Four Essays on Markov-Switching DSGE and Markov-Switching VAR Models

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Four Essays on Markov-Switching DSGE and Markov-Switching VAR Models

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Introduction

The global financial crisis has had profound effects on macroeconomics. It highlighted a magnitude of challenges for the profession. On the one hand, the turmoil emphasized the absence of important characteristics in standard models. On the other hand, the sheer magnitude of the shocks, combined with policy changes, unconventional measures, and new regulations, induced a shift in many macroeconomic variables. These structural breaks, along with the breakdown of standard transmission mechanisms and newly binding constraints, accentuated the importance of non-linearities in macroeconomic models. While non-linear models were not uncommon before, the arsenal of many macroeconomists was dominated by linearised general equilibrium models, Vector Autoregressive Models (VARs), and Error Correction models.

Consequently, the workhorse modelling technique — DSGE modelling — was the primary candidate in need to adapt to the new environment. A multitude of new methods and additions were introduced: partially binding constraints to tackle the zero lower bound, higher order perturbations to approximate wider area around a steady state, transmissions between several steady states, and time-varying parameters, either gradual or sudden, to reflect the new state of the system.

The first half of this thesis falls into this last category, as it examines the effects of rare events such as financial and currency crises through the lens of regime shifting DSGE models. By introducing non-linearities in the form of time-varying parameters that follow a stochastic process, these models show how similar shocks may have different effects on the economy, since agents may react otherwise even under similar circumstances simply due to a different state of the economy.

This is achieved through a novel class of DSGE models — Markov-switching DSGE (MS-DSGE) that aim at capturing the aforementioned non-linearities. These models assume that the economy may take a number of different states, each associated with a set of parameters. In every representation, the relationships between macroeconomic variables are given; however, the economy is allowed to transition between these regimes following a stochastic Markov process. Therefore, even similar shocks may have different effects across the states of the economy. Furthermore, the economic agents are aware that such transitions may occur and take this into account when making their decisions, which introduces further non-linearities in the form of precautionary behaviour.

The introductory chapter presents a small open economy (SOE) model for the Estonian economy, which has had a fixed exchange rate regime (FER) for over two decades. The peg was in the form of a currency board — a special form of a FER where the base money is fully covered by foreign reserves, eliminating the option of the central bank to act as a "lender of last resort". Under the peg, domestic interest rates are expected to converge to the rates of the foreign currency, due to the unlimited convertibility of bills.

Empirically, however, the rates are never a simple identity as it is often assumed in the standard DSGE literature. It is evident from the data that a substantial spread may exist as a consequence of problems in the banking sector or the exchange rate system. This spread may have substantial effects on the economy through abnormally high interest rates.

Therefore, in this model the spread is modelled explicitly and further examined from two perspectives. On the one hand, it may arise from endogenous factors, such as through the international financial position of the country. An indebted country might be demanded a premium when issuing more debt. On the other hand, it may also arise from exogenous factors, such as a financial or currency crisis. Were the economy in financial distress, even small shocks could be amplified and much more pronounced. These features are added by modelling stochastic volatility of the interest rate spread in a regime switching framework. While the standard model would average out periods with abnormally high rates and times with low interest rates, the Markov-switching extension is aligned with the data. The model is estimated with Bayesian techniques. The main findings are that financial shocks play a minor role when the banking sector is stable, whereas in the other case these shocks are large and potentially detrimental to the economy, suggesting how important the credibility of the exchange rate system may be.

The second chapter of this thesis, titled "The regime-dependent evolution of credibility: A fresh look at Hong Kong's linked exchange rate system", builds on that very issue. How important can the effects of loss of credibility be? It estimates a model for the Hong Kong economy, which has had a currency board for almost three decades. This is one of the longest running FER systems, and it has had its share of speculative attacks over the years. If the traders assume that the currency board will not hold, they take positions against it that are shaped by their expectations, whether the currency would appreciate or depreciate following the abandonment of the peg. The pressure on the spot markets induces a premium on the interest rates through the exchange rate parity. Thus, spreads between foreign and domestic interest rates can be positive, even if the financial system is under no scrutiny. Therefore, we can judge the perceived credibility of the currency board by incorporating financial information in the form of the interest and spot rates. We estimate a structural MS-DSGE model and quantify the effects of loss of credibility of the system. Applying the same framework developed for the previous work, we can estimate the size of the shocks driving the interest rate differential. The main finding is that monetary shocks are amplified and may be up to five times as large if the credibility of the board is put into question when compared to a stable FER, which indicates the importance of tackling currency crises swiftly.

The second half of this thesis takes a different approach. It moves away from structural modelling and ventures into the empirical realm of data-driven models, where non-linearities are once more introduced by means of time-varying parameters. Chapter three, titled "The credibility of Hong Kong's currency board system: Looking through the prism of MS-VAR models with time-varying transition probabilities", is a natural continuation of the issue of credibility by addressing a limitation of the MS-DSGE models. Due to their complexity, the probabilities governing the switching parameters have to be constant. This drawback has yet to be resolved in the literature and imposes a serious limitation in scenarios where self-fulfilling expectations fuel the crises. Believing that a regime change may be near could very well influence the likelihood of a shift. This calls for endogenising the transition probabilities between states, which can be achieved in a Markov-switching VAR framework (MS-VAR). The advantage of this setup is that one can pose a set of questions: What captures a loss of credibility in a system? Which are the trigger variables? Does the damage to the confidence in the exchange rate regime stem from fears of the global financial market's or is it solely coming from domestic volatility? In this chapter, we construct a conditional volatility index for Hong Kong and show that uncertainty on the domestic stock markets, as well as the swings of the foreign exchange market for domestic currency, have predictive power over the investor's confidence. Moreover, global uncertainty indicators remain uninformative.

The final chapter on non-linearities in macroeconomics retains the spirit of time varying parameters in Markov-switching models, yet ventures away from the SOE setting of the previous sections. It is titled "Modelling the time variation in Euro area lending spreads" and investigates the apparent divergence of lending rates across the Eurozone in recent years. Governed by common monetary policy, European interest rates exhibited similar trends before and even during the financial crisis, but developed rather peculiarly after 2011. Italy, Spain, Portugal, and Ireland experienced surges in their lending rates, while the policy rate was near zero levels — the transmission of monetary policy has been impaired. While the breakdown in the interest rate pass-through has already been documented in the literature, very little has been found regarding its triggers. This chapter builds an MS-VAR model with time-varying transition probabilities and applies it to the lending rates of Italy, Spain, Ireland, and Portugal relative to Germany's. Under the assumption of no breakdown of the interest rate pass-through, the interest rate differential should react similarly following a common monetary policy shock. By introducing two regimes and endogenous transition probabilities, the model captures the heterogeneity and country specifics of the member states. We find that global risk factors have contributed to higher lending rates in Italy and Spain, and that problems in the banking sector further explain the impairment in Spain, whereas fiscal problems and contagion effects have contributed in Italy and Ireland. We also find that the ECB's unconventional monetary policy announcements have had temporary positive effects in Italy. Due to the zero lower bound, these findings are amplified if EONIA is used as a measure of the policy rate. For Portugal, we do not detect any changes in the pass-through.

1

Financial crises and time-varying risk premia: A Markov-switching DSGE model for Estonia

A key factor in a currency board mechanism is the inherent link between the interest rates of the pegged currency and the foreign rates. While in theory the rates should converge and eventually become identical, in practice they are not always equal. A multitude of factors could influence investor confidence, which forms pressure on the spot markets. For example, the country's financial position, agents' expectations and speculations against the board, or a partial financial collapse can contribute to a persistent interest rate differential. The literature on exchange rate pegs largely ignores this issue. In DSGE models, in absence of money, the mechanism is simulated using a short-cut by closing the exchange rate channel. This leads to a one-to-one relationship between domestic and foreign interest rates [Galí and Monacelli (2005)]. This setup, however, is at odds with empirical evidence. A prime example is the Estonian economy. It has had its former currency, the kroon, first pegged to the German mark and then to the Euro up until 2011 when it joined the European monetary union. Throughout this period the economy has had a multitude of internal and external financial shocks such as banking and financial crises. Figure 1.1 shows the main three-month interbank rate of Estonia, the TALIBOR, introduced in 1996, along with its European counterpart LIBOR.

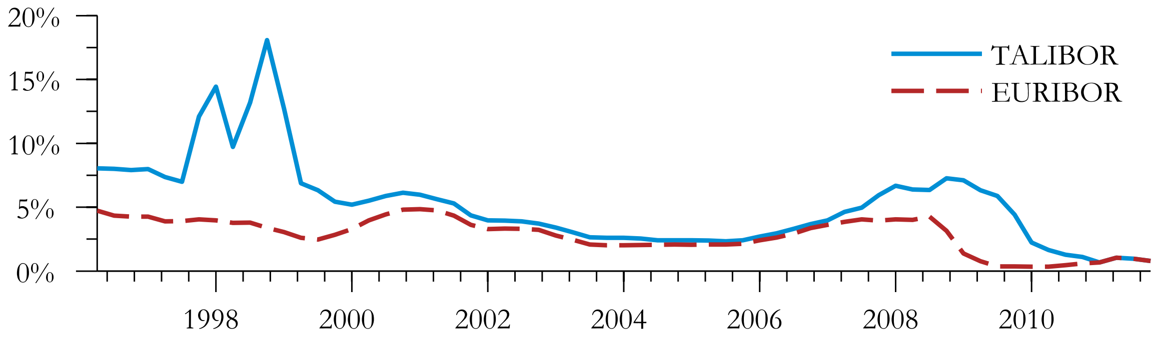


Figure 1.1: *TALIBOR and EURIBOR, annualized three-month interbank Estonian and European interest rates from 1996 to 2012.*

It is evident that for prolonged periods the two rates have been close to an identity, yet have also had times with a fair share of positive interest rate differential. 1997 saw the onset of the Asian crisis that spread to Russia in 1998. Through exposure to Russian assets and investments the Estonian economy experienced an interest rate surge and a credit crunch, which turned into a full-fledged domestic banking crisis that had long-lasting effects up until 2001. The second significant spread is associated with the global financial turmoil, rising sharply in the third quarter of 2008 and lasting until the introduction of the euro in 2011.

Since the devaluation option is relinquished under a currency board, the economy is more sensitive to financial shocks and macroeconomic variables may react differently to economic disturbances. Chapter one builds a DSGE model for the Estonian economy based on Justiniano and Preston (2010) that departs from the literature by deriving the domestic interest rate not only as a function of its foreign counterpart, but also as a function of two additional components.[1] The first one is an endogenous component, which can be interpreted as "debt sensitivity". If domestic agents are heavy borrowers, the spread opens up and it becomes more costly to borrow further. This allows for an endogenous discrepancy between the interest rates. The second component, an external risk premium shock, aims to capture the exogenous part of the spread.

The time-variation present in the development of the interest rates is modelled by means of Markov-switching. The main implications are that a strong currency board helps to stabilize the economy by mitigating the effects of financial shocks. However, a strained mechanism amplifies the financial

[1]The idea is based on Benigno (2001) and Schmitt-Grohé and Uribe (2003), who introduce it in a floating exchange rate framework and Gelain and Kulikov (2009), who estimate a standard DSGE model for Estonia.

disturbances during economic hardship, which puts additional pressure on the economy under distress.[2] These results are based on Bayesian estimation of a Markov-switching DSGE model (MS-DSGE) for the Estonian economy. In contrast, a standard linear DSGE model cannot capture these particular features of a currency board.

The chapter is organised as follows. The next section presents the baseline theoretical model and Section 1.2 introduces the Markov-switching extension and deals with its solution and estimation. Section 1.3 discusses the main findings and Section 1.4 presents alternative specifications for robustness purposes. The final section concludes.

1.1 Model setup

The baseline DSGE model is based on Justiniano and Preston (2010): it features a SOE a lá Monacelli (2005) with incomplete markets, hybrid inflation dynamics, and a multitude of structural shocks. To accommodate the currency board the model is closed via one of the methods outlined in Schmitt-Grohé and Uribe (2003), namely, through the exchange rate channel.

On the demand side, consumers maximize utility by choosing the optimal allocation of consumption and labour, subject to a budget constraint:

$$E_0 \sum_{t=0}^{\infty} \beta^t \vartheta_t \left\{ \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right\}, \tag{1.1}$$

where C_t denotes consumption — a bundle of domestic and foreign goods, N_t denotes labour, and the utility is subject to preference shocks ϑ_t. The parameters β, σ, and φ denote the discount factor, the risk-aversion coefficient, and the Frisch elasticity of labour supply, respectively.

Apart from consuming, the economic agents can invest their income in either domestic bonds B_t or foreign bonds B_t^*, that are Arrow-Debrew securities.[3] The foreign bonds are purchased abroad and denominated in domestic currency through the bilateral exchange rate $\mathcal{E}_t$. The individuals finance their expenditures through several channels. They own firms, which either produce goods for domestic and foreign consumption, or import goods from abroad. Thus, the total income at time t comprises the wage $W_t N_t$, the profits of domestic producers $\Pi_{H,t}$ and those of importers $\Pi_{F,t}$, and the returns on domestic and foreign bonds from the previous period, B_{t-1} and $\mathcal{E}_t B_{t-1}^*$

[2]The model presents an alternative method to Justiniano and Primiceri (2008) in dealing with time-variation in the volatility of macroeconomic shocks.

[3]Following the convention of the open-economy literature the foreign variables are denoted by an asterisk (*) and logs of the variables — with lower-case letters.

respectively. Denoting the CPI by P_t, the formal nominal budget constraint is

$$\begin{aligned} P_tC_t + B_t + \mathcal{E}_tB_t^* =& W_tN_t + \Pi_{H,t} + \Pi_{F,t} + ... \\ & + B_{t-1}(1+i_{t-1}) + \mathcal{E}_tB_{t-1}^*(1+i_{t-1}^*)\Phi(D_t,\phi_t). \end{aligned} \tag{1.2}$$

Domestic bonds pay a nominal return $(1+i_t)$ and foreign bonds are remunerated with an interest $(1+i_t^*)$ and augmented by a debt elastic risk premium $\Phi(D_t,\phi_t)$, which is given by

$$\Phi(D_t,\phi_t) = e^{-\chi(D_t+\phi_t)} \quad \text{with} \quad D_t = \frac{\mathcal{E}_tB_{t-1}^*}{\bar{Y}P_{t-1}}. \tag{1.3}$$

The term $\Phi(D_t,\phi_t)$ is a function adopted from Benigno (2001), Schmitt-Grohé and Uribe (2003), and Gelain and Kulikov (2009). The first argument, D_t, is the real quantity of the consumer's net foreign asset position in relation to steady state output $\bar{Y}$. The intuition behind it is that domestic agents face a cost when participating in world markets. As lenders ($D_t > 0$), the households receive a lower remuneration than the market rate. As borrowers ($D_t < 0$), they pay an endogenous premium over the interest rate. The parameter χ controls the debt sensitivity of the international markets. The second argument, ϕ_t, is an exogenous shock that captures forces outside the model, such as a financial or a currency crisis, that may lead to a risk premium.

Log-linearization of the first order conditions leads to the usual Euler equation and leisure-consumption trade-off:

$$c_t = E_t\{c_{t+1}\} + \frac{1}{\sigma}(E_t\{\pi_{t+1}\} - i_t) + \frac{1}{\sigma}(1-\rho_\vartheta)\vartheta_t, \tag{1.4}$$

where c_t denotes the log of consumption, π_t the inflation rate, and i_t denotes the domestic interest rate.

On the supply side, firms employ labour and maximize profits subject to costs and demand. There exist two types of firms: producers and importers. Producers' prices are determined in a hybrid manner — in every period a share of all firms $(1-\delta_H)$ set their price based on expectations about future demand a lá Calvo (1983), while the rest use past information. Denoting the marginal costs by mc_t, the inflation dynamics for domestic goods are given by

$$(1+\beta\delta_H)\pi_{H,t} = \beta E_t\{\pi_{H,t+1}\} + \delta_H\pi_{H,t-1} + \lambda_H mc_t + \mu_{H,t}, \tag{1.5}$$

with $\mu_{H,t}$ being a stable AR(1) process that describes exogenous cost-push shocks. Import firms buy foreign goods at the world market price P_t^* and sell them domestically at $P_{F,t}$. Given the bilateral exchange rate, any discrepancy ψ_t between the two is a deviation from the "law of one price" defined in logs as

$$\psi_t \equiv e_t + p_t^* - p_{F,t}. \tag{1.6}$$

Thus the inflation dynamics of import prices are

$$(1 + \beta\delta_F)\pi_{F,t} = \beta E_t\{\pi_{F,t+1}\} + \delta_F \pi_{F,t-1} + \lambda_F \psi_t + \mu_{F,t}, \tag{1.7}$$

where δ_F and $\mu_{F,t}$ are defined analogously to the producers' case. CPI inflation π_t is a weighted average of domestic and foreign inflation weighted by their respective share, which, in turn, can be interpreted as the openness of the economy α:

$$\pi_t = (1 - \alpha)\pi_{H,t} + \alpha\pi_{F,t}. \tag{1.8}$$

Furthermore, s_t denotes the terms of trade, while the bilateral real exchange rate is given by q_t. In an economy with a floating exchange rate the dynamics of the nominal exchange rate are determined by the dynamics of the real exchange rate and the inflation rates. In mathematical terms this means

$$\triangle e_t = e_t - e_{t-1} = q_t - q_{t-1} + \pi_t - \pi_t^*. \tag{1.9}$$

Similarly, the uncovered interest rate parity (UIP) condition under incomplete asset markets is

$$(i_t - E_t\{\pi_{t+1}\}) - (i_t^* - E_t\{\pi_{t+1}^*\}) = \triangle e_t - \chi d_t - \phi_t, \tag{1.10}$$

where d_t is a log-linear approximation of D_t around the steady state. In the context of the SOE literature with floating exchange rate [Kollmann (2002), Schmitt-Grohé and Uribe (2003), Justiniano and Preston (2010)], d_t and ϕ_t can be interpreted as deviations form the interest rate parity [Benigno (2001), p.12]. Under flexible exchange rates, the model would be closed by choosing a monetary policy rule that pins down the interest rate i_t. However, in the fixed exchange rate setting the UIP equation will appear as an endogenous monetary policy rule where the domestic interest rate i_t is a function of the foreign interest rate i_t^*, the debt position D_t, and the risk premium shock ϕ_t. Introducing a fixed exchange rate by

$$\triangle e_t = 0, \tag{1.11}$$

and substituting (1.9) in (1.10) leads to the following endogenous interest rate rule:

$$i_t = i_t^* - \chi d_t - \phi_t. \tag{1.12}$$

Here, the risk premium component $(\chi d_t + \phi_t)$ allows for discrepancy between the rates. The debt sensitivity χ is assumed to be strictly positive. If domestic households are net borrowers on the world financial market, they have to pay a premium over the world interest rate $i_t - \chi d_t > i_t^*$, which is determined endogenously. Furthermore, the domestic rate i_t may be subject to an exogenous shock ϕ_t which could also allow for an interest rate differential.

Finally, the evolution of the net foreign asset position, which may be interpreted as the current account, is defined by

$$d_t - \frac{1}{\beta} d_{t-1} = y_t - c_t - \alpha(q_t + \alpha s_t). \tag{1.13}$$

It follows from the optimisation problem of the agents, which may invest either in domestic bonds B_t or foreign bonds B_t^*, yielding an Euler equation for d_t.

The rest of the world is modelled as a collection of AR(1) processes for foreign output y_t^*, foreign inflation π_t^*, and foreign interest rate i_r^* as in Lubik and Schorfheide (2007) and Chen and Macdonald (2012). Thus, in total there are eight exogenous variables, governed by eight innovations: technology ε_t^a, preferences ε_t^ϑ, domestic cost-push shock $\varepsilon_t^{\mu_H}$, import cost-push shock $\varepsilon_t^{\mu_F}$, risk premium shock ε_t^ϕ, world output shock $\varepsilon_t^{y^*}$, world cost-push shock $\varepsilon_t^{\pi^*}$, and world monetary policy shock $\varepsilon_t^{i^*}$:

$$\begin{aligned}
a_t &= \rho_a a_{t-1} + \varepsilon_t^a && \text{with} \quad \varepsilon_t^a \sim N(0, \sigma_a^2), && (1.14)\\
\vartheta_t &= \rho_\vartheta \vartheta_{t-1} + \varepsilon_t^\vartheta && \text{with} \quad \varepsilon_t^\vartheta \sim N(0, \sigma_\vartheta^2), && (1.15)\\
\mu_{H,t} &= \rho_{\mu_H} \mu_{H,t-1} + \varepsilon_t^{\mu_H} && \text{with} \quad \varepsilon_t^{\mu_H} \sim N(0, \sigma_{\mu_H}^2), && (1.16)\\
\mu_{F,t} &= \rho_{\mu_F} \mu_{F,t-1} + \varepsilon_t^{\mu_F} && \text{with} \quad \varepsilon_t^{\mu_F} \sim N(0, \sigma_{\mu_F}^2), && (1.17)\\
\phi_t &= \rho_\phi \phi_{t-1} + \varepsilon_t^\phi && \text{with} \quad \varepsilon_t^\phi \sim N(0, \sigma_\phi^2), && (1.18)\\
y_t^* &= c_{y^*} y_{t-1}^* + \varepsilon_t^{y^*} && \text{with} \quad \varepsilon_t^{y^*} \sim N(0, \sigma_{y^*}^2), && (1.19)\\
\pi_t^* &= c_{\pi^*} \pi_{t-1}^* + \varepsilon_t^{\pi^*} && \text{with} \quad \varepsilon_t^{\pi^*} \sim N(0, \sigma_{\pi^*}^2), && (1.20)\\
i_t^* &= c_{i^*} i_{t-1}^* + \varepsilon_t^{i^*} && \text{with} \quad \varepsilon_t^{i^*} \sim N(0, \sigma_{i^*}^2). && (1.21)
\end{aligned}$$

The main model consists of equations (1.4) through (1.21) and it will be taken as the baseline scenario $\mathcal{M}_1$.[4] The next section deals with the Markov-switching extension.

1.2 The MS-DSGE model

The time variation in the interest rate risk premium is modelled by the means of stochastic volatility. Equation (1.18) is augmented with a regime-dependent variance term $\sigma_\phi^2(s_t)$ under the assumption

[4] A detailed list of the equations can be found in Appendix A.1.

that the state parameter s_t can take two distinct values $s_t = \{1, 2\}$:

$$\phi_t = \rho_\phi \phi_{t-1} + \varepsilon_t^\phi \quad \text{with} \quad \varepsilon_t^\phi \sim N(0, \sigma_\phi^2(s_t)). \tag{1.22}$$

The transition between the regimes is governed by the probability matrix

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \tag{1.23}$$

where $p_{ij} = Prob(s_{t+1} = j | s_t = i)$ is the transition probability from state i to state j.[5] The MS-DSGE model, $\mathcal{M}_2$, can be cast in a state-space form by collecting all endogenous variables in a vector $X := [c, y, i, q, s, \psi, \pi, \pi_H, \pi_F, d, mc]'$ and all exogenous variables in a vector $Z = [\mu_H, \mu_F, \phi, y^*, \pi^*, i^*]'$:

$$B_1(s_t)X_t = E_t\{A_1(s_t, s_{t+1})X_{t+1}\} + B_2(s_t)X_{t-1} + C_1(s_t)Z_t. \tag{1.24}$$

$$Z_t = R(s_t)Z_{t-1} + \epsilon_t \quad \text{with} \quad \epsilon_t \sim N(0, \Sigma(s_t)), \tag{1.25}$$

where the matrices $A_1(s_t), B_1(s_t), B_2(s_t), C_1(s_t)$ and $R(s_t)$ are functions of the model parameters. The solution of this system is presented next.

1.2.1 Solution method

A large body of the MS-DSGE literature is devoted to the technical aspects of solving the state-space system, e.g. Farmer *et al.* (2008), Farmer *et al.* (2011), Foerster *et al.* (2013), Miah (2014), and Cho (2015). Familiar DSGE solution algorithms of Sims (2002) or Schmitt-Grohé and Uribe (2004) are not applicable. For example, a model where each state has a unique and stable equilibrium, yet the Markov-switching system jumps "too often" between the regimes could become unstable. This is referred to as "stability in the second moments" and in contrast to non-switching models, stability in the first moments of the Markov-switching model does not imply stability in the second moments. This is a critical assumption for the standard solution techniques. Consequently, the available solution concepts for MS-DSGE models are mainly centred around stability in the second moments. Davig and Leeper (2007a) show that if the shocks have bounded variance, a stable solution to the Markov-switching system might exist. Farmer *et al.* (2011) and Cho (2015) deal with the concept of

[5]The literature does not follow a single convention. Hamilton (1989) and Kim and Nelson (1999), for example, use $p_{ij} = Prob(s_{t+1} = i | s_t = j)$, so that p_{21} is the transition probability from state 1 to state 2.

mean-square stability with unbounded shocks. The algorithm of Farmer *et al.* (2011) utilises the idea of a minimum state variable solution (MSV) in the sense of McCallum (1983). The method would find all existing solutions, yet the question remains — how to choose among them? Farmer *et al.* (2011) propose a maximum likelihood test and suggest choosing the solution with the lowest test statistic. Cho (2015), on the other hand, derives conditions for determinacy and provides rationale why only one of the MSV solutions is relevant to the economic problems at hand by introducing the so-called "non-bubble condition", which rules out all but one possible solutions, provided it exists.[6] Cho (2015) shows that for several models both methods find the exact same solution. Hence, this chapter adopts the solution strategy of Cho (2015).[7] The method yields the following regime-dependent solution:

$$X_t = \Omega^*(s_t)X_{t-1} + \Gamma^*(s_t)Z_t. \tag{1.26}$$

1.2.2 Data

The model features eleven endogenous and eight exogenous variables in total. For the estimation stage, the solution to the state-space form (1.24) is taken as a transitional equation in conjunction with a measurement equation that relates the model variables to a set of observables denoted by Y_t, namely:

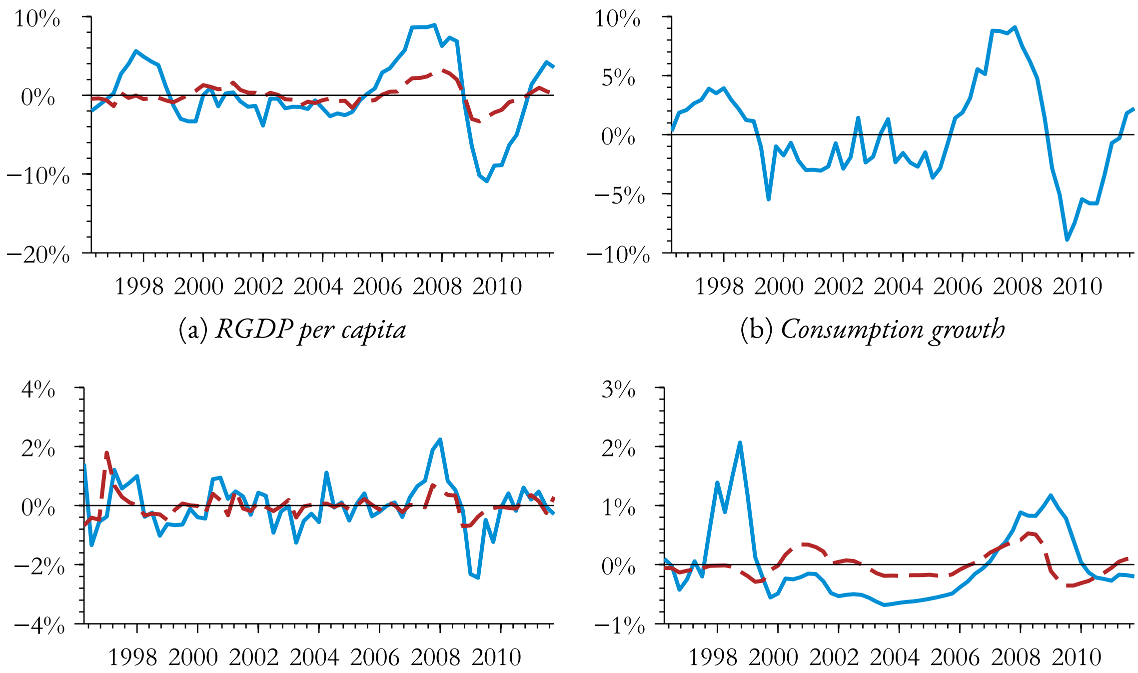
$$Y_t = HX_t. \tag{1.27}$$

With eight exogenous variables up to eight observables are allowed in the likelihood function without the need to introduce measurement errors. For the main models $\mathcal{M}_1$ and $\mathcal{M}_2$ the vector of observables Y_t consists of: Estonian real output per capita, real per capita consumption, inflation and the nominal interest rate, European per capita real output, inflation, and interest rate. Real GDP and real consumption per capita are derived by dividing the original series by the active population. Labour is measured by employment among the individuals from 16 to 64 years of age. Inflation rate is based on quarterly HICP data. The nominal interest rate for Estonia is the three-month TALIBOR and for Europe — the 3-month EURIBOR, both converted to quarterly frequency. The data has been collected from Eurostat. The series are expressed as percentage deviations from trend, where the detrending has been carried out by an HP filter with $\lambda = 1600$.[8]

[6] A technical discussion of the solution method can be found in Appendix A.2.

