# Estimating a DSGE model with Limited Asset Market Participation for the Euro Area\*

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#### Abstract

We estimate a medium scale DSGE model for the Euro Area to gain intuition on the importance of Limited Asset Market Participation (LAMP). Our results suggest that in the recent EMU years LAMP is particularly sizeable (39% of households over the 1993-2012 sample) and important to understand business cycle features. In comparison with the representative household counterpart, the LAMP model is preferred on the grounds of both the Bayes factor and the average forecasting performance. We also find that the LAMP model leads to conclusions about the main determinants of EMU business cycle that are substantially different from those obtained under the representative agent hypothesis. Given these results, the LAMP hypothesis should be part and parcel of empirical DSGE models of the Euro area.

**Keywords:** DSGE, Limited Asset Market Participation, Bayesian Estimation, Euro Area, Business Cycle

**JEL codes:** C11, C13, C32, E21, E32, E37

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# 1 Introduction

The 2007 financial crisis has stimulated the search for new developments in Dynamic Stochastic General Equilibrium (DSGE) models that typically assumed complete financial markets and relied on the representative agent assumption (RA henceforth).

One widespread feature in the new wave of DSGE models is the distinction between lenders and borrowers (Christiano et al., 2010; Curdia and Woodford, 2010; Gerali et al., 2010; Gertler and Kiyotaki, 2010; Gertler and Karadi, 2011; Villa, 2014). These models are suitable for modelling financial and banking shocks but the interest rate policy of the central bank remains a powerful tool, capable of affecting the intertemporal choices of all households. This assumption seems to be at odds with the empirical wealth distribution and with the microeconomic evidence of household behavior. In fact, according to Iacoviello and Pavan (2013), 40% of US households hold no wealth and no debt. Similar figures are observed in the Euro area (see Cowell et al., 2012 for more details.). Anderson et al. (2013) use US microdata to estimate individual-level impulse responses as well as multipliers for government spending and tax policy shocks. They find that the wealthiest individuals behave according to the predictions of standard DSGE models, but the poorest individuals tend to neglect interest rate changes and adopt consumption patterns that closely follow their current disposable income dynamics. For this reason, they suggest that DSGE models should incorporate the Limited Asset Market Participation hypothesis (LAMP henceforth), where a fraction of Non-Ricardian households do not hold any wealth and entirely consume their disposable labor income in each period.

The implications of the LAMP hypothesis have been investigated in a number of theoretical studies (Galí et al., 2004; Bilbiie, 2008; Motta and Tirelli, 2012, 2013, 2014; Albonico and Rossi, 2014). Other theoretical studies have analyzed the potential role played by LAMP in allowing DSGE models to replicate certain business cycle facts, notably the consumption response to public expenditure shocks (Galí et al., 2007; Colciago, 2011) and to investment shocks (Furlanetto et al., 2013), and the reaction of output, hours and consumption to productivity shocks (Furlanetto and Seneca, 2012).

We incorporate the LAMP hypothesis in a medium scale closed economy DSGE model akin to Smets and Wouters (2003, 2007). Some empirical DSGE models of the Euro area (Coenen and Straub, 2005; Ratto et al., 2008; Forni et al., 2009 and Coenen et al., 2012) do account for the LAMP hypothesis. The justification for reconsidering the relative importance of LAMP in the Euro area is based on four considerations. The first one is that we provide a formal comparison of the LAMP and RA models,

highlighting the differences in goodness of fit, in the forecasting performance, in the importance of different shocks in determining observed volatility. To the best of our knowledge, this is the first analysis that explicitly compares the empirical performance of a LAMP model against the standard RA model. The second justification for our empirical analysis is that the relative importance of LAMP might well have changed over different periods. For instance, Bilbiie and Straub (2012, 2013) forcefully argue that structural changes in the degree of asset market participation explain variations in the monetary policy transmission mechanism in the US. We shall therefore investigate how the proportion of Non-Ricardian households has changed over certain sample periods. The third reason is that we shall devote particular attention to the role played by different shocks and by monetary policy in determining the business cycle in the EMU years, in particular during the financial crisis. Finally, our distinction between Ricardian and Non-Ricardian households allows to discuss the distributional effects of the crisis and of the ensuing monetary policy responses. In the recent years concern has grown for income inequality and for the distributional effects of monetary policies (Coibion et al., 2012). This is the first attempt to investigate the issue in an empirical DSGE model of the Eurozone.

Our results in a nutshell. We find that the share of LAMP households is sizable throughout the 1972-2012 sample, about 32%. In comparison with the RA counterpart, the LAMP model is preferred on the grounds of both the Bayes factor and the average forecasting performance. As far as the predictive ability is concerned, the LAMP model has a relative advantage in explaining the dynamics of output, consumption, inflation, and investment during the recent financial crisis. Turning to the analysis of subsample periods, we obtain that the importance of LAMP declines in periods of increasing financial integration and optimism in the European financial markets, such as the apparently successful period that ended with the demise of the hard EMS in 1992-93. By contrast, the period following the EMS collapse and the 2007-financial crisis are associated with a surge in LAMP. Over the 1993-2012 period, the fraction of LAMP is as high as 39%, well above the 34% estimated for the turbulent and highly regulated 1972-81 decade and the 25% obtained for the 1972-92 period.

To sharpen our analysis of the EMU years, we then focus on the model estimated over the 1993-2012 period. The Bayes factor now provides even stronger support for the LAMP model. In the RA model, the risk premium shock is the main driver of output volatility while in LAMP model this role is played by the investment-specific shock. Our intuition is that RA models require risk premium shocks to match consumption correlation with output because all households can smooth consumption. Instead, in the LAMP model investment specific shocks gain of importance because Non-Ricardian households

introduce a Keynesian multiplier effect and raise the correlation between consumption and investments, The observed correlation between these two variables is in fact notoriously difficult to replicate in standard RA models. Finally, both the RA and LAMP models pinpoint the contractionary role of monetary policy shocks during the post-2007 years. According to the LAMP model, in this period consumption of Non-Ricardian households fell dramatically, but this outcome might have been avoided by a more aggressive policy stance.

The remainder of this paper is organized as follows. Section 2 describes the model. Section 3 illustrates the estimation methodology. Section 4 discusses the results of Bayesian estimation. Section 5 concludes.

# 2 The model

There is a continuum of households indexed by  $i \in [0,1]$ . A share  $1-\theta$  of households (Ricardian households, i=o) can access financial markets, trade government bonds, accumulate physical capital, and rent capital services to firms. The remaining  $\theta$  households (Non-Ricardian or LAMP households, i=rt) do not have access to financial markets and consume all their disposable labor income. Each household supplies the bundle of labor services  $h_t^i = \left\{ \int_0^1 \left[ h_t^i(j) \right]^{\frac{1}{1+\lambda_t^w}} dj \right\}^{1+\lambda_t^w}$  that firms demand. For each labor type j, the wage setting decision is allocated to a specific labor union. At the given nominal wage  $W_t^j$ , households supply the amount of labor that firms demand

$$h_t^j = \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}} h_t^d \tag{1}$$

where  $h_t^i = \int_0^1 h_t^j dj$  is the total labor demand. Demand for labor type j is split uniformly across the households, so that households supply an identical amount of labor services,  $h_t = h_t^i$  as in Colciago (2011). Combining these expressions with (1) we obtain:

$$h_t = h_t^d \int_0^1 \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^p}{\lambda_t^m}} dj \tag{2}$$

Labor income is:

$$W_t^i h_t^i = h_t^d \int_0^1 W_t^j \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^{\mu}}{\lambda_t^{w}}} dj$$

Here, the parameter  $\lambda_t^w < 1$  is inversely related to the intratemporal elasticity of substitution between

the differentiated labour services supplied by the households,  $\frac{1+\lambda_t^w}{\lambda_t^w}$ . The parameter  $\lambda_t^w$  is interpreted as a net markup in the household-specific labour market and it is assumed to follow an AR(1) process with i.i.d. Normal error term:  $\log(\lambda_t^w) = (1-\rho_w)\log(\lambda^w) + \rho_w\log(\lambda_{t-1}^w) + \eta_t^w$ .

Households preferences are

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{1}{1-\sigma} \left( \frac{c_t^i}{(c_{t-1})^b} \right)^{1-\sigma} \exp\left( \frac{(\sigma-1)}{1+\phi_l} \left( h_t \right)^{1+\phi_l} \right) \right\}$$
 (3)

where  $c_t^i = \frac{C_t^i}{z_t}$  and  $c_t = \frac{C_t}{z_t}$  are individual and total real consumption levels normalized by a labour-augmenting non-stationary technology shifter  $z_t$ . The presence of  $z_t$  in 3 guarantees that the model has a balanced growth path when productivity is non stationary.<sup>1</sup>

Parameter 0 < b < 1 measures the degree of external habit in consumption. Differently from Smets and Wouters (2007) who use habits in differences, our specification here is based on habits in ratios. According to a popular view, the specification chosen for characterizing consumption habits has little importance in DSGE models based on the representative agent hypothesis (Dennis, 2009). Carroll (2000) pointed out that an infinite or negative marginal utility of consumption might occur under the subtractive formulation of the consumption-to-habit surplus. This outcome is even more likely in macro models that account for external habits, agents heterogeneity and consumption inequality. More specifically to our context, Motta and Tirelli (2013) show that to avoid indeterminacy in LAMP models a relatively strict upper limit must be imposed onto the value of  $\theta$  and/or to the difference habit parameter. The issue is potentially even more relevant here because the standard Dynare estimation routine forces estimates of the posterior distribution to be located in the determinacy region, potentially excluding large values of  $\theta$  (or b), and imposing a downward bias on its estimated value.<sup>2</sup> Here we follow Menna and Tirelli (2014), who show that indeterminacy is a lesser problem under the habit-in-ratio specification adopted in (3). <sup>3</sup> Other contributions constrain habits to be driven by peer-specific consumption levels (Forni et al., 2009; Cogan et al. 2010), and therefore deviate from the "keeping up with the Joneses" hypothesis that is based on observed interactions amongst heterogeneous consumers (Chan and Kogan 2002; Boyce et al. 2010; Frank et al. 2010; Drechsel-Grau and Schmid, 2014). In our context, this choice is open to

<sup>&</sup>lt;sup>1</sup>See Section 2.4 for more details.

<sup>&</sup>lt;sup>2</sup>Even if priors are imposed to avoid indeterminacy region, whenever an invalid posterior draw is encountered, this proposed draw is discarded and the current entry of the MonteCarlo Markov Chain (MCMC) is set to the previous draw. In technical terms, the proposed draw obtains likelihood 0, is rejected, and the MCMC continues. More details in An and Schorfheide (2007).

<sup>&</sup>lt;sup>3</sup>We discuss the determinacy properties of the model in the Appendix.

criticism because it limits the interaction between the two households groups that crucially affects both consumption choices and wage-setting decisions (see Motta and Tirelli, 2013).

Right from the outset it is worth noting that our model accounts for tax rates levied on wage and capital incomes and on households consumption,  $\tau^l$   $\tau^k$  and  $\tau^c$  respectively, and for social contributions levied on labor incomes  $\tau^{wh}$ . In addition, the model incorporates payroll tax rates on firms,  $\tau^{wf}$ , nominal lump sum taxes  $T^i$  and transfers  $TR^i$ . Investigating the role of countercyclical fiscal policies is beyond the scope of the paper, therefore we shall maintain that such taxes are held constant at their steady state level.<sup>4</sup> This choice allows to better characterize both non-Ricardian households disposable income over the cycle and consumption differences between the two consumer groups in steady state. <sup>5</sup>

#### 2.1 Ricardian households

Ricardian households allocate their resources between consumption  $C_t^o$ , investments  $I_t^o$  and government-issued bonds  $B_t^o$ . They receive income from labor services, from dividends  $D_t^o$ , from renting capital services  $u_t^o K_t^o$  at the rate  $R_t^k$  and from holding government bonds. Their budget constraint is:

$$(1 + \tau^{c}) P_{t} C_{t}^{o} + P_{t} I_{t}^{o} + \frac{B_{t+1}^{o}}{\varepsilon_{t}^{b}} = R_{t-1} B_{t}^{o} + \left(1 - \tau^{l} - \tau^{wh}\right) W_{t} h_{t}^{o} + P_{t} D_{t}^{o}$$

$$+ \left(1 - \tau^{k}\right) \left[R_{t}^{k} u_{t}^{o} - a\left(u_{t}^{o}\right) P_{t}\right] K_{t}^{o} + \tau^{k} \delta P_{t} K_{t}^{o} + T R_{t}^{o} - T_{t}^{o}$$

$$(4)$$

Here  $P_t$  is the consumption price index  $R_t$  is the nominal interest rate,  $K_t^o$  is the physical capital stock and  $u_t^o$  defines capacity utilization.  $TR_t^o$  are transfers Ricardian households and  $T_t^o$  are lump-sum taxes.  $\varepsilon_t^b$  is a risk premium shock that affects the intertemporal margin, creating a wedge between the interest rate controlled by the central bank and the return on assets held by the households. It is assumed to follow a first-order autoregressive process with an i.i.d. Normal error term:

$$\log\left(\varepsilon_{t}^{b}\right) = (1 - \rho_{b})\log\left(\varepsilon^{b}\right) + \rho_{b}\log\left(\varepsilon_{t-1}^{b}\right) + \eta_{t}^{b}$$

The capital stock evolves as follows:

<sup>&</sup>lt;sup>4</sup>The only exception are time-varying lump-sum taxes levied on Ricardian households, necessary to ensure that the government intertemporal budget constraint is satisfied in presence of shocks that affect public debt accumulation.

