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Limited Asset Market Participation and the Euro Area Crisis. An Empirical DSGE Kodel*

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Abstract

We estimate a medium scale DSGE model for the Euro area with Limited Asset Market Participation (LAMP). Our results suggest that in the recent EMU years LAMP is particularly sizeable (39% during 1993-2012) and important to understand business cycle features. The Bayes factor and the forecasting performance show that the LAMP model is preferred to its representative household counterpart. In the RA model the risk premium shock is the main driver of output volatility in order to match consumption correlation with output. In the LAMP model this role is played by the investment-specific shock, because Non-Ricardian households introduce a Keynesian multiplier effect and raise the correlation between consumption and investments. We also detect contractionary role of monetary policy shocks during the post-2007 years. In this period consumption of Non-Ricardian households fell dramatically, but this outcome might have been avoided by a more aggressive policy stance.

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 findings in Johnson et al. (2006), Shapiro and Slemrod (2009), Parker et al. (2011) are also consistent with the LAMP model. Some recent research has also suggested that the standard definition of LAMP consumers as hand-to mouth consumers may be extended to incorporate the notion of wealthy but illiquid consumers (Kaplan et al. 2014).

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, 2015; 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 omit to introduce other types of financial frictions, e.g. financial accelerator mechanisms (Bernanke et al. 1999; Christensen and Dib, 2008; Christiano et al. 2010) or borrowing constraints (Kiyotaki and Moore, 1997; Gerali et al. 2010), as they apparently do not allow to outperform a standard New Keynesian model à la Smets and Wouters (2007). This is documented in Brzoza-Brzezina and Kolasa (2013). In fact, it turns out that including financial frictions is essential for replicating fluctuations in financial variables, but the statistical fit is worse than the workhorse New Keynesian model. A similar result is obtained by Suh and Walker (2016) and Lindé, Smets and Wouters (2016). Moreover, Gerali et al. (2010) find that financial shocks contributed to explain the output fall during the 2007 financial crisis, but in their model a bank capital loss cannot replicate the amplitude of the $2007-2008$ downturn.

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. We explicitly compare the empirical performance of a LAMP model against the standard RA model, in a number of respects not considered in the majority of other papers about LAMP. 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

We develop a New Keynesian model with Ricardian and Non-Ricardian agents. For sake of simplicity we devote a more detailed discussion of the model to a separate Technical Appendix.[1] Here we discuss only the main characteristics of 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 θ 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. 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).

[1] The Technical Appendix can be found on the authors' webpages.

Households preferences are

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

where $c_t^i = \frac{C_t^i}{g_z}$ and $c_t = \frac{C_t}{g_z}$ are individual and total real consumption levels normalized by a **deterministic technology growth rate** g_z. The presence of g_z in 1 guarantees that the model has a balanced growth path when productivity is non stationary.[2]

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 θ 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 θ (or b), and imposing a downward bias on its estimated value.[3] Here we follow Menna and Tirelli (2014), who show that indeterminacy is a lesser problem under the habit-in-ratio specification adopted in (1). [4] 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

[2] See Section 2.4 for more details.

[3] 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).

[4] We discuss the determinacy properties of the model in the Appendix.

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, the choice of group-specific habits is open to 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, τ^l τ^k and τ^c respectively, and for social contributions levied on labor incomes τ^{wh}. In addition, the model incorporates payroll tax rates on firms, τ^{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.[5] 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. [6]

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:

$$\begin{aligned} (1+\tau^c) P_t C_t^o + P_t I_t^o + \frac{B_{t+1}^o}{\varepsilon_t^b} &= R_{t-1} B_t^o + \left(1-\tau^l-\tau^{wh}\right) W_t h_t^o + P_t D_t^o \\ &\quad + \left(1-\tau^k\right)\left[R_t^k u_t^o - a\left(u_t^o\right) P_t\right] K_t^o + \tau^k \delta P_t K_t^o + TR_t^o - T_t^o \end{aligned} \tag{2}$$

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. ε_t^b is a risk premium shock that affects the intertemporal margin,

[5] 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.

[6] Motta and Tirelli (2013b) show that steady state redistributive taxation has powerful effects in limiting the indeterminacy region in LAMP models.

creating a wedge between the interest rate controlled by the central bank and the return on assets held by the households.

The capital accumulation equation comprises investment adjustment costs and it is similar to Christoffel et al. (2008, CCW henceforth) specification. The intensity of utilizing physical capital is subject to a proportional cost, as in Christiano et al. (2005). The Ricardian households maximize (1) with respect to C_t^o, B_{t+1}, I_t^o, K_{t+1}^o, u_t^o, subject to (2),the capital accumulation equation, the investment adjustment costs function and the utilization cost function.

Non-Ricardian households (or LAMP) households consume their disposable labor income in each period:

$$\left(1+\tau^c\right) P_t C_t^{rt} = \left(1-\tau^l-\tau^{wh}\right) W_t^{rt} h_t^{rt} + TR_t^{rt} - T_t^{rt} \tag{3}$$

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 scheme $W_t^j = g_z^t \pi_{t-1}^{\chi_w} \bar{\pi}^{(1-\chi_w)} W_{t-1}^j$, where $\bar{\pi}$ is the steady state 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, subject to the labor demand $h_t = h_t^d \int_0^1 \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}} dj$, (2) and (3).

