Monetary Policy Preferences of the EMU and the UK

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Abstract

We estimate the central bank policy preferences for the European Monetary Union and for the UK. In doing so, we extend the theoretical framework suggested by Cecchetti et al. (2002) by assuming that policy preferences change across different regimes either due to the different phases of the business cycle, or due to changes in propagation mechanism, or due to volatility shifts of the underlying structural shocks. Our empirical results suggest that the weight that policy makers put on inflation is typically profound. Furthermore, it appears that volatility shifts of the economic disturbances is the main factor, which generates variation in policy preferences.

Keywords: Monetary policy preferences, multiple equilibria, Markov-switching.

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1 Introduction

In the last two decades, it has become rather evident for the central banks of most, if not all, developed economies that as long as there are no signs of recession in the horizon the objective of achieving and/or maintaining price stability outranks their other statutory objectives, such as reducing unemployment or stimulating growth. Svensson (2001) argues that defining price stability boils down to establishing a monetary policy loss function and in turn maintaining price stability involves minimizing the policy maker's loss function.

While it is easy to show that under a quadratic loss function and linear policy constraints, the optimal interest rate rule is a linear function of state variables, the estimated coefficients are a convolution of the parameters describing policy preferences and the underlying economic structure. Hence, the estimated policy rule is a reduced-form model, which cannot be used to address questions concerning the policy formulation process since it is inherently difficult to interpret changes in the optimal reaction function. In other words, it averages out changes in the estimated parameters of the optimal reaction function although such changes could arise due to very different factors such as a shift in policy preferences, or a change of the central bank's targets, or due to a reduction of the exogenous shocks, or a more efficient implementation of the monetary policy.

In this spirit, a large body of research tries to identify the reasons behind the great moderation, the greater stability of output and inflation in the 1980s and 1990s, the most common of which involve better monetary policy, structural changes of inventory management and good luck. However, potential changes of policy preferences seem to have been ignored. A small albeit pivotal strand of the relevant literature (Cecchetti et al. 2002; Cecchetti, 1998; Dennis 2006; Favero and Raveli, 2003; Ozlale, 2003) has endeavoured to actually obtain estimates of the so-called deep factors such as policy preferences. The key and intuitively plausible assumption that is underlined in all these studies is that over time policy preferences are expected to change and with them the monetary policies of central banks. For this reason, they provide estimates of the changes in the monetary policy preferences typically by splitting the samples into different periods often using structural breaks and stability tests. One of the main disadvantages of this approach is that in a forward looking model agents form expectations accounting for possible parameter changes in the future. The rationale is presented in Davig and Leeper (2007) and Cooley et al. (1982).[1] In this paper, we introduce an

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[1]These papers show that the theoretical norm, which follows Lucas (1976) in

approach that allows for economic agents to form expectations that also account for possible parameter changes in the future.

In particular, we adopt the Markov Regime Switching (henceforth MRS) technique so as to make state dependent both the policy maker's loss function and the optimal policy rule that emerges from it. In the same spirit, Cukierman and Gerlach (2003) provide a convincing argument as to why the loss function of a central bank should depend on the state that the economy is in. They use a loss function the implication of which is that the central bank is more reactive to inflation, or alternatively to output-gap, with deviations from their target level occurring when the economy is in expansion rather than in recession. Beck et al. (2002) generalize this framework and assume a state dependent loss function. Svensson and Williams (2007) and Blake and Zampolli (2010) examine the impact of model uncertainty in the case of the optimal policy rule. Both of these studies assume a quadratic loss function subject to state variables, the dynamics of which follow a Markov process[2]

We demonstrate empirically the usefulness of our approach by estimating the monetary policy preferences of the European Monetary Union (EMU) countries and of the United Kingdom (UK), a selection that is particularly interesting nowadays because recently the consensus on optimal monetary policy has changed within a short period of time. In fact, evidence of high inflation and low economic growth before the Lehmann Brothers collapse in September 2008 has raised a heated debate as to whether the European Central Bank (ECB) and the Bank of England should focus on achieving their inflation target or on promoting economic growth by relaxing monetary policy at the expense of their credibility in not pursuing the objective of price stability. Furthermore, estimating the monetary policy preferences of the EMU and of the UK becomes even more fascinating given that in the period after the collapse of the Lehman Brothers the major central banks around the world have reduced interest rates at historically low levels, shifting now the debate on to the question of whether a loose monetary policy should be coordinated with an expansionary fiscal policy.

From a general perspective, our approach can be viewed as generalising the framework suggested by Cecchetti et al. (2002) by allowing also both policy preferences and the dynamic constraints faced by a central

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treating regime shifts as a one-off event rather than as an ongoing process, is logically inconsistent since agents form expectations that reflect the belief that a regime change is possible. We refer the interested reader to these papers for more in-depth discussions of the topic. Sims et al. (2006) also present empirical evidence, which supports the view that regime changes are not monotonic.

[2]Svensson and Williams (2007) use a model where central bank's loss function is regime dependent.

bank to be regime dependent, effectively changing across the business cycle. To this end, we assume that policy makers minimize a regime dependent quadratic loss function subject to the dynamics of state variables, which follow a Markov process. Subsequently, in this set up the policy reaction function becomes state dependent. Our modelling approach is in line with Salemi (1995) and Sack (2000) who solve an optimal control problem, where the dynamic constraints are estimated using a linear VAR. In particular, following Blake and Zampolli (2010), we estimate policy preferences by solving a dynamic programing problem where the state-variables and shock variances are regime dependent.[3]

We may note that the framework employed by Blake and Zampolli (2010) is very general and it does not facilitate the identification of what drives regime shifts and knowing whether such shifts are the result of level effects (i.e. differences across high and low levels of output and inflation); or policy changes; or changes in shock variances; or changes in the propagation mechanism. We bypass this restriction by estimating policy preferences based on regimes that are identified under four different sets of assumptions. In particular, we estimate a model where only the mean is allowed to change across different regimes; then a model where only the variance of reduced-form shocks takes state dependent values; then a model where only the autoregressive parameters change; and finally, a model where all parameters are allowed to change.

The remainder of this paper proceeds as follows. Section 2 presents the theoretical framework of optimal monetary policy. Section 3 overviews the econometric methodology used to estimate monetary policy preferences and, Section 4 discusses the data utilized and the empirical results of the study. Finally, Section 5 summarizes and concludes.

2   Formalizing Monetary Policy Preferences

This section describes the estimation of central banks' policy preferences. In particular, central banks face an optimal control problem where the dynamics of state variables is assumed to be given by the point estimates of a Markov-switching structural VAR (MS-SVAR). By using the estimated structure and by assuming that the actions of central banks are optimal, we can recover the objective function.