[7] Due to having the switching component in the volatility, the steady state is the same for each regime. This avoids issues that are yet to be resolved in the literature, such as transitions between different steady states.

[8] Both TALIBOR and EURIBOR exhibit non-stationary behaviour. Nevertheless detrending of the interest rate is not a standard practice in the literature. Therefore, several models are estimated, with and without detrending, and



(a) *RGDP per capita* (b) *Consumption growth*

(c) *Inflation* (d) *TALIBOR and EURIBOR*

Figure 1.2: *Detrended and seasonally adjusted quarterly data. Blue line (—) is Estonian data, red line (—) is European data. Source: Eurostat.*

1.2.3 Estimation procedure

Model estimation is carried out by Bayesian methods — assuming a prior on the parameters and combining it with the likelihood function yields the posterior distribution, which is simulated through a Markov-Chain Monte Carlo (MCMC) algorithm. Similar to the solution difficulties, estimation of MS-DSGE models is not straightforward either. This is due to the likelihood function being dependent on the history of the states. Therefore, the Kalman filter is inapplicable, since the number of possible paths grows exponentially with the number of observations. Two approaches are taken in the literature to solve this problem. One possibility is to construct the likelihood function through Gibbs sampling [Kim and Nelson (1999) ch. 9, Bianchi (2012)]. The other option, which is pursued here, is to use Kim's Filter — a combination of Kalman and Hamilton filters, where the possible paths are collapsed through averaging at each step [Kim and Nelson (1999), ch. 5]. This keeps the computation of the likelihood tractable. Let θ collect all the parameters of the model, S be the history of the realised states, and Y — the data matrix, then the posterior distribution

the results remain qualitatively the same. In the main section the model is estimated with an HP-filtered series. The robustness section 1.4 discusses further models.

$p(\theta, P, S|Y)$ can be evaluated using Bayes' rule:

$$p(\theta, P, S|Y) = \frac{p(Y\,|\theta, P, S)\; p(S\,|P)\; p(\theta, P)}{\int p(Y\,|\theta, P, S)\; p(S\,|P)\; p(P, \theta)\; d(\theta, P, S)}. \tag{1.28}$$

$p(Y\,|\theta, P, S)$ is the likelihood of the data conditional on the states, the parameters θ, and the Markovian probability matrix P. $p(S|P)$ is the density of the states conditional on P and $p(\theta, P)$ is the marginal density of the parameters and the transition probabilities. The denominator is the marginal density $p(Y, \theta, P, S)$ given by the law of total probability.
Farmer *et al.* (2009) point out that the posterior distribution might be highly non-Gaussian and the mean values of this distribution may actually lie in a region where the support is flat. Hence, it is of interest to search for the posterior mode rather than the mean. This task, however, may be computationally intensive, as the posterior is often multi-modal and the optimization algorithm may get stuck at a local mode. Farmer *et al.* (2009) propose a specific block-wise optimization algorithm to deal with the problem, while Sargent *et al.* (2009) use a Gibbs sampling version of Chris Sims' CSMINWEL routine, followed by a combination of the BFGS Quasi-Newton algorithm and Fortran's IMSL routine. Nevertheless, Liu and Mumtaz (2011) and Chen and Macdonald (2012) report successful usage of CSMINWEL alone. For the estimation at hand, Sims' routine faced particular difficulties finding the global mode and often got stuck at local maxima with a high likelihood value (as the procedure is actually a minimization algorithm, high values are undesirable). For maximization of the likelihood function the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) has been employed, particularly its extension for DSGE models by Martin Andreasen [Andreasen (2008)]. The procedure is based on evolution strategy algorithms, which do not calculate gradients or approximate numerical derivatives. This is a considerable advantage when the target functions have discontinuities, ridges, or local optima. [Hansen (2006)].

1.2.4 Prior information

The choice of priors is of primary importance when it comes to Bayesian estimation. Unfortunately, only few Estonian micro-studies exist. Gelain and Kulikov (2009) estimate a medium-sized DSGE model, where most priors are, in turn, taken from Smets and Wouters (2003). Here, the parameters are set at standard values for the SOE literature borrowing from Smets and Wouters (2003), Gelain and Kulikov (2009), and Justiniano and Preston (2010). Table 1.1 summarises the first two moments of the parameters.

	Distribution	Mean	Std.Dev.		Distribution	Mean	Std.Dev.
p_{11}	$Beta$	0.9	0.1	ρ_{μ_H}	$Beta$	0.7	0.1
p_{22}	$Beta$	0.9	0.1	ρ_ν	$Beta$	0.7	0.1
β	PM	0.995	—	ρ_ϕ	$Beta$	0.7	0.1
φ	$Gamma$	2	0.25	c_{y^*}	$Beta$	0.85	0.1
θ_H	$Beta$	0.75	0.1	c_{π^*}	$Beta$	0.85	0.1
θ_F	$Beta$	0.5	0.1	c_{i^*}	$Beta$	0.85	0.1
α	PM	0.5	—	σ_{μ_F}	$IGamma$	1	∞
σ	$Gamma$	1	1	σ_{μ_H}	$IGamma$	1	∞
η	$Gamma$	2	0.25	σ_a	$IGamma$	1	∞
δ_H	$Beta$	0.5	0.15	σ_ν	$IGamma$	1	∞
δ_F	$Beta$	0.5	0.15	σ_ϕ	$IGamma$	1	∞
χ	$Gamma$	0.01	0.01	σ_{y^*}	$IGamma$	1	∞
ρ_a	$Beta$	0.7	0.1	σ_{π^*}	$IGamma$	1	∞
ρ_{μ_F}	$Beta$	0.7	0.1	σ_{i^*}	$IGamma$	1	∞

Table 1.1: *Prior distributions and basic moments.* PM *denotes point mass and* $IGamma$ *— inverse Gamma.*

The discount factor β is fixed at 0.995, implying an annual interest rate of about 4%; the coefficient of openness α is set at 0.5. The inverse elasticity of substitution $1/\sigma$ is set to unity. Frisch elasticity of labour supply φ and the elasticity between home and foreign goods η have means of 2 and a standard deviation of 0.25, following Gelain and Kulikov (2009). The Calvo parameter for domestic prices θ_H is chosen to be 0.75, providing an average duration of price contracts of one year. The share of forward- and backward-looking firms and the debt elasticity χ are taken from Justiniano and Preston (2010). The autoregressive coefficients for the shocks hitting the Estonian economy are set at 0.7 and for the European AR(1) processes at 0.85, as in Smets and Wouters (2003). All shocks are of size 1 with an unbounded variance.

Combining the data with the prior and the methods of this section provides the following roadmap for the estimation. The model is solved using an initial set of parameters and the likelihood function is approximated by Kalman's filter for $\mathcal{M}_1$ or by Kim's filter for $\mathcal{M}_2$. The posterior density is then minimized to find the posterior mode using the CMA-ES algorithm with a cut-off criterion for the minimization at 10^{-16}. Since the evolutionary algorithm uses the variance-covariance matrix and evaluates a random number of possible paths at each point, it is less dependent on initial values. The minimization algorithm always converged to the same mode. Once a minimum is obtained, a MCMC procedure is initiated with the inverse Hessian estimated at the posterior mode. Altogether 4 blocks of 375 000 draws are estimated, with the first 75 000 discarded and every 30-th draw afterwards saved for a total volume of 10 000 observations per block. The Metropolis-Hastings constant is tuned to attain an acceptance ratio of roughly 20%. Each MCMC block converged to the same mean.

	Distribution	Prior Mean	$\mathcal{M}_1$	$\mathcal{M}_2 : s_t = 1$	$\mathcal{M}_2 : s_t = 2$
p_{11}	$Beta$	0.900	—	0.936 [0.862, 0.984]	—
p_{22}	$Beta$	0.900	—	0.942 [0.852, 0.993]	—
β	PM	0.995	0.995	0.995	—
φ	$Gamma$	2.000	1.985 [1.608, 2.404]	1.982 [1.598, 2.399]	—
θ_H	$Beta$	0.750	0.910 [0.880, 0.938]	0.912 [0.882, 0.939]	—
θ_F	$Beta$	0.500	0.631 [0.544, 0.717]	0.645 [0.556, 0.733]	—
α	PM	0.500	0.500	0.500	—
σ	$Gamma$	1.000	2.339 [1.371, 3.694]	2.424 [1.434, 3.800]	—
η	$Gamma$	2.000	2.366 [2.011, 2.760]	2.411 [2.062, 2.781]	—
δ_H	$Beta$	0.500	0.215 [0.094, 0.371]	0.217 [0.096, 0.369]	—
δ_F	$Beta$	0.500	0.590 [0.386, 0.786]	0.594 [0.395, 0.788]	—
χ	$Gamma$	0.010	0.028 [0.014, 0.043]	0.017 [0.006, 0.029]	—
ρ_a	$Beta$	0.700	0.698 [0.520, 0.851]	0.703 [0.526, 0.854]	—
ρ_{μ_F}	$Beta$	0.700	0.700 [0.531, 0.847]	0.708 [0.537, 0.853]	—
ρ_{μ_H}	$Beta$	0.700	0.650 [0.480, 0.807]	0.670 [0.499, 0.821]	—
ρ_ν	$Beta$	0.700	0.697 [0.531, 0.842]	0.695 [0.523, 0.841]	—
ρ_ϕ	$Beta$	0.700	0.640 [0.474, 0.789]	0.646 [0.487, 0.792]	—
c_{y^*}	$Beta$	0.850	0.884 [0.790, 0.968]	0.883 [0.786, 0.969]	—
c_{π^*}	$Beta$	0.850	0.545 [0.379, 0.722]	0.548 [0.382, 0.722]	—
c_{i^*}	$Beta$	0.850	0.861 [0.783, 0.933]	0.857 [0.782, 0.925]	—
σ_{μ_F}	$IGamma$	1.000	1.225 [0.857, 1.673]	1.159 [0.799, 1.618]	—
σ_{μ_H}	$IGamma$	1.000	0.458 [0.326, 0.620]	0.425 [0.298, 0.586]	—
σ_a	$IGamma$	1.000	0.855 [0.209, 2.358]	1.060 [0.205, 3.474]	—
σ_ν	$IGamma$	1.000	11.265 [7.040, 17.150]	11.438 [7.154, 17.458]	—
σ_ϕ	$IGamma$	0.800	0.472 [0.406, 0.548]	0.119 [0.090, 0.156]	0.665 [0.533, 0.831]
σ_{y^*}	$IGamma$	1.000	0.684 [0.592, 0.791]	0.685 [0.593, 0.795]	—
σ_{π^*}	$IGamma$	1.000	0.375 [0.321, 0.438]	0.376 [0.321, 0.440]	—
σ_{i^*}	$IGamma$	1.000	0.100 [0.086, 0.116]	0.100 [0.086, 0.116]	—
$\mathbb{M}$:			-430.723	-405.5175	

Table 1.2: *Estimated coefficients at the posterior mean.* $\mathcal{M}_1$*: Model with fixed parameters,* $\mathcal{M}_2$*: MS Model.* $\mathbb{M}$ *denotes the marginal data density estimate. The 95% probability interval is given in brackets.*

1.3 Estimation results

This section lays out the main findings regarding the conventional model $\mathcal{M}_1$ and the MS-DSGE version $\mathcal{M}_2$. At large the parameters are consistent with economic theory. They are aligned with the main results of Gelain and Kulikov (2009) and are representative for a small open economy. Table 1.2 summarises the coefficients.

1.3.1 $\mathcal{M}_1$: A standard DSGE model for Estonia

Beginning with the utility function coefficients, the elasticity of substitution between foreign and home goods η is 2.366, with its posterior density shifted to the right of the prior. This suggests good integration between Estonian and European markets. Indeed, Estonia's exports and imports each have a share of over 50% of GDP. The risk-aversion/inverse elasticity of substitution σ is 2.4, which is a standard value in the absence of capital [Justiniano and Preston (2010)]. Indeed, Gelain and Kulikov (2009) report a value of 1.33 and they do accommodate for capital formation. Since no labour data has been used in the estimation, the Frisch elasticity of labour supply φ is not identified — the posterior density closely overlaps with the prior one at a mean of 2.[9]

Estonia is regarded as a competitive economy and therefore the duration of price contracts θ_H is expected to be low [Randveer and Dabusinskas (2006), Schwab (2011)]. However, the estimate for the Calvo parameter is $\theta_H = 0.9$, which is rather large compared to the literature. It corresponds to price contract duration of over two years. This might be due to weak identification, since the model uses the CPI inflation rate — a composite bundle of domestic and foreign good prices. The HICP series have to identify both θ_H and θ_F. Using the GDP deflator series to approximate inflation, or estimating the model with the terms of trade or with the real exchange rate did not lead to any significant improvement. Nevertheless, as long as CPI inflation is well accounted for, this should not pose a problem. In fact, the simulated model matches the volatility of inflation (see Table 1.3). The duration of price contracts in Europe is estimated around three quarters with $\theta_F = 0.631$, which is similar to the findings in Smets and Wouters (2003).

The values of the autoregressive coefficients match the findings of Gelain and Kulikov (2009), where the prior plays a more important role and the persistence of almost all shocks is around 0.6–0.7. The data seem informative about the volatility of all exogenous variables with the exception of technology. Notably, the volatility of the Estonian structural shocks is higher than that of the European ones,

[9] The prior and posterior distributions for the parameters of $\mathcal{M}_1$ are plotted in the Appendix A.3.

which is an expected feature of smaller economies. The volatility of the risk premium σ_ϕ is estimated at 0.472 and the debt elasticity χ is 0.028. The latter coincides with the value of Gelain and Kulikov (2009), who report a risk premium sensitivity of 0.029. The standard deviation of the risk premium is 0.472, which also is a plausible result: it implies a volatility of the interest rate around 2% on an annual basis. The model scores a marginal data density of $\mathbb{M}_1 = -430.723$, which has been estimated using the Modified Harmonic Mean (MHM) estimator.

Convergence is assessed using both graphical methods and formal tests, following An and Schorfheide (2007). Section A.3 in the Appendix contains the figures and tables for the standard DSGE model $\mathcal{M}_1$. Figure A.1 depicts the prior and posterior densities of $\mathcal{M}_1$'s estimated parameters. Figure A.2 plots the recursive means, while figure A.3 shows the trace plots. All parameters converge within 5000 draws. Table A.1 in Appendix A.3 shows the Raferty-Lewis diagnostics (1.612) and the autocorrelation among the draws. The latter dies out by the 10-th lag for all but the technology and preference shocks. $\mathcal{M}_1$ will be the baseline scenario. The next section presents the Markov-switching extension.

1.3.2 $\mathcal{M}_2$: The Markov-switching case

Model $\mathcal{M}_2$ requires the estimation of three more parameters: p_{11}, p_{22} and $\sigma_\phi(s_t)$. In contrast to $\mathcal{M}_1$, the likelihood value is obtained by Kim's filter. Most of the parameters coincide with the non-switching specification with largely overlapping distributions.[10] Differences are usually in the second or third digit after the decimal, with a few exceptions such as the technology shock volatility parameter.

The maximum likelihood procedure estimates two significantly different coefficients for the risk premium volatility: $\sigma_\phi(1) = 0.119$ and $\sigma_\phi(2) = 0.665$. Both are distinct from the $\mathcal{M}_1$ value of 0.472 [0.406, 0.548], which falls in-between. The high volatility, $\sigma_\phi(2) = 0.665$, translates into a standard deviation of the risk premium component of almost 2.5% annually. Meanwhile, the uncertainty around the low-volatility state is around 11 basis points quarterly, or about half a percentage point annually — only a fifth compared to the high volatility regime.

The probability of being in the high risk premium volatility state is 0.942. This corresponds to roughly 17 quarters or four years on average. The realised states are derived through Hamilton's filter, with Kim's smoothing algorithm employed recursively afterwards to take into account the complete history. The top graph of Figure 1.3 depicts the prevalence of the high volatility state. The

[10] Distribution plots and convergence diagnostics for this specification may be found in Section A.4 of the Appendix.

second regime has been in place from the second quarter of 1997 until the beginning of 2001, and then again for a year during the global financial crisis (2008–2009).

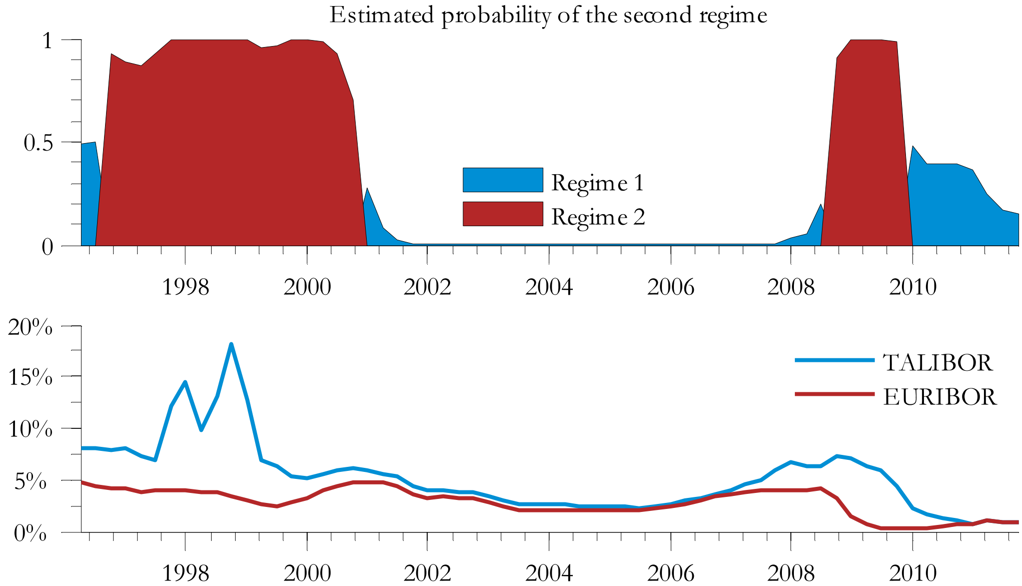


Figure 1.3: *Regime probabilities and interest rates. Top panel: Estimated probability of the high risk premium volatility regime for $\mathcal{M}_2$. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Annualized three-month interbank interest rates.*

The model captures the dynamics of the Estonian interbank interest rate well. The positive differentials between TALIBOR and EURIBOR stand for several important events: a domestic banking and financial crisis, and the global financial turmoil. The interest rate spread between the second quarter of 1997 and 2001 was marked by the Asian and Russian crises and a following banking crisis, which strained the currency board. The former affected investor confidence as the Estonian TALSE index lost over 60% of its value in the third quarter of 1997. Speculations against the currency board emerged and the banking system was put under pressure. The onset of the Russian crisis dealt a huge blow to an already weakened economy. The sharp devaluation of the rouble and exposure to the Russian markets had profound effects on Estonia's economic activity and banking sector. Five out of twelve banks, which held more than 40% of all deposits, experienced heavy distress [Chen *et al.* (2006)]. Between 1996 and 1998 the number of credit institutions went from 15 down to 6. The banks either consolidated, went insolvent or were acquired by large foreign institutions. These events revealed many flaws in the banking sector. As sources of the quake were cited lack of professional know-how, inadequate risk-management, risky portfolios, overexposure to foreign markets, insufficient capital adequacy, weak supervision and ill-practices.

Between the end of 1997 and the beginning of 2002, the central bank (Eesti Pank) took an array of actions to stabilize the banking sector. It introduced a minimum capital requirement, a cap on the amount of loans to a single borrower, and put limits on the allowed foreign exchange exposure. Several laws, such as the Credit Institutions Law and the Law on the Estonian Financial Supervision Agency (EFSA), were amended. The latter came in effect in 2001, while EFSA itself started operations in 2002, which coincides with the return to the first regime predicted by the model.[11]

The global financial crisis met a much stronger banking sector. The 2008 turmoil saw the acquisition of many banks by larger foreign entities, primarily from Sweden, which helped strengthen the sector. No credit institutions went insolvent throughout the downturn. To face any potential runs, Eesti Pank secured an agreement with the Swedish Riskbank for liquidity support that was in place in March-December 2009 [Purfield and Rosenberg (2010)]. As the currency board was in place, the Estonian central bank could not act as a lender of last resort and therefore turned to the parent banks for cooperation in case of liquidity shortage. This is in line with the model's estimation that higher risk was present in the period from 2008Q3 to 2009Q3. The spread between TALIBOR and EURIBOR lasted longer, yet the model identifies that this did not stem from exogenous factors.

1.3.3 Impulse responses

Figure 1.4 shows the impulse responses following a risk premium shock under the standard model $\mathcal{M}_1$ and the two regimes of the main Markov-switching specification $\mathcal{M}_2$. In essence, during stable times the domestic rates do not deviate far from their foreign counterparts as risk premium shocks are small. On the other hand, in stressful times, such as the Estonian banking crisis, the markets and the economy as a whole are much more sensitive to disturbances in the banking sector.

The short run implications of each regime are quite distinct from each other and, as suggested, the static DSGE specification produces a mix of both: it overestimates the effects of shocks to the interest rate during quiet periods and understates the impacts during crises. The reactions of the macroeconomic variables to a shock of the size from the first state are almost negligible. When the currency board is stable, domestic agents have high confidence in the system, which stems in part from the macroeconomic conditions and in part from the reputation of the parent monetary authority. Output and consumption fall only slightly with a fast return to the steady state — in about two quarters. Inflation hardly reacts and so do the terms of trade. Due to the absence of capital in the model, the response of marginal costs is more pronounced. In contrast to the first regime of $\mathcal{M}_2$, $\mathcal{M}_1$ overestimates the fluctuations of the variables. Output and inflation responses overshoot by far the actual responses. The model also suggests worsening of the terms of trade and

[11] For a detailed timeline of the events see Adahl (2002).

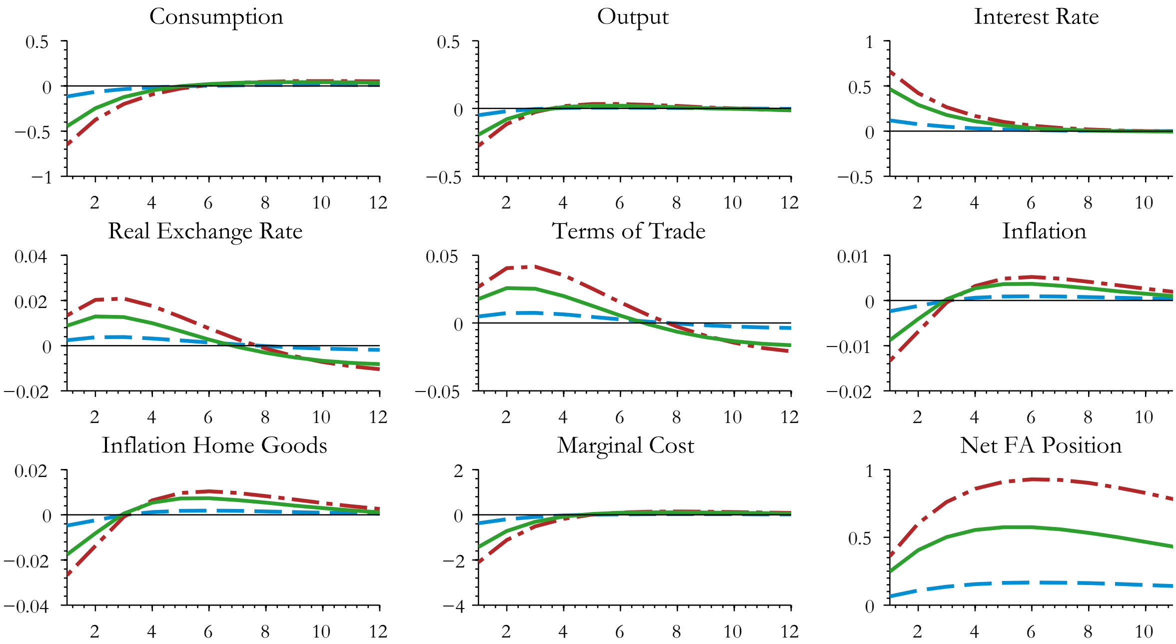


Figure 1.4: *Impulse responses following a risk premium shock for state one* $\sigma_\phi(1)$ *(- -), state two* $\sigma_\phi(2)$ *(-.-), and the non-switching version* $\mathcal{M}_1$ *(—).*

a real exchange rate depreciation after six quarters.

The responses in the high state are more pronounced. High risk premium shocks have long-lasting effects on the economy. Apart from consumption, almost no other variable returns to its steady state level within the first three years. A notable implication of the model is that stronger risk premium shocks lead to cyclical behaviour of many macroeconomic variables. A sharp monetary tightening leads to a decrease in the price level only temporarily — for about three quarters — and is then followed by an increase in inflation. This is an important finding: in a currency board scenario interest rate-related shocks during a crisis not only decrease output, but also put inflationary pressure on the economy. Notably, this result is also a product of the estimated high persistence of domestic price contracts θ_H, so it can be seen as an upper bound. Similar cyclical behaviour is also observed in the terms of trade and the real exchange rate.

The long-run implications of the model are further explored by means of variance decomposition. Consumption is mainly driven by preferences, which is a standard result, especially in the absence of habit formation. About 70% of the variance of consumption is explained by preference shocks. Interest rate shocks play almost no role in the volatility of consumption in the long run, conditional on the first state, yet amount to almost 2% in the second regime. Inflation is mainly driven by foreign price shocks (75%) and then domestic prices (17%), which is not a surprising result for Estonia, considering its trading background. Output volatility is affected by domestic price shocks, while technology shocks do not play an important role. However, the high coefficient of the price stickiness θ_H overestimates the effects of cost-push shocks. It is interesting to note that during normal times, risk premium shocks do not induce any volatility of output (0%), which suggests that the stable currency board can act as a monetary stabilizer in the long run.[12]

Figure 1.5 shows the decomposition of the interest rate series for 12 periods ahead. Its volatility is largely influenced by risk premium shocks (63%) and foreign monetary policy shocks (30%) in the first regime (left panel). However, in the second regime (right panel), it is dominated by the risk premium volatility. While in the first state the effects of the two shocks diminish over time, in the second one, even after five years, risk premium shocks explain up to 80% of the volatility in the series. This illustrates the sensitivity of the interest rate differential to such shocks and their persistence. Hence, in the event of crisis it is important that the authorities act swiftly and step in to calm the markets in order to reduce the risk premium.