<sup>&</sup>lt;sup>5</sup>Motta and Tirelli (2013b) show that steady state redistributive taxation has powerful effects in limiting the indeterminacy region in LAMP models.

$$K_{t+1}^{o} = (1 - \delta) K_t^{o} + \varepsilon_t^{i} \left[ 1 - S \left( \frac{I_t^{o}}{I_{t-1}^{o}} \right) \right] I_t^{o}$$

$$(5)$$

where  $\delta$  is the depreciation rate and  $\varepsilon_t^i$  denotes an investment-specific technology shock that affects the real price of investment. It is assumed to evolve as an AR(1) process with i.i.d. Normal innovation term:  $\log(\varepsilon_t^i) = (1 - \rho_i)\log(\varepsilon^i) + \rho_i\log(\varepsilon_{t-1}^i) + \eta_t^i$ .

The term  $S\left(\frac{I_t^o}{I_{t-1}^o}\right)$  represents investment adjustment costs. In line with Christoffel et al. (2008, CCW henceforth), the adjustment costs function is:

$$S\left(\frac{I_t^o}{I_{t-1}^o}\right) = \frac{\gamma_I}{2} \left(\frac{I_t^o}{I_{t-1}^o} - g_z\right)^2 \tag{6}$$

where  $g_z$  is the steady state trend growth rate of the economy. The intensity of utilizing physical capital is subject to a proportional cost, as in Christiano et al. (2005):

$$a(u_t^o) = \gamma_{u1} (u_t^o - 1) + \frac{\gamma_{u2}}{2} (u_t^o - 1)^2$$
(7)

The Ricardian households maximize (3) with respect to  $C_t^o$ ,  $B_{t+1}$ ,  $I_t^o$ ,  $K_{t+1}^o$ ,  $u_t^o$ , subject to (4), (5), (6) and (7). The first order conditions are:

$$\frac{(c_t^o)^{-\sigma} (c_{t-1})^{b(\sigma-1)} \exp\left(\frac{(\sigma-1)}{1+\phi_l} (h_t^o)^{1+\phi_l}\right) \frac{1}{z_t}}{(1+\tau^c)} = \Lambda_t^o$$
(8)

$$R_t = \pi_{t+1} \frac{\Lambda_t^o}{\beta \varepsilon_t^b \Lambda_{t+1}^o} \tag{9}$$

$$1 = Q_t^o \varepsilon_t^i \left\{ 1 - \gamma_I \left( \frac{I_t^o}{I_{t-1}^o} - g_z \right) \frac{I_t^o}{I_{t-1}^o} - \frac{\gamma_I}{2} \left( \frac{I_t^o}{I_{t-1}^o} - g_z \right)^2 \right\}$$

$$+ \frac{\Lambda_{t+1}^o}{\Lambda_t^o} Q_{t+1}^o \varepsilon_{t+1}^i \beta \gamma_I \left( \frac{I_{t+1}^o}{I_t^o} - g_z \right) \left( \frac{I_{t+1}^o}{I_t^o} \right)^2$$
(10)

$$\frac{\Lambda_{t+1}^{o}}{\Lambda_{t}^{o}}\beta\left\{\left(1-\tau^{k}\right)\left[\frac{R_{t+1}^{k}}{P_{t+1}}u_{t+1}^{o}-a\left(u_{t+1}^{o}\right)\right]+\tau^{k}\delta+Q_{t+1}^{o}\left(1-\delta\right)\right\}=Q_{t}^{o}$$
(11)

$$\frac{R_t^k}{P_t} = \gamma_{u1} + \gamma_{u2} \left( u_t^o - 1 \right) \tag{12}$$

where  $\Lambda_t^o/P_t$  and  $\Lambda_t^oQ_t^o$  are the Lagrange multipliers associated respectively with (4) and (5).  $\Lambda_t^o$  represents the shadow price of a unit of consumption good, thus equation (8) shows the marginal utility of consumption out of income. We define  $\pi_t = \frac{P_t}{P_{t-1}}$  as the gross rate of inflation. Equation (9) is the Euler equation.  $Q_t^o$  measures the shadow price of a unit of investment good. Equations (10) and (11) are the first order conditions for investment and capital respectively. Equation (12) equals the return from capital utilization to its cost. The latter equation implies that  $u_t^o$  is identical across Ricardian households, so that  $u_t^o = u_t$ .

#### 2.2 Non-Ricardian households

LAMP households consume their disposable labor income in each period:

$$(1 + \tau^c) P_t C_t^{rt} = \left(1 - \tau^l - \tau^{wh}\right) W_t^{rt} h_t^{rt} + T R_t^{rt} - T_t^{rt}$$
(13)

#### 2.3 Wage setting

Nominal wages are staggered à la Calvo (1983). In each period, union j receives permission to optimally reset the nominal wage with probability  $(1 - \xi_w)$ . Those unions that cannot re-optimize the wage adjust the wage according to the following scheme:

$$W_t^j = g_{z,t} \pi_{t-1}^{\chi_w} \bar{\pi}_t^{(1-\chi_w)} W_{t-1}^j$$

where  $\bar{\pi}_t$  is the exogenous trend inflation rate.

Following Colciago (2011), we assume that the representative union objective function is a weighted average  $(1 - \theta, \theta)$  of the two households types' utility functions:

$$\max_{\tilde{W}_{t}^{j}} E_{t} \sum_{s=0}^{\infty} \left( \xi_{w} \beta \right)^{s} \begin{cases} \frac{1-\theta}{1-\sigma} \left( \frac{c_{t+s}^{o}}{(c_{t+s-1})^{b}} \right)^{1-\sigma} \exp\left( \frac{(\sigma-1)}{1+\phi_{l}} \left( h_{t+s}^{o} \right)^{1+\phi_{l}} \right) \\ + \frac{\theta}{1-\sigma} \left( \frac{c_{t+s}^{rt}}{(c_{t+s-1})^{b}} \right)^{1-\sigma} \exp\left( \frac{(\sigma-1)}{1+\phi_{l}} \left( h_{t+s}^{rt} \right)^{1+\phi_{l}} \right) \end{cases} \end{cases}$$

subject to (2), (4) and (13).

In doing this we depart from previous empirical DSGE models where the role of LAMP is restricted because it is typically assumed that Non-Ricardian households cannot affect wage-setting decisions.<sup>6</sup> This is a potentially serious shortcoming because wage changes have redistributive effects between the

<sup>&</sup>lt;sup>6</sup>Coenen and Straub (2005) and Coenen, Straub and Trabandt (2012).

two households groups and wage setting decisions may substantially change if they take into account the interests of Non-Ricardian households (Motta and Tirelli, 2014).

The representative union FOC is:

$$0 = E_{t} \sum_{s=0}^{\infty} (\xi_{w} \beta)^{s} (c_{t+s-1})^{b(\sigma-1)} \exp\left(\frac{(\sigma-1)}{1+\phi_{l}} (h_{t+s})^{1+\phi_{l}}\right) h_{t+s}^{j} \cdot \left\{ \tilde{W}_{t}^{j} \frac{(1-\tau_{t+s}^{l}-\tau_{t+s}^{wh})g_{z,t,t+s}\pi_{t,t+s-1}^{\chi_{w}}\bar{\pi}_{t,t+s}^{1-\chi_{w}}}{(1+\tau_{t+s}^{c})P_{t+s}z_{t+s}} \left(1-\frac{1+\lambda_{t+s}^{w}}{\lambda_{t+s}^{w}}\right) \left[(1-\theta) \left(c_{t+s}^{o}\right)^{-\sigma} + \theta \left(c_{t+s}^{rt}\right)^{-\sigma}\right] + \frac{1+\lambda_{t+s}^{w}}{\lambda_{t+s}^{w}} \left[(1-\theta) \left(c_{t+s}^{o}\right)^{-\sigma} MRS_{t+s}^{o} + \theta \left(c_{t+s}^{rt}\right)^{-\sigma} MRS_{t+s}^{rt}\right] \right\}$$

where:

$$\pi_{t,t+s-1} = \begin{cases} 1 & \text{for } s = 0 \\ \pi_t \cdot \pi_{t+1} \cdot \dots \cdot \pi_{t+s-1} & \text{for } s = 1, 2.... \end{cases}$$

$$\bar{\pi}_{t,t+s} = \begin{cases} 1 & \text{for } s = 0 \\ \bar{\pi}_t \cdot \bar{\pi}_{t+1} \cdot \dots \cdot \bar{\pi}_{t+s} & \text{for } s = 1, 2.... \end{cases}$$

$$MRS_t^o = -\frac{U_h^o\left(c_t^o, h_t^o\right)}{U_c^o\left(c_t^o, h_t^o\right)} = c_t^o\left(h_t^o\right)^{\phi_l}$$

$$MRS_t^{rt} = -\frac{U_h^{rt}\left(c_t^{rt}, h_t^{rt}\right)}{U^{rt}\left(c_t^{rt}, h_t^{rt}\right)} = c_t^{rt}\left(h_t^{rt}\right)^{\phi_l}$$

and 
$$g_{z,t,t+s} = \prod_{s=1}^{s} g_{z,t+s}$$
.

The aggregate wage index dynamic equation is:

$$W_{t} = \left[ \xi_{w} \left( g_{z,t} \pi_{t-1}^{\chi_{w}} \bar{\pi}_{t}^{1-\chi_{w}} W_{t-1} \right)^{\frac{1}{\lambda_{w}^{w}}} + (1 - \xi_{w}) \left( \tilde{W}_{t} \right)^{\frac{1}{\lambda_{w}^{w}}} \right]^{\lambda_{t}^{w}}$$

#### **2.4** Firms

#### 2.4.1 Final good firms

The final good  $Y_t$  is produced under perfect competition. A continuum of intermediate inputs  $Y_t(z)$  is combined as in Kimball (1995). The final good producers maximize profits:

$$\max_{Y_t, Y_t^z} P_t Y_t - \int_0^1 P_t^z Y_t^z dz$$

s.t. 
$$\int_0^1 G\left(\frac{Y_t^z}{Y_t}; \lambda_t^p\right) dz = 1$$

with G strictly concave and increasing and G(1) = 1 and  $\lambda_t^p$  is the net price markup, which is assumed to follow an AR(1) process with i.i.d. Normal error term:  $\log(\lambda_t^p) = (1 - \rho_p) \log(\lambda^p) + \rho_p \log(\lambda_{t-1}^p) + \eta_t^p$ . From the first order conditions, we obtain:

$$Y_t^z = Y_t G'^{-1} \left[ \frac{P_t^z}{P_t} \int_0^1 G' \left( \frac{Y_t^z}{Y_t} \right) \left( \frac{Y_t^z}{Y_t} \right) dz \right]$$

#### 2.4.2 Intermediate good firms

Intermediate firms z are monopolistically competitive and use as inputs capital and labor services,  $u_t^z K_t^z$  and  $h_t^z$  respectively. The production technology is:

$$Y_t^z = \varepsilon_t^a [u_t^z K_t^z]^\alpha [z_t h_t^z]^{1-\alpha} - z_t \Phi$$

where  $\Phi$  are fixed production costs.  $\varepsilon_t^a$  defines a transitory total factor productivity shock, evolving as an AR(1) process:

$$\varepsilon_t^a = \rho_l^a \varepsilon_{t-1}^a + \eta_t^a$$

where  $\eta_t^a$  is an i.i.d. Normal innovation term. The term  $z_t$  denotes a labor-augmenting technology process with permanent effects. We posit that  $g_{z,t} = \frac{z_t}{z_{t-1}}$  evolves according to:

$$\log(g_{z,t}) = (1 - \rho_{q_z})\log(g_z) + \rho_{q_z}\log(g_{z,t-1}) + \eta_t^{g_z}$$
(14)

where  $\eta_t^{g_z}$  is an i.i.d. Normal innovation term and  $g_z$  denotes a deterministic trend.

Profits maximization leads to the following:

$$\frac{u_t K_t}{h_t} = \frac{\alpha}{(1-\alpha)} \frac{\left(1 + \tau^{wf}\right) W_t}{R_t^k} \tag{15}$$

In this framework, the capital-labour ratio is equal across firms and the marginal cost is therefore equal across firms:

$$MC_t = \alpha^{-\alpha} \left( 1 - \alpha \right)^{-(1-\alpha)} \left( \varepsilon_t^a \right)^{-1} z_t^{-(1-\alpha)} \left( R_t^k \right)^{\alpha} \left[ \left( 1 + \tau^{wf} \right) W_t \right]^{1-\alpha}$$
(16)

**Price setting** Intermediate goods prices are sticky à la Calvo (1983). Firm z receives permission to optimally reset its price with probability  $(1 - \xi_p)$ . Firms that cannot re-optimize adjust the price according to the following scheme:

$$P_t^z = \pi_{t-1}^{\chi_p} \bar{\pi}_t^{1-\chi_p} P_{t-1}^z$$

The representative firm chooses the optimal price  $\tilde{P}^z_t$  that expected maximizes profits :

$$\max_{\tilde{P}_{t}^{z}} E_{t} \sum_{s=0}^{\infty} \xi_{p}^{s} \Xi_{t,t+s} \left[ \frac{\tilde{P}_{t}^{z} \pi_{t,t+s-1}^{\chi_{p}} \bar{\pi}_{t,t+s}^{1-\chi_{p}}}{P_{t+s}} Y_{t+s}^{z} - \frac{M C_{t+s}}{P_{t+s}} Y_{t+s}^{z} \right]$$

subject to

$$Y_{t+s}^{z} = G'^{-1} \left( \frac{\tilde{P}_{t}^{z} \pi_{t,t+s-1}^{\chi_{p}} \bar{\pi}_{t,t+s}^{1-\chi_{p}}}{P_{t+s}} \int_{0}^{1} G' \left( \frac{Y_{t+s}^{z}}{Y_{t+s}} \right) \frac{Y_{t+s}^{z}}{Y_{t+s}} dz \right) Y_{t+s}$$

where  $MC_t$  is the nominal marginal cost and  $\Xi_{t,t+s}$  is the stochastic discount factor for real payoffs:

$$\Xi_{t,t+s} = \varepsilon^b_{t+s} \beta^s \frac{\Lambda^o_{t+s}}{\Lambda^o_t}$$