We begin with a simple static model that Cecchetti et al. (2002) uses and then we introduce dynamics in line with Sack(2000). The advantage of the simple static model is that it represents the medium-run response and the trade-off that central banks face, while the dynamic model esti-

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[3]Blake and Zampolli (2010) solve an optimal control problem with Markov-switching rational expectations. Note that here, we proxy expectation formation with MS VAR, instead of solving a reduced-form rational expectations model.

mates long-run policy preferences and allows us, amongst other things, to test for the robustness of the results we obtain from the static model. Note that unlike Cecchetti et al. (2002) and Sack (2000), who use a linear VAR model to account for the dynamics of state variables, we use a Markov regime switching model.

Our approach is close to the methodology suggested by Blake and Zampolli (2010), who first solve a Markov switching reduced-form rational expectations model, and based on this solution they produce an optimal time consistent policy rule. The key difference between our study and that of Blake and Zampolli (2010) is that in the first step instead of solving a Markov switching reduced-form rational expectations model, we use a reduced-form MS-VAR model to proxy economic dynamics and market expectations. However, in the second step and in line with Blake and Zampolli (2010), we choose an optimal policy rule consistent with the rule obtained in the first step.

2.1 Estimation of Policy Preferences: The static case

We follow Cecchetti et al. (2002) and derive the trade-off between inflation and output gap variability by assuming that a central bank minimizes a quadratic loss function (QLF), which is subject to linear demand and supply curves:[4]

$$L_t = E[\lambda(\pi_t - \pi^*)^2 + (1 - \lambda)(y_t - y^*)^2] \tag{1}$$

$$y_t = \gamma(i_t - d_t) + s_t, \ \gamma < 0 \tag{2}$$

$$\pi_t = -(i_t - d_t) - \theta s_t \tag{3}$$

where π is inflation, $\pi^* = E(\pi)$ is the inflation target set by a central bank, y denotes output gap, $y^* = E(y)$ is the target of output gap and i_t is the short-term nominal interest rate. The coefficient λ is the weight that the central bank attaches to inflation relative to output stabilization, γ is the inverse slope of the supply curve and θ is the slope of the aggregate demand curve; d_t and s_t stand for the demand and the supply shocks respectively. In this framework, λ represents the medium-run trade-off between inflation and output-gap variability.

Cecchetti et al. (2002) show that the parameter of policy preferences is given as a function of the unconditional variances of inflation (i.e. σ_π^2)

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[4]We begin by assuming that a central bank minimize a contemporaneous rather than a discounting sum of square deviations of output and inflation from their respective target.

and output gap (i.e. σ_y^2) and the estimated value of γ : [5]

$$\frac{\sigma_y^2}{\sigma_\pi^2} = [\frac{\lambda}{\gamma(1-\lambda)}]^2 \tag{4}$$

Equation (4) has the property that for $\lambda = 0$ (the central bank only cares about output-gap variability), $\sigma_y^2/\sigma_\pi^2 = 0$. Likewise, for $\lambda = 1$ (the central bank only cares about inflation variability), $\sigma_y^2/\sigma_\pi^2 = \infty$. We can trace out the entire output-inflation variability frontier by allowing λ to vary between 0 and 1.

We extent the model presented in equations (1)-(3) to a regime switching framework and we obtain a state dependent version of (4), as in (5):

$$\frac{\sigma_y^2(S_t)}{\sigma_\pi^2(S_t)} = \left[\frac{\lambda_{S_t}}{\gamma_{S_t}(\lambda_{S_t}-1)}\right]^2 \tag{5}$$

Equation (5) shows that given the unconditional values of $\sigma_y^2(S_t)$ and $\sigma_\pi^2(S_t)$ the policy preferences of the central bank change as the slope of supply $(1/\gamma_{S_t})$ curve changes across different regimes.[6] Estimates of policy preferences by Checchetti et al. (2002) are based on the assumption that the VAR parameters remain constant over a significant historical period. However, in the case of the EMU, policy went through different regimes. This implies that we need to adopt a statistical model, which accounts for regime changes. Here, we estimate (5) by employing the MS-SVAR suggested by Ehrmann et al. (2003). In line with Cecchetti et al. (2002) we compute the inverse slope $1/\gamma(s_t)$ at each regime as the 12-quarter average of the impact of policy shock on output, divided by the 12-quarter average impact on inflation.

2.2 Estimation of Policy Preferences in a Dynamic Model

We follow Sack (2000) in an attempt to make the analysis more realistic and we introduce dynamics in both demand and supply curves. Sack (2000) solves for an optimal policy rule that minimizes a quadratic loss function subject to dynamics as implied by the VAR estimates. However, we allow policy preferences and economic dynamics to change across the business cycle. Thus, the policy maker minimizes a quadratic intertem-

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[5]For the derivation of (4) see the appendix.
[6]For the derivation of (5) see the appendix.

poral regime-dependent loss function:[7]

$$\sum_{t=0}^{\infty} \beta^t L(z_t, S_t) = \sum_{t=0}^{\infty} \beta^t E_t[z_t' R(S_t) z_t] \qquad (6)$$

subject to:

$$z_t = \sum_{i=0}^{p} A_i(S_t) z_{t-i} + \sum_{i=0}^{p} B_i(S_t) i_{t-i} + v_t^Z(S_t) \qquad (7)$$

$$i_t = \sum_{i=0}^{p} C_i(S_t) z_{t-i} + \sum_{i=0}^{p} D_i(S_t) i_{t-i} + v_t^i(S_t) \qquad (8)$$

where $z_t = [y_t \ \pi_t]'$, $R(St)$ is the regime-dependent matrix of the weights attached to inflation and output-gap stability and i_t is the policy instrument. The interaction between the structure of the economy and the policy reaction function would generate an identification problem. We get around this problem by estimating (7) and (8) using a Markov-switching structural VAR (MS-SVAR) model. In doing so we impose, in each regime, the same recursive structure used by Sack (2000). In particular, we assume that the relevant policy instrument does not enter into the inflation and output equations contemporaneously (i.e. $B_0 = 0$). We also impose the restriction that inflation does not affect output contemporaneously.

To solve the optimization problem we construct a state vector, which includes current and lagged values of non-policy variables z_t and lagged values of the policy variable i_t as follows:

$$X_t = [z_t, z_{t-1}, ..., z_{t-p+1}, i_{t-1}, i_{t-2}, ... i_{t-p}]'$$
$$= [y_t, .. y_{t-p+1}, \pi_t, ..., \pi_{t-p+1}, i_{t-1}, ... i_{t-p+1}, i_{t-p}]$$

The optimal policy will be a solution to the following Bellman equation:

$$V(X_t, S_t = i) = \max_{i_t} \left\{ X_t' R(S_t) X_t + \beta E_t[V(X_{t+1}, S_{t+1} = j)] \right\} \qquad (9)$$

subject to

$$X_{t+1} = C(S_t) + A(S_t) X_t(S_t) + B(S_t) i_t + \epsilon_t \qquad (10)$$

where $V(X_t, S_t = i)$ is the continuation value function of the dynamic programing problem at time t written as a function of the state vector X_t and the unobserved variable S_t. The random variable S_t is assumed to form a Markov chain in $\Lambda = \{1, 2, ... N\}$ with transition probability