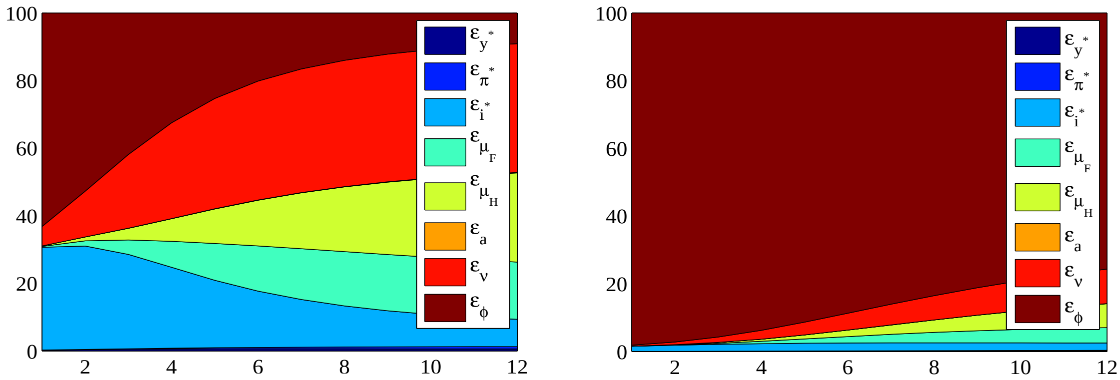


Figure 1.5: *Variance decomposition of the interest rate in state one* $\sigma^2_\phi(1)$ *and state two* $\sigma^2_\phi(2)$.

The model is able to match the volatility of the data. Table 1.3 displays the standard errors of the actual variables and the moments based on 5000 draws from the posterior distribution. In the data output has a standard deviation of 4.5%, while the model would generate a value of 3.5%. Consumption is matched well with an estimated standard error of 4.2% compared to the actual 4.05%. Inflation volatility is also matched and in crisis times the interest rate is estimated to have more than twice the volatility.

[12]The variance decomposition of output, consumption, inflation, and interest rate can be found in Appendix A.5.

	y	c	π	i	y^*	π^*	i^*
data	4.5103	4.0453	0.8323	0.4635	1.3184	0.3754	0.2169
$\mathcal{M}_2$: State 1	3.4937	4.1860	0.8307	0.2480	1.2781	0.4434	0.1710
$\mathcal{M}_2$: State 2	3.5142	4.2666	0.8291	0.6966	1.2705	0.4443	0.1708

Table 1.3: *Actual and model implied second moments of the data based on 5000 simulations.*

1.4 Robustness checks

This section evaluates three additional Markov-switching specifications to test the robustness of the main results. The first one, $\mathcal{M}_3$, allows for regime shifts in the volatilities of all Estonian shocks to ensure that the switching coefficients in $\mathcal{M}_2$ do not pick up other peculiarities of the data. The next model, $\mathcal{M}_4$, deals with the second determinant of the interest rate spread — the debt elasticity χ. It is allowed to switch along with the volatility of the exogenous component σ_ϕ. Finally, $\mathcal{M}_5$ follows a common path in the literature, where the interest rates series are taken in levels. Table 1.5 provides a summary of all models.[13]

$\mathcal{M}_1$:	No regime shifts
$\mathcal{M}_2$:	Switching in the volatility of the risk premium σ^2_ϕ
$\mathcal{M}_3$:	Switching in the volatility in other structural shocks: σ^2_a, σ^2_ϑ, $\sigma^2_{\mu_H}$, $\sigma^2_{\mu_F}$, σ^2_ϕ
$\mathcal{M}_4$:	Switching in σ^2_ϕ and χ
$\mathcal{M}_5$:	Switching in σ^2_ϕ where the interest rate data is not detrended

Table 1.5: *Robustness checks: Additional model specifications.*

1.4.1 $\mathcal{M}_3$: Simultaneous switching in all shocks

In a general equilibrium model, the flexibility of a Markov-switching framework holds a caveat — peculiarities of one time series my propagate through several variables and end up in the additional parameters. Time-variation is a standard feature in macroeconomic and financial data and it might be that any extra parameter acts as a "pressure valve" to the model. If that is the case, allowing more parameters to switch simultaneously would distort the estimates of the risk premium volatility.

[13] Two further robustness checks have been carried out — a linear detrending and a model with a VAR representation. The results are similar across all specifications.

	Distribution	Prior Mean	$\mathcal{M}_1$	$\mathcal{M}_2 : s_t = 1$	$\mathcal{M}_2 : s_t = 2$	$\mathcal{M}_3 : s_t = 1$	$\mathcal{M}_3 : s_t = 2$	$\mathcal{M}_4 : s_t = 1$	$\mathcal{M}_4 : s_t = 2$	$\mathcal{M}_5 : s_t = 1$	$\mathcal{M}_5 : s_t = 2$
p_{11}	$Beta$	0.900	—	0.936 [0.862, 0.984]	—	0.935 [0.848, 0.989]	—	0.929 [0.851, 0.982]	—	0.958 [0.906, 0.991]	—
p_{22}	$Beta$	0.900	—	0.942 [0.852, 0.993]	—	0.937 [0.863, 0.985]	—	0.942 [0.850, 0.993]	—	0.932 [0.858, 0.981]	—
β	PM	0.995	0.995	0.995	—	0.995	—	0.995	—	0.995	—
φ	$Gamma$	2.000	1.985 [1.608, 2.404]	1.982 [1.598, 2.399]	—	1.992 [1.599, 2.422]	—	1.982 [1.601, 2.395]	—	1.990 [1.606, 2.398]	—
θ_H	$Beta$	0.750	0.910 [0.880, 0.938]	0.912 [0.882, 0.939]	—	0.910 [0.879, 0.938]	—	0.913 [0.883, 0.940]	—	0.938 [0.918, 0.955]	—
θ_F	$Beta$	0.500	0.631 [0.544, 0.717]	0.645 [0.556, 0.733]	—	0.655 [0.566, 0.745]	—	0.644 [0.557, 0.730]	—	0.723 [0.642, 0.801]	—
α	PM	0.500	0.500	0.500	—	0.500	—	0.500	—	0.500	—
σ	$Gamma$	1.000	2.339 [1.371, 3.694]	2.424 [1.434, 3.800]	—	2.130 [1.262, 3.377]	—	2.438 [1.454, 3.808]	—	6.750 [4.789, 9.192]	—
η	$Gamma$	2.000	2.366 [2.011, 2.760]	2.411 [2.062, 2.781]	—	2.421 [2.068, 2.816]	—	2.405 [2.046, 2.793]	—	2.259 [1.924, 2.624]	—
δ_H	$Beta$	0.500	0.215 [0.094, 0.371]	0.217 [0.096, 0.369]	—	0.221 [0.100, 0.372]	—	0.216 [0.095, 0.369]	—	0.229 [0.101, 0.385]	—
δ_F	$Beta$	0.500	0.590 [0.386, 0.786]	0.594 [0.395, 0.788]	—	0.539 [0.333, 0.745]	—	0.590 [0.387, 0.788]	—	0.577 [0.372, 0.772]	—
χ	$Gamma$	0.010	0.028 [0.014, 0.043]	0.017 [0.006, 0.029]	—	0.015 [0.006, 0.028]	—	0.014 [0.006, 0.025]	0.024 [0.005, 0.051]	0.025 [0.021, 0.030]	—
ρ_a	$Beta$	0.700	0.698 [0.520, 0.851]	0.703 [0.526, 0.854]	—	0.701 [0.525, 0.854]	—	0.699 [0.524, 0.850]	—	0.700 [0.526, 0.852]	—
ρ_{μ_F}	$Beta$	0.700	0.700 [0.531, 0.847]	0.708 [0.537, 0.853]	—	0.714 [0.555, 0.852]	—	0.706 [0.536, 0.852]	—	0.715 [0.547, 0.858]	—
ρ_{μ_H}	$Beta$	0.700	0.650 [0.480, 0.807]	0.670 [0.499, 0.821]	—	0.660 [0.491, 0.814]	—	0.659 [0.488, 0.816]	—	0.677 [0.509, 0.825]	—
ρ_ν	$Beta$	0.700	0.697 [0.531, 0.842]	0.695 [0.523, 0.841]	—	0.681 [0.507, 0.828]	—	0.693 [0.523, 0.838]	—	0.694 [0.521, 0.840]	—
ρ_ϕ	$Beta$	0.700	0.640 [0.474, 0.789]	0.646 [0.487, 0.792]	—	0.638 [0.469, 0.790]	—	0.641 [0.476, 0.789]	—	0.634 [0.469, 0.784]	—
c_{y^*}	$Beta$	0.850	0.884 [0.790, 0.968]	0.883 [0.786, 0.969]	—	0.885 [0.787, 0.970]	—	0.885 [0.792, 0.968]	—	0.878 [0.782, 0.963]	—
c_{π^*}	$Beta$	0.850	0.545 [0.379, 0.722]	0.548 [0.382, 0.722]	—	0.549 [0.382, 0.724]	—	0.551 [0.386, 0.726]	—	0.553 [0.381, 0.740]	—
c_{i^*}	$Beta$	0.850	0.861 [0.783, 0.933]	0.857 [0.782, 0.925]	—	0.851 [0.775, 0.920]	—	0.857 [0.776, 0.928]	—	0.953 [0.928, 0.976]	—
σ_{μ_F}	$IGamma$	1.000	1.225 [0.857, 1.673]	1.159 [0.799, 1.618]	—	0.966 [0.611, 1.442]	1.245 [0.810, 1.836]	1.160 [0.798, 1.611]	—	0.983 [0.664, 1.379]	—
σ_{μ_H}	$IGamma$	1.000	0.458 [0.326, 0.620]	0.425 [0.298, 0.586]	—	0.403 [0.275, 0.570]	0.474 [0.327, 0.662]	0.433 [0.312, 0.583]	—	0.405 [0.290, 0.548]	—
σ_a	$IGamma$	1.000	0.855 [0.209, 2.358]	1.060 [0.205, 3.474]	—	0.769 [0.207, 2.007]	1.040 [0.212, 3.117]	0.816 [0.206, 2.346]	—	1.088 [0.212, 3.966]	—
σ_ν	$IGamma$	1.000	11.265 [7.040, 17.150]	11.438 [7.154, 17.458]	—	9.569 [5.430, 15.636]	10.440 [6.404, 16.143]	11.473 [7.203, 17.380]	—	33.342 [24.976, 44.307]	—
σ_ϕ	$IGamma$	0.800	0.472 [0.406, 0.548]	0.119 [0.090, 0.156]	0.665 [0.533, 0.831]	0.121 [0.092, 0.160]	0.673 [0.535, 0.842]	0.119 [0.090, 0.156]	0.680 [0.537, 0.866]	0.065 [0.971, 1.610]	1.249 [0.049, 0.081]
σ_{y^*}	$IGamma$	1.000	0.684 [0.592, 0.791]	0.685 [0.593, 0.795]	—	0.686 [0.593, 0.798]	—	0.684 [0.591, 0.793]	—	0.685 [0.588, 0.798]	—
σ_{π^*}	$IGamma$	1.000	0.375 [0.321, 0.438]	0.376 [0.321, 0.440]	—	0.376 [0.322, 0.440]	—	0.376 [0.321, 0.440]	—	0.377 [0.323, 0.443]	—
σ_{i^*}	$IGamma$	1.000	0.100 [0.086, 0.116]	0.100 [0.086, 0.116]	—	0.100 [0.086, 0.118]	—	0.100 [0.086, 0.117]	—	0.104 [0.089, 0.121]	—
$\mathbb{M}$:			-430.723	-405.5175		-409.2437		-405.0004		-415.8807	

Table 1.4: *Estimated coefficients at the posterior mean for all models.* PM *denotes point mass,* $IGamma$ *— inverse Gamma, and* $\mathbb{M}$ *stands for the marginal data density estimate. The 95% probability interval is given in brackets.*

Hence, in this exercise, regime-dependence of all Estonian shocks $\sigma_a^2(s_t)$, $\sigma_\vartheta^2(s_t)$, $\sigma_{\mu_H}^2(s_t)$, $\sigma_{\mu_F}^2(s_t)$, and $\sigma_\phi^2(s_t)$ is allowed for. The prior distributions of the parameters are left identical in both states. Table 1.4 displays the estimated coefficients for all models. Columns five to seven present the results for $\mathcal{M}_2$ and $\mathcal{M}_3$.

Overall, for $\mathcal{M}_3$, the estimates are highly similar to those of the $\mathcal{M}_2$ specification and few are worth noting. The estimates of the risk premium's stochastic volatility in $\mathcal{M}_3$ are $\sigma_\phi^2(1) = 0.121$ and $\sigma_\phi^2(2) = 0.673$, respectively, evaluated at the mean and are thus almost identical to the values reported for $\mathcal{M}_2$; the estimated distributions are mostly overlapping as well. Therefore, the main findings are a feature of the interest-rate series alone. From the non-switching parameters, only the risk aversion coefficient is higher at the mean and the distribution is slightly shifted to the left: $\sigma = 2.1$ compared to 2.4 in $\mathcal{M}_2$. This differnece is complemented by a smaller volatility of the preference shock — higher intertemporal substitution leads to a lower impact of shocks on consumption. The marginal density of this model is $\mathbb{M}_3 = -409.2437$, which is worse than the reported value $\mathbb{M}_2 = -405.5175$ in the original specification.

1.4.2 $\mathcal{M}_4$: Markov-switching debt elasticity

The interest rate equation (1.12) describes the spread between the two rates as a composition of an exogenous and an endogenous part. Europe is currently experiencing severe difficulties with public debt levels and worsening debt positions are being watched closely. Estonia's public debt has been kept small (about 6% to 7% of GDP), however, before and during the financial crisis, Estonia's net external debt fell to almost -40% of GDP before returning to zero levels in 2012. If the sensitivity towards indebtedness has increased and the parameter χ is constant, the model might be misspecified. Therefore, in model $\mathcal{M}_4$ both the debt elasticity parameter χ and the volatility of risk premium are allowed to switch:

$$i_t = i_t^* - \chi(s_t)d_t - \phi_t, \tag{1.29}$$

$$\phi_t = \rho_\phi \phi_{t-1} + \varepsilon_t^\phi \quad \text{with} \quad \varepsilon_t^\phi \sim N(0, \sigma_\phi^2(s_t)). \tag{1.30}$$

The third- and fourth-to-last columns of Table 1.4 present the parameter estimates at the mean with 95% probability intervals for $\mathcal{M}_4$. Again, most non-switching parameters are equal across the models up to the second or third digit after the decimal. The risk premium volatility in the first state $\sigma_\phi(1) = 0.119$ is identical for both models, while the second state parameter has closely overlapping distributions with $\sigma_\phi(2) = 0.665$ and $\sigma_\phi(2) = 0.680$ for $\mathcal{M}_2$ and $\mathcal{M}_4$, respectively. This suggest, that the estimates are robust to this alternative model specification. The other important parameter in the model χ takes the values $\chi(1) = 0.014$ and $\chi(2) = 0.024$ at the mean. The probability intervals, however, reveal that the distributions of $\chi(1)$ and $\chi(2)$ overlap and therefore there is no conclusive evidence regarding the existence of two significantly different values. The marginal density of $\mathcal{M}_4$ is $\mathbb{M}_4 = -405.0004$, which is close to the original $\mathbb{M}_2 = -405.5175$.

1.4.3 $\mathcal{M}_5$: No detrending of the interest rate

In this specification the interest rate series are taken without detrending. Therefore, the spread between the domestic and the foreign series is larger, which is reflected in the estimated coefficients of $\sigma_\phi(1) = 0.05$ and $\sigma_\phi(2) = 1.2$ (last two columns of Table 1.4). Figure 1.6 plots the probability of the second regime, which does not differ from that of the main model — the second regime prevails only two quarters later. The main findings are robust, as both the banking crisis and the global financial turmoil have been characterized by a higher risk premium. The estimated duration of the second regime is shorter compared to the baseline case due to the larger volatility of the interest rate differential. Most estimates are comparable, and in terms of marginal density the model cannot be preferred over the others. It rather ranks as second worst with $\mathbb{M}_5 = -415.88$.

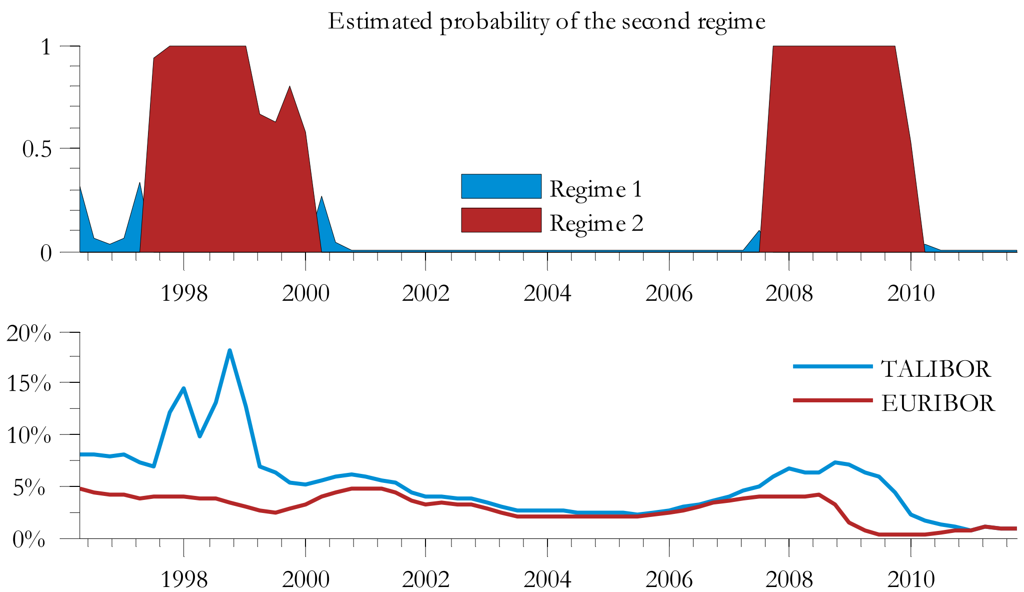


Figure 1.6: *Regime probabilities and interest rates. Top panel: Estimated probability of the high risk premium volatility regime for $\mathcal{M}_5$. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Annualized three-month interbank interest rates.*

1.5 Concluding remarks

In a standard DSGE model of an economy with a currency board, foreign and domestic interest rates are typically modelled as an identity. In reality the rates converge, yet in times of crises a persistent spread may open. When risk premium shocks are studied, the responses of the variables may not represent the reality properly. If the currency board is stable, innovations to the interest rates are rather small and do not have an effect on the economy. In stressful times, however, the system is much more sensitive to financial disturbances.

In this chapter, these issues are addressed by developing a model where the interest rate is a function of several endogenous and exogenous variables, utilizing a Markov-switching framework that captures the periods of persistent spread and increased sensitivity. The domestic interest rate is derived as a function of the foreign rate and a risk premium. The latter is composed of two parts: an endogenous function that represents the indebtedness of the country and an exogenous component. The volatility of the exogenous part is then allowed to switch between two regimes to reflect significant changes in the premium. The model is applied to Estonia, a small open economy with a currency board, which is very suitable for the exercise, having experienced a banking crisis, a financial crisis and booming periods in-between. The stressful periods are well identified as the model captures the time-variation in the volatility of the risk premium. The impulse responses show that the static DSGE model would under-perform its Markov-switching counterpart as it tends to average the volatility of the series. Stronger shocks produce a cyclical behaviour in many series, most notably in inflation, where a sudden sharp increase in the interest rates leads temporarily to deflation and then to inflation. In the long run, the stable currency board minimizes the effects of risk premium shocks — in Estonia, during the booming periods these shocks did not contribute to the volatility of output at all.

While the Markov-switching framework is able to identify the non-linearities of the data, it operates under severe limitations. Due to the “curse of dimensionality” the number of parameters grows disproportionally with the model size. More importantly, the lack of endogeneity in the switching mechanism is a major limitation in any context with self-fulfilling expectations, especially rare events such as a currency or a banking crisis. Many questions arise for potential future research. What might influence the transition mechanism? What triggers the changes in regimes? Recent advancements in the field as in Miah (2014) pave the way for exploring such topics in greater detail.

2

The regime-dependent evolution of credibility: A fresh look at Hong Kong's linked exchange rate system

Recent years have seen a resurgence of interest in exchange rate regimes. In the aftermath of the 1997–1998 Asian crisis and the global recession of 2008–2009, "crisis prevention" came to be viewed as a key criterion in choosing an exchange rate regime. With the partial collapse of the European exchange rate mechanism in September 1992, the notion that corner solutions such as free floats and super-strict pegs were preferable to intermediate regimes became widespread. The thinking was that they were less crisis-prone in the context of today's huge and volatile financial markets on the assumption that investors will otherwise overwhelm intermediate regimes like band systems. Put more bluntly, the options for exchange rate regimes were assumed to have hollowed out to the point where the only choices left to policymakers were whether to let exchange rates float or fix them permanently via a currency board or a monetary union.

This chapter has been co-authored with Prof. Dr Michael Funke.

Consistent with this bipolar view, Hong Kong's currency board system appears to be a textbook corner solution. To pre-empt the weakening of confidence during the Sino-Anglo dispute on the return of Hong Kong's sovereignty to China after 1997, the Hong Kong government adopted a linked exchange rate system on 17 October 1983, a.k.a. the "Black Saturday Crisis". Under this system, the money supply in Hong Kong was fully backed up by US dollars (USD), and the HK dollar (HKD) effectively fixed at a rate of USD/HKD 7.8. Any one of the three note-issuing banks in this system wishing to print HKD notes would have to surrender an equivalent amount of USD (at the official rate) to the Hong Kong Monetary Authority (HKMA) in exchange for "Certificates of Indebtedness" that entitled the note-issuing bank to print a corresponding amount of HKD. Conversely, note-issuing banks could use their Certificates of Indebtedness in HKD to redeem an equivalent amount of USD from the HKMA. A distinctive feature of the system up to May 2005 was that no strong-side boundary existed, meaning that the currency board system was asymmetric. In May 2005, however, the HKMA introduced a symmetric target zone with a HKD/USD band of 7.75 to 7.85.

A common argument for placing restraints on a currency board system is that it confers credibility in the spheres of exchange rate and monetary policy by relinquishing the devaluation option.[2] However, this is not always true. One can point to numerous historical episodes where currency boards have failed to enhance the credibility of the monetary authority. This is because the government retains its right to abandon the scheme and renege on its institutional commitments. In other words, political uncertainty about the preferences of current and future governments can erode credibility.[3] Thus, we ask: how much credibility do policymakers gain by implementing a currency board and what are the effects of losing said credibility?

This paper investigates the notion of credibility by exploiting a key feature of the currency board — the link between domestic and foreign interest rates under a fixed exchange rate. In its simplest form it is given by the textbook version of the uncovered interest rate parity (UIP), which relates the spot exchange rate $\mathcal{S}_t$, the expectation over future exchange rates $E_t\{\mathcal{S}_{t+1}\}$, and the interest rates between two countries i and i^*: $(1 + i_t) = \frac{E_t\{\mathcal{S}_{t+1}\}}{\mathcal{S}_t}(1 + i_t^*)$. Within the fixed exchange rate framework this boils down to an equality between domestic and foreign interest rates. However, if the agents expect an appreciation or depreciation of the currency, i.e. a change in the exchange rate

[2] Currency boards have been found to perform better than soft pegs in terms of economic growth. A growing body of macroeconomic evidence suggests that volatility is detrimental to economic growth, especially when financial opportunities are limited. See, for example, Aghion and Howitt (2009), pp. 329–339.

[3] Oliva *et al.* (2001) present a signalling model to consider the choice between a currency board and a traditional peg. The model shows that the currency board's effectiveness and welfare effects hinge on its credibility.

regime, a spread between the rates will open as they take positions against the board.

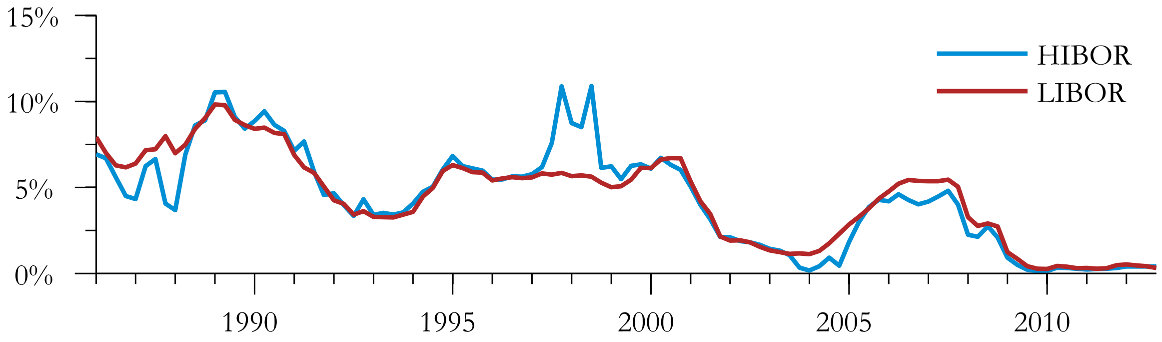


Figure 2.1: *HKD HIBOR and USD LIBOR, annualized three-month interbank interest rates from 1986Q1 to 2012Q4. Sources: Eurostat and Datastream.*

A closer look at the HKD and USD interbank interest rates motivates the UIP theory quite well. Figure 2.1 shows that the HK rate tends to align with the US rate during booming periods, but the forward premia shed light into the time-varying nature of credibility. There is a notable spread after the events of the "Black Monday" — a stock market crash in 1987. Afterwards, with the exception of some small and short-lived discrepancies in 1991 and another one during the Mexican crisis in 1995, the spreads relative to the US were close to zero for most of the 1989–1997 period. The 1997 Asian crisis and its associated turbulence, however, altered the pattern dramatically. The HKD faced speculative pressure and capital outflows as HKD forward rates depreciated. The strategy of market participants was to bid up Hong Kong's interbank rate to benefit from short positions in the futures market. In this acute episode of loss of credibility interest rate differentials surged. In 1998 they began a slow return towards near-zero levels, attained in 2000.

In contrast, financial markets in Hong Kong stayed remarkably calm during the SARS (severe acute respiratory syndrome) outbreak in 2003. If anything, confidence in the linked exchange rate system strengthened. Mirroring this, the interest rate differential between the HKD and the USD remained negligible. Moreover, the global financial crisis of 2008–2009 raised no doubts as to the credibility of Hong Kong's linked exchange rate system. These sharp differences in spread movements between the Asian crisis and the global recession are quite striking given the extreme limits on Hong Kong's policy instruments.

The profile in Figure 2.1 suggests what it might take to call the credibility of Hong Kong's exchange rate system into question. We illustrate this by first drawing on financial market information captured by the behaviour of interest rates in the US and Hong Kong. We take a more sophisticated parity rule and first examine whether we can interpret the spread as coming from endogenous

factors (such as changing real exchange rate or price level differences) or stemming from exogenous factors (e.g. as a currency board crisis), and then look at the implications of changing credibility. We develop a full-fledged DSGE model with Markov-switching (MS-DSGE) to identify and interpret time-varying credibility more precisely and utilise it to study the effects of loss and gain of trust in the exchange rate system. The main appeal of the structural approach is that it allows for a direct economic interpretation of observed movements in the data and fully exploits economic priors.[4]
The remainder of this chapter is organised as follows. The next section lays out the theory, followed by Section 2.2 that deals with the solution and estimation technicalities of MS-DSGE models. Section 2.3 discusses the data used at the estimation stage, which is the main topic of Section 2.4. Section 2.5 presents the economic implications of the model and Section 2.6 discusses the robustness of the results. Finally, Section 2.7 concludes.