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 and simply supply labor on demand at the market wage rate.[7] This is a potentially serious shortcoming because wage changes have redistributive effects between the two households groups and wage setting decisions may substantially the interests of Non-Ricardian households are taken into account (Colciago, 2011; Motta and Tirelli, 2015). It should be noted, however, that in the model there are no labor differences between the two agent groups. In doing this we follow the literature on monetary policy in heterogeneous

[7] Coenen and Straub (2005), Forni Monteforte and Sessa (2009) and Coenen, Straub and Trabandt (2012).

agent models that emphasizes the different financial frictions faced by households (Debortoli and Galí, 2017), and it is not obvious how such different frictions could map into labor market heterogeneities. In addition, our characterization of unionized labor markets that generate wage compression (in this case between Ricardian and non-Ricardian workers) is consistent with the institutional features of European labor markets (Lindquist, 2005; Mourre, 2005; Villanueva, 2015).

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 λ_t^p is the net price markup, which is assumed to follow an AR(1) process with i.i.d. Normal error term.

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 a Cobb-Douglas function $Y_t^z = \varepsilon_t^a [u_t^z K_t^z]^\alpha [g_z^t h_t^z]^{1-\alpha} - g_z^t \Phi$, where Φ are fixed production costs. ε_t^a defines a transitory total factor productivity shock, evolving as an AR(1) process with an i.i.d. Normal innovation term. The term g_z denotes a deterministic growth trend (see Smets and Wouters, 2007).

Price setting. Intermediate goods prices are sticky à la Calvo (1983). Firm z receives permission to optimally reset its price with probability $\left(1 - \xi_p\right)$. Firms that cannot re-optimize adjust the price according to the scheme $P_t^z = \pi_{t-1}^{\chi_p} \bar{\pi}^{1-\chi_p} P_{t-1}^z$.

The representative firm chooses the optimal price $\tilde{P}_t^z$ that maximizes expected profits subject to the demand schedule.

Fiscal policy. The government budget constraint in nominal terms is:

$$P_tG_t+R_{t-1}B_t+TR=B_{t+1}+T_t+\tau^cP_tC_t+\left(\tau^l+\tau^{wh}+\tau^{wf}\right)W_th_t+\tau^k\left[R_t^ku_t-\left(a\left(u_t\right)+\delta\right)P_t\right]K_t$$

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

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

$$\hat{R}_t=\phi_R\hat{R}_{t-1}+\left(1-\phi_R\right)\left(\phi_\pi\hat{\pi}_{t-1}+\phi_y\hat{y}_t\right)+\phi_{\Delta\pi}\left(\hat{\pi}_t-\hat{\pi}_{t-1}\right)+\phi_{\Delta y}\left(\hat{y}_t-\hat{y}_{t-1}\right)+\hat{\varepsilon}_t^r \tag{4}$$

where the hatted variables define log-deviations from steady state. In particular, $\hat{y}_t=\widehat{Y_t/g_z^t}$ is the logarithmic deviation of observed output adjusted by the deterministic growth trend. Variable $\hat{y}_t$ is also interpreted as the output gap measure. Smets and Wouters (2003, 2005, 2007) typically characterize the output gap as deviation from the flexible price equilibrium. This specification, however, runs against the standard justification for assuming that Central Banks follow a simple rule instead of a fully fledged optimal policy. In fact, identification of the flexible price equilibrium output requires a full identification of shocks hitting the economy and of the true model economy.[8] Our choice follows several contributions to the empirical DSGE literature CCW, Christiano et al. (2010), Brzoza-Brzezina et al. (2015), Gerali et al. (2010).

ε_t^r is a monetary shock that follows a first-order autoregressive process with an i.i.d. Normal error term.

[8] **Galí (2008): "While such optimal interest rate rules appear to take a relatively simple form, there exists an important reason why they are unlikely to provide useful practical guidance for the conduct of monetary policy. The reason is that they both require that the policy rate is adjusted one-for-one with the natural rate of interest, thus implicitly assuming observability of the latter variable. That assumption is plainly unrealistic since determination of the natural rate and its movements requires an exact knowledge of (i) the economys "true model," (ii) the values taken by all its parameters, and (iii) the realized value (observed in real time) of all the shocks impinging on the economy."**

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.[9] 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. We do not include the following years to rule out periods where the zero lower bound is possibly binding and thus distorting the behavior of monetary policy described by a Taylor rule. As documented by Hirose and Inoue (2015), the failure to account for the zero lower bound may bias estimated monetary policy parameters and shocks.

Following CCW, the auxiliary equation

$$\hat{e}_t = \frac{\beta}{1+\beta} E_t \hat{e}_{t+1} + \frac{1}{1+\beta} \hat{e}_{t-1} + \frac{(1-\xi_e)(1-\beta\xi_e)}{(1+\beta)\xi_e} \left(\hat{h}_t - \hat{e}_t \right) \tag{5}$$

relates the employment variable, e_t, to the unobserved worked-hours variable, h_t.[10]

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.[11]

[9] 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).

[10] Parameter ξ_e determines the sensitivity of employment with respect to worked hours.

[11] We also tried specifications that include a stochastic growth trend adding a permanent technology shifter 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 θ are 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.

The measurement equations are:

$$Y_t = \begin{bmatrix} \Delta \ln y_t \\ \Delta \ln c_t \\ \Delta \ln i_t \\ \Delta \ln w_t \\ \ln e_t \\ \Delta \ln P_t \\ \ln R_t^a \end{bmatrix} = \begin{bmatrix} \overline{\gamma} \\ \overline{\gamma} \\ \overline{\gamma} \\ \overline{\gamma} \\ \overline{e} \\ \overline{\pi}_* \\ \overline{r} \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} \\ c_t - c_{t-1} \\ i_t - i_{t-1} \\ w_t - w_{t-1} \\ e_t \\ \pi_t \\ r_t \end{bmatrix}$$

where ln denotes 100 times log and $\Delta \ln$ refers to the log difference. Similarly to Smets and Wouters (2007), $\overline{\gamma} = 100(g_z - 1)$ denotes a deterministic growth trend, common to the real variables GDP, 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.[12]

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 β is fixed at 0.99. The steady-state depreciation rate δ is 0.025, corresponding to a 10% depreciation rate per year. The capital share α 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 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.