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[7]A regime-dependent loss function captures the possibility that future policy makers may have different policy preferences from their predecessors. For an analysis of changes in the monetary policy objective see Debortoli and Nunes (2008; 2014).

matrix $P = (p_{ij})'_{ij \notin \Lambda}$. The transition probability p_{ij} is the probability that the economy switches from the current state i to future state j. We assume that the policy makers know the current state of the economy but they are uncertain about the future state.[8] The following matrices A and B depend on the value of the unobserved state variable S_t, and for $i \in \{1, 2, ..N\}$, they are given by

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C = \begin{bmatrix} c_y \\ 0 \\ . \\ 0 \\ c_\pi \\ 0 \\ . \\ . \\ . \\ . \\ 0 \end{bmatrix}, A = \begin{bmatrix} a_{yy}^1 & ... & a_{yy}^{p-1} & a_{yy}^p & a_{y\pi}^1 & a_{y\pi}^2 & ... & a_{y\pi}^{p-1} & a_{y\pi}^p & b_{yi}^2 & ... & b_{yi}^{p-1} & b_{yi}^p \\ 1 & ... & 0 & 0 & 0 & & ... & 0 & 0 & 0 & ... & . & 0 \\ . & ... & . & . & . & & ... & . & . & . & & . & . \\ 0 & ... & 1 & 0 & 0 & & ... & 0 & 0 & 0 & ... & . & 0 \\ a_{\pi y}^1 & ... & a_{\pi y}^{p-1} & a_{\pi y}^p & a_{\pi\pi}^1 & a_{\pi\pi}^2 & ... & a_{\pi\pi}^{p-1} & a_{\pi\pi}^p & b_{\pi i}^2 & ... & b_{\pi i}^{p-1} & b_{\pi i}^p \\ 0 & ... & 0 & 0 & 1 & 0 & ... & 0 & 0 & 0 & ... & 0 & 0 \\ 0 & ... & 0 & 0 & 0 & 1 & ... & . & . & . & ... & 0 & 0 \\ 0 & ... & 0 & 0 & 0 & & ... & 1 & 0 & 0 & ... & 0 & 0 \\ 0 & ... & 0 & 0 & 0 & 0 & ... & 0 & 0 & 0 & ... & 0 & 0 \\ 0 & ... & 0 & 0 & 0 & & ... & 0 & 0 & 1 & ... & 0 & 0 \\ . & ... & . & . & . & & ... & . & . & . & ... & 0 & . \\ 0 & ... & 0 & 0 & 0 & & ... & 0 & 0 & 0 & ... & 1 & 0 \end{bmatrix} \text{ and } B = \begin{bmatrix} b_{yi}^1 \\ 0 \\ . \\ 0 \\ b_{\pi i}^1 \\ 0 \\ . \\ 0 \\ 1 \\ . \\ . \\ 0 \end{bmatrix}
$$

where the coefficients a_{jl}^k, for $k = 1, ..., p-1$, indicates the impact of non-policy variable l on non-policy variable j, b_{li}^k shows the impact of the policy instrument on the non-policy variable l and c_l is the intercept of the non-policy variable l.[9] The superscript k show the lagged value of the relevant variable.[10]

Given the linear quadratic nature of the problem and assuming further that the value function is quadratic, i.e. $V(X_t, S_t = i) = X_t'V_iX_t + 2X_t'\omega + d_i$, the first order conditions will give a set of decision rules of the following form:

$$i_t(z_t, i) = -F_iX_t \tag{11}$$

where

$$F_i = \beta \sum_{j=1}^{N} p_{ij}(B_j'V_jB_j)^{-1}\beta \sum_{j=1}^{N} p_{ij}(B_j'V_jA_jX_t + B_jV_jC_j + B_j\omega_j) \tag{12}$$

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[8]Note that the current state of the economy is given by the filter probability $P(S_t = i|\Psi_t)$, where Ψ_t is the information set available at time t. For details concerning the computation of filter probability see Hamilton (1994).

[9]The subscripts i, j used in a_{jl}^k and b_{li}^k are not the same as those used in the transition probability p_{ij}.

[10] Note that we compute the C, A and B by using the point estimates from the MS-VAR.

$$V_i = R_i + \beta \sum_{j=1}^{N} p_{ij}(A_j'V_jA_j) - \beta \sum_{j=1}^{N} p_{ij}A_j'V_jB_j(B_j'V_jB_j)^{-1}B_j'V_jA_j \quad (13)$$

and

$$\omega_i = \left(I - \beta \sum_{j=1}^{N} p_{ij}A_j'[I - B_j(B_j'V_jB_j)^{-1}B_j']\right)^{-1} \beta \sum_{j=1}^{N} p_{ij}A_j'V_j[I - B_j(B_j'V_jB_j)^{-1}B_j'V_j]C_j$$

$$(14)$$

for $i, j = 1, 2$, (11) and (13) can be written as follows:[11]

$$F_i = \beta \sum_{i=1}^{2} p_{i1}(B_1'V_1B_1)^{-1}\beta \sum_{i=1}^{2} p_{i1}(B_1'V_1A_1X_t + B_1V_1C_1 + B_1\omega_1) +$$

$$\beta \sum_{i=1}^{2} p_{i2}(B_2'V_2B_2)^{-1}\beta \sum_{i=1}^{2} p_{i2}(B_2'V_2A_2X_t + B_2V_2C_2 + B_2\omega_2)$$

$$V_i = R_i + \beta \sum_{i=1}^{2} p_{i1}(A_1'V_1A_1) - \beta \sum_{i=1}^{2} p_{i1}A_1'V_1B_1(B_1'V_1B_1)^{-1}B_1'V_1A_1 +$$

$$+\beta \sum_{i=1}^{2} p_{i2}(A_2'V_2A_2) - \beta \sum_{i=1}^{2} p_{i2}A_2'V_2B_2(B_2'V_2B_2)^{-1}B_2'V_2A_2$$

The optimal decision rule (11) depends on the uncertainty concerning which regime will prevail in the future.[12] However, the response coefficients given in (12) are independent of the variance-covariance matrix Σ_i of the zero-mean disturbances ϵ_t. Thus, with respect to ϵ_t, certainty equivalence holds but not with respect to the matrices of the stochastic parameters. Equation (11) and (13) can be solved by substituting the former into the latter and then iterating the resulting Riccati equation to converge, thereby obtaining a solution for V_i. Once we obtain a solution for V_i, F_i can be determined recursively.

The optimal policy rule in (11) is a function of β, λ, π^* and y^*. In the results that follow, we assume that $\beta = 0.99$, $\pi^* = 2$ and y^* is equal to the sample mean of output growth. For any choice of $\lambda(S_t)$ the optimal policy rule can be calculated. We compute the optimal weights $\lambda(S_t)$ by minimizing the distance between the optimal policy rate and the actual rate where the distance is measured as the residual sum of squared deviations.

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[11] In a similar way we can write ω_i.

[12] This is reflected in equation (12) by the transition probabilities p_{ij}.