Following Smets and Wouters (2007), we define  $\omega_t = \frac{\tilde{P}_t^z}{P_t} \int_0^1 G'\left(\frac{Y_t^z}{Y_t}\right) \frac{Y_t^z}{Y_t} dz$  and  $x_t = G'^{-1}(\omega_t)$ , hence the first order condition is:

$$E_{t} \sum_{s=0}^{\infty} \xi_{p}^{s} \frac{\Xi_{t,t+s}}{P_{t+s}} Y_{t+s}^{z} \left[ \tilde{P}_{t}^{z} \pi_{t,t+s-1}^{\chi_{p}} \bar{\pi}_{t,t+s}^{1-\chi_{p}} + \left( \tilde{P}_{t}^{z} \pi_{t,t+s-1}^{\chi_{p}} \bar{\pi}_{t,t+s}^{1-\chi_{p}} - M C_{t+s} \right) \frac{1}{G'^{-1} \left( \omega_{t+s} \right)} \frac{G'\left( x_{t+s} \right)}{G''\left( x_{t+s} \right)} \right] = 0$$

The aggregate price index dynamic equation is:

$$P_{t} = \left(1 - \xi_{p}\right) \tilde{P}_{t}^{z} G'^{-1} \left(\frac{\tilde{P}_{t}^{z} \int_{0}^{1} G'\left(\frac{Y_{t+s}^{z}}{Y_{t+s}}\right) \frac{Y_{t+s}^{z}}{Y_{t+s}} dz}{P_{t}}\right) + \xi_{p} \pi_{t-1}^{\chi_{p}} \bar{\pi}_{t}^{1-\chi_{p}} P_{t-1} G'^{-1} \left(\frac{\pi_{t-1}^{\chi_{p}} \bar{\pi}_{t}^{1-\chi_{p}} P_{t-1} \int_{0}^{1} G'\left(\frac{Y_{t+s}^{z}}{Y_{t+s}}\right) \frac{Y_{t+s}^{z}}{Y_{t+s}} dz}{P_{t}}\right)$$

#### 2.5 Fiscal policy

The government budget constraint in nominal terms is:

$$P_{t}G_{t} + R_{t-1}B_{t} + TR = B_{t+1} + T_{t} + \tau^{c}P_{t}C_{t} + \left(\tau^{l} + \tau^{wh} + \tau^{wf}\right)W_{t}h_{t} + \tau^{k}\left[R_{t}^{k}u_{t} - (a(u_{t}) + \delta)P_{t}\right]K_{t}$$

where  $G_t$  is public spending and the adjusted value  $g_t = G_t/z_t$  is assumed to follow an exogenous AR(1) process with i.i.d. Normal innovation.

#### 2.6 Monetary policy

Following CCW, the monetary authority sets the nominal interest rate according to a log-linear Taylor rule:

$$\hat{R}_{t} = \phi_{R} \hat{R}_{t-1} + (1 - \phi_{R}) \left( \hat{\bar{\pi}}_{t} + \phi_{\pi} \left( \hat{\pi}_{t-1} - \hat{\bar{\pi}}_{t} \right) + \phi_{y} \hat{y}_{t} \right) + \phi_{\Delta\pi} \left( \hat{\pi}_{t} - \hat{\pi}_{t-1} \right) + \phi_{\Delta y} \left( \hat{y}_{t} - \hat{y}_{t-1} \right) + \hat{\varepsilon}_{t}^{r}$$
(17)

where the hatted variables define log-deviations from steady state. In particular,  $\hat{y}_t = \widehat{Y_t/z_t}$  is the logarithmic deviation of observed output from the trend output level implied by the permanent technology component. Variable  $\hat{y}_t$  is also interpreted as the output gap measure.  $\varepsilon_t^r$  is a monetary shock that follows a first-order autoregressive process with an i.i.d. Normal error term:

$$\log(\varepsilon_t^r) = (1 - \rho_r)\log(\varepsilon^r) + \rho_r\log(\varepsilon_{t-1}^r) + \eta_t^r$$

#### 2.7 Aggregation

The relationship between aggregate and individual variables is:<sup>7</sup>

$$C_t = \theta C_t^{rt} + (1 - \theta) C_t^o$$

$$K_t = (1 - \theta) K_t^o$$

$$I_t = (1 - \theta) I_t^o$$

<sup>&</sup>lt;sup>7</sup>Aggregate and average variables here coincide. For this reason, wealth holdings of Ricardian households are larger than the corresponding aggregates.

$$B_t = (1 - \theta) B_t^o$$

$$d_t = (1 - \theta) d_t^o$$

# 2.8 Market clearing

The aggregate resource constraint:

$$Y_t = C_t + G_t + I_t + a(u_t) K_t$$

Labor market clearing:

$$h_t = \int_0^1 h_t^j dj$$

$$= h_t^d \int_0^1 \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}} dj$$

$$= s_{W,t} h_t^d$$

where  $s_{W,t} = \int_0^1 \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}} dj$  is the wage dispersion across the differentiated labor services. Capital market:

$$u_t K_t = u_t \int_0^1 K_t^z dz$$

Firms' aggregate demand for labor input:

$$h_t^d = \int_0^1 h_t^z dz$$

Good market:

$$\int_0^1 Y_t^z dz = \int_0^1 \left(\frac{P_t^z}{P_t}\right)^{-\frac{1+\lambda_t^p}{\lambda_t^p}} dz Y_t = s_{P,t} Y_t$$

where  $s_{P,t} = \int_{0}^{1} \left(\frac{P_{t}^{z}}{P_{t}}\right)^{-\frac{1+\lambda_{t}^{p}}{\lambda_{t}^{p}}} dz$  is the price dispersion across differentiated goods.

Note that both  $s_{W,t}$  and  $s_{P,t}$  vanish in the log-linearized version of the model.

# 3 Estimation strategy

After being adjusted to obtain a balanced growth equilibrium, the model presented in the previous section is log-linearized around its steady state and then estimated with Bayesian estimation techniques.

Our observables are seven Euro area time series: real GDP, private consumption, inflation, investments, compensation per employee, employment, and short-term nominal interest rate.<sup>8</sup> Inflation has been calculated as the log difference in the GDP deflator. Output, consumption, investments, and wages are transformed in log differences; total employment has been detrended with a linear trend. The data sample is 1972Q2-2012Q4.

Following CCW, the auxiliary equation

$$\hat{e}_t = \frac{\beta}{1+\beta} E_t \hat{e}_{t+1} + \frac{1}{1+\beta} \hat{e}_{t-1} + \frac{(1-\xi_e)(1-\beta\xi_e)}{(1+\beta)\xi_e} \left(\hat{h}_t - \hat{e}_t\right)$$
(18)

relates the employment variable,  $e_t$ , to the unobserved worked hours variable,  $h_t$ .

We include seven structural shocks for our benchmark estimation: transitory TFP shock, risk premium shock, investment specific shock, interest rate shock, wage markup shock, price markup shock and government spending shock. This implies that we set  $\eta_t^{g_z} = 0$  in 14. <sup>10</sup>

The measurement equations are:

$$Y_t = egin{bmatrix} \Delta \ln y_t \ \Delta \ln c_t \ \Delta \ln i_t \ \Delta \ln w_t \ \ln e_t \ \ln R_t^a \ \end{bmatrix} egin{bmatrix} \overline{\gamma} \ \overline{\gamma} \ \overline{\gamma} \ \overline{\gamma} \ \overline{\gamma} \ \overline{\gamma} \ \end{array} egin{bmatrix} y_t - y_{t-1} \ c_t - c_{t-1} \ i_t - i_{t-1} \ w_t - w_{t-1} \ \overline{\epsilon} \ \overline{\pi}_* \ \overline{r} \ \end{array} egin{bmatrix} w_t - w_{t-1} \ \overline{\tau} \ \end{array} egin{bmatrix} e_t \ \overline{\tau} \ \end{array}$$

where ln denotes 100 times log and  $\Delta \ln$  refers to the log difference. Similarly to Smets and Wouters (2007),  $\bar{\gamma} = 100(g_z - 1)$  denotes a deterministic growth trend, common to the real variables GDP,

 $<sup>^{8}</sup>$ We use quarterly data from the AWM database (Fagan, Henry and Mestre, 2001,  $13^{th}$  update). Data are taken in a convenient transformation as in Smets and Wouters (2007) and Coenen et al. (2012).

<sup>&</sup>lt;sup>9</sup>Parameter  $\xi_e$  determines the sensitivity of employment with respect to worked hours.

 $<sup>^{10}</sup>$ We also tried specifications that include the permanent technology shock either in place of the government spending shock or as an additional source of disturbance. In both cases we observed a fall in the marginal data densities and identification problems for some parameters. Nevertheless, the posterior estimates of the LAMP fraction  $\theta$  ere very close to what we obtain in our preferred specification and the LAMP model outperformed the Ra one in terms of the Bayes factor. More detailed results are available upon request.

consumption, investment and wages. Further,  $\overline{\pi}_* = 100(\overline{\pi} - 1)$  is the quarterly steady-state inflation rate,  $\overline{r} = 100(\beta^{-1}g_z\overline{\pi} - 1)$  is the steady-state nominal interest rate, and  $\overline{e}$  is the steady-state employment, normalized at zero.

Over the last few years, Bayesian estimation of DSGE models has become very popular. As stressed by An and Schorfheide (2007), there are essentially three main characteristics. First, the Bayesian estimation is system-based and fits the solved DSGE model to a vector of aggregate time series, as opposed to the GMM which is based on equilibrium relationships, such as the Euler equation for the consumption or the monetary policy rule. Second, it is based on the likelihood function generated by the DSGE model rather than the discrepancy between DSGE responses and VAR impulse responses. Third, prior distributions can be used to incorporate additional information into the parameter estimation.

On a theoretical level, the Bayesian estimation takes the observed data as given, and treats the parameters of the model as random variables. In general terms, the estimation procedure involves solving the linear rational expectations model described in the Section 2. The solution can be written in a state space form, i.e. as a reduced form state equation augmented by the observation (measurement) equations. At the next step, the Kalman Filter is applied to construct the likelihood function. Prior distributions are important to estimate DSGE models. According to An and Schorfheide (2007), priors might downweigh regions of the parameter space that are at odds with observations which are not contained in the estimation sample. Priors could add curvature to a likelihood function that is (nearly) flat for some parameters, given a strong influence to the shape of the posterior distribution. Posterior distribution of the structural parameters is formed by combining the likelihood function of the data with a prior density, which contains information about the model parameters obtained from the other sources (microeconometrics, calibration, and cross-country evidence), thus allowing to extend the relevant data beyond the time series that are used as observables. Numerical methods such as Monte-Carlo Markov-Chain (MCMC) are used to characterize the posterior with respect to the model parameters.<sup>11</sup>

#### 3.1 Calibration and priors

Following the recent medium scale DSGE models, we calibrate a number of parameters (Table 1). In particular, the discount factor  $\beta$  is fixed at 0.99. The steady-state depreciation rate  $\delta$  is 0.025, corresponding to a 10% depreciation rate per year. The capital share  $\alpha$  is set at 0.3. The monetary authority's long-run (net) annualized inflation objective  $\bar{\pi} - 1$  is 1.9%, consistent with the ECB's quantitative definition of

<sup>&</sup>lt;sup>11</sup>See Smets and Wouters (2003, 2007), Dynare Manual and An and Schorfheide (2007) for more details on Bayesian estimation of DSGE models.

price stability (see CCW). The steady state growth rate  $g_z$  is set at 2% in annual terms, in line with CCW. The elasticity of the demand for goods is set at 6, which implies a 20% net price markup in steady state. The steady state wage markup is also set at 20%. The ratios of fiscal variables to GDP and the steady state tax rates are borrowed from Coenen et al. (2012) and are collected in Table 1. In particular, government spending to GDP ratio is fixed at 21.5%, in line with the sample average, and public-debt-to-GDP ratio is set at 60% in annual terms, in line with the Maastricht objective. We derive the difference between aggregate transfers and taxes to GDP ratios (tr/y - t/y) as a residual from the steady state government budget constraint. Similarly to Coenen et al. (2012), transfers to Non-Ricardian households are calibrated to obtain a steady state consumption ratio between the two groups  $(c^{rt}/c^o)$  around 0.8 at the prior mean.

The remaining parameters are estimated with Bayesian techniques. Priors, reported in Table 2, are set in line with the literature on Euro area model estimation (see CCW, Coenen et al. (2012) and Smets and Wouters (2003, 2005)). In particular, parameters measuring the persistence of the shocks are set to be Beta distributed, with mean 0.5 and standard deviation 0.1 and the standard errors of the innovations are assumed to follow an Inverse-gamma distribution. The parameters governing price and wage setting, habits, utilization elasticity, interest rate smoothing and the steady state fraction of LAMP are also Beta distributed. The fraction of LAMP  $\theta$  is assumed to be Beta distributed with mean 0.3 and standard deviation 0.1, in line with Coenen et al. (2012).

Risk aversion, the inverse of Frisch elasticity and the parameters of the Taylor rule are Normally distributed, whereas the parameter defining investment adjustment costs is Gamma distributed.

