.90	9.08	29.95	5.96	32.42	7.96	10.72
$\hat{\pi}_t$ (HC)	25.93	24.00	5.60	1.69	32.67	2.17	7.93
$\hat{R}_t$ (HC)	88.44	1.30	1.49	1.91	1.68	0.27	4.90

7 Figures

Figure 1: Monetary policy shock (benchmark case)

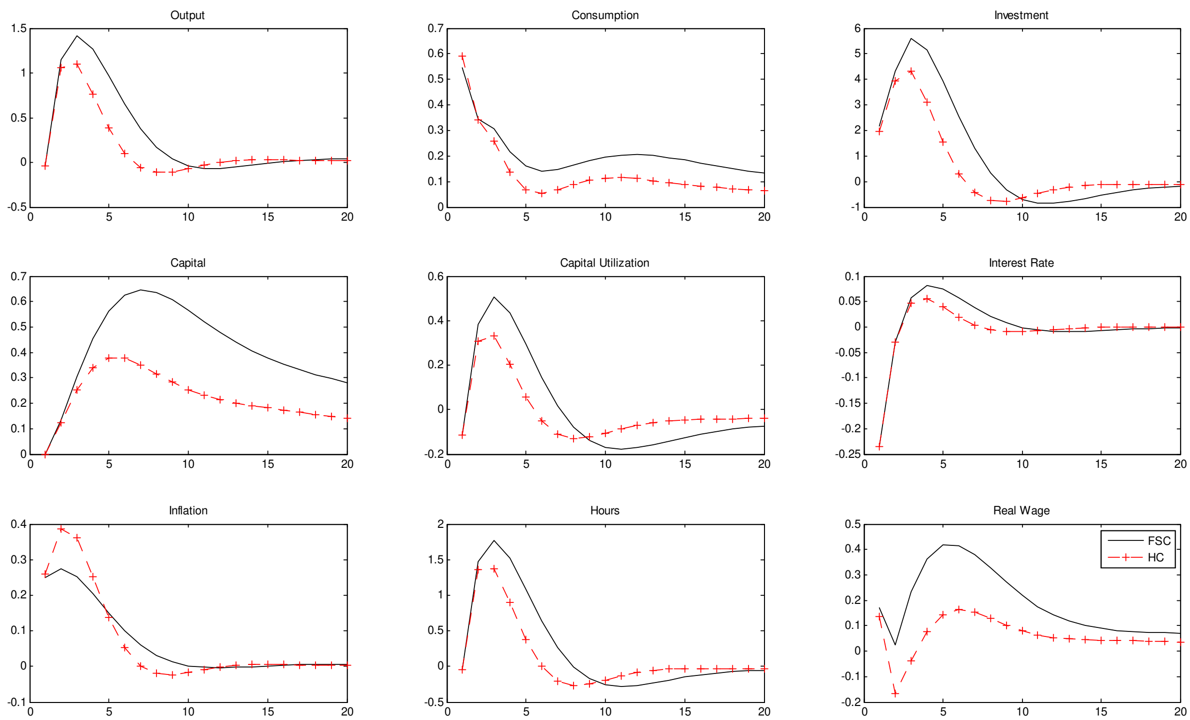

Figure 2: Neutral technology shock (benchmark case)