[12] See Smets and Wouters (2003, 2007), Dynare Manual (Adjemian et al., 2014) and An and Schorfheide (2007) for more details on Bayesian estimation of DSGE models.

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 θ 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.

Table 1: Calibrated parameters

parameter	value
β	0.99
δ	0.025
α	0.3
α_p	6
λ_p	0.2
λ_w	0.2
$\bar{\pi}-1$	0.0047
g_z-1	0.005
$\frac{b}{y}$	2.4
$\frac{g}{y}$	0.215
τ^c	0.223
τ^l	0.116
τ^k	0.35
τ^{wh}	0.127
τ^{wf}	0.232

4 Results

4.1 The full sample estimates

Table 2 shows the posterior estimates of the structural parameters and coefficients governing shock processes.[13] 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 θ (Uniform (0.01, 0.99)), and we obtained $\theta = 0.342$.[14] 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 $\theta = 0.336$.[15] Figure 1 plots the complete posterior distributions obtained from our benchmark prior for θ and the Uniform. It is apparent that the the results are very similar.[16]

In Table 2 we also present the estimates for the RA model.[17] The LAMP and RA models

[13] 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.

[14] See the Appendix for more details.

[15] The marginal data density in these two cases was -734.4 and -733.7 respectively.

[16] We also performed robustness checks of the estimates. If we estimate the capital share, α , the deterministic trends for inflation, $\overline{\pi}$, and output, $\overline{\gamma}$, the posterior means of the deterministic trends are fairly close to our calibration but the posterior mean for α is about 20%. This result, which is very close to the one obtained in Smets and Wouters (2007) for the US, is at odds with the data. In fact during our sample period the capital income share was always above 30% and larger than 40% since 1990. Moreover, both the RA and LAMP models show convergence problems. However,the estimates for the LAMP fraction do not change much with respect to the original result (0.317), being 0.310 (and 0.298 when calibrating α but estimating $\overline{\pi}$ and $\overline{\gamma}$). We also slightly modified the priors for Calvo prices and wages parameters, narrowing the prior standard deviation. Price and wage stickiness is lower but always around 0.9 and indexation on prices, already low in our original estimates, now is even lower. These results hold for both the RA and the LAMP models. In this case again the share of LAMP is estimated to be 0.299 and the Bayes factor is still in favor of the LAMP model.

[17] 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 RMSE). 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

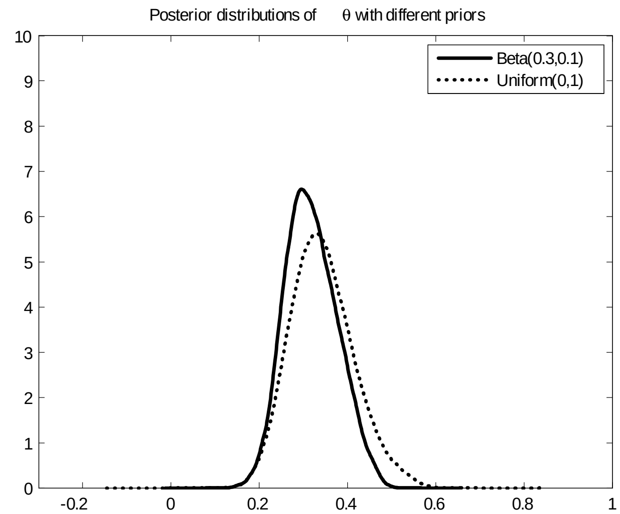


Figure 1: Posterior densities for the fraction of LAMP using different prior distributions.

are characterized by similar posterior distributions for the common parameters, with the notable exceptions of productivity shocks standard deviation, σ^a, and the risk aversion coefficient σ: both are significantly larger in the RA case. The marginal data density[18] (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 deviation and the cross-correlations with output obtained with the LAMP model are always closer (but for employment) to the data moments.

Finally, we perform a forecasting comparison between the two models. Table 4 shows the ratio of the root mean squared forecast error (RMSFE) of the LAMP model relative to

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.

[18]For more technical details about the marginal data density, see An and Schorfheide (2007) and Bekiros and Paccagnini (2014a and 2014b).