#### 4 Results

#### 4.1 The full sample estimates

Table 2 shows the posterior estimates of the structural parameters and coefficients governing shock processes.<sup>12</sup> Visual diagnostics of the estimation results can be found in Figure 11 in the Technical Appendix, where we plot prior and posterior distributions that are substantially different for most parameters. The estimate for the fraction of LAMP households,  $\theta = 0.317$ , is close to the 0.3 prior. We therefore checked for the robustness of this prior by re-estimating the model with a flat prior on  $\theta$  (Uni-

<sup>&</sup>lt;sup>12</sup>All the marginal posterior distributions are unimodal, MCMC's convergence criteria are satisfied. As robustness check, Metropolis-Hastings convergence graphs suggest a fast and efficient convergence for all parameters. The posterior distributions are based on four Markov chains with 250,000 draws, with 50,000 draws being discarded as burn-in draws. The average acceptance rate is roughly 25 percent.

Table 1: Calibrated parameters

parameter	value
β	0.99
$\delta$	0.025
$\alpha$	0.3
$\alpha_p$	6
$\lambda_p$	0.2
$\lambda_w$	0.2
$\bar{\pi}-1$	0.0047
$g_z - 1$	0.005
$\frac{b}{u}$	2.4
$\frac{b}{y}$ $\frac{g}{y}$	0.215
$ au^{g}_{c}$	0.223
$ au^l$	0.116
$ au^k$	0.35
$ au^{wh}$	0.127
$ au^{wf}$	0.232

form (0.01, 0.99)), and we obtained  $\theta = 0.342.^{13}$  In this case, posterior distributions for the remaining parameters remain close to our benchmark estimates. We also experimented with a prior based on a beta distribution (mean=0.5, std dev=0.2) obtaining  $\theta = 0.336.^{14}$ 

In Table 2 we also present the estimates for the RA model.<sup>15</sup> The LAMP and RA models are characterized by similar posterior distributions for the common parameters, with the notable exceptions of productivity shocks standard deviation,  $\sigma^a$ , and the risk aversion coefficient  $\sigma$ : both are significantly larger in the RA case. The marginal data density<sup>16</sup> (MDD in the Table 2) is -732 for the LAMP model and -740 for the RA model, which can be translated into a Bayes factor of exp[8] in favor of a better fit produced by the LAMP model. We can interpret the magnitude of the Bayes factor using the Kass and Raftery (1995) criterion, that multiplies the log of the Bayes factor by two, as recently proposed by Curdia et al. (2014) and Merola (2014). In our case, the Kass and Raftery criterion amounts to 16, suggesting a strong evidence in favor of the LAMP model. Moreover, Table 3 shows that both the output standard

 $<sup>^{13}</sup>$ See the Appendix for more details.

 $<sup>^{14}</sup>$ The marginal data density in these two cases was -734.4 and -733.7 respectively.

<sup>&</sup>lt;sup>15</sup>Empirical DSGE models must be tested for misspecification. Smets and Wouters (2007) discuss how Bayesian estimated medium scale DSGE models are able to compete in in-sample with Classical VAR (comparing the marginal data density) and in out-of-sample with Bayesian VAR (comparing RMSFE). Only the hybrid models, used to detect possible misspecifications, such as the DSGE-VAR (Del Negro and Schorfheide, 2004) and the DSGE-Factor Augmented VAR (Consolo, Favero, and Paccagnini, 2009) can outperform a medium scale model in in-sample and out-of-sample comparisons. We estimated the DSGE-VAR counterpart for the both the RA and the LAMP model, but we did not find relevant misspecification problems and the DSGE-VAR estimates do not produce a significant difference for either model. For this reason, the DSGE-VAR model is not included in our empirical comparison.

<sup>&</sup>lt;sup>16</sup>For more technical details about the marginal data density, see An and Schorfheide (2007) and Bekiros and Paccagnini (2014a and 2014b).

deviation and the cross-correlations with output obtained with the LAMP model are always closer (but for employment) to the data moments.

Table 2: Prior and posterior distributions of estimated parameters (1972:Q2-2012Q4)

	Prior	r distrib		Posterior distribution					
parameters					LAMP			RA	
	shape	mean	$\operatorname{std} \operatorname{dev}$	post. mean	90% H	PD interval	post. mean	$90\%~\mathrm{HI}$	PD interval
$\sigma$	norm	1	0.375	1.391	1.185	1.585	1.921	1.684	2.153
b	beta	0.7	0.1	0.789	0.679	0.897	0.802	0.693	0.921
$\phi_l$	norm	2	0.75	2.734	1.744	3.740	1.762	0.699	2.773
heta	beta	0.3	0.1	0.317	0.224	0.417	-	-	-
$\gamma_I$	gamma	4	0.5	4.163	3.325	4.900	4.222	3.367	5.062
$\sigma_u$	beta	0.5	0.15	0.930	0.886	0.976	0.872	0.808	0.939
$\chi_p$	beta	0.75	0.1	0.142	0.107	0.177	0.139	0.107	0.171
$\xi_p^{'}$	beta	0.75	0.1	0.897	0.891	0.900	0.899	0.897	0.900
$\chi_w$	beta	0.75	0.1	0.746	0.594	0.909	0.477	0.323	0.634
${\xi}_w$	beta	0.75	0.1	0.920	0.901	0.939	0.922	0.893	0.951
$\xi_e^-$	beta	0.5	0.15	0.839	0.819	0.860	0.870	0.851	0.889
$\phi_r$	beta	0.9	0.05	0.856	0.821	0.890	0.839	0.796	0.881
$\phi_{m{\pi}}$	norm	1.7	0.1	1.732	1.612	1.849	1.715	1.568	1.860
$\phi_y$	norm	0.12	0.05	0.251	0.202	0.302	0.266	0.220	0.315
$\phi_{\Delta y}^{}$	norm	0.063	0.05	0.152	0.111	0.193	0.138	0.100	0.176
$\phi_{\Delta\pi}$	norm	0.3	0.1	0.145	0.092	0.196	0.148	0.097	0.199
$(y+\Phi)/y$	norm	1.45	0.25	1.476	1.329	1.618	1.220	1.049	1.386
$ ho_a$	beta	0.5	0.1	0.952	0.950	0.953	0.949	0.943	0.953
$ ho_b$	beta	0.5	0.1	0.948	0.942	0.953	0.935	0.918	0.953
$ ho_i$	beta	0.5	0.1	0.579	0.477	0.677	0.775	0.713	0.835
$ ho_r$	beta	0.5	0.1	0.381	0.290	0.469	0.452	0.346	0.563
$ ho_p$	beta	0.5	0.1	0.728	0.610	0.847	0.671	0.566	0.776
$ ho_w^-$	beta	0.5	0.1	0.809	0.763	0.855	0.838	0.792	0.885
	beta	0.5	0.1	0.942	0.931	0.953	0.947	0.939	0.953
$egin{array}{c}  ho_g \ \sigma^a \end{array}$	invg	0.1	2	0.871	0.700	1.034	1.208	0.953	1.461
$\sigma^b$	invg	0.1	2	0.170	0.147	0.193	0.154	0.130	0.177
$\sigma^i$	invg	0.1	2	0.489	0.421	0.555	0.370	0.318	0.421
$\sigma^r$	invg	0.1	2	0.164	0.146	0.183	0.163	0.144	0.182
$\sigma^p$	invg	0.1	2	0.088	0.053	0.123	0.109	0.074	0.143
$\sigma^w$	invg	0.1	2	0.100	0.082	0.119	0.084	0.068	0.100
$\sigma^g$	invg	0.1	2	0.363	0.327	0.398	0.348	0.316	0.381
MDD						-731.9			-740.2

Table 3: Key variables: data and model estimated moments

sample 1972-2012	DATA	LAMP	RA
standard deviation output	0.646	0.819	0.846
correlations v	with outp	ut	
inflation	0.136	-0.079	-0.147
consumption	0.699	0.710	0.759
${\rm investment}$	0.811	0.747	0.643
short term interest rate	0.059	-0.114	-0.128
wage	0.340	0.197	0.111
${\it employment}$	-0.072	-0.077	-0.071

Finally, we perform a forecasting comparison between the two models for the period from 2002:Q1 to 2012:Q4. Table 4 shows the ratio of the root mean squared forecast error (RMSFE) of the LAMP model relative to the RA model for a horizon of 4 step-ahed forecasts<sup>17</sup>. Values smaller than one denote that the LAMP model shows a better forecasting performance. To check the statistical significance of these ratios, we report the pvalue of the Clark and West (2006) test applicable for nested models as in this case. The forecasting accuracy of the LAMP model is statistically better for all variables, except the interest rate. However, for this latter variable we cannot discriminate between the two models.

Table 4: Root Mean Square Forecast Error. All RMSFE are computed as a ratio to the RMSFE in the RA model.

out-of-sample 2002-2012	RMSFE	pvalue Clark and West test
output	0.91	0.10
${ m consumption}$	0.89	0.00
inflation	0.92	0.00
${\rm investment}$	0.96	0.01
short term interest rate	1.12	0.89
wage	0.86	0.04

In Figure 1, we investigate the evolution of the difference between the RMSFE of the RA and of the LAMP models. For each observation, the RMSFEs are computed using the 12 previous quarters (see Del Negro and Schorfheide (2012) for more details). On average, the LAMP model has a better forecasting performance, but the ranking between the two models is not stable over time. For output and consumption, the LAMP model is the best model in terms of prediction after 2007. The LAMP hypothesis appears to be important to explain the dynamics of key macroeconomic series such as output, consumption, inflation, and investment during the recent financial crisis. By contrast, the RA model outperforms the LAMP model in forecasting the short term interest rate.

#### 4.2 LAMP in different periods

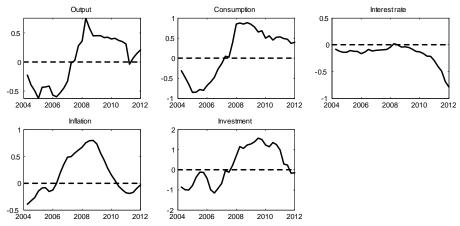
Our empirical analysis accounts for a relatively long time span, encompassing the turbulent 1970s, the great moderation period, and the financial crisis. Our estimated fraction of LAMP households is substantially larger than the fraction found in Coenen et al. (2012),  $\theta = 0.18$  for the sample 1985:Q1 to 2010:Q2.

<sup>18</sup> By contrast, in Forni et al. (2009) the fraction is estimated in a range of 0.34-0.37 for the sample

<sup>&</sup>lt;sup>17</sup>We generate unconditional forecasts taking each 20th draw from the final 150,000 parameter draws (with the first 30,000 draws used as burn-in period) produced by the Metropolis-Hastings algorithm, which gives us 6,000 draws from the posterior distribution. The point forecasts are calculated as means of these draws. For more technical details, see Kolasa et al. (2012) and Kolasa and Rubaszek (2014).

<sup>&</sup>lt;sup>18</sup>Coenen and Straub (2005), obtain  $\theta = 0.37$  over the sample 1980:Q1-1999:Q4, but the estimated marginal data density for the LAMP model is always smaller than the one obtained for the corresponding RA model.

Figure 1: Forecast comparison: LAMP vs RA model. A value greater than zero indicates that the LAMP model attains a lower RMSFE.



1980:Q1-2005:Q4. However, these results are obtained under different theoretical assumptions and for different sample periods.<sup>19</sup>. To shed light on a possibly changing role of LAMP, we re-estimate the model for selected subsamples. The sample 1972-81 coincides with the Great Inflation period and with a phase where financial markets were tightly regulated. Then, the extended sub-sample 1972-92 incorporates the disinflation period and the "hard EMS" phase. Finally, we concentrate on the post-Maastricht period that led to EMU inception and to the financial crisis years.

Table 4 shows that significant variations in the posterior estimates seem to concern only a limited subset of parameters, i.e., relative to the full sample estimates, in the 1970s the fractions of non-optimizing wage and price setters,  $\xi_w$  and  $\xi_p$ , were relatively smaller, whereas the inflation indexation parameters  $\chi_p$  and  $\chi_w$  were relatively larger. This is in line with the interpretations of the "great moderation" period that emphasizes the importance of the adjustment to a low inflation environment. We also observe clear evidence of "great moderation" for the post Maastricht sample in both real and nominal shocks, with the notable exceptions of larger (but less persistent) risk premium shocks and of larger and more persistent investment specific shocks.

Given our full sample estimate, where  $\theta = 0.317$  (HPD interval 0.224-0.417), we find that the point estimate for the fraction of LAMP is relatively larger in the 1972-81 period,  $\theta = 0.34$  (HPD interval 0.182-0.497), and it substantially decreases in the 1972-1992 sample with  $\theta = 0.247$  (HPD interval 0.144-0.351). Finally, the estimated posterior mean for the LAMP parameter in the 1993-2012 period,  $\theta = 0.39$ ,

<sup>&</sup>lt;sup>19</sup>Moreover, the estimated models have different features and observed variables. In Forni et al. (2009) and Coenen et al. (2012) the DSGE model includes fiscal variables; in addition, Coenen et al. (2012) consider an open economy with fiscal variables.