3 Econometric Methodology

A key input in estimating policy preferences for the static dynamic model is the point estimates of a MS-SVAR model.[13] MS SVAR is a two-step procedure combining two important developments of VAR analysis: Markov regime-switching and identification. In the first step we estimate a reduced-form MS VAR model, where we allow all estimated parameters to be state dependent:

$$X_t = c(S_t) + \sum_{j=1}^{p} A(S_t) X_{t-j} + B(S_t) u_t \qquad (15)$$

$$\Omega(s_t) = E[B(S_t) u_t u_t' B(S_t)'] = B(S_t) \Sigma_u(S_t) B(S_t)' \qquad (16)$$

where

$$X_t = \begin{pmatrix} y_t \\ \pi_t \\ i_t \end{pmatrix}, \; c(S_t) = \begin{pmatrix} c_{1,s_t} \\ c_{2,s_t} \\ c_{3,s_t} \end{pmatrix}, \; u = \begin{pmatrix} u_{1,s_t} \\ u_{2,s_t} \\ u_{3,s_t} \end{pmatrix},$$

In the second step, we identify the impulse matrix $B(s_t)$, which can be used to extract the contemporaneous interactions among the elements of X_t. Identification of $B(s_t)$ requires n^2 restrictions within each regime. Estimation of $\Omega(s_t)$ provides $[n(n+1)/2]$ restrictions. Thus, full identification requires another $n(n-1)/2$ extra restrictions. Sims (1992) derives these restrictions by ordering endogenous variables recursively.[14] We choose the recursive form of identification by imposing the restriction that the policy instrument does not enter into the inflation and output equations.[15] We also impose the restriction that inflation does not affect output contemporaneously.

The model in (15) and (16) allows all the parameters to be affected by regime shifts. In such a setup, it is not clear what distinguishes the different regimes. In particular, it is not clear if changes of the unobserved state variable are associated with the phase of business cycles (i.e. switches in the intercept), with changes in the propagation mechanism (i.e. changes in the dynamic structure of the autoregressive MS-VAR coefficients) or with the changes of the MS-VAR errors (i.e. changes in the variance of innovations). To examine the impact of the possible

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[13]Note that we compute γ_{S_t} in (5) by using the regime-depedent impulse responses of output and inflation to interest rate shocks. Alternatively, point estimates of the reduced-form MS-VAR are used as an input in (10).

[14]In this set up, endogenous variables are ordered and it is assumed that the fundamental disturbances have contemporaneous effects on the variable in question itself and on all the other variables below it.

[15]The same recursive identification scheme has been used by Ehrmann et al. (2003).

sources of regimes shifts, we estimate four different models. The first model, presented in (15) and (16), accounts for the joint contribution of all potential factors. We denote this general model as model A.

Then, we estimate a model under the assumption that only the intercepts change across regimes, while the autoregressive parameters and the variance covariance matrix of reduced-form shocks remain constant. In this setup regimes are identified as low and high growth and high and low inflation. We call this model as model B:

$$X_t = c(S_t) + \sum_{j=1}^{p} A_j X_{t-j} + B u_t \tag{17}$$

$$\Omega = B \Sigma_u B' \tag{18}$$

Note that the impact matrice B remains constant across different regimes (i.e. $B(S_t) = B$). Therefore, the impulse responses are not affected by changes of $c(S_t)$ and policy preferences as computed by (5) in the static model are independent of regime shifts. However, this is not the case for the dynamic model where the optimal weights $\lambda(S_t)$ as extracted by the Riccati equations in (13) are still regime-dependent.[16] For example, in (11)-(14), even if the impact matrix is time-invariant (i.e. $B_j = B$), the matrices of optimal reaction and the value of functions (i.e. F_i, V_i) are functions of regime-dependent matrices such as C_j, A_j, and R_i. If the static model is true then we do not expect, in the dynamic model, policy preferences to change across the different states of the unobserved variable S_t.

Then, and in line with the main bulk of the literature on great moderation, we assume that regime changes are driven by better luck. We consider a MS-VAR model where regime shifts are confined to the variance of structural innovations while the impulse matrix B is invariant across the states of S_t.[17] Thus, in the static model, policy preferences remain unchanged across different regimes. We call this model, model C:

$$X_t = c + \sum_{j=1}^{p} A_j X_{t-j} + B u_t \tag{19}$$

$$\Omega(S_t) = B \Sigma_u(S_t) B' \tag{20}$$

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[16]This is because the inputs of Riccati equations were extracted from the reduce-form MS-VAR. In particular, the impulse matrix B identified in the MS-SVAR is not used in the case of the dynamic model.

[17]This approach resembles the ones suggested by Rigobon (2003) and Rigobon and Sack (2003) for identification of structural VAR through heteroscedasticity. However, the authors assume that changes in the covariance structure occur at fixed points during the sample period.

Lanne et al. (2010) show that identification of B can be achieved if:

$$\Omega(S_t) = BB' \text{ for } S_t = 1$$

and

$$\Omega(s_t) = B\Phi(S_t)B' \text{for } S_t = 2, ..., N$$

where $\Phi(S_t)$ is a diagonal matrix with positive elements. If there are only two regimes (i.e., $S_t = 1, 2$) identification requires that the elements of $\Phi(S_t)$ are distinct. Model C has been used in the great moderation literature to test the null hypothesis of good luck.

Finally, we estimate a model where only the propagation mechanism, as computed by the autoregressive matrices is subject to regime shifts:

$$X_t = c + \sum_{j=1}^{p} A(s_t)X_{t-j} + Bu_t \tag{21}$$

We call equation (21) model D. Note that the autoregressive parameters reflect both the formation of market expectations and structural relationships among economic agents. However, the economic behavior of market agents described by the impulse matrix B is assumed to be constant across regimes. Thus, changes in the propagation mechanism are driven by changes in market expectations.[18] Model D indicates the impact that changes in the formation of market expectations have on policy preferences.

4   Data and Empirical Results

This section discusses our empirical results concerning both the static and dynamic models. We focus on the cases of the euro area and of the UK. In what follows we utilize a trivariate MS VAR model, which includes the policy instrument, inflation and output growth. We allow both the VAR coefficients and the coefficients of variance covariance matrix to vary across states. We also employ a four-variable model by adding the spread between the 6-year long-term and 3-month short-term interest rate into the trivariate model. We include the spread between long-term and short-term interest rate as the proxy for market expectations. We use on a monthly basis the three-month treasury bill rate as a proxy for the policy instrument. The treasury bill rate is available both for all countries used to construct the euro area series and

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[18]A usefull servey of the propagation (i.e. persistence) literature are available in Stock and Watson (1988), Pesaran and Lee (1993) and Pesaran et al. (1993). See also Pivetta and Reis (2007) for changes in inflation persistence and monetary policy and Pancrazi and Vukotic (2013) for changes in output percistence and monetary policy.

for the whole period of investigation.[19],[20] We also use monthly CPI and industrial production to construct the inflation rate and the industrial production growth rate.[21]

4.1 Estimation of Policy Preferences: The Case of the Static Model

We compute the policy preferences and the slope of the supply curve for the period March 1979 to August 2008.[22],[23] Figure 1 shows the filter probabilities of regime 1 for model A. In line with empirical regularities, the probability of regime 1 in EMU is low for the period before 1986 where eleven realignments took place. The probability of regime 1 is also low in 1990 when the German unification took place and the low economic growth in EMU emerged.[24] The probability of regime 1 falls during the speculative attacks in 1992, 1993 and 1995. Thus, the filter probabilities provide strong evidence that regime 1 is associated with the high growth and low volatility regime.