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

parameters	Prior distribution			Posterior distribution					
				LAMP			RA		
	shape	mean	std dev	post. mean	90% HPD interval		post. mean	90% HPD interval	
σ	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
ϕ_l	norm	2	0.75	2.734	1.744	3.740	1.762	0.699	2.773
θ	beta	0.3	0.1	0.317	0.224	0.417	-	-	-
γ_I	gamma	4	0.5	4.163	3.325	4.900	4.222	3.367	5.062
σ_u	beta	0.5	0.15	0.930	0.886	0.976	0.872	0.808	0.939
χ_p	beta	0.75	0.1	0.142	0.107	0.177	0.139	0.107	0.171
ξ_p	beta	0.75	0.1	0.897	0.891	0.900	0.899	0.897	0.900
χ_w	beta	0.75	0.1	0.746	0.594	0.909	0.477	0.323	0.634
ξ_w	beta	0.75	0.1	0.920	0.901	0.939	0.922	0.893	0.951
ξ_e	beta	0.5	0.15	0.839	0.819	0.860	0.870	0.851	0.889
ϕ_r	beta	0.9	0.05	0.856	0.821	0.890	0.839	0.796	0.881
ϕ_π	norm	1.7	0.1	1.732	1.612	1.849	1.715	1.568	1.860
ϕ_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
ρ_a	beta	0.5	0.1	0.952	0.950	0.953	0.949	0.943	0.953
ρ_b	beta	0.5	0.1	0.948	0.942	0.953	0.935	0.918	0.953
ρ_i	beta	0.5	0.1	0.579	0.477	0.677	0.775	0.713	0.835
ρ_r	beta	0.5	0.1	0.381	0.290	0.469	0.452	0.346	0.563
ρ_p	beta	0.5	0.1	0.728	0.610	0.847	0.671	0.566	0.776
ρ_w	beta	0.5	0.1	0.809	0.763	0.855	0.838	0.792	0.885
ρ_g	beta	0.5	0.1	0.942	0.931	0.953	0.947	0.939	0.953
σ^a	invg	0.1	2	0.871	0.700	1.034	1.208	0.953	1.461
σ^b	invg	0.1	2	0.170	0.147	0.193	0.154	0.130	0.177
σ^i	invg	0.1	2	0.489	0.421	0.555	0.370	0.318	0.421
σ^r	invg	0.1	2	0.164	0.146	0.183	0.163	0.144	0.182
σ^p	invg	0.1	2	0.088	0.053	0.123	0.109	0.074	0.143
σ^w	invg	0.1	2	0.100	0.082	0.119	0.084	0.068	0.100
σ^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 with output			
inflation	0.136	-0.079	-0.147
consumption	0.699	0.710	0.759
investment	0.811	0.747	0.643
short term interest rate	0.059	-0.114	-0.128
wage	0.340	0.197	0.111
employment	-0.072	-0.077	-0.071

the RA model for the forecasting period 2002:Q1 to 2012:Q4, for 4 step-ahead forecasts as horizon [19].

Table 4 provides evidence how the LAMP model can outperform the RA model. With the exception of the short term nominal interest rate, all ratios are lower than 1 and we can reject the null of identical forecasting accuracy according to Clark and West test (2006) for nested model. However, for the short term interest rate the null cannot be rejected, while for output it is rejected at 10% level of significance.

To highlight the time-varying relative forecasting performance of the two models, Figure 2 plots the difference between the root mean squared forecast errors (RMSFE) of the RA and LAMP models. For each observation, the RMSFEs are computed using the 12 previous quarters (see Del Negro and Schorfheide (2012) for more details). For output, consumption, investment, and inflation, the LAMP model is clearly preferred since the onset of the Great Financial Crisis. The two models exhibit a similar forecasting performance of the nominal interest rate until 2009, but the RA model is unambiguously preferred since then.

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

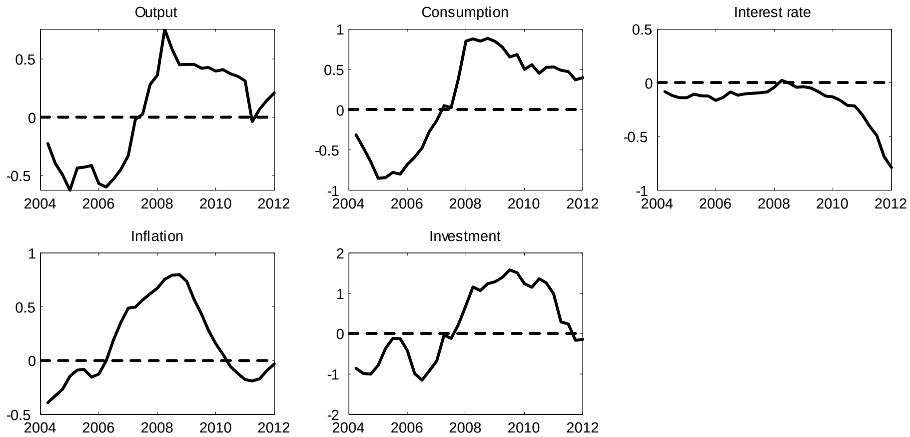
out-of-sample 2002-2012	RMSFE	pvalue Clark and West test
output	0.91	0.10
consumption	0.89	0.00
inflation	0.92	0.00
investment	0.96	0.01
short term interest rate	1.12	0.89
wage	0.86	0.04

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),

[19] 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).

Figure 2: Forecast comparison: LAMP vs RA model. A value greater than zero indicates that the LAMP model attains a lower RMSFE.



$\theta = 0.18$ for the sample 1985:Q1 to 2010:Q2. [20] By contrast, in Forni et al. (2009) the fraction is estimated in a range of 0.34-0.37 for the sample 1980:Q1-2005:Q4. However, these results are obtained under different theoretical assumptions and for different sample periods.[21]. 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 subsample 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. We find that the fraction of LAMP is very high in the 1972-81 period and substantially decreases in the 1972-1992 sample, suggesting that the post 1981 EMS years were characterized by relatively easy access to credit. By contrast, we observe a sharp increase for the post Maastricht period. The sharp increases that we observe after 1992 can be interpreted as the consequence of financial markets retrenchment in response to a crisis. Figure 3 reinforces our claim that θ distribution has changed over time, and especially during

[20] 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.

[21] 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.

the final subsample.