2.1 The model

We use a Markov-switching DSGE model to study the credibility of Hong Kong's linked exchange rate system. It is based on the seminal works of Monacelli (2005) and Justiniano and Preston (2010) in combination with a fixed exchange rate and a Markov-switching component in the volatility of the interest rate risk premium.[5] In this section we briefly present the key equations of the log-linearised system.
On the demand side, consumers choose the optimal amount of consumption c_t following the usual Euler equation with habit formation:

$$c_t - hc_{t-1} = (E_t\{c_{t+1}\} - hc_t) + \frac{1-h}{\sigma}(E_t\{\pi_{t+1}\} - i_t) + \frac{1-h}{\sigma}(1-\rho_\vartheta)\vartheta_t, \tag{2.1}$$

$$\vartheta_t = \rho_\vartheta \vartheta_{t-1} + \varepsilon_t^\vartheta \quad \text{with} \quad \varepsilon_t^\vartheta \sim N(0, \sigma_\vartheta^2). \tag{2.2}$$

Consumption c_t is a bundle of domestic and foreign items, π_t stands for CPI inflation, i_t denotes the nominal interest rate, and ϑ_t is a preference shock that follows an AR(1) process with normal innovations ε_t^ϑ and standard deviation σ_ϑ. The parameters in the Euler equation are: h, which represents the habit parameter; σ — the risk-aversion/inverse of the elasticity of substitution, and

[4]In recent years, the popularity of DSGE models with tight theoretical restrictions has gained ground. The trick is to make a model that closely approximates reality. The dominant pre-recession 2008–2009 DSGE paradigm viewed financial factors and/or credibility issues largely as a sideshow. The rapidly growing DSGE literature now seeks to remedy these known weaknesses, so the value of this line remains contested, see Caballero (2010).

[5]Liu and Mumtaz (2011) provide an extension of Justiniano and Preston (2010) to a Markov-switching DSGE framework from a floating exchange rate perspective.

ρ_ϑ — the autoregressive coefficient of the preference shock.

On the supply side, there are two types of producers: domestic firms, which satisfy the demand for domestic goods, and import firms that introduce foreign goods to the domestic market. Each type of firm sets the price for its respective good a lá Calvo (1983) in a hybrid manner, i.e. firms are forward looking but have a degree of past indexation. This setup leads to the following dynamics of home goods inflation $\pi_{H,t}$ and foreign goods inflation $\pi_{F,t}$:

$$(1+\beta\delta_H)\pi_{H,t} = \beta E_t\{\pi_{H,t+1}\} + \delta_H\pi_{H,t-1} + \lambda_H(\theta_H)mc_t, \tag{2.3}$$

$$(1+\beta\delta_F)\pi_{F,t} = \beta E_t\{\pi_{F,t+1}\} + \delta_F\pi_{F,t-1} + \lambda_F(\theta_F)\psi_t + \mu_{F,t}, \tag{2.4}$$

where δ_H and δ_F denote the indexation parameters for the home and foreign economy, β is the the discount factor, and λ_H and λ_F are both functions of the Calvo parameters θ_H and θ_F, respectively. These parameters govern the duration of price contracts. The higher the parameters θ_H and θ_F, the longer prices remain unchanged, while low values are associated with higher competition as firms adjust their prices more frequently. The final determinant of domestic goods inflation $\pi_{H,t}$ is the marginal costs of the the firms mc_t.

We assume that the prices of foreign goods abroad and the prices of foreign goods at home do not necessarily have to be identical, i.e. the "law of one price" does not have to hold. The deviations from the law are represented by ψ_t. In particular, this assumption relaxes the potentially tight link between the real exchange rate q_t and the terms of trade v_t [Monacelli (2005)]:

$$\psi_t = q_t - (1-\alpha)v_t, \tag{2.5}$$

with α denoting the share of foreign goods in the consumption basket — a measure for the openness of the economy.

Both $\pi_{H,t}$ and $\pi_{F,t}$ are subject to exogenous shocks. The marginal costs mc_t are driven by a technology process a_t with innovations ε_t^a, while foreign prices are subject to cost-push shocks $\mu_{F,t}$ with innovations $\varepsilon_t^{\mu_F}$:

$$a_t = \rho_a a_{t-1} + \varepsilon_t^a \quad \text{with} \quad \varepsilon_t^a \sim N(0,\sigma_a^2), \tag{2.6}$$

$$\mu_{F,t} = \rho_\mu \mu_{F,t-1} + \varepsilon_t^{\mu_F} \quad \text{with} \quad \varepsilon_t^{\mu_F} \sim N(0,\sigma_{\mu_F}^2). \tag{2.7}$$

Exchange rate dynamics in SOE models are determined by the uncovered interest rate parity relation.

In a floating exchange rate setup, the UIP is given by

$$(i_t - E_t\{\pi_{t+1}\}) - (i_t^* - E_t\{\pi_{t+1}^*\}) = \triangle e_t - \chi d_t - \phi_t. \tag{2.8}$$

Following Benigno (2001), Schmitt-Grohé and Uribe (2003), and Justiniano and Preston (2010), the exchange rate dynamics are not only affected by inflation and interest rate differentials, $(E_t\{\pi_{t+1}^*\} - E_t\{\pi_{t+1}\})$ and $(i_t - i_t^*)$, respectively, but also by two additional components. The term d_t represents the net foreign asset position. In an open economy, the agents may either borrow and save domestically or tap into international markets. The net amount invested in foreign assets d_t evolves according to

$$d_t = y_t - (c_t + \alpha(q_t + \alpha v_t)) + \frac{1}{\beta} d_{t-1}, \tag{2.9}$$

where y_t denotes domestic output. The intuition behind this equation is that the difference between actual production and domestic consumption plus the trade balance can be invested into, or borrowed from, international markets.

The last term in equation (2.8), ϕ_t, is an exogenous AR(1) process, driven by innovations ε_t^ϕ that can be interpreted as a UIP shock in the floating exchange rate literature:

$$\phi_t = \rho_\phi \phi_{t-1} + \varepsilon_t^\phi. \tag{2.10}$$

The distributional assumption over ε_t^ϕ will be discussed shortly.

DSGE models are typically closed by a Taylor rule. Since Hong Kong has a currency board, we close the model by introducing a pegged exchange rate in accordance with Schmitt-Grohé and Uribe (2003) and Galí and Monacelli (2005):

$$\triangle e_t = 0. \tag{2.11}$$

Substituting through the UIP (2.8), we derive an important relationship between domestic and foreign interest rates, and namely, that domestic rates i_t are an endogenous function of the foreign rates i_t^*, the net foreign asset position d_t, and the exogenous process ϕ_t:

$$i_t = i_t^* - \chi d_t - \phi_t. \tag{2.12}$$

This derivation introduces several appealing properties to the model. First, the interest rates are not modelled as an identity as in Galí and Monacelli (2005), which is not supported by the data (see Figure 2.1). Furthermore, an interest rate differential might arise from endogenous factors — an indebtedness of the domestic agents, $d_t < 0$, would induce a premium over the foreign interest rate

i_t^*. Hence it would be more costly for the agents to borrow further. Finally, the component ϕ_t can capture exogenous events such as speculations against the board.
In order to model the credibility of the Hong Kong's linked system, we allow for time variation in the risk premium by introducing regimes into the variance of the innovation ε_t^{ϕ}.[6]

$$\phi_t = \rho_\phi \phi_{t-1} + \varepsilon_t^{\phi} \quad \text{with} \quad \varepsilon_t^{\phi} \sim N(0, \sigma_\phi^2(s_t)). \tag{2.13}$$

Here, $\sigma_\phi^2(s_t)$ is modelled as a regime dependent variable through a Markov-switching process with states $s_t = \{1, 2\}$ and a transition matrix

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \tag{2.14}$$

where p_{ij} is the transition probability from state i to state j. The argument is that lower credibility of the system should lead to a risk premium and higher volatility of the interest rates [Genberg and Hui (2011)].
By construction, we impose a rather strong assumption that the economy may only fall into specific (and a finite number of) regimes. This choice requires further motivation. From a technical point of view if the data do not support two distinctive cases — if the estimated distributions of the coefficients overlap — additional regimes are inappropriate. Moreover, introducing more cases greatly increases the computational burden at the estimation stage.[7]
Two theories have been put forward to explain regime switches in the risk premium. The first one relates the concept of sunspot shocks to agents' expectations. Here, sunspot shocks cause multiple equilibria (a low-risk premium equilibrium if rational agents are not worried about sunspot shocks, and a high-risk premium equilibrium if agents believe such shocks to be bad). Thus, if for some reason the markets believe a currency crisis to be underway, it happens. Jeanne and Masson (2000) propose an empirical test of sunspot-driven multiple equilibria in the currency crisis context. They

[6] Engel and Hamilton (1990) and Engel (1994) have modelled exchange rates alternating between appreciation and depreciation regimes in a Markovian fashion. Their approach has a modicum of success in capturing the nonlinearity and regime shifts of the underlying time series and in forecasting. In contrast, Marsh (2000) shows that the Markov-switching modelling approach offers sound in-sample fit but usually fails to deliver a superior out-of-sample forecast due to parameter instability over time.

[7] The main pitfall is the "curse of dimensionality." A three-state Markov-switching model requires the identification of six coefficients in the probability matrix. The fact that the last column is a linear combination of the other two poses a significant problem at the estimation stage when the posterior mode is maximized. Furthermore, the Hessian at the posterior mode grows by almost three hundred elements (from 729 to 1024). These have to be estimated numerically, which greatly increases the margin for error. Moreover, the posterior distribution of a multi-state model may be highly non-Gaussian, which complicates the exploration of the posterior space for the Markov-Chain Monte Carlo procedure [Sims *et al.* (2008)].

prove that the effects of sunspot shocks are absorbed by discrete jumps in the intercept of a regression of the currency devaluation probability on fundamental variables. Therefore, a Markov regime-switching test can be used as a test for sunspot equilibria, as illustrated in Mouratidis (2008).

The second theory for regime-switching uses the "animal spirits" concept of De Grauwe (2010) and De Grauwe and Kaltwasser (2012). Here, boundedly rational and imperfectly informed agents use heuristics to make decisions in the foreign exchange market. Again, agents' psychological movements are self-fulfilling as waves of optimism and pessimism lead to fluctuations of the exchange rate even if the underlying fundamentals are unaltered by an exogenous shock. The theory of animal spirits shaping exchange rates is also consistent with a two-state regime-switching model. Finally, since reduced exchange rate volatility might translate into higher interest rate volatility, modelling the dynamics of the exchange rate through the interest rate in more detail is of particular interest.

The small open economy is represented by equations (2.1) through (2.14). We introduce three further AR(1) processes to describe the dynamics of the foreign variables output y_t^*, inflation π_t^* and interest rate i^*:

$$\begin{aligned} y_t^* &= c_{y^*} y_{t-1}^* + \varepsilon_t^{y^*} \quad \text{with} \quad \varepsilon_t^{y^*} \sim N(0, \sigma_{y^*}^2), && (2.15) \\ \pi_t^* &= c_{\pi^*} \pi_{t-1}^* + \varepsilon_t^{\pi^*} \quad \text{with} \quad \varepsilon_t^{\pi^*} \sim N(0, \sigma_{\pi^*}^2), && (2.16) \\ i_t^* &= c_{i^*} i_{t-1}^* + \varepsilon_t^{i^*} \quad \text{with} \quad \varepsilon_t^{i^*} \sim N(0, \sigma_{i^*}^2). && (2.17) \end{aligned}$$

We are now ready to solve the model. First, we collect all endogenous variables in the vector X and the exogenous variables in Z. The state-space representation of a MS-DSGE model can be written in the general form as

$$B_1(s_t)X_t = E_t\{A_1(s_t, s_{t+1})X_{t+1}\} + B_2(s_t)X_{t-1} + C_1(s_t)Z_t, \tag{2.18}$$

$$Z_t = R(s_t)Z_{t-1} + \epsilon_t \quad \text{with} \quad \epsilon_t \sim N(0, \Sigma(s_t)). \tag{2.19}$$

The matrices $B_1(s_t)$, $A_1(s_t)$, $B_2(s_t)$, $C_1(s_t)$ and $R(s_t)$ are functions of the model parameters. In the next section, we discuss how to solve and estimate (2.18) and (2.19) with actual data.

2.2 Solution and estimation

Introducing Markov-switching to DSGE models is a relatively new research area. There is yet no established way to solve and approximate these models. Several solution methods have been proposed by Davig and Leeper (2007b), Farmer *et al.* (2011), Foerster *et al.* (2013), Miah (2014), and Cho (2015). Notably, all revolve around the idea of a Minimal-State Variable (MSV) solution introduced by McCallum (1983) but explore different avenues. Davig and Leeper (2007b) use the notion of bounded shocks, while the latter three employ the concept of Mean Square Stability (MSS). As MS-DSGE models may have more than one stable solution, each method needs to offer a way for choosing among them. In models where the shocks are unbounded Farmer *et al.* (2011) and Cho (2015) provide checks for uniqueness and determinacy.[8] The former propose a test to choose among several solutions, while the latter introduces the concept of a "no-bubble condition". Intuitively, this concept is based on forward-solving the state-space system. It can be shown that in the limit, only one of the multiple solutions leads to a non-explosive path and thus can be economically relevant.[9] Due to this appealing property we choose the algorithm of Cho (2015) to solve our model.

The solution takes the form

$$X_t = \Omega^*(s_t)X_{t-1} + \Gamma^*(s_t)Z_t, \tag{2.20}$$

where $\Omega^*(s_t)$ and $\Gamma^*(s_t)$ are functions of the parameters and the states.

Equation (2.20) may be combined with a measurement equation for likelihood-based estimation. In standard DSGE models the likelihood function can be evaluated by means of the Kalman filter. However, due to the Markov-switching extension, the filter is not operable. Therefore to approximate the likelihood value we use Kim's filter, as laid out in Kim and Nelson (1999), which combines the Kalman filter with Hamilton's filter as in Hamilton (1989). The intuition behind Kim's filter is as follows. At any given point in time t, using Kalman's filter we evaluate the likelihood function for each possible state transition. Since we may switch between k states, we have k^2 possible paths that give k^2 likelihood values. As the number of paths grows exponentially, computation quickly becomes intractable. Therefore at each t, we use Hamilton's filter to evaluate the transition probabilities across all state combinations and use these probabilities as weights for the individual likelihood values. Essentially, at each time point we collapse k^2 likelihood values into one by weighted averaging.

The model is estimated via Bayesian methods. We evaluate the posterior distribution by imposing a prior distribution on the parameters, including the coefficients of the transition matrix P. Let θ collect all the parameters of the model, S be the history of the realised states and Y the data matrix,

[8] Foerster *et al.* (2013) follow Farmer *et al.* (2011), while the method of Miah (2014) does not guarantee the finding of all stable solutions.

[9] For a detailed explanation see Cho (2015).

then the posterior $p(\theta, P, S|Y)$ can be evaluated using Bayes' rule:

$$p(\theta, P, S|Y) = \frac{p(Y\,|\theta, P, S)\; p(S\,|P)\; p(\theta, P)}{\int p(Y\,|\theta, P, S)\; p(S\,|P)\; p(P, \theta)\; d(\theta, P, S)}. \tag{2.21}$$

Here, $p(Y\,|\theta, P, S)$ is the likelihood of the data conditional on the states S, the parameters θ and the Markovian probability matrix P. Furthermore, $p(S|P)$ denotes the marginal density of the states conditional on P and $p(\theta, P)$ is the marginal density of the parameters and the probabilities. The denominator is the marginal density $p(Y, \theta, P, S)$, given by the law of total probability.
We maximize the posterior using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) of Andreasen (2008). This strategy uses a variance-covariance matrix to search for the maximum. Thus, it avoids the need to calculate numerical derivatives and has an advantage when the function has discontinuities, ridges, or local optima, which is more likely in the Markov-switching case compared to a standard DSGE model [Hansen (2006), Van Binsbergen *et al.* (2012)]. We employ a Markov-Chain Monte Carlo (MCMC) procedure to approximate the posterior distribution. For each model we initiate four runs of 250 000 draws, from which the first 50 000 are discarded and the rest are thinned by saving every 20^{th} draw to reach a sample of 10 000 per batch. In all cases, the parameters converge to the same means.[10]

2.3 Data

We have seven variables that are driven by exogenous innovations: technology a_t, preferences ϑ_t, import prices $\mu_{F,t}$, risk premium ϕ_t, foreign demand y_t^*, foreign inflation π_t^* the foreign interest rate i_t^*. Thus, we can use up to seven series at the estimation stage. In the baseline scenario we choose five variables to represent the domestic economy and two variables for the world economy. We use Hong Kong data on output, inflation, consumption, terms of trade, and the HIBOR series. For the foreign variables we take US data on output and the USD LIBOR. Output is measured in real per-capita terms, where the trend component has been removed via an HP filter with a smoothing parameter of 1600. The inflation rate is the log difference of quarterly CPI. Consumption is measured as HP-filtered real consumption per capita. Terms of trade are given in logs and we add a measurement error R_ν as is common in the literature. Both interest rate series are taken in levels. All variables have been seasonally adjusted. The data spans from the first quarter of 1986 to the last quarter of 2012,

[10] An alternative approach to the MCMC method is to use a Gibbs sampler, or more precisely "Metropolis within Gibbs" as in Bianchi (2012). This method, however, can be computationally more intensive.

altogether 108 observations. Hong Kong data has been collected from the HKMA and the Hong Kong statistical office. US data has been obtained through Datastream. We have the following measurement equation:

$$\begin{bmatrix} \triangle GDP_t \\ \triangle CONS_t \\ INFL_t \\ HIBOR_t \\ TOT_t \\ \triangle GDP_t^{US} \\ LIBOR_t \end{bmatrix} = \begin{bmatrix} y_t \\ c_t \\ \pi^{(q)} + \pi_t \\ i^{(q)} + i_t \\ v_t + R_v \\ y_t^* \\ i^{(q)*} + i_t^* \end{bmatrix}, \tag{2.22}$$

where $\pi^{(q)}$, $i^{(q)}$, and $i^{(q)*}$ denote the means of the variables. As a benchmark we estimate a standard DSGE model with no regime switching, labelled as $\mathcal{M}_1$, and then a Markov-switching version $\mathcal{M}_2$. Next we turn to the prior that we impose on the parameters and present the main findings.

2.4 Priors and posterior estimates

Table 2.1 presents the parameters of the model. The second and third column present the prior distributions and means, while the last three columns show the posterior estimates. The 95% probability intervals for each parameter are shown in brackets.

The prior calibration is based on several studies of the Hong Kong economy. We follow Funke *et al.* (2011) and Funke and Paetz (2013) for the parameters for which their model and ours imply coherent dynamics: the Frisch elasticity of labour supply φ, the elasticity of substitution between domestic and foreign goods η, the intertemporal elasticity of substitution σ, the habit formation parameter h, and the persistence and variance of shocks. Due to the absence of a financial sector and capital, which imply different price dynamics, we look toward other studies for the price rigidity parameters θ_H and θ_F. The estimates seem to vary quite a bit. Genberg and Pauwels (2005) suggest a rather short price stickiness of about two to three quarters, while the findings of Razzak (2003) and Cheng and Ho (2009) correspond to seven to eight quarters of constant prices. We set the prior on price contracts fairly low, $\theta_H = \theta_F = 0.375$, based on Genberg and Pauwels (2005) and the degree of backward-looking agents δ_H and δ_F at 0.2 in the baseline case. We set the debt sensitivity parameter χ at 0.01 as in Justiniano and Preston (2010). We fix the discount factor β and the coefficient of openness α. The former is calibrated to match the steady state annual interest rate of 4.06% and the latter is set at 0.5, implying that domestic and foreign goods have equal shares in the consumer basket.

	Distribution	Prior Mean	$\mathcal{M}_1$	$\mathcal{M}_2 : s_t = 1$	$\mathcal{M}_2 : s_t = 2$
p_{11}	$Beta$	0.950	—	0.961 [0.904, 0.993]	—
p_{22}	$Beta$	0.950	—	0.964 [0.925, 0.991]	—
β	PM	0.983	0.983	0.983	—
φ	$Gamma$	2.000	2.010 [1.625, 2.431]	2.029 [1.639, 2.458]	—
θ_H	$Beta$	0.375	0.861 [0.834, 0.887]	0.854 [0.825, 0.881]	—
θ_F	$Beta$	0.375	0.843 [0.812, 0.874]	0.846 [0.814, 0.878]	—
α	PM	0.500	0.500	0.500	—
σ	$Gamma$	1.000	2.684 [1.752, 3.809]	2.524 [1.564, 3.752]	—
η	$Gamma$	2.000	2.282 [1.895, 2.701]	2.412 [2.026, 2.815]	—
h	$Beta$	0.200	0.565 [0.459, 0.666]	0.575 [0.461, 0.682]	—
δ_H	$Beta$	0.200	0.422 [0.281, 0.564]	0.426 [0.291, 0.567]	—
δ_F	$Beta$	0.200	0.712 [0.602, 0.811]	0.706 [0.603, 0.802]	—
χ	$Gamma$	0.010	0.014 [0.009, 0.019]	0.017 [0.013, 0.021]	—
ρ_a	$Beta$	0.700	0.908 [0.777, 0.975]	0.905 [0.777, 0.973]	—
ρ_{μ_F}	$Beta$	0.700	0.918 [0.830, 0.972]	0.894 [0.790, 0.962]	—
ρ_ν	$Beta$	0.700	0.546 [0.381, 0.713]	0.541 [0.374, 0.703]	—
ρ_ϕ	$Beta$	0.700	0.705 [0.531, 0.857]	0.697 [0.524, 0.844]	—
c_{y^*}	$Beta$	0.850	0.900 [0.825, 0.968]	0.891 [0.820, 0.957]	—
c_{π^*}	$Beta$	0.850	0.649 [0.543, 0.743]	0.661 [0.562, 0.745]	—
c_{i^*}	$Beta$	0.850	0.923 [0.894, 0.951]	0.931 [0.898, 0.959]	—
σ_{μ_F}	$IGamma$	2.000	0.264 [0.202, 0.342]	0.273 [0.208, 0.354]	—
σ_a	$IGamma$	2.000	5.459 [4.216, 7.002]	5.142 [3.984, 6.628]	—
σ_ν	$IGamma$	2.000	11.001 [8.370, 14.300]	10.869 [8.290, 14.233]	—
σ_ϕ	$IGamma$	2.000	0.292 [0.260, 0.329]	0.101 [0.082, 0.126]	0.511 [0.418, 0.629]
σ_{y^*}	$IGamma$	1.000	0.550 [0.492, 0.615]	0.546 [0.488, 0.614]	—
σ_{π^*}	$IGamma$	1.000	1.540 [1.322, 1.797]	1.486 [1.282, 1.725]	—
σ_{i^*}	$IGamma$	1.000	0.134 [0.119, 0.150]	0.133 [0.119, 0.150]	—
R_v	$Normal$	0.000	-0.001 [-0.298, 0.296]	-0.000 [-0.117, 0.116]	—

Table 2.1: *Estimated coefficients at the posterior mean. $\mathcal{M}_1$: Model with fixed parameters; $\mathcal{M}_2$: Markov-switching model; 95% credible interval in brackets. PM indicates "point mass", $IGamma$ denotes the inverse Gamma distribution.*

The persistence of the foreign variables is centred around 0.85, which we obtain by fitting an AR(1) model to the series. The variance of all domestic innovations is chosen so that it is smaller in the US compared to Hong Kong. Finally, we assume that the probability of switching between regimes has a mean of 0.95, which implies an average duration of each regime of about 5 years with a standard deviation of 2.5 years.

The posterior estimates are in line with the literature on Hong Kong. The risk aversion coefficient σ is around 2.6, which is a typical value for a small open economy. The Frisch elasticity of labour supply φ is not identified due to the absence of labour series and is therefore centred around the prior distribution. The habit parameter $h = 0.56$ shows that consumption smoothing is an important factor in Hong Kong. The data supports rather sticky prices with $\theta = 0.86$. This is also evident in the backward-looking component $\delta_H = 0.4$, which is in line with Razzak (2003) and Cheng and Ho (2009), even though we impose a smaller value as a prior. This finding is robust even if the inflation rate is approximated by the GDP deflator instead of the CPI. Technology and import shocks are relatively persistent with $\rho_a = 0.91$ and $\rho_{\mu_F} = 0.92$, respectively. The preference shock has a moderate persistence of $\rho_\nu = 0.5$. We now turn to the time-varying coefficients.

2.5 Assessing the credibility of Hong Kong's exchange rate system

We model the credibility of the Hong Kong exchange regime as a two-state process, allowing the volatility of the risk premium σ_ϕ^2 to vary over time. Our hypothesis is that if the credibility of the system is low, agents would be willing to take positions against it. Such short or long positions on the stock market would pressure the fixed exchange rate regime and in turn increase the volatility of the interest rate differential. We estimate two distinct parameter values with non-overlapping posterior distributions (plotted on Figure 2.2), suggesting heteroskedasticity of the risk premium. The means of $\sigma_\phi(1)$ and $\sigma_\phi(2)$ lie at 0.101 and 0.511, respectively.

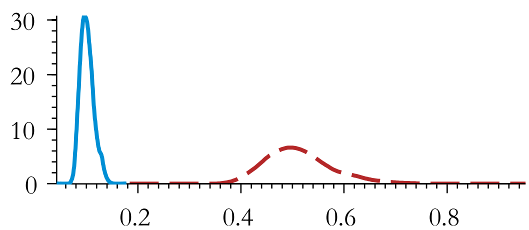


Figure 2.2: *Posterior densities of the switching parameter $\sigma_\phi(s_t)$ under the first (—) and second regime (- -).*

Using the Hamilton filter we estimate the occurrence probability of each regime throughout the sample. We plot the probability for the second state in Figure 2.3. The bottom plot depicts the US and Hong Kong interest rates. The figure clearly indicates time variation in the risk premium on

HIBOR. Three episodes are of particular interest. In the first, the probability peaks to one in the third quarter of 1987 and drops back after the third quarter of 1990. Next, we see a similar pattern throughout the Asian crisis, particularly between 1997Q2 and 1999Q2. Finally, there is a lone spike right before 2005 with a value of 0.8. We consider each episode in turn.

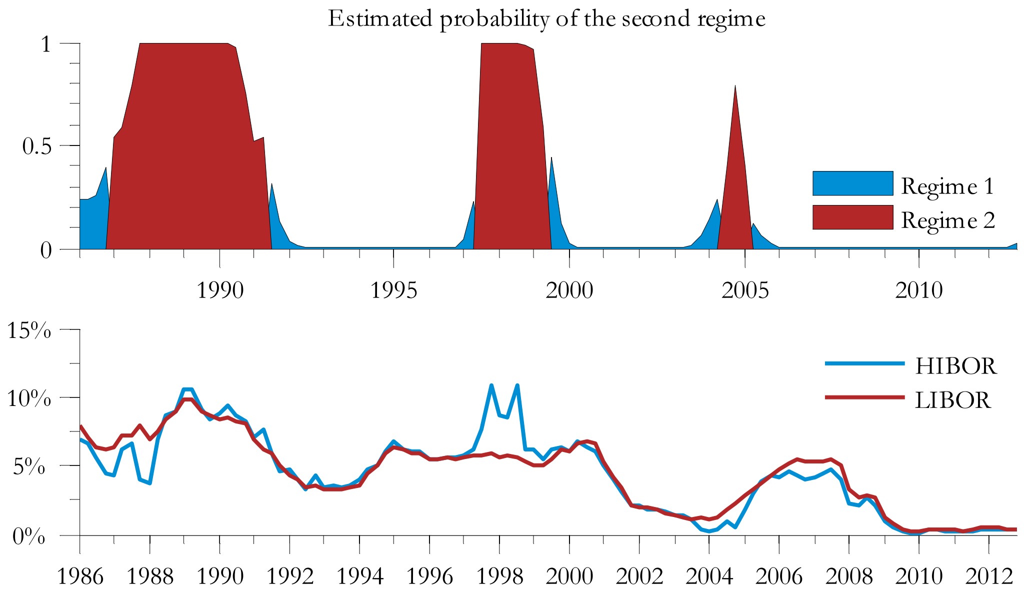


Figure 2.3: *Regime probabilities and interest rates. Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Annualized three-month interbank interest rates.*

The Hong Kong stock market crashed on October 19, 1987 with shares losing almost half of their value.[11] The crisis spread quickly to other Asian markets, Europe and the US. Major indices such as the FTSE and Dow Jones lost over 20% of their value in a matter of days. The crash put severe pressure on Hong Kong's currency board. This is captured in the model by a switch in the risk premium volatility exactly in the third quarter of 1987. Even though the interest rates converged back two quarters later, the credibility of the board could not be restored as easily. The second regime prevailed for two more years. This finding exploits the rich structure of the DSGE model. The economy went into a recession as GDP shrank for six consecutive quarters. With the economy recovering throughout 1992 and interest rates declining, trust in the mechanism restored. Over the following seven years, the HIBOR was almost identical to the LIBOR, with the exceptions of two minor discrepancies in 1991 and the Mexican crisis in 1995.