Table 5: Prior mean estimates of the LAMP model over different subsamples.

parameters	an estimates	LAMP		RA
1	72:Q2-81:Q4	72:Q2-92:Q4	93:Q2-12:Q4	93:Q2-12:Q4
$=$ $\sigma$	1.655	1.445	2.157	1.827
b	0.649	0.713	0.741	0.749
$\phi_l$	2.217	2.753	2.217	2.321
$\theta$	0.341	0.247	0.390	_
$\gamma_I$	4.178	3.452	4.018	3.817
$\sigma_u$	0.878	0.925	0.797	0.819
$\chi_p$	0.403	0.282	0.229	0.224
$\xi_p^{^r}$	0.601	0.837	0.895	0.896
$\chi_w$	0.722	0.786	0.621	0.480
$\xi_w^-$	0.805	0.925	0.919	0.920
$\xi_e^-$	0.753	0.857	0.795	0.800
$\phi_{r}$	0.748	0.774	0.876	0.840
$\phi_{\pi}$	1.665	1.820	1.725	1.764
$\phi_y$	-0.072	0.203	0.152	0.132
$\phi_{\Delta y}$	0.108	0.129	0.137	0.127
$\phi_{\Delta\pi}$	0.338	0.223	0.146	0.158
$(y+\Phi)/y$	1.443	1.424	1.554	1.385
$ ho_a$	0.893	0.949	0.938	0.938
$ ho_b$	0.698	0.939	0.388	0.942
$ ho_i$	0.484	0.307	0.827	0.576
$ ho_r$	0.415	0.458	0.512	0.491
$ ho_p$	0.468	0.789	0.538	0.532
$ ho_w$	0.607	0.688	0.829	0.812
$egin{array}{c}  ho_g \ \sigma^a \end{array}$	0.840	0.917	0.908	0.863
	1.393	1.493	0.506	0.661
$\sigma^b$	0.276	0.166	0.286	0.102
$\sigma^i$	0.481	0.530	0.535	0.444
$\sigma^r$	0.308	0.229	0.084	0.082
$\sigma^p$	0.356	0.104	0.093	0.105
$\sigma^w$	0.300	0.160	0.062	0.066
$\sigma^g$	0.503	0.400	0.283	0.289
MDD			-230.6	-243.9

(HPD interval 0.316-0.466) is strikingly larger than in the full sample case. These results do not fit well with a conventional interpretation of the great moderation as a period when credit availability increased and access to financial markets was easier. In fact, the fall in the importance of LAMP appears to be a feature of the 1981-1992 period when several countries benefited from large capital inflows and from a reduction in domestic interest rate spreads as a consequence of the membership in the (increasingly) hard EMS. The post-92 crisis phase might have been characterized by a financial retrenchment. To check for this point, we re-estimate the model over the 1972-1998 period, obtaining  $\theta = 0.36$  (HPD interval 0.262-0.465). In addition, when we restrict the post-1992 sample excluding the financial crisis years, we obtain  $\theta = 0.36$  (HPD interval 0.258-0.449). This last result and the contribution of the LAMP hypothesis to the post-2007 forecasts of output, consumption and investment analyzed in the previous section, suggest

an intriguing analogy between the EMS 1992 collapse and the recent financial crisis as periods when the role of AMP increases..

#### 4.3 A LAMP model for the EMU years

Between 1993 and 1999, the Maastricht Treaty forced EMU accession candidates to seek nominal convergence to the German levels, and there is ample evidence of continuity between the Bundesbank and the ECB in its early years (Issing et al., 2011). Thus our estimates for the post-1992 period may well characterize a model for the EMU years.

Turning to a comparison between the LAMP and RA models (see Table 4), we find that for this sample the marginal data density is -231 in the LAMP model, and -244 in the RA model. The Bayes factor, approximately exp[13], and the Kass and Raftery criterion, around 26, are now larger than in the full sample case, showing a very strong evidence in favor of the LAMP model. Under LAMP, we estimate more volatile and far less persistent risk-premium shocks, and more volatile and persistent investment-specific shocks. Technology shocks are less volatile and equally persistent in the LAMP model.

Table 5 reports the variance decomposition for the LAMP and RA models. It is easy to see that the bulk of output growth volatility in the LAMP model is caused by investment-specific shocks, whereas in the RA model the risk premium shock has a predominant role. We also obtain that in the RA model the risk premium shock is almost the only source of consumption volatility. By contrast, in the LAMP model, risk premium and investment specific shocks have similar weights in explaining consumption volatility, followed by interest rates and productivity shocks. Turning to inflation, both models assign a minuscule weight to monetary shocks and a very important role to wage markup (LAMP model) and to productivity shocks (RA model).

Summing up, the risk premium shock is the main driver of output, consumption and interest rates in the RA model. This is not surprising, because all households can smooth consumption by adjusting their capital holdings, and risk premium shocks are required to match consumption volatility and its correlation with output. These shocks play instead a limited role in the LAMP model. Our interpretation is that LAMP raises the correlation between consumption and output, and the need for consumption-specific shocks is therefore limited. Figure 2 reports IRFs to a 1% risk premium shock for the two estimated models. In the RA model all households reduce consumption and investment falls because households anticipate a prolonged real interest rate decline, in line with previous estimates for the Euro area (Smets and Wouters, 2005). By contrast, the LAMP model generates near-muted responses of the

Table 6: Variance decomposition (in percent) for the sample 1993-2012

	$\Delta c$	$\Delta y$	$\pi$	$\Delta w$	$\Delta i$	r	$\Delta c^{rt}$	$\Delta c^o$	
		LAMP							
$\overline{\eta^a}$	13.01	6.60	16.68	0.93	1.02	15.29	29.93	2.21	
$\eta^b$	30.04	11.56	0.01	0.07	1.22	0.63	3.52	26.91	
$\eta^i$	22.23	48.10	13.39	4.82	85.55	33.27	19.91	27.95	
$\eta^r$	14.98	9.77	0.63	1.08	3.19	0.92	4.27	9.99	
$\eta^p$	7.82	5.22	10.57	7.22	1.38	0.57	6.44	4.08	
$\eta^w$	11.50	6.27	57.96	85.84	7.09	47.45	32.46	27.53	
$\eta^g$	0.42	12.46	0.75	0.04	0.57	1.87	3.48	1.33	
				R	A				
$\overline{\eta^a}$	3.93	4.90	44.76	2.47	1.92	16.60	-	-	
$\eta^b$	74.46	55.16	20.03	20.69	23.97	72.95	-	-	
$\eta^i$	2.73	14.18	2.19	1.32	65.53	3.93	-	-	
$\eta^r$	13.32	10.10	0.59	2.55	4.24	1.30	-	-	
$\eta^p$	3.32	4.24	20.18	16.91	3.10	1.05	-	-	
$\eta^w$	1.71	0.80	12.05	55.98	0.86	3.32	-	-	
$\eta^g$	0.53	10.62	0.20	0.07	0.37	0.85			

main macroeconomic variables. This is almost entirely caused by the lower estimated persistence of the shock, which is less than half of the one obtained in the RA model (0.39 versus 0.94).

Figure 3 shows IRFs to an expansionary investment-specific shock.<sup>20</sup> In the RA model all households raise investment and smooth consumption growth, so the implied correlation between investment and output is relatively small, due to the absence of second-round effects of consumption increase on total demand (Keynesian multiplier). Instead, in the LAMP model Non-Ricardian households increase their consumption because the surge in investment raises labor income. As a result, the response of aggregate consumption and output is unambiguously stronger than in the RA model.<sup>21</sup>

In addition to the presence of Non-Ricardian household, different estimates for parameters and shock distributions determine asymmetries in the dynamic performance of the RA and LAMP models. To better understand the role of the Non-Ricardian households group, we also investigate the counterfactual responses of key macroeconomic variables to a stochastic simulation of the LAMP model where we impose  $\theta = 0$  (see Table 6).<sup>22</sup> With the notable exception of consumption,<sup>23</sup> the standard deviations of output, inflation, the real wage and investment fall substantially when  $\theta = 0$ .

<sup>&</sup>lt;sup>20</sup>The specific role of LAMP in explaining the co-movements of consumption with investment and output, observed in the data, was first discussed in Furlanetto et al. (2013).

<sup>&</sup>lt;sup>21</sup> After a slight initial fall, Ricardian households consumption rises well above the levels observed for the RA model. This is due to the favourable redistributive effect associated to the fall of the labor income share.

<sup>&</sup>lt;sup>22</sup>Simulations are based on the posterior estimates for the sample 1993:Q2-2012:Q4 (LAMP model), reported in Table 4.

<sup>&</sup>lt;sup>23</sup>Consumption decisions of the two household groups are negatively correlated and almost cancel out in the aggregate.

Figure 2: Impulse responses to a 1% risk premium shock. Solid lines: LAMP model. Dotted lines: RA model. Structural parameters and shock persistences are set at the posterior mean values for each specification. Estimation sample: 1993:Q2-2012:Q4.

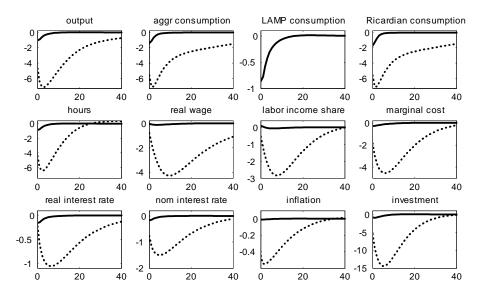


Figure 3: Impulse responses to a 1% investment specific shock. Solid lines: LAMP model. Dotted lines: RA model. Structural parameters and shock persistences are set at the posterior mean values for each specification. Estimation sample: 1993:Q2-2012:Q4.

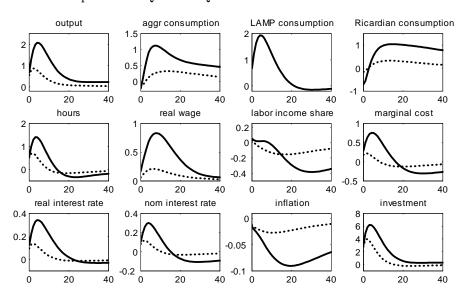


Table 7: Simulated standard deviations						
$y_t  \pi_t  c_t  w_t$						
LAMP model	9.45	2.03	9.45	15.92		
LAMP model with $\theta = 0$	8.09	1.43	9.39	13.76		

#### 4.3.1 Historical decomposition of output growth

We now investigate how shocks contributed to the business cycle in the EMU years. We concentrate on the historical decomposition of output growth for the post-1999 period, that is, the period of ECB operational activity. Figure 4 presents results for the LAMP and RA models.

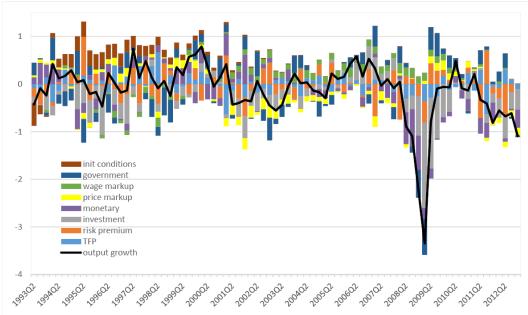
The two models yield similar results about the role of monetary policy shocks (to be discussed in section 4.3.3 below), but suggest different interpretations of the non-policy shocks contributions to the crisis. According to the RA model, the risk premium shock played a dominant role, whereas according to the LAMP model the investment shock was the key driver. Thus, according to the RA model the crisis period was mainly characterized by an increase in the wedge between the central bank interest rate and the return on assets in the hand of households. This reduced current consumption, increased the cost of capital and lowered the value of investment, as in Smets and Wouters (2007). In the LAMP model, the investment-specific shock might pick up the effect of financial disintermediation on the efficiency of the process that allows to transform savings into future capital inputs.<sup>24</sup>

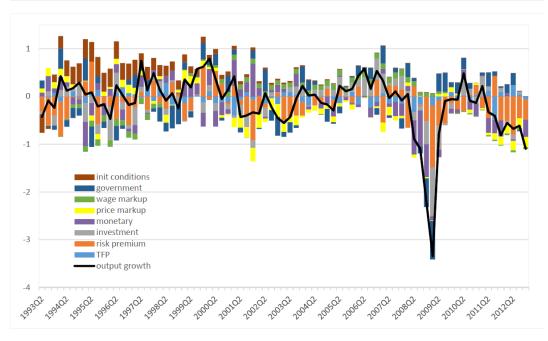
#### 4.3.2 Consumption inequality over the business cycle

Our empirical model provides estimates of consumption dynamics for the two household groups and for the relative importance of the underlying shocks that determined them. From Table 5 it is easy to see that investment-specific and wage markup shocks play a relatively large role for both groups, whereas risk-premium (productivity) shocks are important only for Ricardian (LAMP) households. It is important to bear in mind that shocks have typically different and sometimes opposite effects on consumption of the two groups. We have already discussed investment specific and risk premium shocks. In Figure 5 we report consumption dynamics for the remaining shocks. Monetary shocks have symmetrical effects: the reduction in Ricardian households consumption lowers demand and labor income, triggering the fall in consumption of non-Ricardian households. A similar result obtains under price markup shocks that are associated to a contractionary monetary policy response. Technology, wage markup and public expenditure shocks

<sup>&</sup>lt;sup>24</sup> Justiniano et al. (2011) distinguish between an investment-specific technology shock and a disturbance that affects the ability to turn savings into capital, finding that the latter played an important role in the US financial crisis. Pursuing their modelling strategy is beyond the scope of this paper.

Figure 4: Historical decomposition of output growth (estimated sample: 1993:Q2-2012:Q4), LAMP model: upper panel, RA model: lower panel.

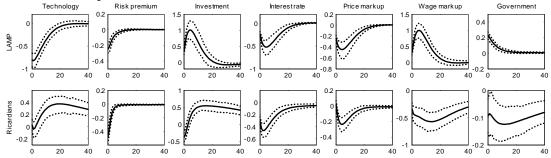




cause asymmetrical consumption dynamics. Due to price stickiness, technology and wage markup shocks have powerful income redistribution effects that drive Non-Ricardian households consumption, whereas Ricardians mainly react to the Central Bank decision to accommodate the technology shock and to curb the inflationary effect of the wage shock. Finally, the model replicates the different consumption response to a public expenditure shock that was first documented in Galí et al. (2007).