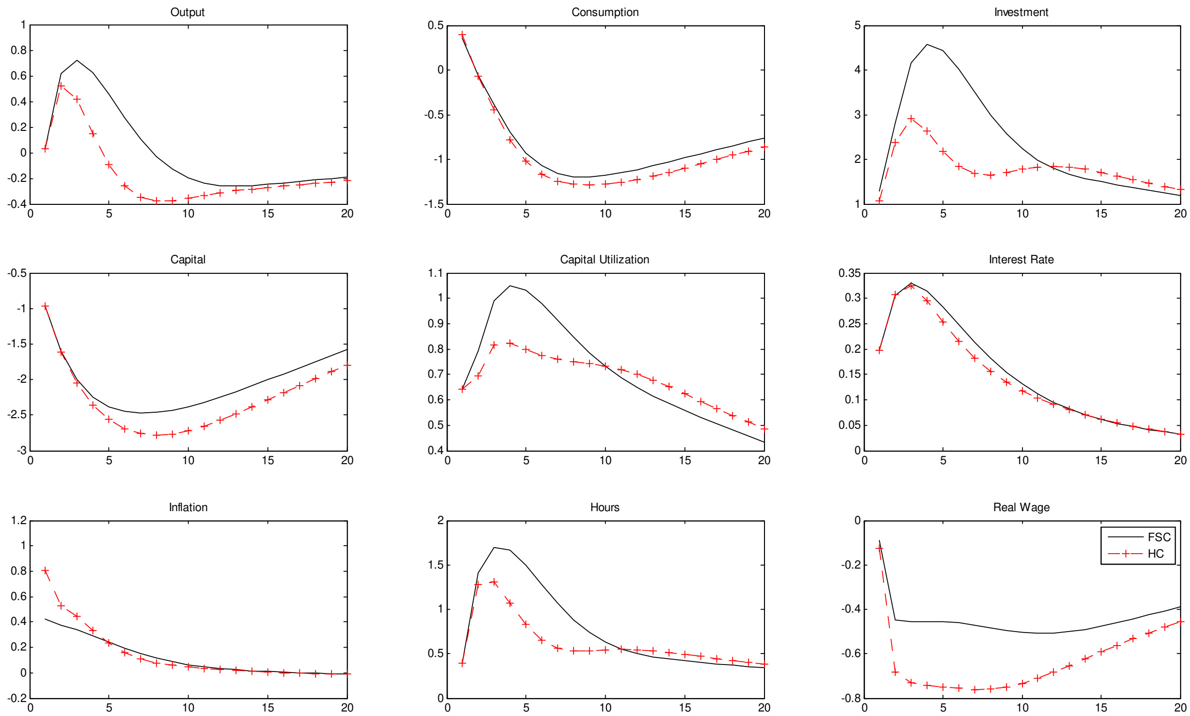

Figure 3: Capital-embodied technology shock (benchmark case)

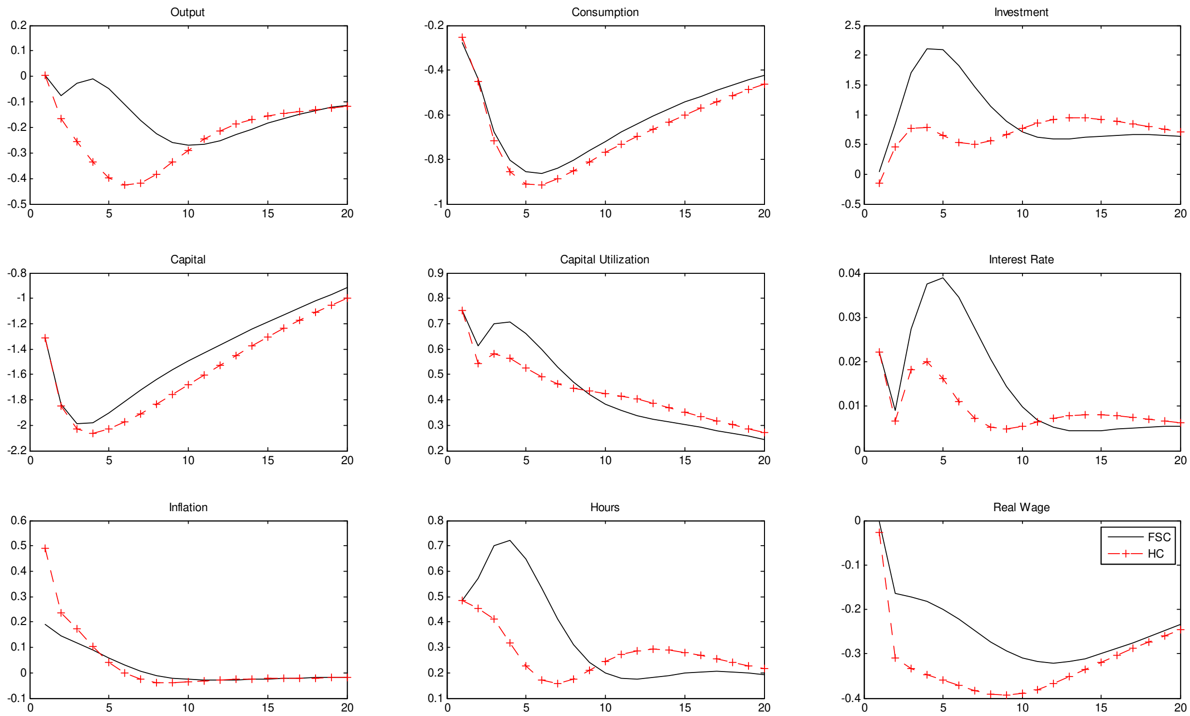

Figure 4: Price markup shock (benchmark case)