Similarly, in the UK the probability of regime 1 is broadly in line with evidence produced elsewhere. Specifically, Benati (2008) shows that the long-run response to inflation was weaker for the period before 1979-1990 and there was a marked increase under the Thatcher administration. There was also a further increase after the introduction of the October 1992 inflation targeting regime.[25] Thus, the probability of regime 1

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[19]Euro area data are constructed as a weighted average of seven EMU countries. Namely, Germany, France, Italy, Spain, the Netherlands, Belgium and Finland. Although the aggregate GDP of these represents more than 92 percent of euro area GDP, we scale the weight so that it represents 100 percent of euro area GDP. The weights are taken from an updated vesrion of the Area-Wide Model (AWM) database (see Fagan, Henry and Mestre 2001). In particular we use the following weights: For Germany 0.362, for France 0.242, for Italy 0.165, for Spain 0.097, for the Netherlands 0.067, for Belgium 0.042 and for Finland 0.021.

[20]We could also use the short-term money market rate given by the 60b line of International Financial Statistics (IFS) data base. However, it is only available for the period before the introduction of the euro single currency.

[21]Data for CPI and industrial production were extracted from lines 64 and 99 of the IFS data base.

[22]We exclude, in our analysis, the period after the recent financial crisis because of the zero lower bound of nominal interest rates problem.

[23]We have picked up the number of lags in the estimation of the reduced form MS-VAR models using the Akaike Information Criterion.

[24]Both incidents raised doubts about the optimality of low inflation policy pursued by the Deutsche Bundesbank.

[25]Benati (2008), who, using a time-varying structural VAR analysis, shows that there is violation of the Taylor principle during the 1980s, where the estimated long-run inflation coefficient fluctuates between 0.7 and 0.8. However, after the introduction of the October 1992 inflation targeting the long-run coefficient on inflation

is low in periods where monetary policy violates the Taylor principle by accommodating inflationary pressures. Under such circumstances, expected inflation becomes self-fulfilling. This implies that if regime 1 coincides with active monetary policy then the level and the volatility of inflation is expected to be lower in regime 1 than in regime 2. The probability of regime 1 is also low for the period between 2001 and 2003.[26]

Figures 2 and 3 are based on a trivariate MS-SVAR model and present the impulse response of inflation to monetary policy shocks both for the UK and for the EMU.[27] There is some evidence of the price puzzle in both regimes but it is a lot more persistent and stronger in regime 2. It is worth noting at this point, however, that the price puzzle might be an artefact of an omitted variable such as expected inflation.[28] Canova et al. (2007) get round the omitted variable problem by using proxies of expected inflation.[29] Here, we use as a proxy of expected inflation the spread between the six-year long-term interest rate and the three-month treasury bill rate. However, the price puzzle is still somewhat present even in the augmented four-variable MS-SVAR model.[30] Evidence of the price puzzle after accounting for expected inflation indicates that either the proxy of expected inflation is not accurate or that the price puzzle is due to supply shocks.[31]

In summary, although model A encompasses all potential factors, which drive regime shifts, the filter probabilities and the impulse response function provide evidence that regime 2 coincides with passive monetary policy, self-fulfilling expectations, high inflation and high volatility. At this point it is worth noting that the volatility changes could also

increased substantially reaching a value of 1.4.

[26] Groen et al. (2009) argue that there may have been temporary breaks induced by the large volatilities in housing and energy market after 2000. Groen et al. (2009) show, by developing a multivariate extension of the CUSUM test, that the UK RPI inflation was subject to structural breaks in 2001, 2003 and 2005.

[27] The confidence intervals have been computed using bootstrapping. For more details see Ehrmann et al. (2001) and the Appendix of this paper.

[28] If a VAR omits expected inflation then the supposed monetary policy shock will capture the positive correlation between inflation and the relevant policy rate.

[29] Bernake, Boivin an Eliaz (2005) and Boivin, Giannoni and Mihov (2009) also tackle the omitted variable problem by allowing some factors extracted by a large dataset to enter into the VAR.

[30] For the sake of brevity we do not present the impulse response function of the four-variable MS-SVAR model here. The relevant graphs are available from the authors upon request.

[31] This is because the implication of the impulse response from a misspecified VAR is similar to the implication of the response to a supply shock. This raises some concern for the policy makers in distinguishing policy shocks from supply shocks, especially for regimes with high uncertainty.

come from two non-exclusive sources: changes of the unforecastable disturbances and/or changes of how these disturbances propagate throughout the whole economy. Below, we discuss how our results change when we estimate the policy preferences by controlling for each potential source of regime shifts.

The third and the fourth column of Table 1 presents the results from the trivariate and the quadrivariate model A. The first observation is that most of the $\lambda(S_t)$s are very high. Estimated policy preferences indicate that both the EMU and the UK put more weight on inflation stability, than on output growth stability, in the regime where the slope of the supply curve (i.e. $1/\gamma$) is steeper.[32] Countries emphasize price stability in regimes where the disinflation cost in terms of output growth is low.

Next, the fifth and the sixth columns of Table 1 present the results from Model B in which only the intercept is allowed to change across regimes. Although in this setup policy preferences are time-invariant, the results are still comparable to those obtained from Model A. In particular, the weights on inflation are still high both for the EMU and for the UK. However, for the EMU, while in the trivariate case the weight on inflation is lower than the relevant weights of Model A, it is higher in the model that includes four variables.[33] The results seem to be driven by the slope of optimal policy frontier, which is flatter for higher values of γ.[34] Thus, policy makers emphasize inflation in regimes where the trade-off between inflation and output growth variability is lower. For the UK, inflation has higher impact on policy maker's loss function in Model A than in Model B, which implies that it is not only the phase of the business cycle that affects the policy preferences but also changes in the magnitude of the VAR forecast errors and/or changes of how these disturbances propagate throughout the economy.

Then we turn to examine the impact that changes in the volatility of forecast errors have on policy preferences. Columns seven and eight present the results from Model C in which only changes in the volatility of the forecast errors are allowed to change across regimes. We observe that for the trivariate case the weights put on inflation both for the EMU and the UK are slightly lower than the average value of weights estimated in Model A. However, for the extended model the importance of inflation on the policy maker's loss function is higher in model C than in model A. Note also that in model C the behaviour and expectations

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[32]This implies a flatter optimal policy frontier.