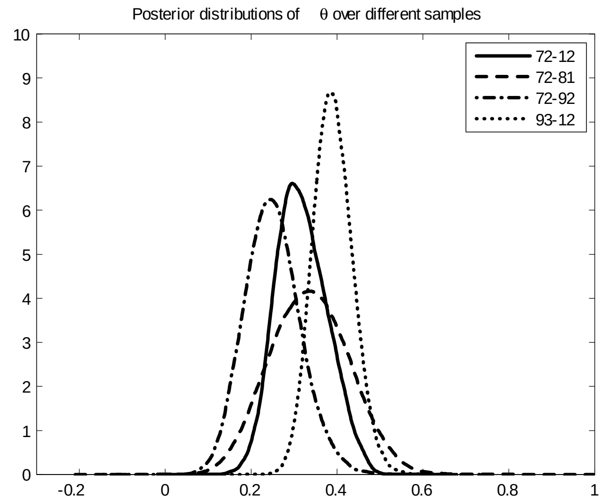


Figure 3: Posterior distributions of the fraction of LAMP over different samples.

Table 5 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, ξ_w and ξ_p, were relatively smaller, whereas the inflation indexation parameters χ_p and χ_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, $\theta = 0.39$, (HPD interval 0.316-0.466) is strikingly larger

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

parameters	LAMP			RA
	72:Q2-81:Q4	72:Q2-92:Q4	93:Q2-12:Q4	93:Q2-12:Q4
σ	1.655	1.445	2.157	1.827
b	0.649	0.713	0.741	0.749
ϕ_l	2.217	2.753	2.217	2.321
θ	0.341	0.247	0.390	-
γ_I	4.178	3.452	4.018	3.817
σ_u	0.878	0.925	0.797	0.819
χ_p	0.403	0.282	0.229	0.224
ξ_p	0.601	0.837	0.895	0.896
χ_w	0.722	0.786	0.621	0.480
ξ_w	0.805	0.925	0.919	0.920
ξ_e	0.753	0.857	0.795	0.800
ϕ_r	0.748	0.774	0.876	0.840
ϕ_π	1.665	1.820	1.725	1.764
ϕ_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
ρ_a	0.893	0.949	0.938	0.938
ρ_b	0.698	0.939	0.388	0.942
ρ_i	0.484	0.307	0.827	0.576
ρ_r	0.415	0.458	0.512	0.491
ρ_p	0.468	0.789	0.538	0.532
ρ_w	0.607	0.688	0.829	0.812
ρ_g	0.840	0.917	0.908	0.863
σ^a	1.393	1.493	0.506	0.661
σ^b	0.276	0.166	0.286	0.102
σ^i	0.481	0.530	0.535	0.444
σ^r	0.308	0.229	0.084	0.082
σ^p	0.356	0.104	0.093	0.105
σ^w	0.300	0.160	0.062	0.066
σ^g	0.503	0.400	0.283	0.289
MDD			-230.6	-243.9

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 LAMP 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 5), 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 6 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. These results are confirmed by the forecast error variance decomposition, which we show for 1, 4, 10 and 30 quarters ahead (Table 7). Notice how the wage markup shocks play a limited role in explaining output growth volatility. Smets and Wouters (2005) and CCW obtained similar results.

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).

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

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

Table 7: Forecast error variance decomposition of output growth

	1	4	10	30
	LAMP			
η^a	10.01	6.78	7.90	7.65
η^b	21.21	14.80	13.86	12.80
η^i	31.81	48.04	47.64	48.92
η^r	14.81	12.62	12.25	12.24
η^p	1.91	3.81	3.87	4.17
η^w	0.28	0.67	1.98	2.67
η^g	19.97	13.27	12.49	11.55
	RA			
η^a	2.84	3.41	4.63	4.68
η^b	43.96	40.02	37.91	37.67
η^i	15.25	15.32	15.68	15.47
η^r	16.81	15.90	15.81	15.77
η^p	3.63	9.44	9.84	10.51
η^w	0.17	0.86	1.87	2.24
η^g	17.34	15.05	14.25	13.66

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 4 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 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 5 shows IRFs to an expansionary investment-specific shock.[22] 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.[23]

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 8).[24] With the notable

[22] 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).

[23] 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.

[24] Simulations are based on the posterior estimates for the sample 1993:Q2-2012:Q4 (LAMP model), reported in Table 5.

Figure 4: 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.

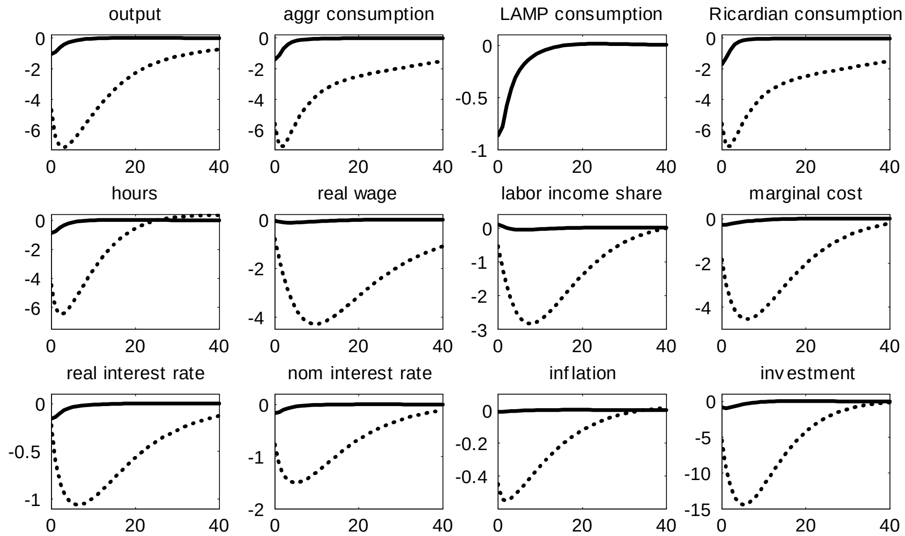
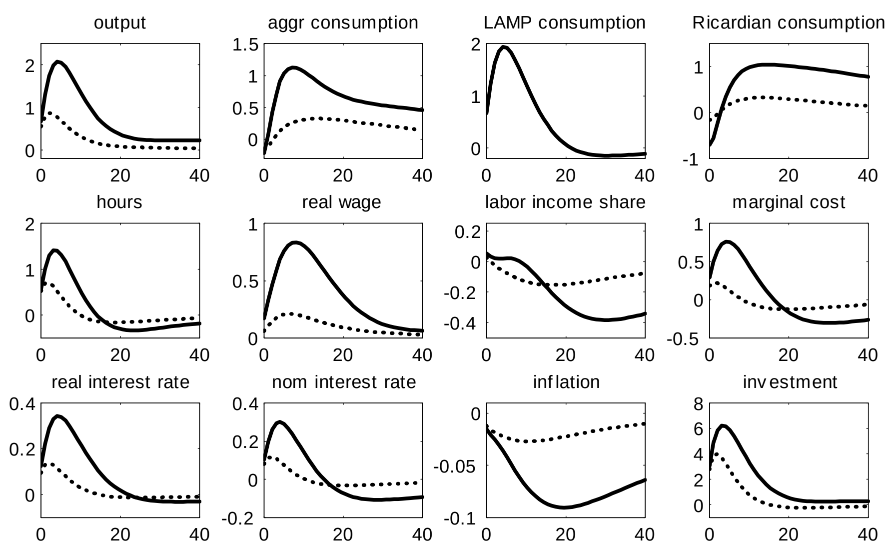