Figure 6 presents the historical decomposition of consumption growth for the two groups,  $\Delta \hat{c}_t^o$  and  $\Delta \hat{c}_t^{rt}$  respectively. As one could expect, Ricardian households consumption dynamics are relatively less volatile ( $\sigma_{\Delta \hat{c}_t^o} = 0.58$ ,  $\sigma_{\Delta \hat{c}_t^{rt}} = 0.82$ ). In addition, consumption of LAMP households shows a tendency to fall relative to Ricardians', especially during the last part of the sample. More specifically, in the 2007-2010 period Ricardian households managed to substantially smooth their consumption, whereas in 2011-2012 the risk premium shocks had a relatively strong effect. LAMP consumers where badly hit by investment and productivity shocks both in 2007-2010 and in 2011-2012.

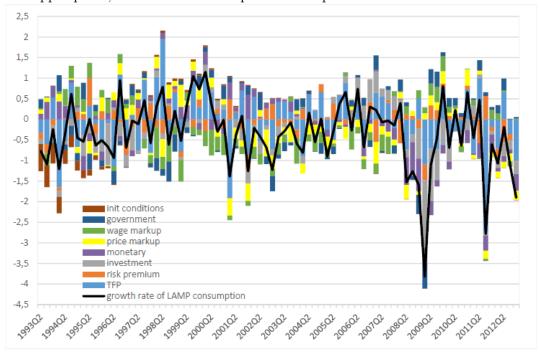
Figure 5: IRFs of LAMP and Ricardians' consumption to the different shocks. Solid line: posterior mean response. Dotted lines: posterior 90% HPD bands.

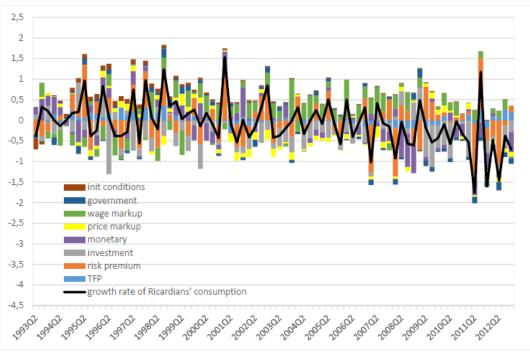


# 4.3.3 ECB policies in retrospect, a missed opportunity?

Results in Table 5 show that, according to both the RA and the LAMP model, only a small part of business cycle volatility is explained by monetary policy shocks, suggesting that the ECB closely adhered to the estimated policy rule (17). Looking at Figure 4, we do observe expansionary shocks after the burst of the IT bubble in 2001-2002, but the verdict is caustic if we look at more recent years. In fact, we observe a negative contribution of the interest rate shocks to economic growth during 2008-2009 recession. According to both models, interest rate shocks contributions to the recession in these years were significant. This is broadly in line with popular beliefs about the late response of the ECB to the crisis. Indeed, the ECB kept the interest rate on the main refinancing operations fixed at 4% from June

Figure 6: Historical decomposition of consumption growth (estimated sample: 1993:Q2-2012:Q4), LAMP consumption: upper panel, Ricardians' consumption: lower panel.

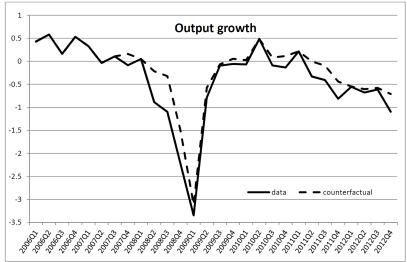


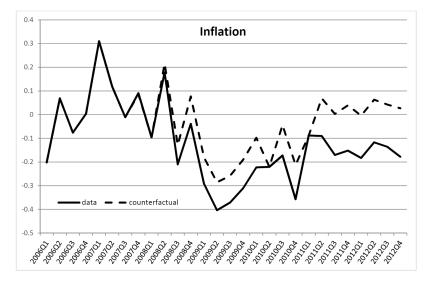


2007 till July 2008, when it even increased interest rates by 25 basis points. Interest rates in the Euro area started decreasing gradually only from October 2008.

Over the period 2007Q4-2012Q4, the cumulated output growth deviation from trend has been -12.6%. The corresponding cumulative deviation of inflation from its target level - 0.47 on a quarterly basis - was -3.5%. As a counterfactual exercise, we set to zero the negative monetary policy shocks in this period, obtaining that the cumulated output growth deviation from trend falls to -7.6% (see Figure 7, upper panel) and the corresponding cumulative deviation of inflation is -1.2% (see Figure 7, lower panel). Thus, inflation would have remained below its target level in a medium-term scenario.

Figure 7: Counterfactual exercise. Output growth: deviation from trend of quarterly output growth. Inflation: quarterly rate as deviation from the medium term target.

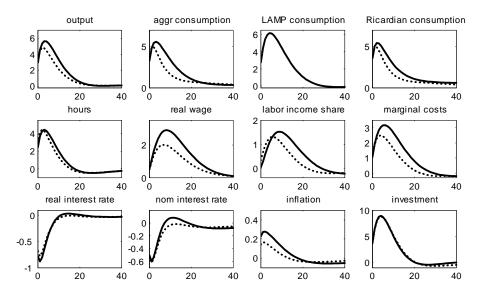




Adherence to simple rules certainly strengthens credibility and reputation. However, one might argue that in exceptional times, such as the post-2007 period, reputation should then be used to limit the adverse

effects of unprecedented shocks. What would have been the impact of a more aggressive discretionary policy during the crisis period? Figure 8 shows IRFs to a 1% negative interest rate shock. The investment response is particularly strong.<sup>25</sup> Consumption of LAMP households benefits from the surge in labor incomes and reacts more vigorously than consumption of Ricardian households. The overall output response is quite large relative to the corresponding inflation increase.

Figure 8: Impulse responses to a 1% interest rate shock. Solid lines: LAMP model. Dotted lines: RA model. Structural parameters and shock persistences are set at the posterior mean values for each specification. Estimation sample: 1993:Q2-2012:Q4.



# 5 Conclusions

The LAMP hypothesis is important to understand EMU business cycle, especially in the aftermath of the recent financial crisis. Given the tighter credit standards we might expect in the near future, the relatively large proportion of LAMP households is likely to remain an important feature of EMU.

Our results call for a reconsideration of ECB policies that should account for households heterogeneity. In this regard, theoretical LAMP models have shown that monetary policies and shocks can have powerful redistributive effects, paving the way for fiscal stabilization policies that should openly interact with central bank actions. Given our findings about the size of LAMP, ECB actions should take into account the "non conventional effects" of fiscal policies under LAMP.

<sup>&</sup>lt;sup>25</sup>Lewis et al. (2014) highlight the importance of the large negative investment gaps for explaining the output downturn in the EuroArea.

In addition, our estimates downplay the importance of risk premium shocks as a determinant of the output losses during the financial crisis. It would be interesting to assess the empirical effects of LAMP in models that explicitly account for financial frictions and for a banking sector. The analysis of these issues is left for future research.

# References

- [1] Albonico A, Rossi L, 2014. Policy Games, Distributional Conflicts, and the Optimal Inflation, Macroeconomic Dynamics, available on CJO2014. doi:10.1017/S1365100513000825.
- [2] Altug S, 1989. Time-to-Build and Aggregate Fluctuations: Some New Evidence, International Economic Review, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, vol. 30(4), pages 889-920, November.
- [3] An S, Schorfheide F, 2007. Bayesian Analysis of DSGE Models, Econometric Reviews, Taylor & Francis Journals, vol. 26(2-4), pages 113-172.
- [4] Anderson E, Inoue A, Rossi B, 2013. Heterogeneous Consumers and Fiscal Policy Shocks, CEPR Discussion Papers 9631, C.E.P.R. Discussion Papers.
- [5] Bekiros SD, Paccagnini A, 2014a. Bayesian forecasting with small and medium scale factor-augmented vector autoregressive DSGE models, Computational Statistics & Data Analysis, Elsevier, vol. 71(C), pages 298-323.
- [6] Bekiros SD, Paccagnini A, 2014b. Macroprudential Policy and Forecasting using Hybrid Models with Financial Frictions and State-Space Markov-Switching TVP-SVARs, Macroeconomic Dynamics, available on CJO2014. doi:10.1017/S1365100513000953.
- [7] Bilbiie FO, 2008. Limited asset market participation, monetary policy and (inverted) aggregate demand logic. Journal of Economic Theory 140, 162–196.
- [8] Bilbiie FO, Straub R, 2012. Changes in the output Euler equation and asset markets participation, Journal of Economic Dynamics and Control, Elsevier, vol. 36(11), pages 1659-1672.
- [9] Bilbiie FO, Straub R, 2013. Asset Market Participation, Monetary Policy Rules, and the Great Inflation, The Review of Economics and Statistics, MIT Press, vol. 95(2), pages 377-392, May.
- [10] Boyce CJ, Brown GDA, Moore SC, 2010. Money and Happiness: Rank of Income, Not Income, Affects Life Satisfaction. Psychological Science, Vol.21 (No.4), pp. 471-475 ISSN 0956-7976.
- [11] Calvo GA, 1983. Staggered prices in a utility-maximizing framework, Journal of Monetary Economics, Elsevier, vol. 12(3), pages 383-398, September.
- [12] Carroll CD, 2000. Solving consumption models with multiplicative habits, Economics Letters, Elsevier, vol. 68(1), pages 67-77, July.

- [13] Chan YL, Kogan L, 2002. Catching Up With The Joneses: Heterogeneous Preferences And The Dynamics Of Asset Prices, Journal of Political Economy, v110(6,Dec), 1255-1285.
- [14] Christiano LJ, Eichenbaum M, 1992. Liquidity Effects and the Monetary Transmission Mechanism, American Economic Review, American Economic Association, vol. 82(2), pages 346-53, May.
- [15] Christiano LJ, Eichenbaum M, Evans CL, 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy, Journal of Political Economy, University of Chicago Press, vol. 113(1), pages 1-45, February.
- [16] Christiano LJ, Motto R, Rostagno M, 2010. Financial Factors in Economics Fluctuations, Working Paper Series 1192, European Central Bank.
- [17] Christoffel K, Coenen G, Warne A, 2008. The New Area-Wide Model of the Euro area: a micro-founded open-economy model for forecasting and policy analysis, Working Paper Series 0944, European Central Bank.
- [18] Clark T, West KD, 2006. Using Out-of-sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis, Journal of Econometrics 135, 155-186.
- [19] Coenen G, McAdam P, Straub R, 2008. Tax reform and labour-market performance in the Euro area: A simulation-based analysis using the New Area-Wide Model, Journal of Economic Dynamics and Control, Elsevier, vol. 32(8), pages 2543-2583, August.
- [20] Coenen G, Straub R, 2005. Does Government Spending Crowd in Private Consumption? Theory and Empirical Evidence for the Euro Area, International Finance, Wiley Blackwell, vol. 8(3), pages 435-470, December.
- [21] Coenen G, Straub R, Trabandt M, 2012. Fiscal Policy and the Great Recession in the Euro Area, American Economic Review, Papers & Proceedings, American Economic Association, vol. 102(3), pages 71-76, May.
- [22] Cogan JF, Cwik T, Taylor JB, Wieland V, 2010. New Keynesian versus old Keynesian government spending multipliers, Journal of Economic Dynamics and Control, Elsevier, vol. 34(3), pages 281-295, March.
- [23] Colciago A, 2011. Rule-of-thumb consumers meet sticky wages. Journal of Money, Credit and Banking 43, 325–353.
- [24] Consolo A, Favero CA and Paccagnini A, 2009. On the Statistical Identification of DSGE Models,

- Journal of Econometrics, 150, 99-115.
- [25] Cowell F, Karagiannaki E, McKnight A, 2012. Mapping and measuring the distribution of household, LSE Research Online Documents on Economics 51288, London School of Economics and Political Science, LSE Library.
- [26] Curdia V, Ferrero A, Ng GC, Tambalotti A, 2014. Has U.S. Monetary Policy Tracked the Efficient Interest Rate? Federal Reserve Bank of San Francisco Working Paper Series, 2014-12.
- [27] Curdia V, Woodford M, 2010. Credit Spreads and Monetary Policy, Journal of Money, Credit and Banking, Blackwell Publishing, vol. 42(s1), pages 3-35, 09.
- [28] Del Negro M, Schorfheide F, 2004. Priors from General equilibrium Models for VARs, International Economic Review, 45, 643-673.
- [29] Del Negro M, Schorfheide F, 2012. DSGE Model-Based Forecasting, prepared for Handbook of Economic Forecasting, Volume 2.
- [30] Dennis R, 2009. Consumption Habits in a New Keynesian Business Cycle Model, Journal of Money, Credit and Banking, Blackwell Publishing, vol. 41(5), pages 1015-1030, 08.
- [31] Drechsel-Grau M, Schmid KD, 2014. Consumption—savings decisions under upward-looking comparisons, Journal of Economic Behavior & Organization, Elsevier, vol. 106(C), pages 254-268.
- [32] ECB, 2008. Modelling the Euro Area Economy, Monthly Bulletin, 10th anniversary of the ECB.
- [33] Fagan G, Henry J, Mestre R, 2001. An area-wide model (AWM) for the Euro area, Working Paper Series 0042, European Central Bank.
- [34] Forni L, Monteforte L, Sessa L, 2009. The general equilibrium effects of fiscal policy: Estimates for the Euro area. Journal of Public Economics, vol. 93(3-4), pages 559-585.
- [35] Frank RH, Levine AS, Dijk O, 2010. Expenditure Cascades, http://srn.com/abstract=1690612.
- [36] Furlanetto F, Seneca M, 2012. Rule-of-Thumb Consumers, Productivity, and Hours, Scandinavian Journal of Economics, Wiley Blackwell, vol. 114(2), pages 658-679, 06.
- [37] Furlanetto F, Natvik GJ, Seneca M, 2013. Investment shocks and macroeconomic co-movement, Journal of Macroeconomics, Elsevier, vol. 37(C), pages 208-216.
- [38] Galí J, López-Salido D, Vallés J, 2004. Rule-of-thumb consumers and the design of interest rate rules, Journal of Money, Credit and Banking 36, 739–764.