[33]In particular, we compare the weight on Model B with the average values of the weights across regimes (i.e. λ_1 and λ_2) of Model A.

[34]In Model A, γ_1 and γ_2 are higher than γ in model B.

of economic agents, as reflected in the impact matrix and in the auto-gregressive coefficients, are assumed to be invariant across the different volatility states. Thus, in this setup, volatility changes are perceived as structural breaks – which the relevant literature often calls endogenous to signify the fact that they are modelled. Our results indicate that policy makers follow a policy against the wind: they respond to the uncertainty concerning the variance of structural shocks by increasing the weight they put on inflation. We also observe that for the UK the slope of the optimal policy frontier is almost flat, which indicates that there is no trade-off between inflation and output-growth.[35]

Finally, the last two columns of Table 1 present the results from Model D in which only the propagation mechanism is allowed to change across regimes. The results show very little support that this mechanisms produces changes since not only is the weight on inflation less than the corresponding weights of Model A but also the results from the quadri-variate EMU model are rather implausible. However, the lower weights on inflation in Model D, does not necessarily imply that the propagation mechanism has no role on the switches of policy preferences. But it does indicate at the very least that it is not the only factor.

Overall, the results from the static model imply that all factors are likely to play a role in the difference of policy preferences. However, it is worth noting that the evidence from Model C underline more emphatically the importance of inflation as compared to the more flexible Model A. Thus, a key finding is that the uncertainty concerning the volatility of structural shocks might be the most important factor that yields changes in policy preferences.

4.2 The Case of the Dynamic Model

The static model simplifies the analysis by looking only at the medium-horizon averages and by estimating the slope of the supply curve based on impulse responses. However, evidence of price puzzle and question marks about the ability of structural VAR to identify structural shocks, demands further tests to robustify our inference.[36] Thus, we adopt the framework suggested by Blake and Zampolli (2010) and by recursive

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[35]This is a rather strong result but the filtered probabilities show that it may be attributed to the fact that the high volatility regime does not contain many observations.

[36]Benati and Surico (2009) argue that there is a fundamental disconnection between what is structural within a Dynamic Stochastic General Equilibrium (DSGE) model and what is defined as structural based on the structural VAR representation implied by the same DSGE model. Castelnuevo and Surico (2009) show that this argument is robust to an alternative identification approach based on sign restrictions, which do not impose recursiveness.

estimates of equations (11)-(14) we obtain an optimal policy path for the policy instrument. In doing so, we compute the optimal weights by minimizing the distance between the optimal policy rate and the actual rate where the distance is measured by the residual sum of squared deviations.

The results of this exercise are summarized in Table 2. For the general Model A presented in the third and fourth columns, the results are consistent with the basic results obtained from the static model; but only for regime 1. Note that on the basis of filter probabilities and empirical regularities, we argue above that regime 1 coincides with the low volatility high growth regime. Thus, we observe that the weights put on inflation are high only for the low volatility regime. Similarly, the striking finding is the very low weights on inflation in the high volatility regime. And although the low volatility regime is associated with the high-growth period, evidence of low weights on inflation is not consistent with the results of Table 1 and the weights found in earlier studies that used a linear framework. The key implication of our results is that in a low growth regime, policy makers seem to switch policy preferences to some extent from inflation to output growth.

This is consistent with evidence from Model C where the weight put on inflation is low in both regimes. The low influence of inflation on policy preferences might be due to the possibility of regime changes. For example, expectations that the high volatility regime can appear again in the future might affect current policy preferences. However, the low relative weight on inflation is not consistent with results obtained from the static analysis of Model C. The discrepancies between the static and dynamic analysis might be due to the fact that the static analysis reflects the medium-run trade-off between inflation and output-gap stabilization while the dynamic analysis focuses on the long-run trade off. Estimates from Model B and D indicate that policy makers do indeed follow a policy against the wind; they focus only on the stabilization of inflation. The only exception to this rule is Model D for the UK with four-variables, where the weight put on inflation is rather low in both regimes.

In summary, the results from the dynamic analysis seem rather mixed. In the majority of the cases examined, policy makers appear to focus mainly on inflation stability. And unlike the overall picture drawn from the dynamic analysis, Model C indicates that inflation has low weight on policy makers' objective function.

5   Summary and Conclusions

The aim of this paper is to estimate the monetary policy preferences of the EMU countries and of the UK, which we undertake by building upon

the framework suggested by Cecchetti et al. (2002) and extending it with policy preferences that change across the different regimes. Specifically, we assume that the stochastic process of inflation and output gap follows a Markov process, and we estimate policy preferences first for a model with no dynamics in the demand and supply curves and second for a more realistic model where dynamics are introduced. Moreover, we have also examined the impact of the three main factors to determine the source of the regime shifts, namely the different phases of the business cycle, changes of the underlying propagation mechanism, and volatility shifts of the structural shocks.

Our empirical results from the static model show that monetary policy makers in the EMU and in the UK put a lot of weight on inflation variability. The static analysis also shows that the main source of the time variation of policy preferences is the volatility change of economic disturbances. In the same vein, the dynamic analysis also provides evidence that policy makers put a lot of emphasis on inflation stability. However, there are some notable exceptions. For example, in the high volatility regime of the general model (Model A) the relative importance of inflation in the policy objective function is low. Also in line with the static analysis, we observe that volatility shifts of economic disturbances is the main factor to drive variations of policy preferences. But unlike the static analysis, the weight that is put on inflation stability is lower for the model in which regime shifts are driven by volatility changes.