Figure 5: Impulse responses to a 1% investment specific shock. Solid lines: LAMP model. Dotted lines: RA model. Structural parameters and shock persistences are set at the posterior mean values for each specification. Estimation sample: 1993:Q2-2012:Q4.



exception of consumption,[25] the standard deviations of output, inflation, the real wage and investment fall substantially when $\theta = 0$.

Table 8: Simulated standard deviations

	y_t	π_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

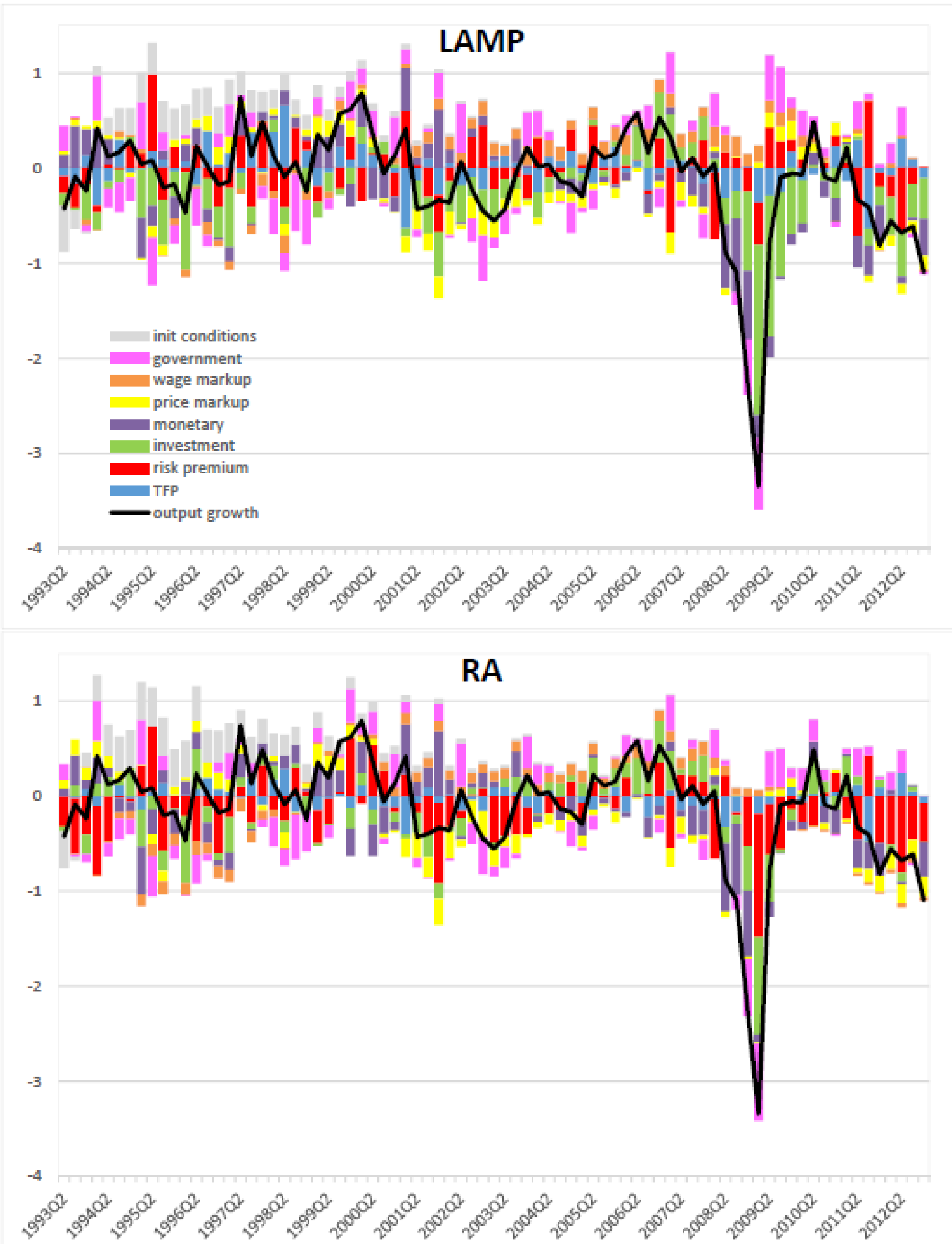
We now investigate how shocks contributed to the business cycle in the EMU years. We concentrate on the historical decomposition of output growth for the post-1999 period, that is, the period of ECB operational activity. Figure 6 presents results for the LAMP and RA models.