The Asian crisis provoked considerable speculation against the HKD in futures markets. The 3-month HIBOR reached an all-time high, rising even more than during the Black Monday aftermath,

[11] There is a vast body of literature documenting the events and the aftermath of the Black Monday. See e.g. Roll (1988), Malliaris and Urrutia (1992), and Carlson (2006).

while daily levels jumped to 16%–18% as speculators bet against the currency board on futures markets. The credibility of the linked exchange rate system was again put into question as interest rates surged. The HKMA responded in September 1998 with seven technical measures to strengthen the mechanism.[12] Those measures included a weak-side commitment against speculative attacks and depreciation and easing the borrowing conditions for the banks. The interest rate differential fell from 5% in the second quarter of 1998 down to 0.8% in the third before returning to almost zero levels towards the end of 1999. Our findings suggest an almost immediate reaction to the stance taken by the HKMA with a delay of only one quarter. A similar result has been found in Genberg and Hui (2011), who assess the credibility of the linked exchange rate system with a reduced-form model, and in Kwan *et al.* (2001), who look at credibility from a target-zone model perspective.

The third episode appears to have been short lived. In 2004, the HKD was put under appreciation pressure. The futures market drove the interest rates down over the expectation that the HKMA would follow potential moves from the mainland for appreciation against the dollar [Genberg and Hui (2011), p. 289]. As the technical measures of 1998 introduced only a weak-side commitment, the system was ill-prepared to cope with pressures on the strong side. Therefore, the currency board was modified to create a symmetric band around the rate of USD/HKD 7.8 in May 2005. This helped calm the markets and narrow the interest-rate differential.

We find no evidence of a regime change throughout the financial crisis of 2008–2009, even though there seems to be a negative differential similar to the appreciation pressures in 2004. Hence, the spread is stemming from endogenous factors. In fact, the stability of the mechanism was never questioned throughout the crisis and the monetary authority was never pushed to act.

Our framework allows us to analyse responses of the macroeconomic variables in each regime separately. Figure 2.4 plots the impulse responses following a risk premium shock for the standard DSGE model and the MS-DSGE version. When agents trust the currency board, the risk premium is small to non-existent. Consequently, risk premium shocks play a negligible role for the macroeconomic variables, both real and nominal. Consumption and output fall slightly on impact. Due to the habit formation, consumption declines further before slowly returning to the steady state. Falling demand and prices force the firms into an internal devaluation, as they reduce marginal costs. The lower prices of domestic goods, lower production costs, and the fixed exchange rate lead to a temporary upswing in GDP growth. The economy becomes more competitive with falling domestic prices and the terms of trade improve.

[12] The official press release is available at the HKMA website: http://www.hkma.gov.hk/eng/key-information/press-releases/1998/980905.shtml.

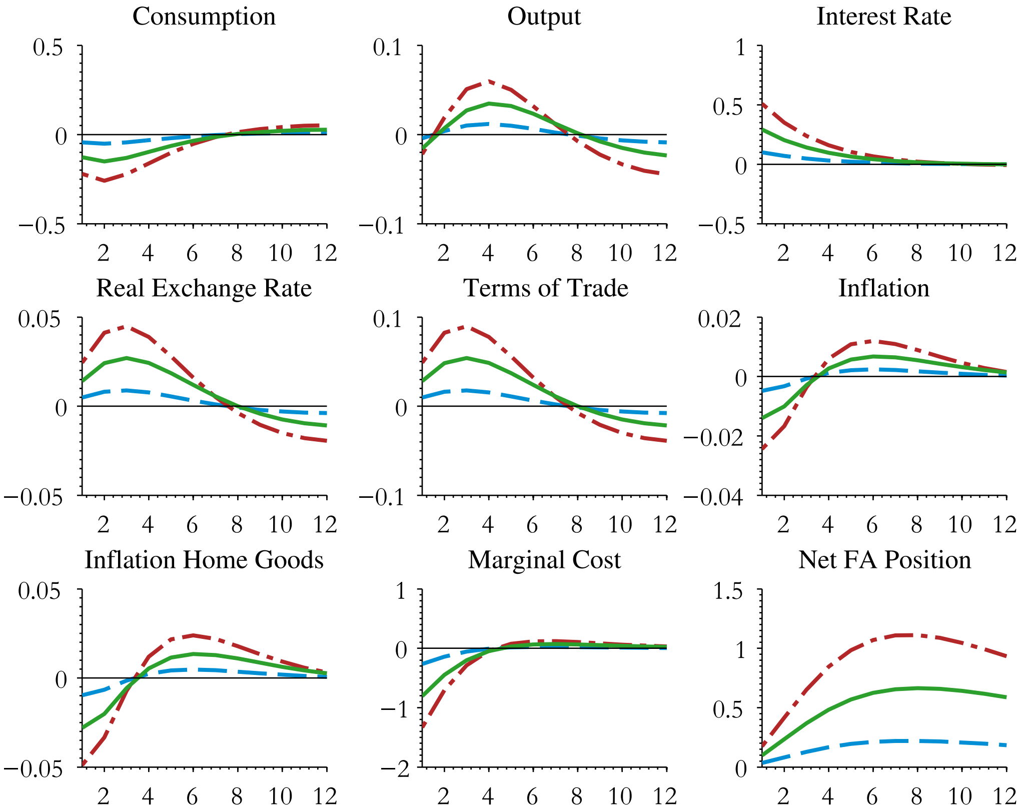


Figure 2.4: *Impulse responses following a risk premium shock for state one: "high credibility" $\sigma_\phi(1)$ (- -), state two: "low credibility" $\sigma_\phi(2)$ (-.-), and the no-switching version $\mathcal{M}_1$ (—).*

As evident from Figure 2.4, the standard DSGE model covers a "middle-ground" scenario. The impulse responses overestimate the reactions of macroeconomic variables during times when the board is perceived as credible and underestimate the nature of interest rate shocks during the "non-credible" regime. In the second regime all variables exhibit strong cyclical behaviour. Larger risk premium shocks translate in higher macroeconomic uncertainty and volatility. Consumption falls much lower compared to the first regime and the temporary spike in output growth is mitigated by a GDP contraction in the medium run. The crisis is associated with large capital outflows as agents divert investments into foreign assets.

The main takeaway is that crisis periods in particular have non-linear effects on the economy because they can induce an adverse feedback loop. A low credibility regime leads to a widening of interest rate spreads, which in turn leads to a contraction of GDP that worsens financial market conditions and widens interest rate spreads even further. This leads to a further contraction of GDP, and so on. Faced with the possibility of an adverse feedback loop, the HKMA likely needs to aggressively pursue a transparent and credible commitment to a specific exchange rate target.

Further insight into the nature of exchange rate credibility can be inferred from a variance decomposition analysis. We estimate the determinants of the interest rate volatility conditioning on each state and present the results in Figure 2.5.[13]

The left panel plots the variance decomposition of the interest rate i_t associated with the high credibility state over time. On impact, the variance of the domestic interest rate is mainly driven by the variation in the foreign rate, up to 55%, while the rest is mostly attributed to the risk premium shock. However, both of these determinants are prominent only in the short run until the main drivers technology and preference kick in.

The right panel, associated with the low credibility state, paints a different picture. The main driver behind the variance of domestic rates is not the dynamics of the foreign rates. Over 90% of the variance is explained by the risk premium shock. Moreover, this finding is highly persistent — even after three years the explained volatility is over 60%. This implies that once a risk premium forms, it remains present for prolonged periods unless the HKMA intervenes. The interpretation is that it takes time for trust in the linked exchange rate system to be restored.

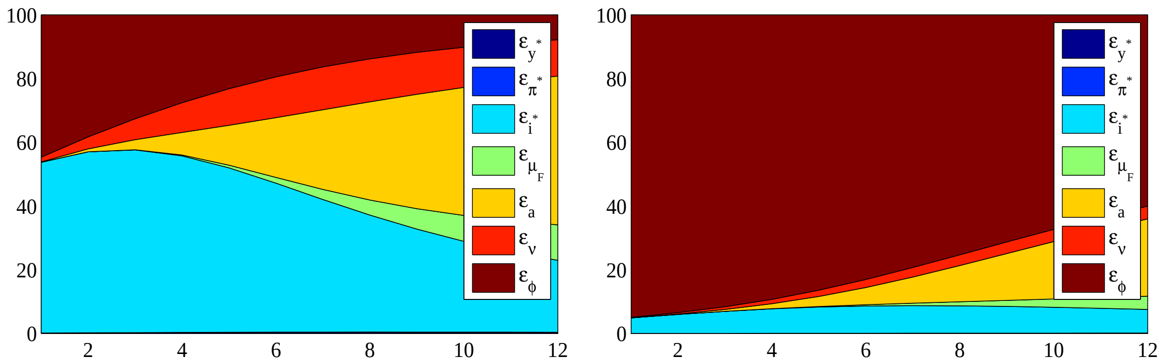


Figure 2.5: *Variance decomposition of the interest rate for state one: "high credibility" $\sigma_\phi(1)$ and state two: "low credibility" $\sigma_\phi(2)$. The X-axis shows the variance decomposition horizon in quarters, the Y-axis is in per cent.*

2.6 Robustness checks

We perform two types of robustness checks to test the sensitivity of the results. The first one is to estimate the same $\mathcal{M}_2$ model specification, but with different data series. We explore several strategies: (i) using the GDP deflator as a proxy for inflation; (ii) substituting the terms of trade with US inflation; (iii) substituting the real exchange rate for the terms of trade. In all cases, the identified time-varying coefficients are similar and the endogenously estimated regime probabilities

[13] The full tables with all variables may be found in Section B.1 in the Appendix.

do not change.

In the second type of checks, we keep the dataset as in the main MS specification and allow more coefficients to switch. The need for this comes from the nature of general equilibrium models, where all variables are interlinked. The more flexible Markov-switching specification may allow for peculiarities of one time series to propagate through the model.

We therefore estimate a third model, $\mathcal{M}_3$, where we allow for heteroskedasticity in all exogenous variables, that is, we allow for time-variation in σ_ϕ (the risk premium), σ_a (technology), σ_{μ_F} (inflation of imports), and σ_ν (preferences). The key results are plotted in Figure 2.6. The four plots depict the posterior densities of the switching parameters. Our findings remain unchanged. The risk premium coefficient is around 0.1 for the "high credibility regime" and 0.5 for the "low credibility regime", exactly as in the core model $\mathcal{M}_2$. Switching in other parameters cannot be detected as the posterior densities largely overlap. This supports our modelling strategy in two ways. First, its serves as evidence that the captured heteroskedasticity is indeed a product of the interest rate and does not feed in from other variables in the structural model. Second, it shows that no additional switching parameters for the volatilities are needed, as they do not provide further insight. The estimates of the remaining parameters in the extended model are also similar to those in $\mathcal{M}_2$.[14]

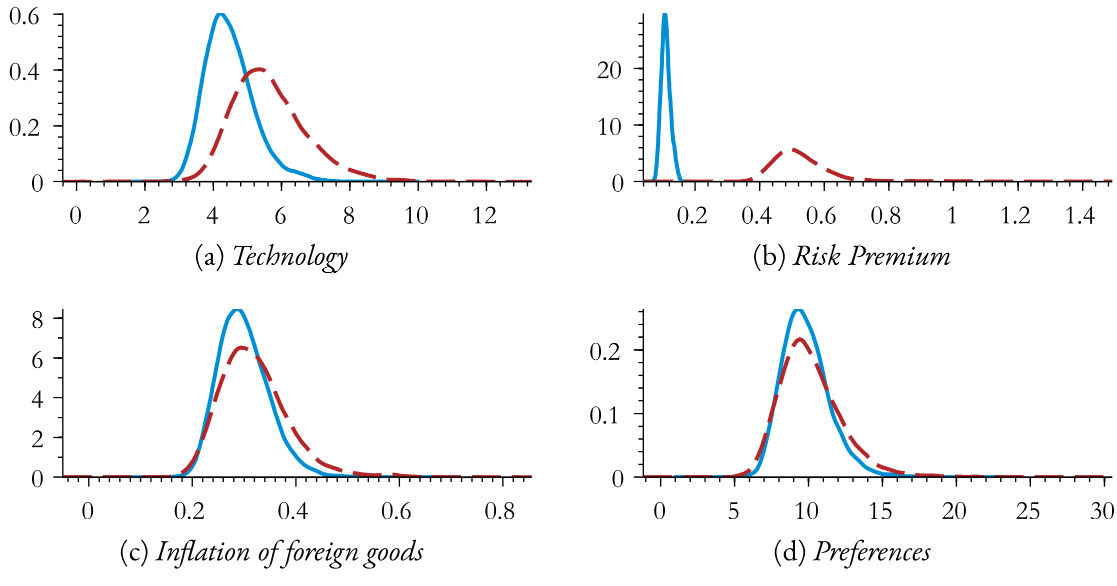


Figure 2.6: $\mathcal{M}_3$: *Posterior densities of the switching parameters technology σ_a, the risk premium σ_ϕ, import cost-push shock σ_{μ_F}, and preferences σ_ν. Regime one (—) and regime two (- -).*

[14]Section B.3 in the Appendix presents a full table with the estimated parameters of this model.

2.7 Concluding remarks

This chapter provides a fresh look at the credibility of Hong Kong's linked exchange rate system through the lens of a structural model with stochastic volatility. Utilizing a novel Markov-switching DSGE approach, we extract evidence from financial information that the currency board has faced a loss of credibility during several prolonged periods, and even during times when interest-rate differentials have otherwise been negligible.[15]

We are essentially modelling the exchange rate regime credibility as a non-linear process with two distinct regimes. In this setup, we can see that in periods of high credibility the economy barely reacts to interest-rate shocks, yet in times of speculation against the exchange rate mechanism the economic system is much more sensitive than a standard model without time-varying parameters would predict. Through conditional variance decomposition we show that the loss of credibility may have prolonged effects before trust in the system is restored. Indeed, after the Asian crisis and during the appreciation pressure in 2005, the HKMA had to step up and strengthen the currency board before credibility could be restored.

A drawback of the proposed models is that they are not able to capture the endogeneity of regime shifts. The switching parameters are exogenous, so the analysis does not allow for counterfactual policy analysis. To capture the effects of policy, one needs to know how the parameters of the Markov-switching process would have evolved for other policies. This, of course, is the Lucas critique and requires endogenisation of the switching parameters in the tradition in Filardo (1994). While MS-DSGE models are not yet able to address this critique, a handful of reduced-form models have incorporated endogenous transition probabilities and this is the main focus of the next chapter.

[15]The ability of Markov-switching frameworks to generate non-trivial connections between the dynamics of the endogenous variables and the level of uncertainty is particularly intriguing in light of the attention that uncertainty has recently received, see Bloom (2009).

3

The credibility of Hong Kong's currency board system: Looking through the prism of MS-VAR models with time-varying transition probabilities

In order to overcome financial crisis episodes, currency board exchange rate regimes have been implemented with success in countries such as Argentina, Bulgaria, Estonia, and Hong Kong as a tool to safeguard external financial stability. Hong Kong introduced a currency board system in 1983. Against the background of severe crises, Argentina and Estonia adopted currency board systems in 1991 and 1992, respectively, and Bulgaria in 1997. Under the arrangement the monetary base is fully backed by foreign currency reserves. Typically, changes in the monetary base are fully matched by corresponding changes in foreign reserves at the fixed exchange rate of the reserve currency, i.e. there exists 100% reserve backing.

This chapter has been co-authored with Prof. Dr Michael Funke.

The recent revival of interest in currency board systems originates from the "hollowing out of the middle" exchange rate regime literature [Fischer (2001)], as well as the experience of the global financial crisis. The rationale for the bipolar view is that corner solutions such as free floats and super-strict pegs are preferable to intermediate regimes because they are less crisis-prone in the context of today's volatile financial markets, on the assumption that investors will otherwise sooner or later overwhelm intermediate regimes like band systems. Bluntly, the exchange rate regime policy options were assumed to have hollowed out to the point where the only choices left to policymakers were whether to let exchange rates float or fix them permanently via a currency board or a monetary union.[2]

The Hong Kong government adopted the currency board system on October 17, 1983 during the "Black Saturday Crisis". Under the board, the money supply in Hong Kong is fully backed up by US dollars (USD), and the HK dollar (HKD) is effectively fixed at the rate of USD/HKD 7.80. Any one of the three note-issuing commercial banks wishing to print HKD notes would have to surrender an equivalent amount of USD (at the official rate) to the Hong Kong Monetary Authority (HKMA) in exchange for so-called "Certificates of Indebtedness", which entitle the bank to print a corresponding amount of HKD. Conversely, note-issuing banks can use their certificates of indebtedness in HKD to redeem an equivalent amount of USD from the HKMA. A distinctive feature of the system up to May 2005 was that no strong-side boundary existed, i.e. the currency board system was asymmetric. In May 2005, however, there was a sweeping transformation. The HKMA introduced a symmetric target zone with a narrow HKD/USD band of [7.75, 7.85].[3] While exchange rate interventions at the boundaries of the band are automatic, the HKMA also reserves the right to inject or withdraw liquidity intra-marginally.

The default view on a currency board system is that it lends credibility to the exchange rate and monetary policy by relinquishing the devaluation option. However, this is not always the case, as one can point to numerous historical episodes where currency boards fail to enhance the credibility of the monetary authority. This is because the government retains its right to abandon the scheme and renege on its institutional commitments. In other words, political uncertainty about the preferences of current and future governments can erode credibility. With respect to Hong Kong's currency board system, we illustrate this by drawing on financial market information captured by

[2]Williamson (1995) explains what a currency board is and discusses the pros and cons of the exchange rate regime. The author emphasizes that currency board systems may be quite attractive to small, open economies and a useful monetary arrangement for countries emerging from a very deep macroeconomic crisis, but that their disadvantages outweigh these advantages in large open economies.

[3]For a thorough review of the advancement towards a symmetric system see Chen *et al.* (2013).

the behaviour of interest rates in the US and Hong Kong. Because currency board rigidity ties the hands of HKMA, the system aligns Hong Kong's interest rates to the US ones.

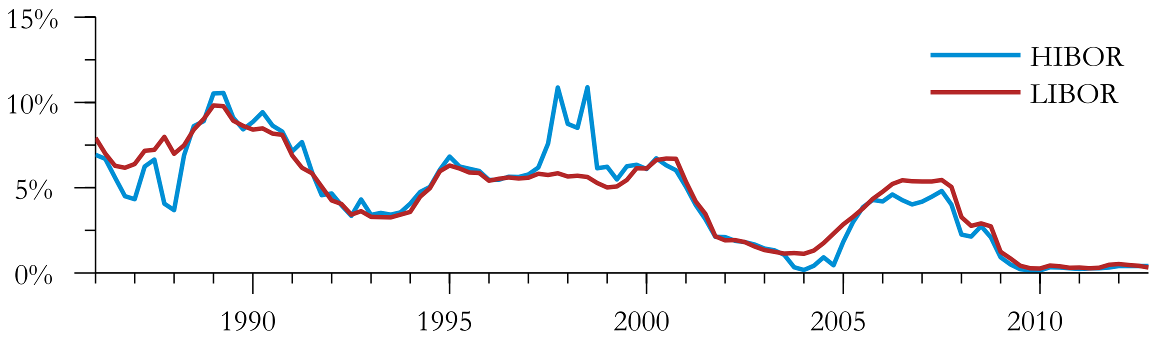


Figure 3.1: *HKD HIBOR and USD LIBOR, annualized 3-month interbank rates from 1986Q1 to 2012Q4. Source: Eurostat and Datastream*

Figure 3.1 reveals that interest rates have been on equal levels in normal periods, but the interest parity has broken down in turbulent times. The task, therefore, is to account for a succession of higher credibility periods, followed by sub-periods of lower credibility.[4] It is apparent that the stock market crash at the end of the 1980s put severe pressure on Hong Kong's currency board. The system was again put to the test by the Asian financial crisis of 1997 – 1998, when the HKD suffered a series of attacks from speculators and an acute episode of credibility loss. This contagion effect was caused by speculative attacks on other Asian currencies and forced various countries to abandon their linked exchange rate systems (LERS). The third noteworthy episode appears to have been short lived. Subsequently, the HKD was subject to appreciation pressure in 2004. The futures market drove the interest rates down in the expectation that the HKMA would follow potential moves from the mainland for appreciation against the USD. Finally, a striking feature that merits recognition is that, despite the great turmoil, Hong Kong's currency board system did not suffer from risk-aversion-induced capital outflows in the wake of the global financial crisis. Instead, after the collapse of Lehman Brothers and during the broadening and deepening global financial crisis, an unwinding of carry trade occurred. In this context, investors liquidated their offshore investments and repatriated funds to Hong Kong. This was further strengthened by that fact that the HKD's hard peg to the USD made it a safe-haven choice in times of market turbulence. As might be expected, these inflows put upward pressure on the HKD/USD exchange rate, quickly pushing it towards the strong-side limit. Moreover, in the further course of the global financial

[4]The empirical research investigating the credibility of pegged exchange rate systems was initiated by Svensson (1991) and Svensson (1993). He develops various techniques to extract devaluation expectations from interest rate differentials. De Grauwe (1994) also uses interest rate differentials to shed light on time-varying credibility.

crisis abundant liquidity provided by advanced economies' central banks and optimism about the Chinese economy led to an increasing demand for HKD assets by foreign investors.

Given the above, the question arises as to what has triggered the occasional scepticism over the suitability and/or sustainability of Hong Kong's currency board system? Since the inception of the global financial crisis of 2008 – 2009, which brought financial markets into turmoil, we now have extensive theoretical research suggesting that the pricing of assets, including exchange rates, may be non-linear. Recent papers have stressed the importance of non-linear effects and amplification dynamics during financial crises. The theory suggests that relatively small shocks can have large spillover effects [Brunnermeier and Pedersen (2008)]. Moreover, Brock *et al.* (2009) have shown that hedging instruments may produce non-linear dynamics and destabilize markets. Bianchi (2011) and Jermann and Quadrini (2012) have formalised the idea of a regime-dependent role of financial markets. Looking at exchange rates, Jeanne and Masson (2000) have addressed sunspot-driven multiple equilibria in the exchange rate context. They prove that the effects of sunspot shocks are absorbed by discrete jumps in the intercept of a regression of the currency devaluation probability on fundamental variables. Therefore, a Markov regime-switching test can be used to identify sunspot equilibria. An alternative theory for regime-switching uses the "animal spirits" concept of De Grauwe (2010) and De Grauwe and Kaltwasser (2012). Here, boundedly rational and imperfectly informed agents use heuristics to make decisions in the foreign exchange market. Again, agents' psychological movements are self-fulfilling, as waves of optimism and pessimism lead to fluctuations of the exchange rate even when the underlying fundamentals are unaltered by an exogenous shock. However, it should be noted that different authors point to a variety of causal mechanisms. A number of studies have examined the idea of regime-switching credibility in exchange rate dynamics. See, for example, Sarantis and Piard (2004), Arestis and Mouratidis (2005), Chen (2006) and Altavilla and De Grauwe (2010). One way to capture (albeit in a reduced-form way) the impact of financial factors shaping credibility is to employ Markov-switching VAR (MS-VAR) models with time-varying transition probabilities. In our view, such models have much to contribute and offer us a promising avenue of empirical research.[5]

Even though the currency board system has a long history in Hong Kong, empirical evidence on its perceived sustainability and credibility remains scant. However, three papers have recently addressed the issue head-on. Genberg and Hui (2011) have provided econometric evidence using option-based

[5] While MS-VAR models with endogenous switching are capable of providing information on the mechanism triggering regime changes, they come at the price of considerable added complexity compared to traditional Markov-switching models with exogenous jumps.

measures. Blagov and Funke (2013) have analysed the time-varying credibility of Hong Kong's currency board system employing a structural open-economy MS-DSGE modelling framework with conventional New Keynesian foundations. Finally, Chen *et al.* (2013) have modelled the revamping of Hong Kong's currency board system in 2005 as a symmetric two-sided system with a narrow exchange rate band. Our non-linear modelling approach complements and extends these lines of enquiry by highlighting the mechanism triggering time-varying credibility. We create a volatility index, based off of the Hang Seng Index, that proves informative for Hong Kong's currency board perception.

The remainder of the chapter is organised as follows. In the next section we describe how to think about the time-varying changes in credibility from a conceptual standpoint. In Section 3.2 we discuss the model's estimation methods. Section 3.3 presents the data introduces the trigger variables, while Section 3.4 discusses the empirical results. Section 3.5 deals with the robustness checks and the final section concludes.

3.1 Theoretical specification

To model the time-varying credibility of Hong Kong's currency board we turn to the theoretical framework of Filardo (1994). Using Bayesian methods, we estimate a VAR model with regime-dependent parameters and time-varying transition probabilities (henceforth MS-BVAR). The advantage of this model is that it allows us to endogenise the probabilities associated with the regime switching. The structural MS-BVAR of order l can be written in the general form as

$$A_0(s_t)y_t = a_0(s_t) + A_1(s_t)y_{t-1} + ... + A_l(s_t)y_{t-l} + \varepsilon_t, \tag{3.1}$$

where y_t is a $(N \times 1)$ vector, $t = 1, ..., T$, and the intercept $a(s_t)$ and the $(N \times N)$ coefficient matrices $A_j(s_t)$, $j = 1, ..., l$, are subject to regime shifts with s_t denoting the corresponding state. The $(N \times 1)$ vector of i.i.d. structural innovations ε_t follows a normal distribution with state-dependent variance: $\varepsilon \sim N(0, \Psi(s_t))$. Assuming that $A_0(s_t)$ is known and invertible the model can be rewritten in the following reduced form:

$$y_t = c(s_t) + B_1(s_t)y_{t-1} + ... + B_p(s_t)y_{t-p} + u_t, \tag{3.2}$$

where $c(s_t) = A_0^{-1}(s_t)a_0(s_t)$ and $B_j(s_t) = A_0^{-1}(s_t)A_j(s_t)$, $j = 1, ..., l$. The reduced form residuals are given by $u_t = A_0^{-1}(s_t)\varepsilon_t \sim N(0, \Sigma(s_t))$, where $\Sigma(s_t) = A_0^{-1}(s_t)\Psi(s_t)A_0^{-1}(s_t)'$.