- [39] Galí J, López-Salido D, Vallés J, 2007. Understanding the effects of government spending on consumption, Journal of the European Economic Association 5 (1), 227–270.
- [40] Gerali A, Neri S, Sessa L, Signoretti F, 2010. Credit and Banking in a DSGE Model of the Euro Area, Journal of Money, Credit and Banking, 42:107-141.
- [41] Gertler M, Karadi, P, 2011. A Model of Unconventional Monetary Policy, Journal of Monetary Economics, Elsevier, vol. 58(1), pages 17-34.
- [42] Gertler M, Kiyotaki N, 2010. Financial Intermediation and Credit Policy in Business Cycle Analysis, Discussion paper.
- [43] Iacoviello M, Pavan M, 2013. Housing and debt over the life cycle and over the business cycle, Journal of Monetary Economics, Elsevier, vol. 60(2), pages 221-238.
- [44] Issing O, Gaspar V, Angeloni I, Tristani O, 2011. Monetary Policy in The Euro Area. Cambridge University Press ISBN0-521-78324-0.
- [45] Kass R, Raftery A, 1995. Bayes factors. Journal of the American Statistical Association 90, 773-795.
- [46] Kim J, 2000. Constructing and estimating a realistic optimizing model of monetary policy, Journal of Monetary Economics, Elsevier, vol. 45(2), pages 329-359, April.
- [47] Kimball MS, 1995. The Quantitative Analytics of the Basic Neomonetarist Model, Journal of Money, Credit and Banking, Blackwell Publishing, vol. 27(4), pages 1241-77, November.
- [48] Kolasa M, Rubaszek M, 2014. Forecasting with DSGE models with financial frictions, International Journal of Forecasting, forthcoming.
- [49] Kolasa M, Rubaszek M, Skrzypczynski P, 2012. Putting the New Keynesian DSGE Model to the Real- Time Forecasting Test, Journal of Money, Credit and Banking, 44 (7), 1301–1324.
- [50] Kydland FE, Prescott EC, 1982. Time to Build and Aggregate Fluctuations, Econometrica, Econometric Society, vol. 50(6), pages 1345-70, November.
- [51] Justiniano A., Primiceri G., Tambalotti A., 2011. Investment Shocks and the Relative Price of Investment Review of Economic Dynamics, Elsevier for the Society for Economic Dynamics, vol. 14(1), pages 101-121, January.
- [52] Leeper EM, Sims CA, 1994. Toward a Modern Macroeconomic Model Usable for Policy Analysis, NBER Chapters, in: NBER Macroeconomics Annual 1994, Volume 9, pages 81-140 National Bureau of Economic Research, Inc.

- [53] Lewis, C., Pain, N., Strasky, J, Menkyna, F., (2014), "Investment Gaps after the Crisis", OECD Economics Department Working Papers, No. 1168, OECD Publishing, Paris. DOI: http://dx.doi.org/10.1787/5jxvgg76vqg1-en
- [54] McGrattan ER, 1994. The macroeconomic effects of distortionary taxation, Journal of Monetary Economics, Elsevier, vol. 33(3), pages 573-601, June.
- [55] Menna L, Tirelli P, 2014. The Equity Premium in a DSGE Model with Limited Asset Market Participation, mimeo.
- [56] Merola R, 2014. The role of financial frictions during the crisis: an estimated DSGE model, Dynare Working Papers Series No. 33.
- [57] Motta G, Tirelli P, 2012. Optimal Simple Monetary and Fiscal Rules under Limited Asset Market Participation, Journal of Money, Credit and Banking, Blackwell Publishing, vol. 44(7), pages 1351-1374, October.
- [58] Motta G, Tirelli P, 2013. Limited Asset Market Participation, Income Inequality and Macroeconomic Volatility, Working Papers 261, University of Milano-Bicocca, Department of Economics, revised Dec 2013.
- [59] Motta G, Tirelli P, 2014. Money Targeting, Heterogeneous Agents, and Dynamic Instability, Macroeconomic Dynamics, available on CJO2014. doi:10.1017/S1365100513000394.
- [60] Ratto M, Roeger W, Veld J, 2008. QUEST III: an estimated DSGE model of the Euro area with fiscal and monetary policy, European Economy - Economic Papers 335, Directorate General Economic and Monetary Affairs (DG ECFIN), European Commission.
- [61] Rotemberg JJ, Woodford M, 1996. Real-Business-Cycle Models and the Forecastable Movements in Output, Hours, and Consumption, American Economic Review, American Economic Association, vol. 86(1), pages 71-89, March.
- [62] Smets F, Wouters R, 2003. An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area, Journal of the European Economic Association, MIT Press, vol. 1(5), pp. 1123-1175.
- [63] Smets F, Wouters R, 2005. Comparing shocks and frictions in US and Euro area business cycles: a Bayesian DSGE Approach, Journal of Applied Econometrics, vol. 20(2), pp. 161-183.
- [64] Smets F, Wouters R, 2007. Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach, American Economic Review, American Economic Association, vol. 97(3), pp. 586-606.

[65] Villa S, 2014. Financial frictions in the Euro Area and the United States: a Bayesian assessment, Macroeconomic Dynamics, forthcoming.

# A Technical Appendix

## A.1 Model determinacy

As discussed in the text, the presence of LAMP and consumption habits raises some concern for model determinacy. Figure 9 shows that, under a habit-in-ratio specification, the model is determined when  $\theta \in [0; 0.95]$ ,  $b \in [0; 0.8]$  and the remaining parameters are set at the prior mean values defined in Table 2. Result are less favorable when we consider the habit-in-difference specification (see Figure 10). As a matter of fact, only  $\theta < 0.05$  would be consistent with model determinacy at the estimated posterior mean b = 0.79 that we obtain under habits in ratios.

As a robustness check we estimate the model with habits in differences. The posterior mean for parameter b is estimated to be 0.55 at the posterior mean with a 90% HPD interval between 0.44 and 0.69 (in the benchmark model the HPD interval for b is [0.68; 0.90]). At this lower posterior value for b the posterior for  $\theta$  is instead even larger than in our benchmark model (the posterior mean is 0.56 and the 90% HPD interval is [0.47; 0.66]). However, in this case visual diagnostic of results signals serious identification problems for b and, to a lesser extent, the CRRA parameter  $\sigma$ .

Figure 9: Determinacy area for the benchmark model (habits in ratios), + stands for determinacy, x for indeterminacy combinations.

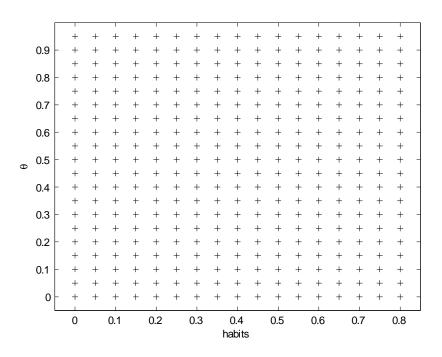
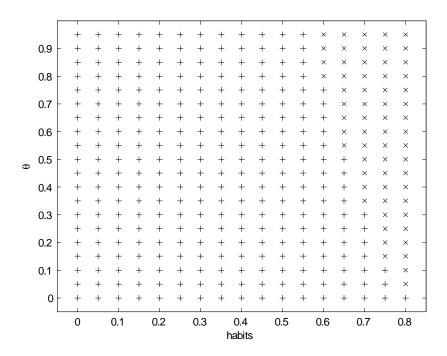


Figure 10: Determinacy area for the model with habits in differences (+ stands for determinacy, x for indeterminacy combinations).



### A.2 Non-linear equations

After deriving the first order conditions for Ricardian agents, unions and firms, we adjust all growing variables for growth to obtain a stationary equilibrium. In this case, lower case letters stand for "adjusted" variables, for example,  $y_t = \frac{Y_t}{z_t}$ . Notice that  $w_t = \frac{W_t}{P_t z_t}$  and  $\lambda_t^o = \Lambda_t^o z_t$ . We end up the following set of non linear equations:

$$(c_t^o)^{-\sigma} c_{t-1}^{b(\sigma-1)} \exp\left(\frac{(\sigma-1)\varepsilon_t^l}{1+\phi_l} h_t^{1+\phi_l}\right) = \lambda_t^o (1+\tau^c)$$

$$(19)$$

$$R_t = \pi_{t+1} g_{z,t+1} \frac{\lambda_t^o}{\beta \varepsilon_t^b \lambda_{t+1}^o} \tag{20}$$

$$1 = Q_{t}^{o} \varepsilon_{t}^{i} \left\{ 1 - \gamma_{I} \left( g_{z,t} \frac{i_{t}}{i_{t-1}} - g_{z} \right) g_{z,t} \frac{i_{t}}{i_{t-1}} - \frac{\gamma_{I}}{2} \left( g_{z,t} \frac{i_{t}}{i_{t-1}} - g_{z} \right)^{2} \right\}$$

$$+ g_{z,t+1} \frac{\lambda_{t+1}^{o}}{\lambda_{t}^{o}} Q_{t+1}^{o} \varepsilon_{t+1}^{i} \beta \gamma_{I} \left( g_{z,t+1} \frac{i_{t+1}}{i_{t}} - g_{z} \right) \left( \frac{i_{t+1}}{i_{t}} \right)^{2}$$

$$(21)$$

$$\frac{1}{g_{z,t+1}} \frac{\lambda_{t+1}^{o}}{\lambda_{t}^{o}} \beta \left\{ \left( 1 - \tau^{k} \right) \left[ r_{t+1}^{k} u_{t+1} - a \left( u_{t+1} \right) \right] + \tau^{k} \delta + Q_{t+1}^{o} \left( 1 - \delta \right) \right\} = Q_{t}^{o}$$
(22)

$$r_t^k = \gamma_{u1} + \gamma_{u2} \left( u_t - 1 \right) \tag{23}$$

$$k_{t+1} = (1 - \delta) \frac{k_t}{g_{z,t}} + \varepsilon_t^i \left[ 1 - \frac{\gamma_I}{2} \left( g_{z,t} \frac{i_t}{i_{t-1}} - g_z \right)^2 \right] i_t$$
 (24)

$$(1 + \tau^c) c_t^{rt} = \left(1 - \tau^l - \tau^{wh}\right) w_t h_t + t r_t^{rt} - t_t^{rt}$$
(25)

$$g_{t} + \frac{R_{t-1}}{\pi_{t}} \frac{b_{t}}{g_{z,t}} + tr_{t} = b_{t+1} + t_{t} + \tau^{c} c_{t} + \left(\tau^{l} + \tau^{wh} + \tau^{wf}\right) w_{t} h_{t} + \tau^{k} \left[r_{t}^{k} u_{t} - (a(u_{t}) + \delta)\right] \frac{k_{t}}{g_{z,t}}$$
(26)

$$y_t = c_t + g_t + i_t + \frac{a(u_t)k_t}{g_{z,t}}$$
 (27)

$$c_t = \theta c_t^{rt} + (1 - \theta) c_t^o \tag{28}$$

$$0 = E_{t} \sum_{s=0}^{\infty} (\xi_{w} \beta)^{s} c_{t+s-1}^{b(\sigma-1)} \exp\left(\frac{(\sigma-1)}{1+\phi_{l}} (h_{t+s})^{1+\phi_{l}}\right) (\tilde{w}_{t})^{-\frac{1+\lambda_{t+s}^{w}}{\lambda_{t+s}^{w}}} \left(\frac{\pi_{t,t+s-1}^{\chi_{w}} \bar{\pi}_{t,t+s}^{1-\chi_{w}}}{w_{t+s} \pi_{t,t+s}}\right)^{-\frac{1+\lambda_{t+s}^{w}}{\lambda_{t+s}^{w}}} h_{t+s}^{d} \cdot \left\{ \tilde{w}_{t} \frac{(1-\tau^{l}-\tau^{wh})\pi_{t,t+s-1}^{\chi_{w}} \bar{\pi}_{t,t+s}^{1-\chi_{w}}}{(1+\tau^{c})\pi_{t,t+s}} \left(1-\frac{1+\lambda_{t+s}^{w}}{\lambda_{t+s}^{w}}\right) \left[ (1-\theta) \left(c_{t+s}^{o}\right)^{-\sigma} + \theta \left(c_{t+s}^{rt}\right)^{-\sigma} \right] + \frac{1+\lambda_{t+s}^{w}}{\lambda_{t+s}^{w}} \left[ (1-\theta) \left(c_{t+s}^{o}\right)^{-\sigma} MRS_{t+s}^{o} + \theta \left(c_{t+s}^{rt}\right)^{-\sigma} MRS_{t+s}^{rt} \right] \right\}$$

$$(29)$$

$$w_{t} = \left[ \xi_{w} \left( \frac{\pi_{t-1}^{\chi_{w}} \bar{\pi}_{t}^{1-\chi_{w}}}{\pi_{t}} w_{t-1} \right)^{\frac{1}{\lambda_{t}^{w}}} + (1 - \xi_{w}) \left( \tilde{w}_{t} \right)^{\frac{1}{\lambda_{t}^{w}}} \right]^{\lambda_{t}^{w}}$$
(30)

$$\frac{u_t k_t}{h_t g_{z,t}} = \frac{\alpha}{(1-\alpha)} \frac{\left(1+\tau^{wf}\right) w_t}{r_t^k} \tag{31}$$

$$mc_t = \alpha^{-\alpha} (1 - \alpha)^{-(1-\alpha)} (\varepsilon_t^a)^{-1} \left( r_t^k \right)^{\alpha} \left[ \left( 1 + \tau^{wf} \right) w_t \right]^{1-\alpha}$$
(32)