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.[26]

[25] Consumption decisions of the two household groups are negatively correlated and almost cancel out in the aggregate.

[26] 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 6: Historical decomposition of output growth (estimated sample: 1993:Q2-2012:Q4), LAMP model: upper panel, RA model: lower panel.

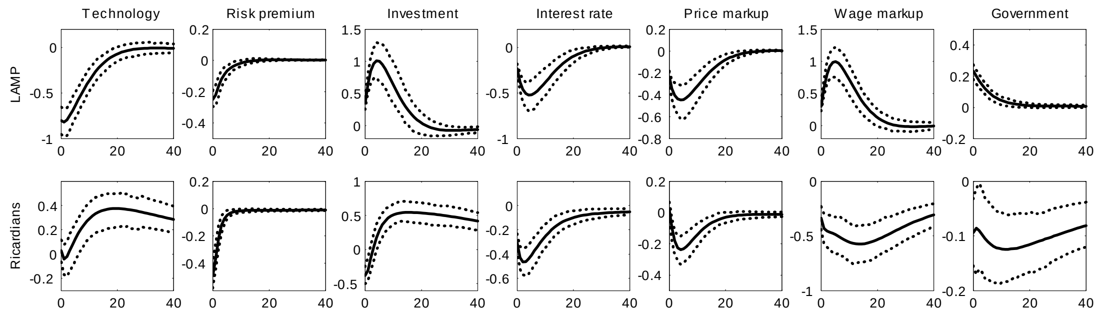


4.3.2 Consumption inequality over the business cycle

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 6 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 7 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 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 8 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 7: 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 6 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 (4). Looking at Figure 6, 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 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 9, upper panel) and the corresponding cumulative deviation of inflation is -1.2% (see Figure 9, lower panel). Thus, inflation would have remained below its target level in a medium-term scenario.

Figure 8: Historical decomposition of consumption growth (estimated sample: 1993:Q2-2012:Q4), LAMP consumption: upper panel, Ricardians' consumption: lower panel.

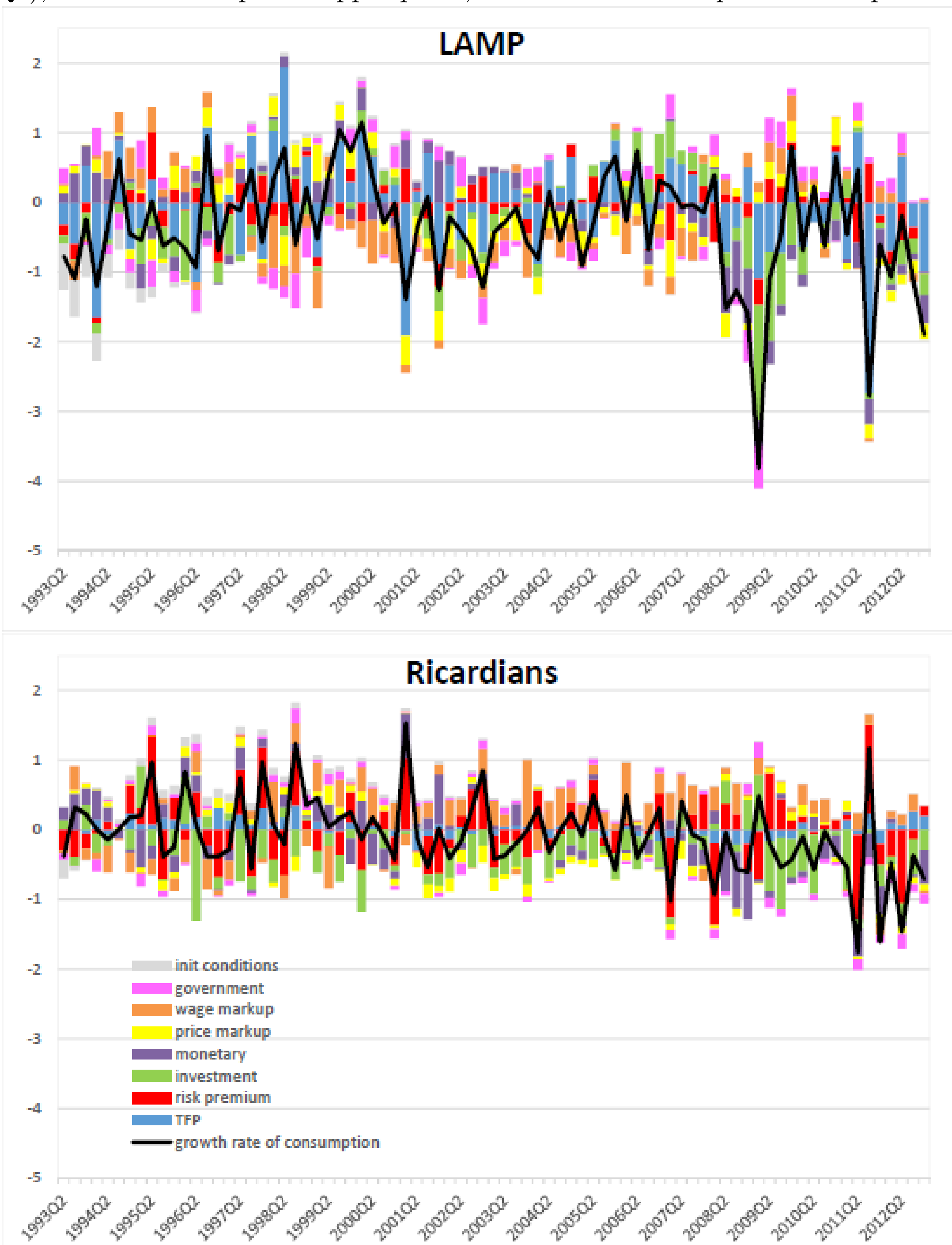
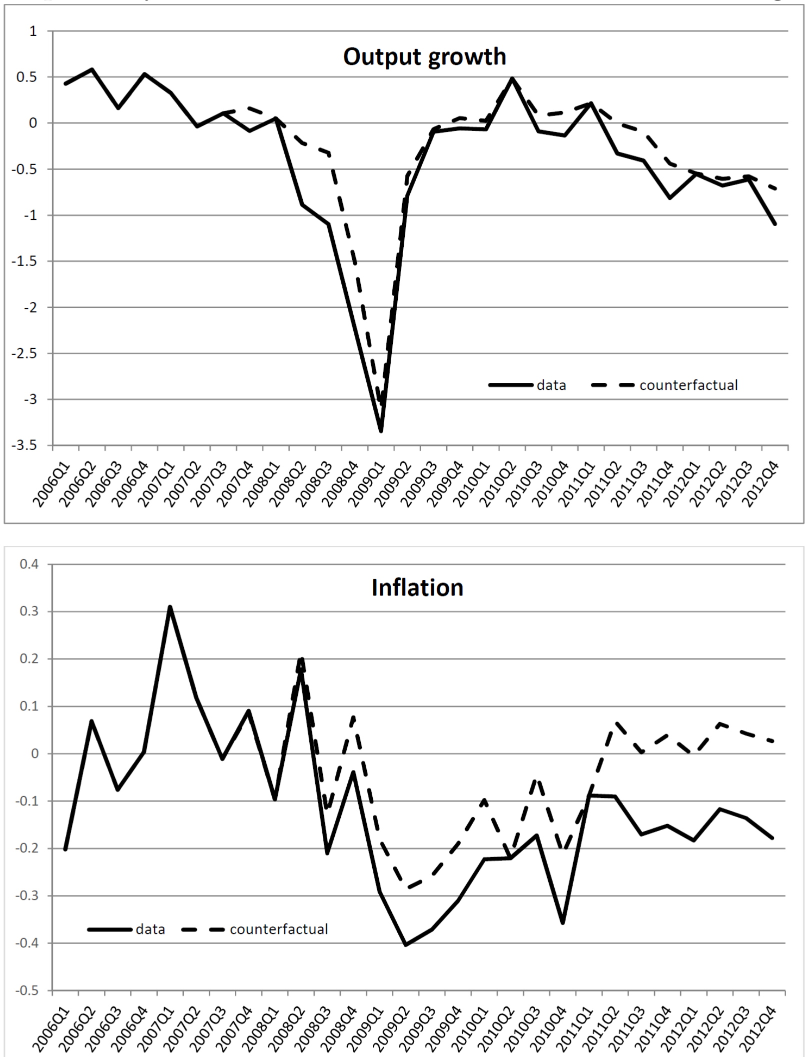