The state dependence is modelled as a stochastic Markov process with transition matrix

$$P = \begin{bmatrix} p(z) & 1-p(z) \\ 1-q(z) & q(z) \end{bmatrix}. \tag{3.3}$$

The transition probability from state one to state one is given by $p(z)$ and the transition probability from state two to state two — by $q(z)$. In contrast to a fixed transition probability model, both $p(z)$ and $q(z)$ are functions of a leading variable z and are determined by a latent variable model as in Filardo (1994) and Filardo and Gordon (1998):

$$s_t^* = \gamma_0 + \gamma_1 z_{t-m} + \gamma_2(s_{t-1} - 1) + \omega_t, \tag{3.4}$$

where s_t^* is unobserved, $\omega_t \sim N(0,1)$ w.l.o.g [Filardo and Gordon (1998), p. 104], and m denotes the lag of z_t, which is required to avoid potential endogeneity issues as well as to accommodate the fact that the information for the leading variable is only available end-of-period. We use one, two, three and four lags at the estimation stage. The observable state variable s_t is defined as:

$$s_t = \begin{cases} 1, & \text{if } s_t^* < 0, \\ 2, & \text{if } s_t^* \geq 0. \end{cases} \tag{3.5}$$

The transition probabilities across regimes $p(z)$ and $q(z)$ are obtained by transformation through the cumulative distribution function (CDF) of the standard normal distribution:

$$p(z) \quad = \quad Prob(s_t = 1 | s_{t-1} = 1) = \Phi(-\gamma_0 - \gamma_1 z_{t-m}), \tag{3.6}$$

$$q(z) \quad = \quad Prob(s_t = 2 | s_{t-1} = 2) = 1 - \Phi(\gamma_0 - \gamma_1 z_{t-m} - \gamma_2). \tag{3.7}$$

The parameter γ_1 allows us to evaluate the informativeness of the leading variable z_t and measure its influence on the frequency of regime switches. The model nests the fixed probabilities case if $\gamma_1 = 0$. Hence, it can be tested whether the indicator variable contains any information regarding the probability of switching between the regimes.

The VAR model given in (1) – (4) provides a parsimonious way to capture the non-linear momentum of shocks resulting from a complicated structure of lagged interdependencies. In general, the presence of time-variation in the coefficients adds to the curse of dimensionality and some creativity is required to obtain meaningful parameter estimates and responses to the underlying shocks, which is the main topic of the next section.

3.2 Statistical inference

The model is estimated using Bayesian methods. We combine the likelihood function with prior information to evaluate the posterior distribution using a Gibbs sampler. Inference can be divided in two stages: (i) estimating the VAR, given the path of observed states and (ii) estimating the transition probabilities and the trajectory of the regimes, given the VAR coefficients.
We begin by expressing equation (3.2) as a VAR(1):

$$Y = XB + U. \tag{3.8}$$

A common way to introduce prior information in a BVAR is via the dummy observations strategy of Theil and Goldberger (1961) as outlined in Banbura *et al.* (2010). This approach introduces priors on the autoregressive coefficients through a matrix Y_d, and on the variance-covariance matrix and the intercept through a matrix X_d. The strategy is equivalent to introducing a Minnesota prior. The matrices of the dummy observations are:

$$Y_d = \begin{bmatrix} \frac{diag(\delta_1\sigma_1,...,\delta_N\sigma_N)}{\lambda} \\ \mathbf{0}_{N(l-1)\times N} \\ \cdots\cdots\cdots \\ diag(\sigma_1, ..., \sigma_n) \\ \cdots\cdots\cdots \\ \mathbf{0}_{1\times N} \\ \frac{diag(\delta_1\mu_1,...,\delta_N\mu_N)}{\tau} \end{bmatrix}, \qquad X_d = \begin{bmatrix} \frac{J_l\otimes diag(\delta_1\sigma_1,...,\delta_n\sigma_n)}{\lambda} & \mathbf{0}_{Nl\times 1} \\ \mathbf{0}_{N\times Nl} & \mathbf{0}_{N\times 1} \\ \cdots\cdots\cdots\cdot & \cdots\cdots\cdot \\ \mathbf{0}_{1\times Nl} & \epsilon \\ \frac{\mathbf{1}\otimes diag(\delta_1\mu_1,...,\delta_N\mu_N)}{\tau} & \mathbf{0}_{N\times 1} \end{bmatrix}. \tag{3.9}$$

Above, $\delta_1, ..., \delta_N$ control the tightness of the prior on the first lag, while $\sigma_1, ..., \sigma_N$ are the diagonal elements of the estimated reduced form variance-covariance matrix $\hat{\Sigma}$. The means of the time-series in the vector y_t are denoted by $\mu_1, ..., \mu_N$. The parameters λ and τ control the long-range dependence of the VAR process and the prior on the sum of coefficients, respectively and ϵ denotes the prior for the constant. We follow Banbura *et al.* (2010) and set $\lambda = 0.2$, $\tau = 5\lambda$, and impose a flat prior on the constant $\epsilon = 0.001$. Defining $Y^* = [Y', Y_d']'$, and $X^* = [X', X_d']'$ the VAR boils down to

$$Y^* = X^*B^* + U^*. \tag{3.10}$$

It follows that the OLS parameter estimates are given by:

$$B^* = (X^{*'}X^*)^{-1}(X^{*'}Y^*), \tag{3.11}$$

$$\tilde{\Sigma} = (Y^* - X^*B^*)'(Y^* - X^*B^*). \tag{3.12}$$

Letting $\boldsymbol{\beta} = vec(B^*)$, the posterior distributions of the estimates B^* and the residual variance-covariance matrix $\tilde{\Sigma}$ are:

$$p(\boldsymbol{\beta}|\tilde{\Sigma}) \sim N(\boldsymbol{\beta}, \tilde{\Sigma} \otimes (X^{*'}X^*)^{-1}), \tag{3.13}$$

$$p(\tilde{\Sigma}|\boldsymbol{\beta}) \sim iW(\hat{\Sigma}, T^* + 2 + (1 + Nl)), \tag{3.14}$$

where iW denotes the inverse Wishart distribution and T^* is the length of Y^*. Finally, we impose an uninformative prior on the parameters in the transition probability equations (3.6) and (3.7) to infer from the data whether our indicator variable z_t is predictive for the regime changes.

Inference on this form of the MS-VAR is straightforward once the vector of realised states $S_T = [s_1, ..., s_T]'$ is known, as the model collapses to n^s linear Bayesian VARs. The vector of regimes may be obtained through the Hamilton filter. Letting $\mathcal{P} = [p_1(Z), ..., p_T(Z)]'$, $\mathcal{Q} = [q_1(Z), ..., q_T(Z)]'$, and k denoting the iteration number, estimation is done via the Gibbs sampler as follows:

0. Set initial conditions for the parameters of interest $\{\tilde{\beta}_0, \tilde{\Sigma}_0, \Gamma_0, \mathcal{P}_0, \mathcal{Q}_0\}$.
1. Draw $S_{T,k}$ using the Hamilton filter conditional on $\tilde{\beta}_{k-1}, \tilde{\Sigma}_{k-1}, \Gamma_{k-1}, \mathcal{P}_{k-1}$, and $\mathcal{Q}_{k-1}$.
2. Draw $\tilde{\beta}_k$ conditional on $\tilde{\Sigma}_{k-1}$ and $S_{T,k}$, eq. (3.13).
3. Estimate $\hat{\Sigma}$ and draw $\tilde{\Sigma}_k$ conditional on $\tilde{\beta}_k$, eqs. (3.2) and (3.14).
4. Estimate the probit model using $S_{T,k}$ and obtain Γ_k, $\mathcal{P}_k$, and $\mathcal{Q}_k$, eq. (3.4).
5. Set $k = k + 1$. Go back to step 1.

Following the roadmap specified above, we run the Gibbs sampler 30 000 times. We discard the first 25 000 as a burn-in period, leaving us with 5000 draws in total.[6] We assess the convergence using standard methods as presented in An and Schorfheide (2007), such as recursive means and trace plots (see Appendix C.6). In the following section we lay out the data and apply the estimation procedure to Hong Kong's currency board system.

[6]We confine ourselves to two-state MS-VAR models. This makes the approach amenable to applied work. Estimating more than two states greatly reduces the sample size and increases the number of coefficients exponentially.

3.3 Data and identification

Due to the added complexity from the Markov-switching specification we try to keep the set of variables in the VAR small. We choose three core variables: per capita real quarterly GDP growth rate (expressed in log differences), the quarterly CPI inflation rate and the spread between the 3-month HIBOR and the 3-month LIBOR. The Hong Kong data, presented on Figure 3.2, consist of 100 quarterly observations from 1987Q2 to 2012Q4.

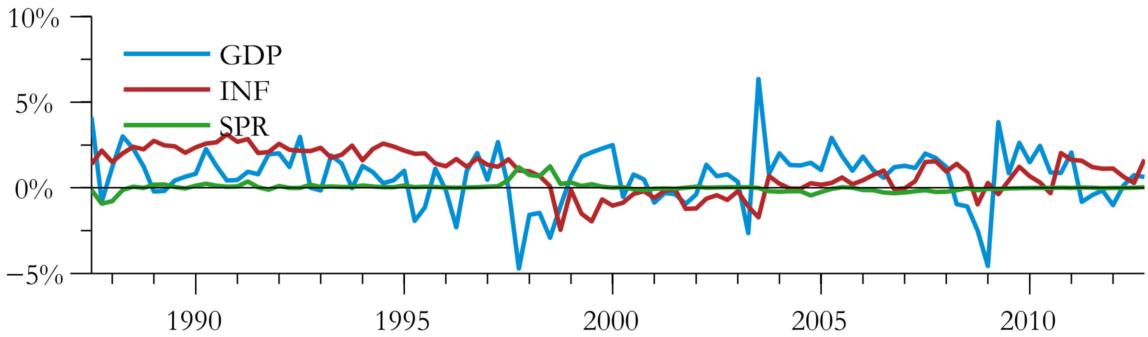


Figure 3.2: *Data for the VAR variables. GDP growth rate, CPI inflation rate, and the HIBOR-LIBOR spread. Quarterly data from 1986Q1 to 2012Q4. Source: The Hong Kong census and statistics department.*

Within the MS-BVAR framework with time-varying transition probabilities the choice of the indicator variable z is of primary importance. The chosen series should have a leading property and be representative of the expectations of the economic agents. Moreover, it should capture the uncertainty in the economy. Equity markets provide an informative gauge of the price of uncertainty. They reveal investors' assessments of how risks affect economic decisions, conveniently summarised in present value terms. For example, a surge in stock market volatility reflects the uncertainty over future growth, and the unpredictability of the associated HKMA policy response and governments.[7] Hence, it is natural to start with an equity volatility index. In order to capture the uncertainty of Hong Kong's financial markets, we turn to the Hang Seng index (HSI), which starts in 1969. We estimate the daily return on the HSI and then use a GARCH(1,1) model to extract the conditional volatility. The aggregated quarterly Hang Seng Volatility Index (HSVI) is depicted in Figure 3.3 against the Chicago Board Options Exchange Market Volatility Index (VIX) and the Financial Stress Index of the Federal Reserve Bank of St. Louis. It is evident that the development of the HSVI captures the swings of the global financial markets. Moreover, one can identify several spikes which

[7] An obvious concern, however, is over-causality. Since stock markets are forward looking and respond to economic forecasts, the MS-VAR-based results might simply reflect a tendency for financial markets to become more volatile and unpredictable when an economic downturn looms on the horizon.

are unique for the Hong Kong economy.

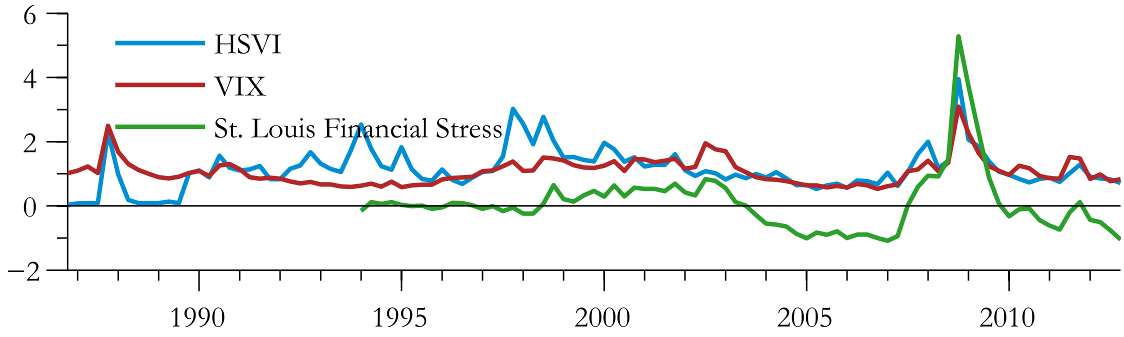


Figure 3.3: *HSVI, VIX, and the St.Louis Financial Stress Index. Rescaled for comparison. Source: Author's own calculations, Bloomberg, and the Federal Reserve Bank of St. Louis.*

We use a standard Cholesky decomposition for the VAR identification. We follow the literature in ordering the nominal variables last, assuming no contemporaneous response of the real variables to changes in the nominal variables in the current period.

In order to study the potential trigger variables regarding loss and gain of credibility we need to be able to identify the states of the credible versus the non-credible regime. From a technical point of view, we also need a strategy to deal with the problem of state labelling. Stemming from the theory of the uncovered interest rate parity, domestic and foreign interest rates should align if the exchange rate expectations of the economic agents coincide with the current rate, i.e. if the agents believe that the LERS would stand, there should be no spread between HIBOR and LIBOR. Be that not the case the agents could take a long or a short position against the board putting pressure on the system. This would lead to a negative or a positive spread, respectively. Therefore, we pursue a solution to the state labelling problem through the HIBOR-LIBOR spread equation in the VAR. We propose two regime identification strategies: according to (i) the conditional mean of the interest rate spread, where the higher conditional mean is attributed to state two, and according to (ii) the reduced form variance of the interest rate, such that higher variance of the interest rate spread is attributable to the second regime.

Note that while this does solve the state labelling problem, it does not impose the regimes ex-ante. If there are no distinct regimes, the estimated posterior distributions of the model coefficients would overlap and the associated impulse responses would be similar.

3.4 Baseline estimation results

Figure 3.4 presents the state-contingent impulse responses following a one standard deviation shock. We assume that once a shock is realised, the system cannot switch between regimes. The impulse responses are plotted with the standard 68% probability intervals from the posterior distribution. The blue lines represent the system dynamics in the first regime, which we will explore first. The red lines depict the reactions of the variables in the second state.

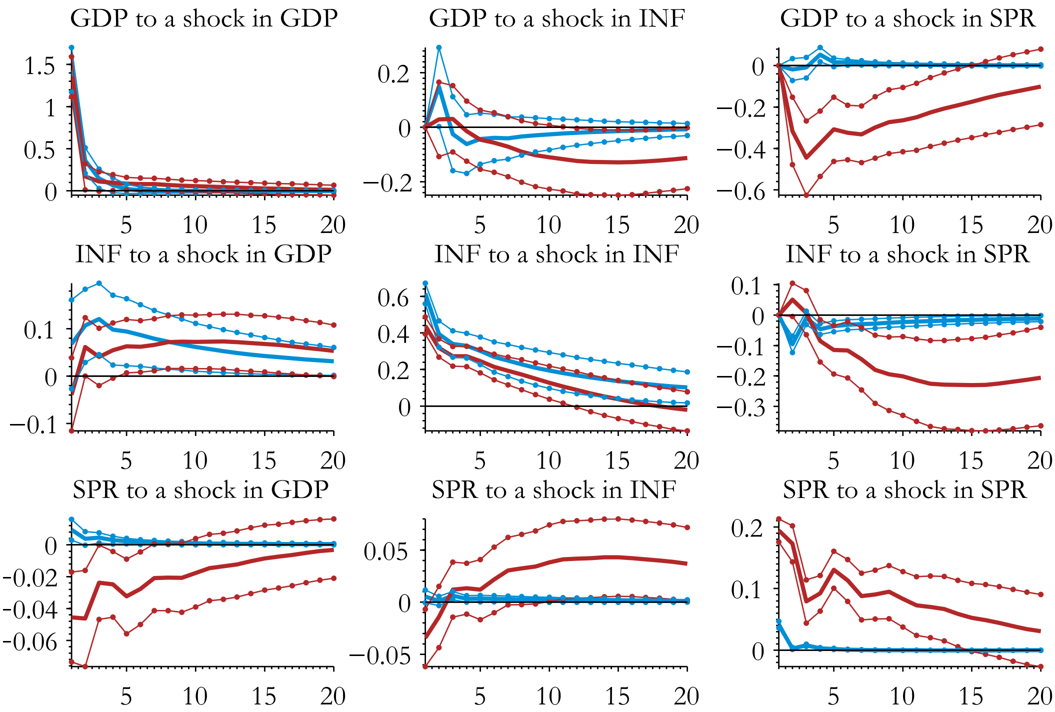


Figure 3.4: *State-contingent impulse responses to one standard deviation shock for regime one (blue) and regime two (red) with standard 68% probability intervals. MS-BVAR with the HSVI as leading variable.*

The first column of Figure 3.4 plots the impulse responses of the variables to an unexpected shock in GDP. Inflation reacts pro-cyclically — the rising demand gradually pushes prices up. Over the first twelve quarters inflation rises by more than one and a half per cent. The interest rate spread does rise with confidence bands above zero, yet the magnitude is quite low — about a hundredth of a percentage point on impact. These dynamics replicate a standard supply shock.

The responses of the variables following an inflation shock are depicted in the second column of Figure 3.4. There is no effect on output in the first state and the interest rate differential does not react to price changes in the first regime. This behaviour can be explained by the absence of autonomous monetary policy, which does not allow the monetary authority to interact and adjust the interest rates. Moreover, GDP growth does not react significantly to inflation movements.

Finally, investigating the effects of an interest rate differential shock (Figure 3.4, third column), we see that an opening of the spread does not seem to have a significant effect on output growth. Moreover, the standard deviation of interest rate shocks is low, about 0.05 per cent. While GDP does not move significantly, inflation reacts strongly — at twice the magnitude of the shock.

On first glance, the system behaves similarly in the second state, yet there are also several important differences. Both the supply shock and the inflation shock have comparable effects. Moreover, the size of both the GDP shock and the inflation shock is similar to that of their counterparts in the first state — the model does not identify heteroskedasticity in GDP or inflation.[8]

The notable difference between the two regimes lies in the interest rate differential. Following a supply shock in the second regime the spread closes, albeit also marginally. Inflation shocks seem to have a short-lived negative impact. Furthermore, the responses of GDP and inflation are also distinct following a heterogenous development of the domestic and foreign interest rates. The variance of the interest rate differential is about four times as large as in the first state. Most importantly, a positive HIBOR-LIBOR spread leads to a twice as large drop in output. An unexpected rise of 0.2 per cent would curb GDP growth by 0.4 per cent within a year. This suggests that a two per cent difference, as experienced throughout the Asian crisis, has had detrimental effects on the economy. Inflation does not react significantly at first but begins a gradual decline after about four quarters. While the empirical nature of the estimation method does not allow us to attach a structural interpretation to the regimes, the dynamics coincide with the economic theory of a low and high credibility state of the linked exchange rate system. If the currency board is stable, unexpected movements of the spread are low in magnitude and the economy hardly reacts to them. On the other hand, the spread could have large effects on the economy if the market does not perceive the currency board as credible. Agents put enormous pressure on the interest rates by taking positions against the fixed exchange rate system. This increases uncertainty, which in turn takes its toll on the economy as GDP and inflation fall. The inverse relation between the spread movement and a positive supply shock further conforms to this hypothesis, as rising demand improves financial conditions and hence stabilizes the economy. Naturally, the switching in all variables captures more than just the perceptions toward the currency board.[9] Even if the regime identification strategy does not completely isolate the credibility issue due to the reduced-form nature of the model, it still

[8] The reduced-form variance-covariance matrices are presented in Appendix C.1.

[9] It should be stressed that reverse causation may lead to an attenuation bias in the present context, since reduced perceived sustainability of the currency board may shape the Markov-switching trigger variable. Therefore, any significant coefficient should provide a lower bound for the absolute value of the "true" coefficient.

identifies the heterogeneity in interest rate dynamics, which is of major interest for one of the main questions: what is driving the regime changes?[10]

Figure 3.5 depicts the estimated probability of the realised state in the top panel, along with the time-varying transition probabilities $p(z)$ and $q(z)$ from equations (3.6) and (3.7) in the bottom panels. The system switches to the second regime after the stock-market crash in 1987, where it remains until 1991. Then, its probability peaks at one again during the Asian and Russian crises, as well as around the dot-com bubble. The next switch to the second regime is in the middle of 2003. This reflects the lagged economic effects of the severe acute respiratory syndrome (SARS) epidemic that began in Hong Kong and China. The epidemic had a considerable impact, especially in the services sector, increasing costs and sharply curbing demand, mostly in tourism-related businesses.[11] Moreover, the second state is prevalent during the appreciation pressures on the Renminbi prior to 2005 and all the way up to the global financial crisis at the end of 2008.

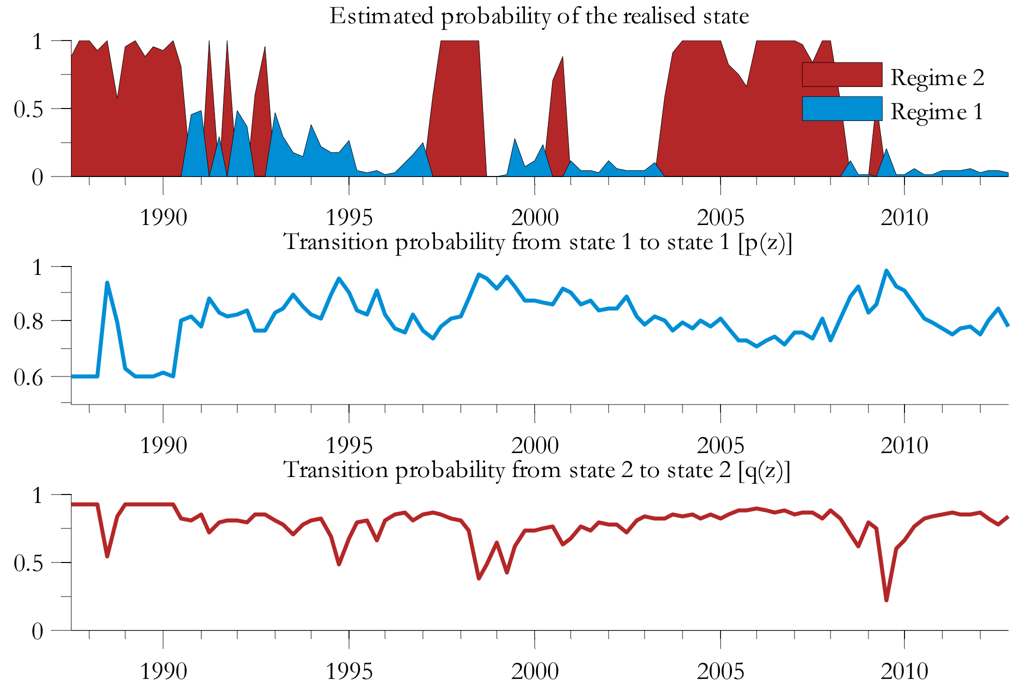


Figure 3.5: *Estimated regimes and transition probabilities. Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Middle panel: Probability to stay in regime one* $p(z)$*. Bottom panel: Probability to stay in regime two* $q(z)$.

The time-varying transition probabilities provide additional insight into the nature of regime

[10]The estimation results provide an explanation for asymmetries in business cycles in the spirit of Van Nieuwerburgh and Veldkamp (2006). In bad times agents react faster to shocks than in good times.

[11]For detailed surveys on the economic impacts of the SARS epidemic in Hong Kong, see WHO (2003) and Knobler *et al.* (2004).

switching. It is evident from Figure 3.5 that the HSVI is informative. Moreover, the parameter estimate $\hat{\gamma}_1$ is significantly different from zero.[12] The probability $p(z)$ — associated with lower volatility of the spread and pro-cyclical relation between output and inflation — varies much more compared to the second state. The second regime is more persistent, suggesting that credibility is harder to gain than to lose. The probability of staying in the first regime is at its lowest following the 1987 stock market crash, and picks up only after the end of the crisis in 1990. We can also observe a steady decline after 1995 leading all the way up to the Asian crisis. Furthermore, we observe anticipatory signals in the transition probability for the second state, which declines at the end of 1998, signalling the recovery and the end of the contagion effects from the Asian and Russian crises. The appreciation pressures in 2004 were accompanied by a steady decline in the probability for the first state, which implies that there actually was predictive information contained in the HSVI. Similar to the findings of chapter two, we note that the financial crisis was not particularly burdensome for the currency board, as evidenced by the strong rise in $p(z)$ after 2006 — the economy switched back to the first regime in 2009.[13]

Overall, these results highlight that short-lived volatility shocks may lead to a significant propagation and amplification with medium term impacts upon the perceived sustainability of the exchange rate regime. In the next section we enrich the benchmark model and discuss alternative channels that may give rise to time-varying credibility.

3.5 Robustness checks

We run a multitude of alternative models to asses the robustness of our results. We first explore the effect of other financial indicators on the switching mechanism in order to better understand what has driven the changes in regimes. Then, we turn to the assumption of heteroskedasticity and reduce the number of parameters that take regime-dependent values in our model.

We will look at several different indicators and check whether we can gain additional insight regarding the Hong Kong economy. These variables, plotted on Figure 3.6, are: the Chicago Board Options Exchange Market Volatility Index (VIX), the Equity Market Uncertainty Index (EMUI) developed by Baker *et al.* (2015), the St. Louis Financial Stress Index (STLOU), and the spread between the 1-year HKD forward rate and the spot rate (FDmS).

[12] Table C.1 in the Appendix provides the estimates from the probit regression for several specifications of the trigger variable.

[13] Hong Kong's financial institutions have coped relatively well with the global financial crisis due to their high capital adequacy ratios and their minimal exposure to securitised products.

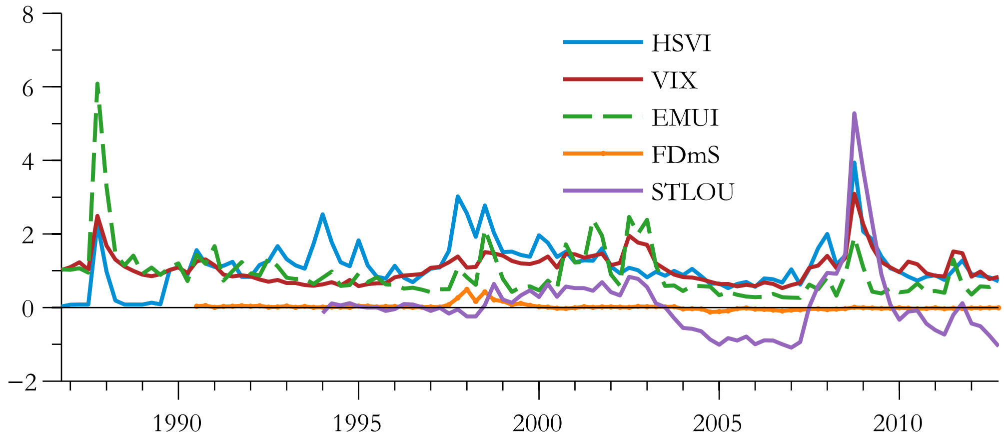


Figure 3.6: *Alternative trigger variables. Rescaled for descriptive purposes.*

3.5.1 VIX as trigger variable

VIX is a broad index derived from S&P500 options. It has the appealing property for a leading variable of incorporating the one month ahead expectations of agents regarding stock market volatility. Therefore, it is a natural starting point for our robustness analysis. Figure 3.6 displays the VIX for the period from 1987 to the end of 2012. We plot the transition probabilities of the model on Figure 3.7. As evident, with minor exceptions, they are flat. Therefore, VIX is uninformative for the Hong Kong economy. Indeed, as the probability intervals for $\hat{\gamma}_1$ contains the zero, the model is reduced to a fixed probabilities case.[14] This is an important finding — having a peg to the U.S. dollar, one might expect the Hong Kong market sentiment to be influenced by the swings of U.S. financial markets. However, domestic financial conditions appear more informative regarding the dynamics of the interest rate differential.