$$s_{P,t}y_t = \varepsilon_t^a \left( u_t \frac{k_t}{g_{z,t}} \right)^\alpha \left( h_t^d \right)^{1-\alpha} - \Phi$$
 (33)

$$E_{t} \sum_{s=0}^{\infty} \left(\xi_{p} \beta\right)^{s} \varepsilon_{t}^{b} \frac{\lambda_{t+s}^{o}}{\lambda_{t}^{o}} y_{t+s}^{z} \left[ \tilde{p}_{t}^{z} \frac{\pi_{t,t+s-1}^{\chi_{p}} \bar{\pi}_{t,t+s}^{1-\chi_{p}}}{\pi_{t,t+s}} \left( 1 + \frac{1}{G'^{-1} \left(\omega_{t+s}\right)} \frac{G'\left(x_{t+s}\right)}{G''\left(x_{t+s}\right)} \right) - mc_{t+s} \frac{1}{G'^{-1} \left(\omega_{t+s}\right)} \frac{G'\left(x_{t+s}\right)}{G''\left(x_{t+s}\right)} \right] = 0$$

$$(34)$$

$$1 = (1 - \xi_p) \tilde{p}_t^z G'^{-1} \left( \tilde{p}_t^z \int_0^1 G' \left( \frac{y_t^z}{y_t} \right) \frac{y_t^z}{y_t} dz \right)$$

$$+ \xi_p \pi_{t-1}^{\chi_p} \bar{\pi}_t^{1-\chi_p} \pi_t^{-1} G'^{-1} \left( \pi_{t-1}^{\chi_p} \bar{\pi}_t^{1-\chi_p} \pi_t^{-1} \int_0^1 G' \left( \frac{y_t^z}{y_t} \right) \frac{y_t^z}{y_t} dz \right)$$

$$(35)$$

$$tr_t = \theta t r_t^{rt} + (1 - \theta) t r_t^o \tag{36}$$

$$t_t = \theta t_t^{rt} + (1 - \theta) t_t^o \tag{37}$$

$$h_t = s_{W,t} h_t^d (38)$$

$$s_{W,t} = \int_0^1 \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}} dj \tag{39}$$

$$s_{P,t} = \int_{0}^{1} \left(\frac{P_t^z}{P_t}\right)^{-\frac{1+\lambda_t^p}{\lambda_t^p}} dz \tag{40}$$

$$MRS_t^o = c_t^o h_t^{\phi_l} \tag{41}$$

$$MRS_t^{rt} = c_t^{rt} h_t^{\phi_l} \tag{42}$$

## A.3 Set of log-linearized equations

After log-linearizing the model around its non-stochastic steady state and making some algebra, we obtain a system composed by 16 equation and 16 endogenous variables. Hatted variables stand for variables in log deviation from their steady state, for example:  $\hat{y}_t = \log\left(\frac{y_t}{y}\right)$ . Notice also that fiscal variables, such as government spending, have been defined in deviation from steady state output, for example:  $\hat{g}_t = \frac{g_t - g}{y}$ .

$$\hat{c}_{t}^{o} = \hat{c}_{t+1}^{o} + \frac{(1-\sigma)b}{\sigma} \left( \hat{c}_{t} - \hat{c}_{t-1} \right) - \frac{1}{\sigma} \left( \hat{\varepsilon}_{t}^{b} + \hat{R}_{t} - \hat{\pi}_{t+1} - \hat{g}_{z,t+1} \right) + \frac{(1-\sigma)h^{1+\phi_{l}}}{\sigma} \left( \hat{h}_{t+1} - \hat{h}_{t} \right)$$
(43)

$$\hat{\imath}_{t} = \frac{1}{\gamma_{I}g_{z}^{2}(1+\beta)} \left(\hat{Q}_{t}^{o} + \hat{\varepsilon}_{t}^{i}\right) - \frac{1}{1+\beta}\hat{g}_{z,t} + \frac{1}{1+\beta}\hat{\imath}_{t-1} + \frac{\beta}{1+\beta}\hat{\imath}_{t+1} + \frac{\beta}{1+\beta}\hat{g}_{z,t+1}$$

$$(44)$$

$$-\hat{R}_{t} - \hat{\varepsilon}_{t}^{b} + \hat{\pi}_{t+1} + \frac{\beta}{g_{z}} \left( 1 - \tau^{k} \right) r^{k} \hat{r}_{t+1}^{k} + \frac{\beta}{g_{z}} \left( 1 - \delta \right) \hat{Q}_{t+1}^{o} = \hat{Q}_{t}^{o}$$
(45)

$$\hat{r}_t^k = \frac{\gamma_{u2}}{r^k} \hat{u}_t = \frac{\sigma_u}{1 - \sigma_u} \hat{u}_t \tag{46}$$

$$\hat{k}_{t+1} = \frac{(1-\delta)}{g_z} \hat{k}_t + \frac{i}{k} \hat{i}_t - \frac{(1-\delta)}{g_z} \hat{g}_{z,t} + \frac{i}{k} \hat{\varepsilon}_t^i$$
(47)

$$(1+\tau^c)\frac{c^{rt}}{c}\hat{c}_t^{rt} = \left(1-\tau^l-\tau^{wh}\right)\frac{wh}{c}\left(\hat{w}_t+\hat{h}_t\right)$$

$$\tag{48}$$

$$0 = -\frac{c}{y}\hat{c}_t + \hat{g}_t + \frac{i}{y}\hat{i}_t - \hat{y}_t + \frac{\gamma_{u1}k}{yg_z}\hat{u}_t$$
 (49)

$$\hat{c}_t = \theta \frac{c^{rt}}{c} \hat{c}_t^{rt} + (1 - \theta) \frac{c^o}{c} \hat{c}_t^o \tag{50}$$

$$(1 + \beta \chi_p) \hat{\pi}_t = \chi_p \hat{\pi}_{t-1} + \beta \hat{\pi}_{t+1} - \beta (1 - \chi_p) \hat{\pi}_{t+1} + (1 - \chi_p) \hat{\pi}_t + A \frac{(1 - \beta \xi_p) (1 - \xi_p)}{\xi_p} (\widehat{mc}_t + \hat{\lambda}_t^p)$$

$$(51)$$

$$\hat{w}_{t} = -\frac{(1 - \xi_{w})(1 - \xi_{w}\beta)}{(1 + \beta)\xi_{w}}\hat{w}_{t} + \frac{(1 - \xi_{w})(1 - \xi_{w}\beta)}{(1 + \beta)\xi_{w}}\frac{\lambda^{w}}{1 + \lambda^{w}}\hat{\lambda}_{t}^{w} 
+ \frac{(1 - \xi_{w})(1 - \xi_{w}\beta)}{(1 + \beta)\xi_{w}(\varpi + 1)} \left\{ \left[ \frac{\sigma\varrho\left(\frac{e^{rt}}{e^{o}} - 1\right)}{(\varrho + 1)} + 1 \right] \widehat{MRS}_{t}^{o} + \left[ \varpi - \frac{\sigma\varrho\left(\frac{e^{rt}}{e^{o}} - 1\right)}{(\varrho + 1)} \right] \widehat{MRS}_{t}^{rt} \right\} 
+ \frac{\beta}{1 + \beta}\hat{w}_{t+1} + \frac{1}{1 + \beta}\hat{w}_{t-1} + \frac{\chi_{w}}{1 + \beta}\hat{\pi}_{t-1} - \frac{(1 + \beta\chi_{w})}{1 + \beta}\hat{\pi}_{t} + \frac{\beta}{1 + \beta}\hat{\pi}_{t+1} + \frac{(1 - \chi_{w})}{1 + \beta}\hat{\pi}_{t} - \frac{\beta}{1 + \beta}(1 - \chi_{w})\hat{\pi}_{t+1}$$
(52)

$$\widehat{MRS}_t^o = \hat{c}_t^o + \phi_l \hat{h}_t \tag{53}$$

$$\widehat{MRS}_t^{rt} = \hat{c}_t^{rt} + \phi_l \hat{h}_t \tag{54}$$

$$\hat{u}_t + \hat{k}_t - \hat{h}_t - \hat{g}_{z,t} = \hat{w}_t - \hat{r}_t^k \tag{55}$$

$$\widehat{mc}_t = -\hat{\varepsilon}_t^a + \alpha \hat{r}_t^k + (1 - \alpha)\,\hat{w}_t \tag{56}$$

$$\hat{y}_{t} = \frac{y + \Phi}{y} \hat{\varepsilon}_{t}^{a} + \frac{\alpha (y + \Phi)}{y} \hat{k}_{t} + \frac{\alpha (y + \Phi)}{y} \hat{u}_{t} + \frac{(1 - \alpha) (y + \Phi)}{y} \hat{h}_{t} - \alpha \frac{y + \Phi}{y} \hat{g}_{z,t}$$

$$(57)$$

$$\hat{R}_{t} = \phi_{R} \hat{R}_{t-1} + (1 - \phi_{R}) \left( \hat{\bar{\pi}}_{t} + \phi_{\pi} \left( \hat{\pi}_{t-1} - \hat{\bar{\pi}}_{t} \right) + \phi_{y} \hat{y}_{t} \right) + \phi_{\Delta\pi} \left( \hat{\pi}_{t} - \hat{\pi}_{t-1} \right) + \phi_{\Delta y} \left( \hat{y}_{t} - \hat{y}_{t-1} \right) + \hat{\varepsilon}_{t}^{r}$$
 (58)

with  $A = \frac{\left(1 + \frac{G''(x)}{G'(x)}\right)}{\left(2 + \frac{G'''(x)}{G''(x)}\right)} = \frac{1}{\lambda^p \alpha^p + 1}$  (where  $\lambda^p$  is steady state price markup and  $\alpha^p$  is the steady state elasticity of substitution between goods),  $\varrho = \frac{\theta}{1 - \theta} \left(\frac{c^{rt}}{c^o}\right)^{-\sigma}$  and  $\varpi = \varrho \frac{c^{rt}}{c^o}$ .

The estimated shocks are:

$$\hat{\varepsilon}_t^a = \rho_a \hat{\varepsilon}_{t-1}^a + \eta_t^a$$

$$\hat{\varepsilon}_t^i = \rho_i \hat{\varepsilon}_{t-1}^i + \eta_t^i$$

$$\hat{\varepsilon}_t^r = \rho_r \hat{\varepsilon}_{t-1}^r + \eta_t^r$$

$$\hat{\lambda}_t^p = \rho_p \hat{\lambda}_{t-1}^p + \eta_t^p$$

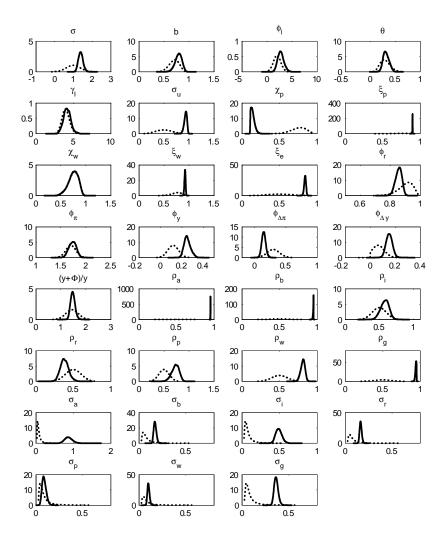
$$\hat{\lambda}_t^w = \rho_w \hat{\lambda}_{t-1}^w + \eta_t^w$$

$$\hat{\varepsilon}_t^b = \rho_b \hat{\varepsilon}_{t-1}^b + \eta_t^b$$

$$\hat{g}_t = \rho_g \hat{g}_{t-1} + \eta_t^g$$

# A.4 Priors and posteriors distributions

Figure 11: Prior (dotted line) and posterior (solid line) distributions of estimated parameters and standard deviations, 1972:Q2-2012:Q4.



# A.5 Robustness on the prior for $\theta$ : a uniform distribution

Table 8: Posterior estimates for the sample 1972:Q2-2012:Q4 with a uniform distribution for  $\theta$ 

parameters	post. mean	90% HF	PD interval
$\sigma$	1.378	1.171	1.578
b	0.773	0.647	0.901
$\phi_l$	3.073	2.234	3.960
$\theta$	0.342	0.223	0.460
$\gamma_I$	3.900	3.196	4.583
$\sigma_u$	0.931	0.889	0.975
$\chi_p$	0.146	0.107	0.183
$\xi_p^{'}$	0.897	0.894	0.900
$\chi_w$	0.681	0.508	0.845
$\xi_w$	0.929	0.911	0.947
$\xi_e$	0.841	0.821	0.860
$\phi_{r}$	0.832	0.794	0.874
$\phi_\pi$	1.676	1.551	1.797
$\phi_y$	0.248	0.202	0.294
$\phi_{\Delta y}^{}$	0.148	0.110	0.185
$\phi_{\Delta\pi}$	0.161	0.106	0.214
$(y+\Phi)/y$	1.458	1.325	1.588
$ ho_{m{a}}$	0.952	0.950	0.953
$ ho_b$	0.948	0.943	0.953
$ ho_i$	0.594	0.492	0.702
$ ho_r$	0.420	0.319	0.518
$ ho_p$	0.741	0.649	0.841
$ ho_w^{'}$	0.786	0.722	0.851
$ ho_g$	0.942	0.931	0.953
$\sigma^{a}$	0.888	0.716	1.053
$\sigma^b$	0.172	0.148	0.196
$\sigma^i$	0.484	0.415	0.555
$\sigma^r$	0.167	0.148	0.186
$\sigma^p$	0.086	0.056	0.114
$\sigma^w$	0.102	0.078	0.125
$\sigma^g$	0.362	0.326	0.398
MDD			-734.4

Figure 12: Prior (dotted line) and posterior (solid line) distributions of estimated parameters and standard deviations, 1972:Q2-2012:Q4, uniform distribution for  $\theta$ .