Figure 9: Counterfactual exercise. Output growth: deviation from trend of quarterly output growth. Inflation: quarterly rate as deviation from the medium term target.

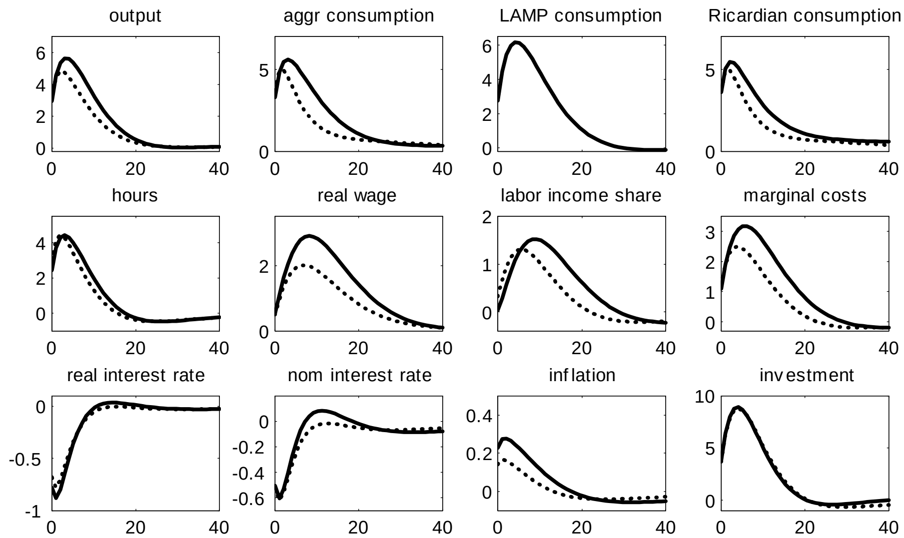


Adherence to simple rules certainly strengthens credibility and reputation. However, one might argue that in exceptional times, such as the post-2007 period, reputation should then be used to limit the adverse effects of unprecedented shocks. What would have been the impact of a more aggressive discretionary policy during the crisis period? Figure 10 shows IRFs to a 1% negative interest rate shock. The investment response is particularly strong.[27] 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

[27] Lewis et al. (2014) highlight the importance of the large negative investment gaps for explaining the output downturn in the EuroArea.

large relative to the corresponding inflation increase.

Figure 10: 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.

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.

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