In terms of prevalence of the second regime, the VIX does not offer additional insight compared to the HSVI, with some minor exceptions around the dot-com bubble and the boom in the middle of the nineties (see Figure 3.7). The model still identifies the stock-market crash of 1987, the Asian crisis and the Russian crisis as the periods of increased interest rate spread rate volatility, along with the 2004–2008 period.

While the stock market volatility of the S&P500 options might not be directly informative for the currency board of Hong Kong, other types of uncertainty may play an important role. We look at the perceptions of the public captured by economic news next. Scott Baker, Nicholas Bloom and Steven Davis have developed the Equity Market Uncertainty Index, which analyses the narrative structure and specific keywords from a broad selection of newspaper articles on financial news to

[14] See Table C.1 in the Appendix for details.

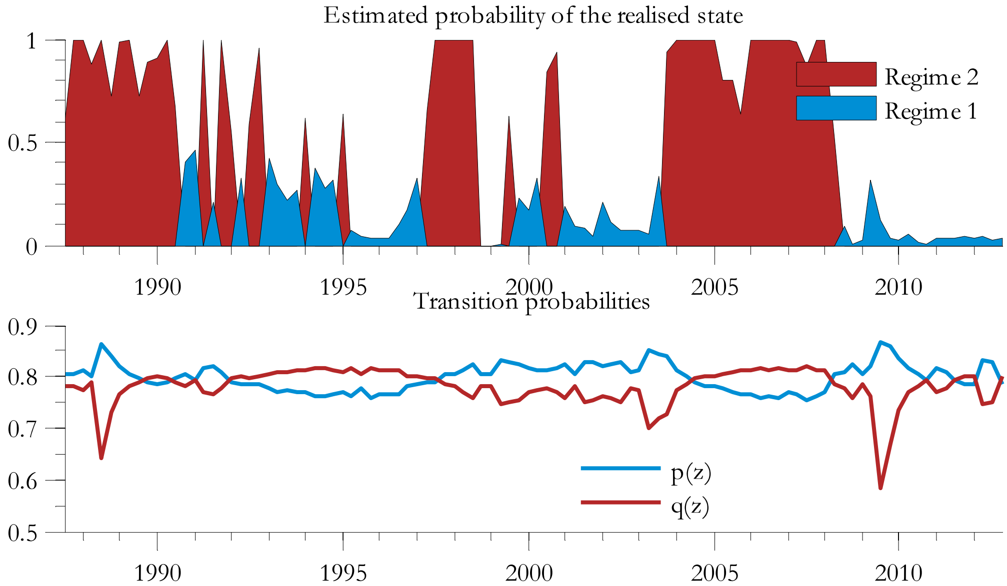


Figure 3.7: *Regime switching and transition probabilities (VIX). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities* $p(z)$ *and* $q(z)$*.*

gauge the uncertainty in the macroeconomy [Baker *et al.* (2015)].

3.5.2 EMUI as trigger variable

One rationale for choosing the EMUI as a trigger variable is that agents may be highly uncertain about the sustainability of the exchange rate regime, even though volatility of economic aggregates is still low. In other words, direct measures of subjective uncertainty rather than measures of volatility may be better suited to capture the full amount of uncertainty in the economy. Figure 3.8 shows the transition probabilities implied by the model with the EMUI as the leading variable. As evident by the bottom graph, uncertainty on the equity markets has only a minimal effect on the variation of the transition probabilities. The credible interval for $\hat{\gamma}_1$ again contains zero. Similarly to VIX, it does not bring additional insight regarding the switching mechanism. The probabilities are flat around 0.8, which implies on average longer and approximately equal durations for both regimes. So far, both robustness check specifications confirm the estimated regime switches of the main model and the macroeconomic system, depicted by the impulse response functions, behaves as before.[15] The crisis periods are associated with higher volatility of the spread and lower volatility of output and inflation. Shocks to the interest rate spread in the first regime have no significant effect on output or inflation, while the system reacts negatively in the second regime, where both output

[15] See Figures C.2 and C.3 for the impulse responses under VIX and EMUI in the Appendix.

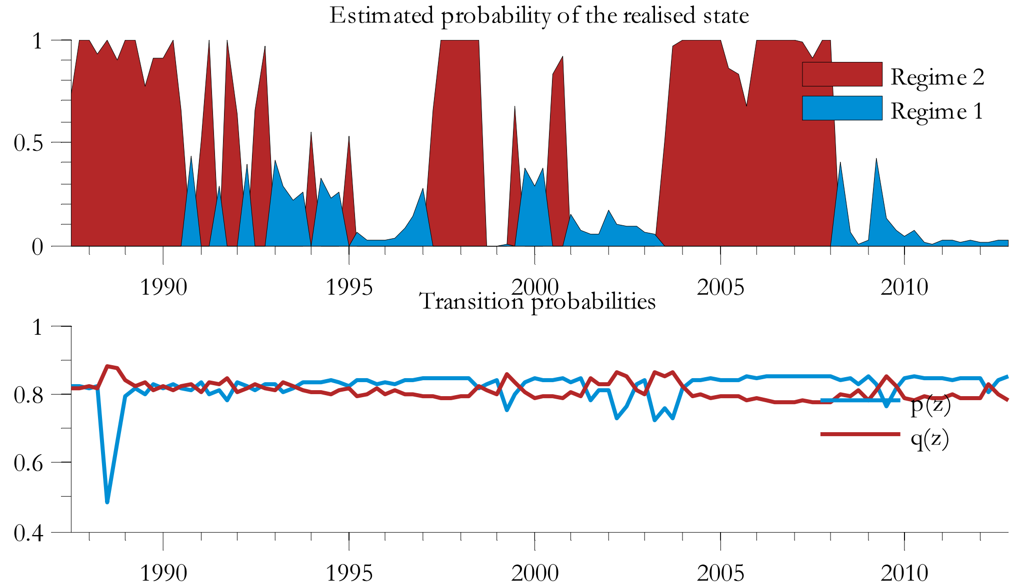


Figure 3.8: *Regime switching and transition probabilities (EMUI). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities* $p(z)$ *and* $q(z)$*.*

and inflation contract for prolonged periods after an opening of the spread. Nevertheless, the global volatility variables bring no additional information regarding the regime-switching behaviour.

3.5.3 St. Louis Financial Stress Index as trigger variable

Next we turn our attention to the St. Louis Financial Stress Index, composed by the Federal Reserve Bank of St. Louis. It is a composite index comprised of a multitude of financial time series such as six yield spreads, eighteen weekly financial series and other macroeconomic indicators. Therefore, it differs from the EMUI, being based on raw data, and it provides different information than the VIX, which is based solely on S&P500 options. The index, presented in Figure 3.6, is centred around zero, that represents the average financial stress on the markets. Positive and negative values represent above average and below average financial stress, respectively. STLOU is only available from 1993 onwards, which reduces our sample by 24 observations.

The model with the financial stress indicator presents interesting and different results compared to the other estimations. It is informative for the Hong Kong economy, as $\hat{\gamma}_1$ is significantly different from zero and the most variation in the transition probabilities is around the periods following the SARS outbreak in 2003 to the end of the global financial crisis (see Figure 3.9, bottom panel). Due to data availability constraints, there is nothing we can say regarding the stock market crash in 1987 and its aftermath. The transition probability $p(z)$ declines somewhat from 0.85 to 0.8 prior to the

Asian and Russian crises and rises only after 1998. This means that the probability of switching to the second regime $(1 - p(z))$ is increasing. The index shows a steady decline in $p(z)$ beginning in 2004 and leading all the way up to the global financial crisis, reaching its lowest levels during the appreciation pressure in 2004 and once more in the middle of 2007. Furthermore the estimates for $q(z)$ are on rather high, around 0.9, implying a long average duration of the second regime. Consequently, the economy was much longer in the state of high interest rate volatility. After a brief stint during 1995, the realised probability of the second state reaches one at the onset of the Asian crisis and remains high throughout the turbulent period all the way up to 2001, except for a minor fall below 0.5 in the beginning of the new century.

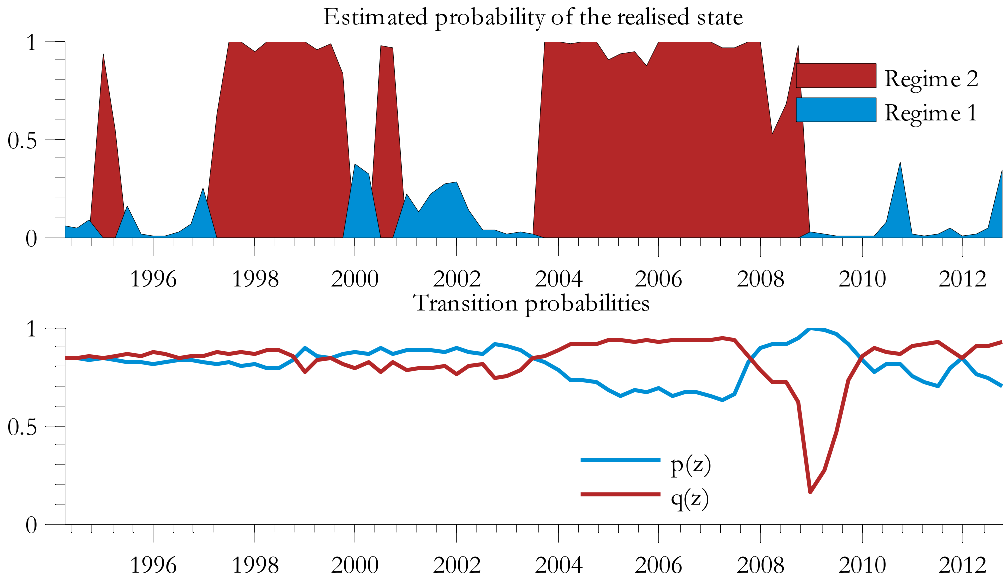


Figure 3.9: *Regime switching and transition probabilities (STLOU). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities* $p(z)$ *and* $q(z)$*.*

The next switch to the second regime is in the middle of 2003, similar to our main indicators. The economy does not return to the first state until 2009. This model also associates higher volatility of output with the first regime, which explains the sharp rise in the transition probability of the first regime throughout the financial crisis, when demand declines sharply.

The model does not imply highly different macroeconomic dynamics compared to the baseline case. Figure 3.10 presents the impulse responses from both states. Notably, the spread closes faster following a positive output growth shock — a fall of about 0.1 per cent, with a cumulative effect of about half a percentage point over the course of one year. In the second regime the spread immediately reacts positively to a rise in prices and inflation, in contrast to the gradual rise in the baseline scenario. Another difference is the marginally significant positive response of output growth following a shock to the spread.

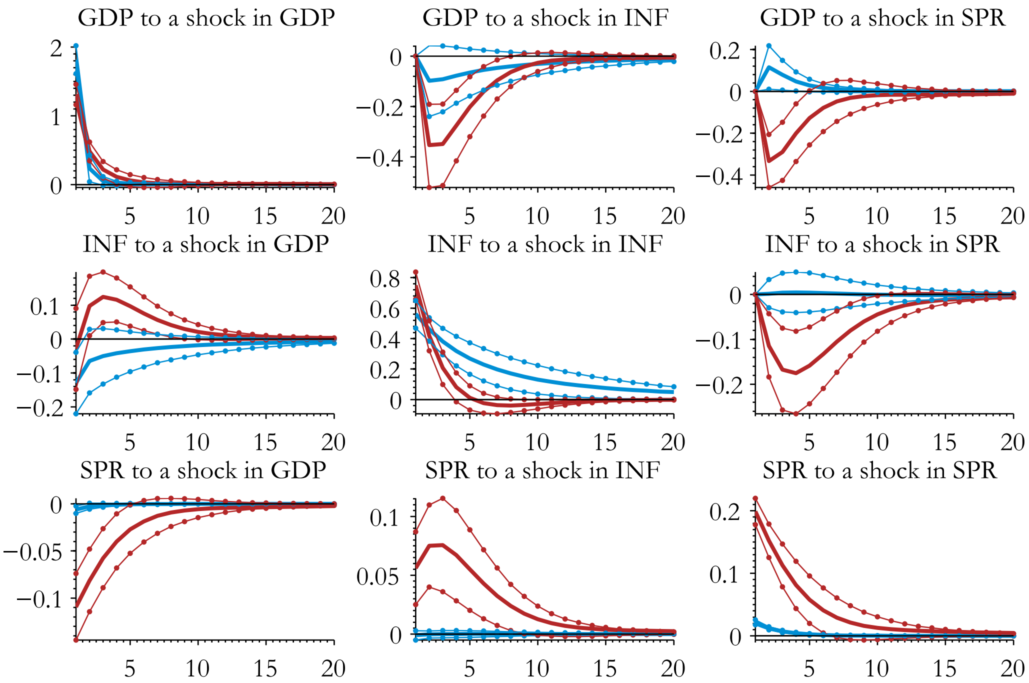


Figure 3.10: *State-contingent impulse responses to one standard deviation shock for regime one (blue) and regime two (red) with standard 68% probability intervals. MS-BVAR with the STLOU index as leading variable.*

3.5.4 HKD 1Y forward premium over the spot rate as trigger variable

As we are interested in the credibility of the exchange rate system, it is natural to look at the dynamics of the Hong Kong dollar. We estimate the forward premium on the one-year HKD forward exchange rate and use it as a leading variable in the model. The series starts from 1991Q1 and supposedly captures the depreciation pressures of the Asian and the Russian crisis and the appreciation pressures of 2004–2005 and is thus relevant for our analysis.

Estimating the model with the forward premium yields similar quantitative results, with the two states characterised by a varying degree of interest rate differential volatility and dissimilar covariances between the variables. Figure 3.11 presents the transition probabilities and the estimated regimes. The spot market premium is especially informative around the Russian crisis — there is a sharp rise in the transition probability from the first to the second regime $(1 - p(z_t))$ beginning from 1998 and, analogously, an increase in the $q(z)$. On the other hand, there is not much variation in the transition probability around the end of 2004, even though the model identifies a regime change. Hence, the appreciation pressures on the spot market were not well captured. This implies that a positive forward premium is more influential for the interest rate differential, than a negative one.

This is in line with the textbook case of a fixed exchange rate system, where the monetary authority can defend against appreciation pressures easier than against depreciation pressures.

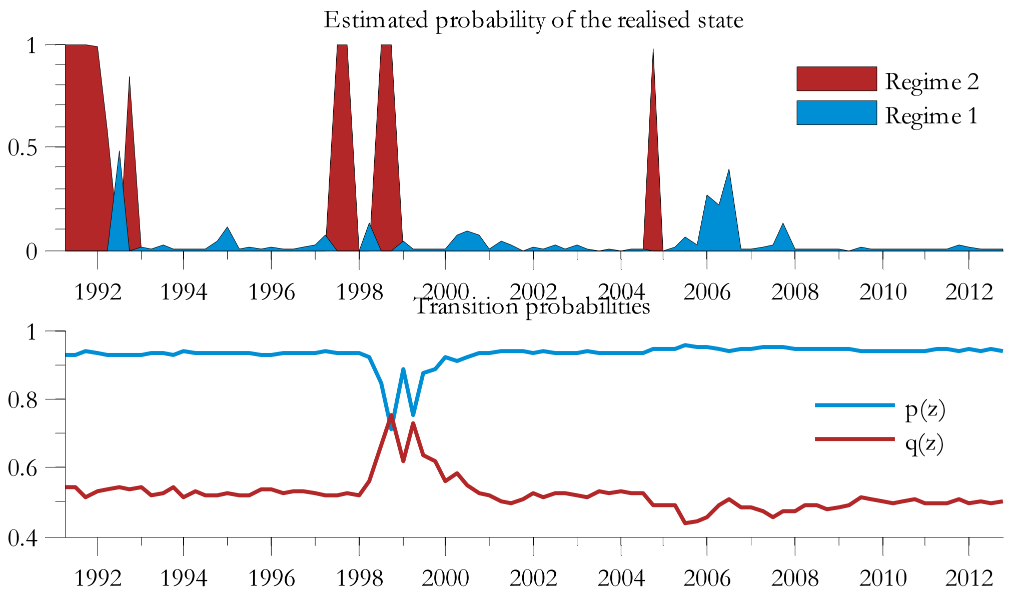


Figure 3.11: *Regime switching and transition probabilities (FDmS). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities* $p(z)$ *and* $q(z)$*.*

Figure 3.11 echoes the empirical finding of the second chapter, where the regime of low credibility of the currency board is prevalent from the end of the 1987 until 1992 and from the second quarter of 1997 to the end of 1999 with a lone spike around 2005. The forward premium on the HKD as a trigger variable leaves us with a similar picture as Figure 2.3 from the previous chapter, with the minor exception of a drop in the first quarter of 1998. Compared to the HSVI findings, Figure 3.11 is starkly different. Particularly the 2003–2008 period, which has been identified as the second regime in the model with the HSVI as a trigger variable, is attributed to the first state here. This suggests that the our own index contains more information than the forward premium on the HKD.

The current model exhibits different behaviour in terms of impulse responses as well, due to the much smaller sample size for the second regime. We observe a stronger response of the spread following a supply shock, compared to the baseline model. After an inflation shock, GDP falls in the second regime, while the spread rises instantly, neither of which was as pronounced in the baseline model. The explanation for this lies in the fact that the second state is less persistent here and the impulse responses are driven by the turbulent Asian and Russian crises.

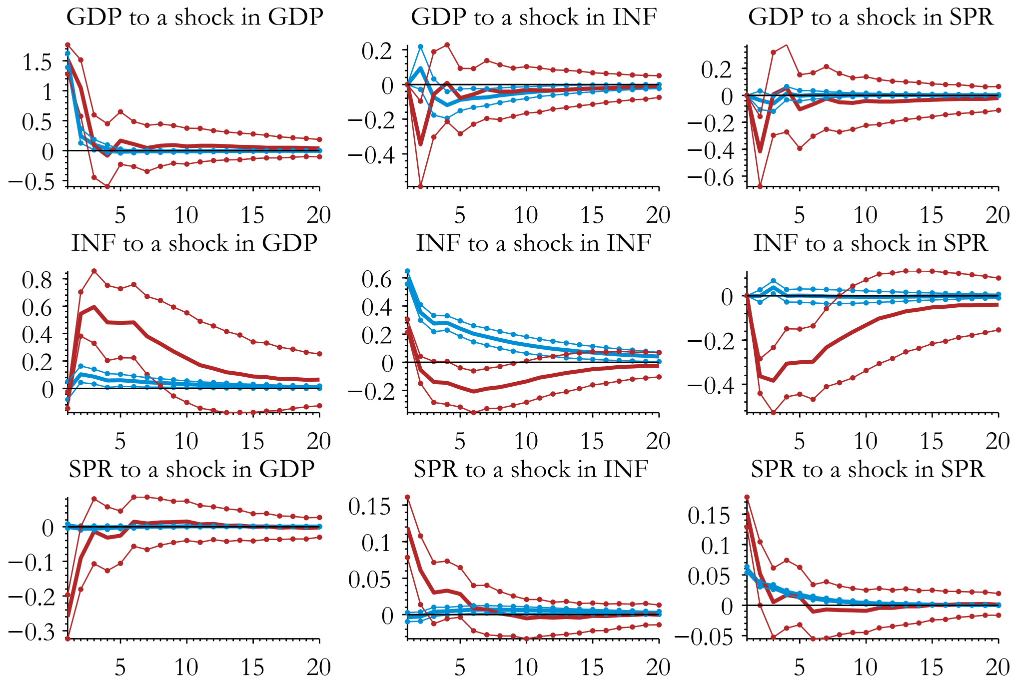


Figure 3.12: *State-contingent impulse responses to one standard deviation shock for regime one (blue) and regime two (red) with standard 68% probability intervals. MS-BVAR with the FDmS as leading variable.*

3.5.5 Markov-switching coefficients and homoskedasticity

Finally, we want to check whether our findings are driven by heteroskedasticity. We therefore abandon the assumption of state-dependent variance and rather estimate the VAR model

$$A_0(s_t)y_t = c_0(s_t) + A_1(s_t)y_{t-1} + ... + A_p(s_t)y_{t-p} + \varepsilon_t, \tag{3.15}$$

where $\varepsilon \sim N(0, \Sigma)$.[16] As the shocks of the variables are equalised across states we cannot use the regime identification strategy based on different variances and are thus confined to identification via the conditional mean strategy. The impulse response functions are presented in Figure 3.13, while the estimated transition probabilities and realised states in Figure 3.14.

The system dynamics are highly similar to the baseline case. Again, output growth does not react to spread shocks in the first regime, yet it declines sharply in the second. The most notable difference to the heteroskedastic model is the response of the spread to inflation shocks, which picks up immediately, in contrast to the delayed response in the main model (see Figure 3.4) and the similar movement of output growth following a shock to inflation.

[16] We augment the standard model following Krolzig (1997). A roadmap for the estimation of a MS-BVAR with invariant variance-covariance matrix is provided on p. 187.

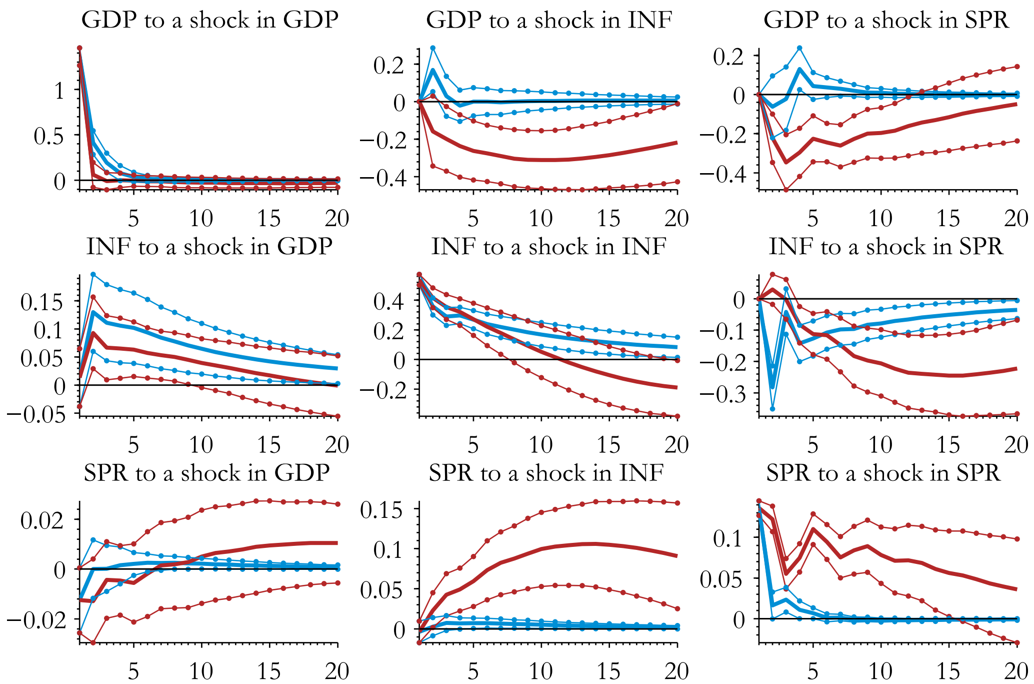


Figure 3.13: *State-contingent impulse responses to one standard deviation shock for regime one (blue) and regime two (red) with standard 68% probability intervals. Homoskedastic MS-BVAR with the HSVI as leading variable.*

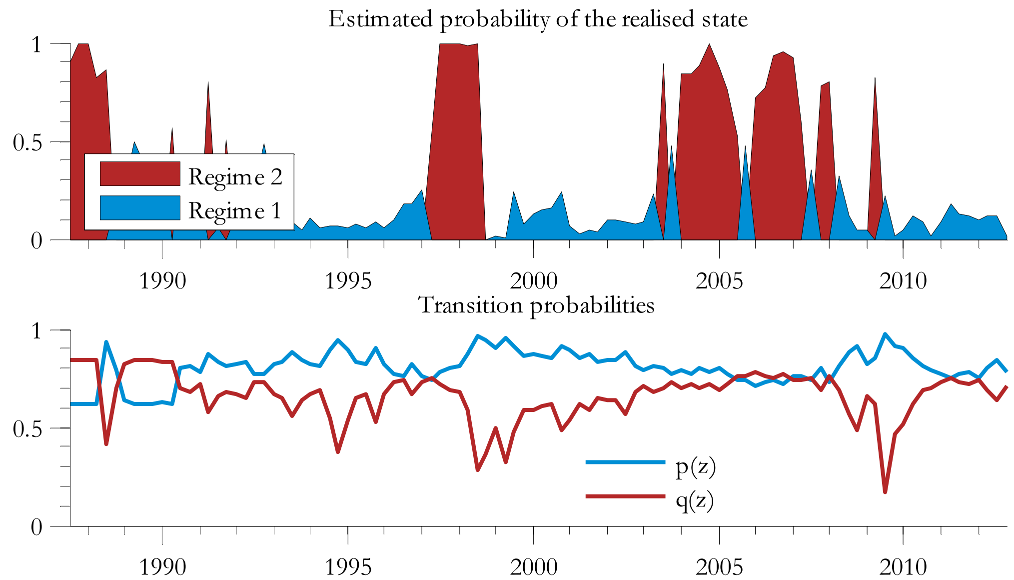


Figure 3.14: *Regime switching and transition probabilities (HSVI with homoskedasticity). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities $p(z)$ and $q(z)$.*

The estimated realisations of the two states (Figure 3.14) are also not much different than the baseline case (Figure 3.5). In the current model the second regime is less persistent after the stock-market crash of 1987, and there are no regime changes around the dot-com bubble or the SARS outbreak in 2003. This finding is analogous to the finding in the previous section with the forward premium as a leading variable. It leads us to conclude that the SARS outbreak was not associated with a loss of credibility for the board. As in all other robustness exercises, the homoskedastic model does not identify the global financial crisis as a special event for the fixed exchange rate system.

3.6 Concluding remarks

Hong Kong is an economy heavily involved in trade, and the Hong Kong dollar is one of the most traded currencies, hence a stable exchange rate is of high importance. A key feature of the HKD is that it is pegged to the U.S. dollar via a currency board. As a result, the domestic interbank interest rates tend to align with the U.S. rates. Stable currency board and financial sector ensure the stability of the financial system as a whole. However, in turbulent times, currency boards also come under scrutiny, which can lead to abnormally high or low interest rates and wide spreads with respect to foreign rates — a direct consequence of agents taking positions against the board in accord with their expectations.

Precisely this non-linear feature of currency boards is the motivation for this chapter to employ a Markov-Switching VAR with time-varying transition probabilities to study the effects of currency board credibility on Hong Kong's economy. What exactly does exchange rate regime credibility mean? Which economic policy tools are available, and what challenges do they pose for policy makers? These issues are still open for debate. Furthermore, the global financial crisis highlighted the crucial role and the non-linear nature of economic and financial shocks. We believe that our MS-VAR framework makes a useful step towards a more complete understanding of the role of uncertainty and volatility shocks on time-varying exchange rate regime credibility.

We turn to the framework of Filardo (1994) and Filardo and Gordon (1998) where regime switching is governed by macroeconomic fundamentals. To address the non-linear nature of the data, we allow for switching in all coefficients and estimate two regimes which are quite distinct from each other. The first one is associated with a low interest rate spread volatility, higher inflation volatility, and largely positive covariances between output, inflation and interest rate spread. The second state is characterised by negative covariances between the variables, as well as an interest rate spread volatility of much higher magnitude. In other words, using the reduced form approach, we are able to capture the dynamics of Hong Kong's economy, whose properties are similar to those observed in recessions with the interest rate differential playing an important role. Most notably, in the first regime the spread has almost non-existent pro-cyclical effect on output and inflation, while in the second a positive differential is found to be detrimental to the economy.