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Figure 1: Filter probabilities of the low volatility regime
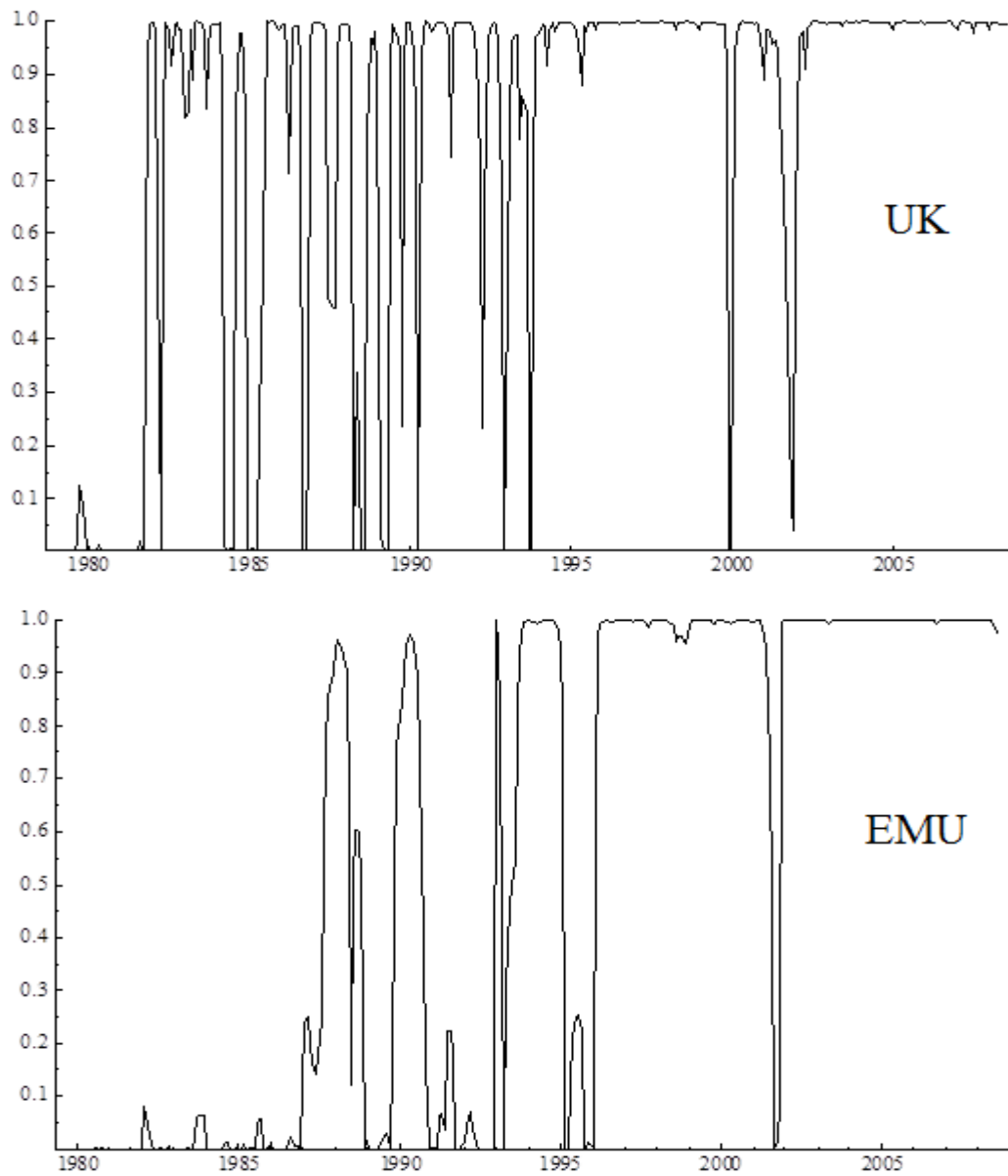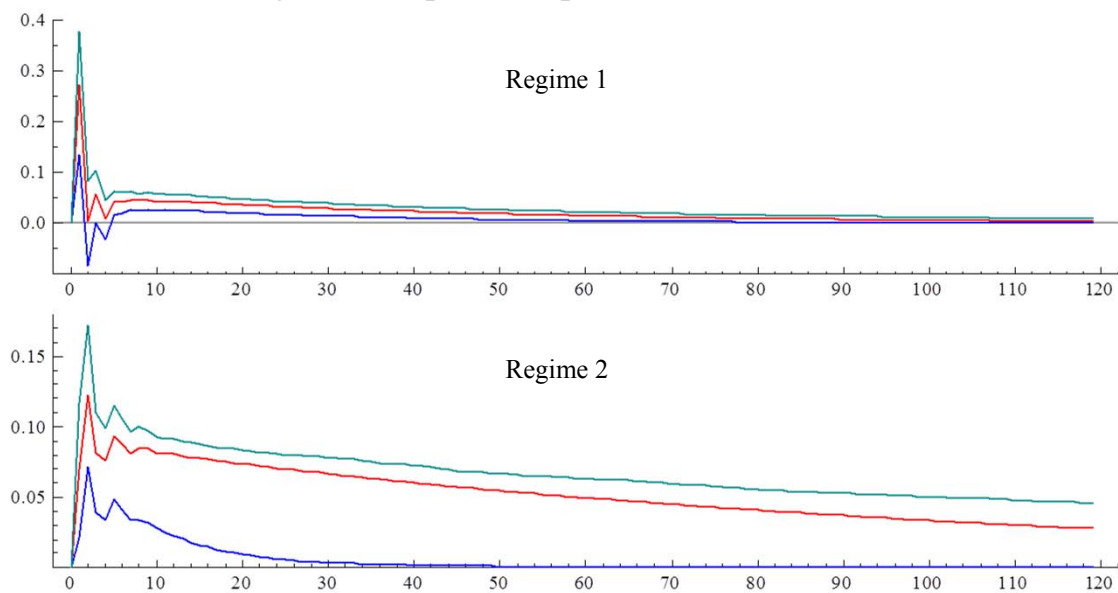

Notes: the two graphs depict for the UK and the EMU the filter probability at each point in time that the process is in regime 1; the complement of this gives the probability that the process is in the other regime.

Figure 2: Impulse-responses - UK inflation
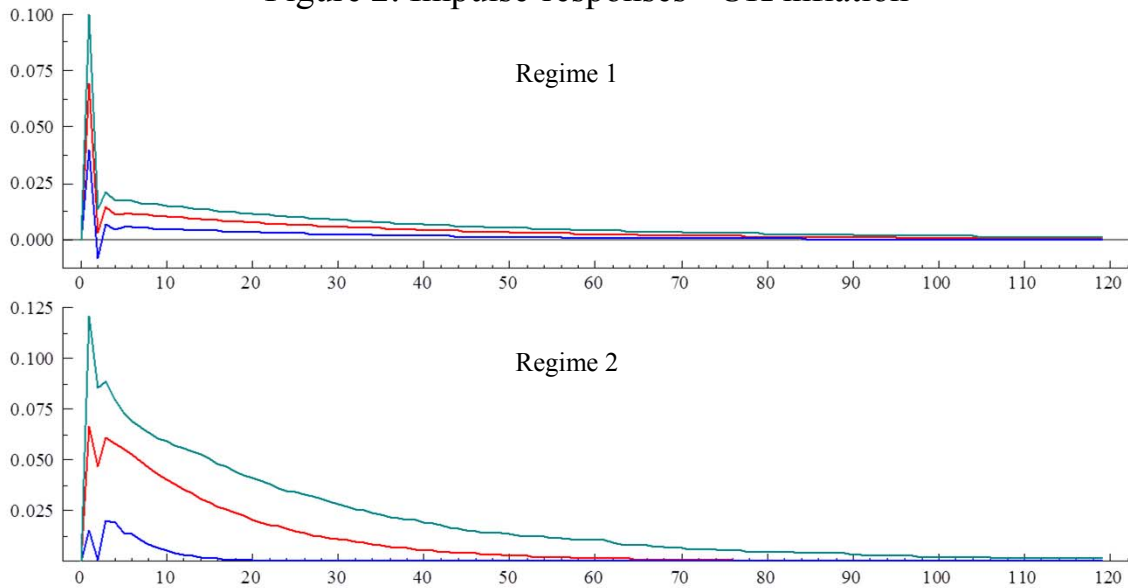
Regime 1

Regime 2

Notes: the impulse-response graphs depict for the first (Regime 1) and the second (Regime 2) volatility regimes the response of inflation to a (positive) shock in interest rates. The upper and lower lines in each graph are the 84% and 16% confidence intervals respectively obtained by bootstrapping.

Figure 3: Impulse-responses - EMU inflation

Regime 1

Regime 2

Notes: the impulse-response graphs depict for the first (Regime 1) and the second (Regime 2) volatility regimes the response of inflation to a (positive) shock in interest rates. The upper and lower lines in each graph are the 84% and 16% confidence intervals respectively obtained by bootstrapping.

Table 1: Estimated policy preferences
based on static policy constraints

	parameters	Model A		Model B		Model C		Model D	
		UK	EMU	UK	EMU	UK	EMU	UK	EMU
3 variables	γ_1	-38.2	-2.6	-1.4	-3.1	-1.6	-2.6	-4.1	-2
	γ_2	-2.3	-2	-1.4	-3.1	-1.6	-2.6	-0.1	-0.3
	λ_1	99%	93%	88%	87%	89%	86%	90%	91%
	λ_2	84%	91%	88%	87%	89%	86%	15%	63%
4 variables	γ_1	-34.2	-1	-1.6	-1.7	-5.2	-75.9	-4.2	120.4
	γ_2	-10.7	-0.6	-1.6	-1.7	-5.2	-75.9	-1.2	-0.02
	λ_1	99%	84%	89%	78%	96%	99%	90%	100%
	λ_2	96%	75%	89%	78%	96%	99%	72%	8%

Notes: the table depict the values of the γ and λ parameters for the trivariate and quadrivariate variants of the four models namely Model A (the most flexible one), Model B (with the regime switching mechanism affecting only the intercepts), Model C (with the regime switching mechanism affecting only the variances), and Model D (with the regime switching mechanism affecting only the autoregressive terms). The subscripts 1 and 2 indicate Regime 1 and Regime 2 respectively.

Table 2: Estimated policy preferences
based on dynamic policy constraints

	parameters	Model A		Model B		Model C		Model D	
		UK	EMU	UK	EMU	UK	EMU	UK	EMU
3 variables	λ_1	97%	98%	99%	99%	99%	12%	99%	99%
	λ_2	25%	17%	99%	99%	99%	12%	98%	99%
4 variables	λ_1	99%	60%	99%	99%	40%	33%	22%	99%
	λ_2	9%	26%	91%	99%	40%	24%	9%	99%

Notes: the table depict the values of the γ and λ parameters for the trivariate and quadrivariate variants of the four models namely Model A (the most flexible one), Model B (with the regime switching mechanism affecting only the intercepts), Model C (with the regime switching mechanism affecting only the variances), and Model D (with the regime switching mechanism affecting only the autoregressive terms). The subscripts 1 and 2 indicate Regime 1 and Regime 2 respectively.

6 Appendix

6.1 Derivation of Optimal Policy Preferences for the Static Model

The combination of the quadratic loss function, equation (1), and the linear constraints, equations (2) and (3), yields a linear reaction function, as in equation (22):

$$i_t = ad_t + bs_t \tag{22}$$

Substituting this optimal policy relationship, equation (22), into equations (2) and (3), we obtain the respective variances σ_y^2 and σ_π^2. Thus, we can write (1) in terms of σ_y^2 and σ_π^2. Then minimization of (1) yields:

$$a = 1 \tag{23}$$

and

$$b = \frac{\lambda(\gamma - \theta) - \gamma}{\lambda(1 - \gamma^2) + \gamma^2} \tag{24}$$

Substituting (23) and (24) into σ_y^2 and σ_π^2 , it is easy to show that the ratio σ_y^2/σ_π^2 is a function of the policy preferences λ, and of the inverse of the slope of the supply curve γ, as in equation (25):

$$\frac{\sigma_y^2}{\sigma_\pi^2} = [\frac{\lambda}{\gamma(1 - \lambda)}]^2 \tag{25}$$

Using the unconditional values of σ_π^2 and σ_y^2 and the estimated value of γ, we can infer the policy preference parameter λ. Equation (25) has the property that for $\lambda = 0$ (the central bank only cares about output-gap variability), $\sigma_y^2/\sigma_\pi^2 = 0$. Likewise, for $\lambda = 1$ (the central bank only cares about inflation variability), $\sigma_y^2/\sigma_\pi^2 = \infty$. We can trace out the entire output-inflation variability frontier by allowing λ to vary between 0 and 1.

There is empirical evidence (Hamilton and Lin, 1996; Ang and Bekaert, 1998) that macroeconomic variables follow a regime switching process. Thus, we can also extent the loss function (1) to account for a state-dependent Philips curve:[37]

$$E_t[L_t|S_t, \Omega_t] = p_t L_e + (1 - p_t)L_R \tag{26}$$
$$E_t[L_t|S_t, \Omega_t] = p_t[\lambda_e \pi^2 + (1 - \lambda_e)y_t^2] + (1 - p_t)[\lambda_R \pi^2 + (1 - \lambda_R)y_t^2] \tag{27}$$

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[37] For an analysis of changing monetary policy objectives see Debortoli and Nunes (2008).

subject to (28) and (29):

$$y_t = \gamma_{S_t}(i_t - d_t(S_t)) + s_t(S_t) \tag{28}$$

$$\pi_t = -(i_t - d_t(S_t)) - \theta s_t(S_t) \tag{29}$$

where Ω_t is the information set available at time t; S_t is an unobserved state variable at time t, p_t indicates the probability for given Ω_t, S_t is in expansion (i.e. $P(S = e|\Omega_t)$, where the subscripts e and R indicate that the relevant variables are in expansion and recession respectively. In line with the linear model we can show the optimal policy frontier in a state-dependant format, as in equation (30):

$$\frac{\sigma_y^2}{\sigma_\pi^2} = \left[\frac{\lambda_{S_t}}{\gamma_{S_t}(\lambda_{S_t} - 1)} \right]^2 \tag{30}$$

6.2   Bootstrapping

The procedure consists of five steps:

1) **Create a history for the unobserved state** S_t. This can be done recursively using the estimation of transition probability matrix P. At each point of time we draw random number from the uniform distribution [0,1] and compare it with the estimated transition probability to determine whether there is regime switching.

2) **Create history for the endogenous variables**. This is done recursively on the basis of estimated models presented in (17)-(21). All parameters are replaced by their estimated values and residuals are drawn from a standard normal distribution $u_t \tilde{} N(0, I_n)$. The different models are then estimated recursively using the artificial hidden state S_t generated above.

3) **Estimation of MS VAR**. Estimate a MS VAR using the artificial data generated in step one and two. Estimation gives bootstrapping estimates of parameters presented in models (17)-(21).

4) **Identification.** Impose the same identifying restrictions on the artificial data as those imposed on the actual data. This step provides bootstrapping estimates of the structural parameters.

5) **Calculate the bootstrapping estimates of the response vector**. Compute the impulse response by substituting the bootstrapping estimates of impulse and autoregressive matrices into the impulse response functions.