We employ an array of indicators to examine the trigger variables that influence the regime switching behaviour. We find that important global indicators such as VIX or the Equity Market Uncertainty Index do not seem to provide additional information regarding the transition between regimes, while the St. Louis Financial Stress Index does prove informative for the regime-switching around the time of the global financial crisis. We conclude that volatility in the global financial markets does not affect the stability of the Hong Kong exchange rate system. We create our own volatility index, the HSVI, based off of the conditional volatility of the Hang Seng Index and find that swings in the domestic financial markets and the forward premium on the Hong Kong dollar provide anticipatory signals and interesting insights on Hong Kong's linked exchange rate system.

4

Modelling the euro area lending spreads

The events triggered by the global financial crisis 2008 – 2009 have proved to be some of the most significant economic phenomena observed in recent decades. The costs of the downturn have far exceeded that of any previous post-WWII recession. Moreover, not only did financial developments trigger the downturn, but as events unfolded, the financial sector found itself at the epicentre of the crisis. The collapse of major financial institutions, reduced asset values, the interruption of credit flows, the loss of confidence in bond and credit markets, and the fear of default by euro area countries, were all extraordinary economic occurrences. In addition, aggressive monetary interventions during the crisis charted new ground both in scale and in scope.

Although unconventional monetary policy was intended to ease funding conditions for firms and ultimately boost investment and growth as a result, a divergent development of sovereign and corporate bond yields occurred. The reason is that liability-driven investors — those who invest in order to earn enough of a return to pay future obligations, such as insurers — which own about a

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This chapter has been co-authored with Prof. Dr Michael Funke and Richhild Moessner. The views expressed here do not represent the views of the Bank for International Settlements.

quarter of euro-denominated sovereign debt, have bid up bond prices despite vanishing yields partly because they are obliged to do so by regulators. An unintended consequence of the new regulatory regime has been to entice firms into so-called safe havens amid falling yields.

For economists, the consequence of these events has been a revival of the macro-finance nexus, as well as a growing interest in non-linear modelling approaches. The analytical models that have become standard in the field over the last generation seem to have been unsuited to explaining what was occurring during this unusually significant episode, and are now unable to incorporate most of the widely accepted accounts of it. If the economy is subject to important non-linearities, certain results that derive from linear models do not carry over, with major implications for the monetary policy transmission channel.

Interest rate pass-through is of central importance for monetary policy. With the adoption of a common currency, the euro area was faced with the challenge that a single policy had to account for the heterogeneity among its members. As such, the transmission of monetary policy of the European Central Bank (ECB) has been an important topic for researchers. Before the financial crisis, many studies found that while interest rates appear to be sticky in the short run, there exists complete long-term pass-through, and the adoption of a single monetary policy has improved the transmission and the velocity of the short-run pass-through [Bindseil and Seitz (2001), Angeloni *et al.* (2003), Sander and Kleimeier (2004), De Bondt (2005), Affinito and Farabullini (2006), Gambacorta (2008)]. However, the recent crises — the global financial turmoil and the euro area sovereign debt crisis — have put the banking systems under severe stress. Interest rates far higher than in Germany and the associated credit squeeze are threatening one of the fundamental aims of the euro area: to create a single market with an integrated economy. This may also perpetuate the euro area's two-speed recovery with higher growth in countries like Germany and Austria compared with the southern tier. There is mounting evidence that the fragmentation of financial markets has increased, and that lending and policy rates in the euro area have diverged significantly. This, in turn, has had heterogeneous effects on the monetary policy transmission across the different member states [Cihak *et al.* (2009), Gambacorta and Marques (2011), Ciccarelli *et al.* (2013), Al-eyd and Berkmen (2013), Illes and Lombardi (2013), Paries *et al.* (2014), Hristov *et al.* (2014a)].

While the breakdown in the pass-through has been documented thoroughly, numerous questions remain unanswered. What has driven the change in the interest rate pass-through among euro area member countries during the crisis? What were the trigger variables? Are there country-specific fundamentals that affect lending spreads or is it a matter of flight-to-quality and flight-to-safety concerns? We consider the hypothesis that non-linear dynamics have driven lending spreads during the crisis. Initial shocks to economic fundamentals may have been exacerbated by endogenous mechanisms. How does the pricing of risk take place and can we identify endogenous factors triggering amplification? The answers will assist in the monitoring and pricing of risk, as well as in the prevention of financial fragmentation. This work joins a growing literature that has centred on identifying non-linearities using formal statistical methods.[2]

We investigate the heterogeneous effects of monetary policy across several euro area countries through the lens of a quasi-non-linear Vector Autoregressive model (VAR) subject to regime shifts with endogenous transition between the states. We incorporate the switching mechanism through time-varying transition probabilities that help us identify potential triggers.[3] In this set up, model uncertainty takes the form of different models that follow a Markov process. It can be thought of as a setup encompassing a number of possible representations of the world.

A few studies have investigated the joint variation of macro fundamentals and credit spreads by incorporating the possibility of regime shifts [e.g. David (2008)], and a handful have documented the change in interest rate pass-through. Cihak *et al.* (2009) use a standard bi-variate VAR in the spirit of De Bondt (2005) and a general equilibrium framework to show a slowdown in the pass-through. They also analyse unconventional monetary policy measures and demonstrate that to a certain extent they have helped alleviate the problem. Ciccarelli *et al.* (2013) quantify the heterogeneous effects of monetary policy on GDP across the member states by means of a recursive VAR and document the time-variation in interest rate pass-through. Furthermore, they show that the effect on GDP of monetary policy shocks is amplified through the credit channel, and that the bank-lending channel has been non-existent due to unconventional monetary policy measures of the ECB. Hristov *et al.* (2014b) examine the effectiveness of the Outright Monetary Transmission Program (OMT) of the ECB by means of a time-varying parameter VAR (TVP-VAR) based on Primiceri (2005), and Paries *et al.* (2014) capture the breakdown in interest rate pass-through by a single equation framework. The model is extended to account for bond yields, which partly explain the lending spreads. Hristov *et al.* (2014a) document the incompleteness of the pass-through after the crisis using a panel VAR and a DSGE model. Aristei and Gallo (2014) also use the simple bi-variate framework of De Bondt (2005)

[2] See Silvestrini and Zaghini (2015) for an up-to-date survey of the theoretical and empirical contributions exploring the linkages between financial factors and the real economy in non-linear frameworks.

[3] Evidence that macroeconomic time series follow a Markov process has led macroeconomists to develop monetary policy frameworks with regime shifts. For example, Svensson and Williams (2009) have developed a general form of model uncertainty that remains tractable, using so-called Markov-jump-linear-quadratic models. There is a growing body of Markov-switching DSGE and VAR models [Sims *et al.* (2008), Farmer *et al.* (2009), Farmer *et al.* (2011), Bianchi (2012), Davig and Doh (2014) among others].

in the context of a Markov-switching VAR (MS-VAR) and a Markov-switching Error Correction Model (VECM) with exogenous probabilities, and establish lower efficiency and time-variation in the transmission of monetary policy. Our study differs significantly from Aristei and Gallo (2014) since our framework has the important addition of endogenous transition probabilities to address the question at hand.

There are a couple of novel studies that argue that if one takes several considerations into account, the high lending rates might be explained even in the face of near zero policy rates. Ciccarelli *et al.* (2013) and Illes *et al.* (2015) suggest that after the crisis the interbank rate might not be a good proxy for bank funding costs and thus should not be taken as a major determinant for the lending rates, because access to funds was impaired after the meltdown. Illes *et al.* (2015) create a benchmark for bank funding costs for each country both in the short and the long-term, which accounts for the levels of the lending rates. They construct a weighted average cost of liabilities (WACL), which consists of several components including covered bonds, five-year credit default swaps, deposit liabilities and open market operations. Von Borstel *et al.* (2015) utilise a factor-augmented VAR (FAVAR) model to incorporate sovereign and bank funding risk, conventional and unconventional monetary policy, and argue that it is not the interest rate pass-through that has changed, but rather its composition. Our results hold even if we account for the zero lower bound and the impairment in the bank funding channel.

This chapter is organised as follows. The next section introduces the key data in our study, namely lending rates and sovereign bond yields. Section 4.2 presents the econometric methodology, Section 4.3 lays out the central results, and discusses potential problems and extensions to the main specification. Finally, Section 4.4 concludes.

4.1 Lending spreads and sovereign bond spreads

We consider the heterogeneous time-variation across the euro area of long-term lending rates to non-financial firms. We use monthly data from the ECB for interest rates on loans over €1 million, other than revolving loans and overdrafts, convenience and extended credit card debt to non-financial firms for new businesses, with maturities over one year [ECB (2003)]. We examine four countries in this study: Italy, Spain, Ireland, and Portugal and consider the spread of the long-term lending rate to Germany, $r_t^h = R_t^h - R_t^{DE}$, where R_t^h is the long-term lending rate in country h at time t.[4]

[4]Since the Markov switching estimator performs better for long time series, Greece has not been considered due to data availability issues. On the contrary, the longer time series for the other countries fit suit.

All countries are identified by the respective two-letter ISO code. As a link between the short-term policy rate and the long-term lending rate we include 10-year government bond yield spreads relative to Germany as an endogenous variable, $g_t^h = G_t^h - G_t^{DE}$, which reflect country specific market sentiment. Monthly data for the evolution of lending rate spreads and government bond yield

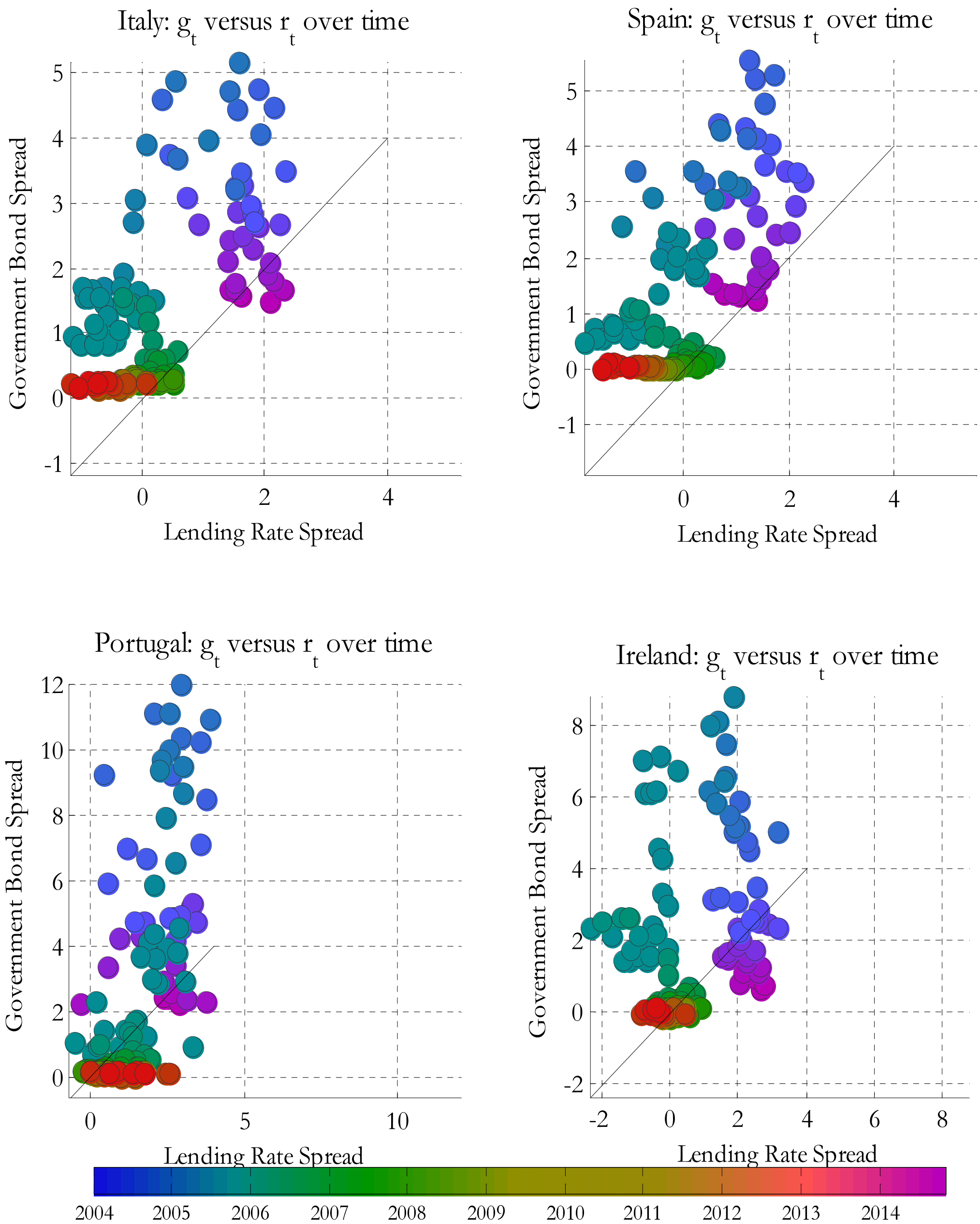

Figure 4.1: *Government bond spread (g_t) versus lending rate spread (r_t), relative to Germany. in per cent. Source: Author's own calculations.*

spreads over time (with evolution over time denoted by different colours) is shown in Figure 1 for each of the four euro area countries. We can see that at the beginning of the sample period, in 2004, government bond yield spreads tended to be close to zero for all four countries. Lending rate spreads for Italy, Spain, and Ireland were even negative in many instances in 2004. At the height of the euro area sovereign debt crisis, government bond yield spreads rose to much higher values than the lending spreads, before falling back considerably towards the end of the sample period. Although lending rate spreads did not rise as much as government bond spreads, they tended to remain elevated towards the end of the sample period.

4.2 Econometric methodology

To study the changes in the interest rate pass-through we assume the following data generating process of a structural VAR with time-varying parameters:

$$A_0(s_t)y_t = a(s_t) + A_1(s_t)y_{t-1} + ... + A_l(s_t)y_{t-l} + \varepsilon_t, \tag{4.1}$$

where $A_0(s_t), ..., A_l(s_t)$ are coefficient matrices, $a(s_t)$ is a vector of constants, and the structural innovations ε_t follow a normal distribution with mean zero and stochastic volatility: $\varepsilon_t \sim N(0, \Psi(s_t))$. Each set of coefficients is associated with the respective state $s_t = \{1, ..., n^s\}$, where n^s is the number of regimes.[5] The vector y_t contains n endogenous variables and l denotes the lag order, selected according to standard information criteria. We use three lags for Spain, four for Italy, two for Ireland and two for Portugal. To determine the maximum lag length for the tests, we follow Schwert (1989). We assume endogeneity of all variables in the system and estimate the dynamics of purely exogenous shocks.[6] Assuming a two-state stochastic Markov process ($n^s = 2$), the shifts across regimes are governed by transition probabilities given by the probability matrix

$$P = \begin{bmatrix} p(Z) & 1 - p(Z) \\ 1 - q(Z) & q(Z) \end{bmatrix}. \tag{4.2}$$

Instead of assuming an exogenous switching mechanism, we set both p and q as the outcome of a probit model with regressors collected in the vector of trigger variables $Z_t = [1, z_{1,t}, ..., z_{k,t}]$. Let

[5] Jovanovic (1989) has shown that in case of sunspots it is necessary to distinguish the dynamics of the fundamentals process from the sunspot process. A Markov regime-switching model provides a flexible framework that allows to distinguish between the two processes. The regime shifts can then be interpreted as jumps between multiple equilibria.

[6] The Markov-switching framework poses complications for empirical work that attempts to estimate how interest rate spreads respond to changes in monetary policy. The complications arise due to the non-linearity in the decision rule, implying that the interest rate pass-through is a function of the regime. Borrowing language from Leeper and Zha (2003), an interest rate pass-through within the band where the decision rule is approximately linear can be referred to as a "modest" monetary policy intervention. A "non-modest" policy intervention causes agents to alter their inference regarding the current regime, resulting in a response that is greatly at odds with the predictions of fixed-regime models.

s_t^* be a latent variable determined by the following regression:

$$s_t^* = \gamma_0 + \gamma_1 z_{1,t-m} + ... + \gamma_k z_{k,t-m} + \omega_t. \tag{4.3}$$

The error term in equation (3) follows a standard normal distribution $\omega_t \sim N(0,1)$ and we set the lag of the trigger variables m to 1 to address potential endogeneity problems. The vector of coefficients $\Gamma = [\gamma_0, \gamma_1, ..., \gamma_k]'$ is of primary interest for this study, as the variables governing the transition probabilities would prove crucial for describing the nature of the euro area crisis. Moreover, statistically significant effects of contagion variables on transition probabilities would lead to the conclusion that lending spreads are not only driven by fundamentals but also by contagion, e.g. due to confidence effects. Significance of both fundamentals and contagion variables would indicate that various crisis models are not mutually exclusive.

Under the assumption of two regimes the threshold for the observable counterpart s_t of the latent variable s_t^* is defined as:

$$s_t = \begin{cases} 1, & \text{if } s_t^* < 0, \\ 2, & \text{if } s_t^* \geq 0. \end{cases} \tag{4.4}$$

Therefore, the transition probabilities are determined by the following probit model:

$$p(Z) = P(s_t = 1|s_{t-1} = 1) = P(\omega_t \leq -Z_{t-m}\Gamma) = \Phi(-Z_{t-m}\Gamma), \tag{4.5}$$

$$q(Z) = P(s_t = 2|s_{t-1} = 2) = P(\omega_t \geq -Z_{t-m}\Gamma) = 1 - \Phi(-Z_{t-m}\Gamma). \tag{4.6}$$

The complete model, given by equations (4.1) – (4.6), is based on Goldfeld and Quandt (1973), Filardo (1994), and Filardo and Gordon (1998) and nests the case of fixed probabilities if the variables in Z are not informative for the probit regression.

The assumption of the existence of two states is not innocuous. In general, specifying a Markov regime-switching model requires a test to confirm the presence and the number of multiple regimes. The first step is to test the null hypothesis of one regime against the hypothesis of Markov switching between two regimes. If the null hypothesis can be rejected, then one can proceed to estimate the Markov regime-switching models with two or more regimes. Conducting proper inference, however, is exceptionally challenging. In particular, testing for the number of regimes requires the use of nonstandard test statistics and critical values that may differ across model specifications. Cho and White (2007) demonstrate that because of the unusually complicated nature of the null space, the appropriate measure for a test of multiple regimes is a quasi-likelihood-ratio (QLR) statistic. They provide an asymptotic null distribution for this test statistic from which critical values can be calculated. Unfortunately, Carter and Steigerwald (2012) establish that the estimator computed using the QLR-likelihood is inconsistent if the covariates include lagged dependent variables. Thus, this test cannot be applied to our modelling setup.

As we cannot pin down the amount of regimes by statistical inference, we have to take another approach. We choose two-states for the data generating process in (4.1). Our choice is motivated by the main question — has there been a change in interest rate pass-through, and if so, what has been driving it? One approach to answer the question would be to use a gradual change in the model parameters as Ciccarelli et al. (2013) and Hristov *et al.* (2014a). The other extreme is modelling a binary outcome. Even though we cannot test for the presence of two regimes directly, the advantage of the Bayesian approach lies in the fact that it does not impose that regimes be significantly different from one another as we use the same prior in both states. If the data do not support distinct parameters, we would find overlapping posterior distributions of the coefficients and similar impulse responses. On the other hand, if there are more than two regimes and there is even higher fragmentation among euro area members, our results will average the multiple states in two distinct sets and may be interpreted as a lower bound, i.e. the "true" impulse responses would be even more pronounced.[7] A final consideration is the computational efficiency and the curse of dimensionality. Every additional state reduces the sample size proportionally, while increasing the number of parameters to be estimated exponentially, which speaks against additional states.

4.2.1 Bayesian analysis

We cast the model of equation (4.1) in a reduced form by pre-multiplying the structural form with the impact matrix $A_0(s_t)^{-1}$ and redefining all coefficient matrices accordingly

$$y_t = b(s_t) + B_1(s_t)y_{t-1} + ... + B_l(s_t)y_{t-l} + u_t. \tag{4.7}$$

The residuals $u_t \sim N(0, \Sigma(s_t))$ in equation (4.7) and their connection to the structural shocks is of primary interest in any VAR study. For this link we choose a standard Cholesky decomposition, which is consistent with the pass-through literature. This choice is motivated by the economic theory that policy rates determine lending rates and can do so instantaneously, but not vice versa. The reduced-form VAR(l) model may be rewritten in its VAR(1) form by imposing $Y = [y_1, ..., y_T]'$,

[7] For an application of two state models to monetary policy, term structure and bond/CDS spreads see, for example, Amisano and Tristani (2009), Lanne *et al.* (2010), and Blommestein *et al.* (2012).

$X = [X_1, ..., X_T]'$ with $X_t = [y'_{t-1}, ..., y_{t-l}, 1]'$, $U = [u_1, ..., u_T]'$, and $\beta = [B_1, ..., B_l, b]'$:

$$Y = XB + U. \tag{4.8}$$

For the estimation we employ Bayesian methods and incorporate the priors following Banbura et al. (2010). This is achieved by augmenting the vectors of endogenous and exogenous variables by the following matrices:

$$Y_d = \begin{bmatrix} \Lambda \cdot \hat{\Sigma}/\lambda \\ \mathbf{0}_{n(l-1)\times n} \\ \cdots\cdots\cdots \\ \hat{\Sigma} \\ \cdots\cdots\cdots \\ \mathbf{0}_{1\times n} \\ \Lambda \cdot \mathbf{M}/\tau \end{bmatrix}, \qquad X_d = \begin{bmatrix} J_l \otimes \Lambda \cdot \Sigma/\lambda & \mathbf{0}_{nl\times 1} \\ \mathbf{0}_{n\times nl} & \mathbf{0}_{n\times 1} \\ \cdots\cdots\cdots\cdots & \cdots\cdots\cdots \\ \mathbf{0}_{1\times nl} & \epsilon \\ \mathbf{1} \otimes \Lambda \cdot \mathbf{M}/\tau & \mathbf{0}_{n\times 1} \end{bmatrix}. \tag{4.9}$$

Here, $\hat{\Sigma} = diag(\sigma_1, ..., \sigma_n)$ is the estimated variance-covariance matrix of the residuals from equation (4.7), which we weigh by a matrix $\Lambda = diag(\delta_1, ..., \delta_n)$. The weights δ control how informative more recent lags are compared to older periods. Since our system is generally short, these parameters are not of crucial interest. $M = diag(\mu_1, ..., \mu_n)$ are the average levels of the endogenous variables y_t, and $J_l = diag(1, ..., l)$. The parameter λ is the overall tightness of the prior, which ranges in $[0, \infty]$, with 0 being a pure random walk and infinity — the OLS estimates; ϵ denotes the prior on the constant. Furthermore, we incorporate Bayesian shrinkage by means of the hyperparameter τ. Finally, the operator "$\cdot$" denotes elementwise multiplication. For the choice of these parameters we follow Banbura et al. (2010) and set $\lambda = 0.1$, $\varepsilon = 0.01$, $\tau = 10\lambda$, and μ_i equal to the mean of the y_i vector.

Combining (4.8) with (4.9) leads to the following specification:

$$Y^* = X^* \tilde{\beta} + U^*, \tag{4.10}$$

where $Y^* = [Y', Y_d^{*'}]'$, $X^* = [X', X_d^{*'}]'$, and $U^* = [U', U_d^{*'}]'$. Taking the OLS estimate of $\tilde{\beta}$ in (4.10) as $\tilde{\beta} = (X^{*'}X^*)^{-1}X^{*'}Y^*$, we impose an inverse Wishart prior on its variance

$$\tilde{\Sigma} \sim iW\left(\hat{\Sigma}, T^* + 2 + (1 + nl)\right), \tag{4.11}$$

where T^* denotes the number of rows in Y^*. Therefore, the posterior distribution of interest becomes

$$vec(\tilde{\beta})|\tilde{\Sigma}, Y^* \sim N\left(vec(\tilde{\beta}), \tilde{\Sigma} \otimes (X^{*'} X^*)^{-1}\right). \tag{4.12}$$

Inference on this form of the MS-VAR is straightforward once the vector of realised states $S_T = [s_1, ..., s_T]$ is known, as the model collapses to $n^s = 2$ linear Bayesian VARs. The vector of regimes, in turn, may be obtained through the Hamilton filter. Letting $\mathcal{P} = [p_1(Z), ..., p_T(Z)]'$ and $\mathcal{Q} = [q_1(Z), ..., q_T(Z)]'$, estimation is carried out via the Gibbs sampler in the following order of events. Given initial conditions for the parameters of interest $\{\tilde{\beta}_0, \tilde{\Sigma}_0, \Gamma_0, \mathcal{P}_0, \mathcal{Q}_0\}$ and denoting an arbitrary iteration number by k, we:

1. Draw $S_{T,k}$ using the Hamilton filter conditional on $\tilde{\beta}_{k-1}, \tilde{\Sigma}_{k-1}, \Gamma_{k-1}, \mathcal{P}_{k-1}$, and $\mathcal{Q}_{k-1}$.
2. Draw $\tilde{\beta}_k$ conditional on $\tilde{\Sigma}_{k-1}$ and $S_{T,k}$, eq. (4.12).
3. Estimate $\hat{\Sigma}$ and draw $\tilde{\Sigma}_k$ conditional on $\tilde{\beta}_k$, eqs. (4.7) and (4.11).
4. Estimate the probit model using $S_{T,k}$ to obtain $\Gamma_k, \mathcal{P}_k$, and $\mathcal{Q}_k$, eq. (4.3).
5. Set $k = k + 1$. Go back to step 1.

We employ 50 000 iterations and discard the first 35 000 as a burn-in phase. In Section D.7 in the Appendix we present the trace and recursive means plots to assess convergence in the spirit of An and Schorfheide (2007).

4.2.2 Explanatory variables in the regime-switching VAR

The interest-rate pass through consists of two stages. In the first stage, the ECB lends funds to financial institutions in its open market operations at the policy rate which determines the interbank rate. The second stage is the transmission from the interbank rate to the lending rates for non-financial institutions. The ECB sets a corridor for the policy rate and adjusts it several times a year, which makes the official policy rate a step-wise function — unsuitable for empirical analysis. Typically, the literature assumes that the first-stage transmission is always perfect in the sense that interbank rates such as the overnight EONIA rate or the EURIBOR are a good proxy for the policy rate. Nevertheless, recent studies have noted that this may not be an appropriate choice any more. On one hand, Hassler and Nautz (2008) document that the link in the first stage has broken down. On the other, the zero lower bound plays an important role in studying interest rate pass-through, because the lending rates move freely even when this constraint is binding for the money market rate. Thus, empirical models might "capture" a breakdown in the pass-through solely due to the flatness of the proxy for the policy rate. As an alternative the literature has suggested using a different proxy for the policy rate, namely a shadow short rate (SSR) [Wu and Xia (2014), Krippner (2014), Pericoli and Taboga (2015) and von Borstel *et al.* (2015)]. This shadow rate is derived from non-linear term structure models and is allowed to take negative values, which alleviates the problem of the zero lower bound. Unfortunately, this does not come without a cost. Since the shadow rate series are rather a theoretical construct, they do not represent interest rates at which economic agents can transact [Krippner (2014)]. Hence they do not reflect the banks' funding costs.

Thus, choosing a proxy for the policy rate is not a straightforward task. To this end, we explore several different specifications. In the main section we employ the EONIA as the policy rate i_t, while in the robustness section we estimate the model using alternative measures — the shadow estimates of Wu and Xia (2014), Krippner (2014), and Pericoli and Taboga (2015).

To summarise, in our model long-term lending rate spreads r_t^h are explained by the policy rate i_t, approximated by EONIA or a shadow short rate, and the 10-year government bond yield spread g_t^h, which we use as a proxy for market expectations and a link between short-term and long-term rates. Therefore, the vector of endogenous variables y_t^h for country h at time t is given by

$$y_t^h = \begin{bmatrix} i_t & g_t^h & r_t^h \end{bmatrix}'. \tag{4.13}$$

We plot the time series for each country in Figure 4.2.

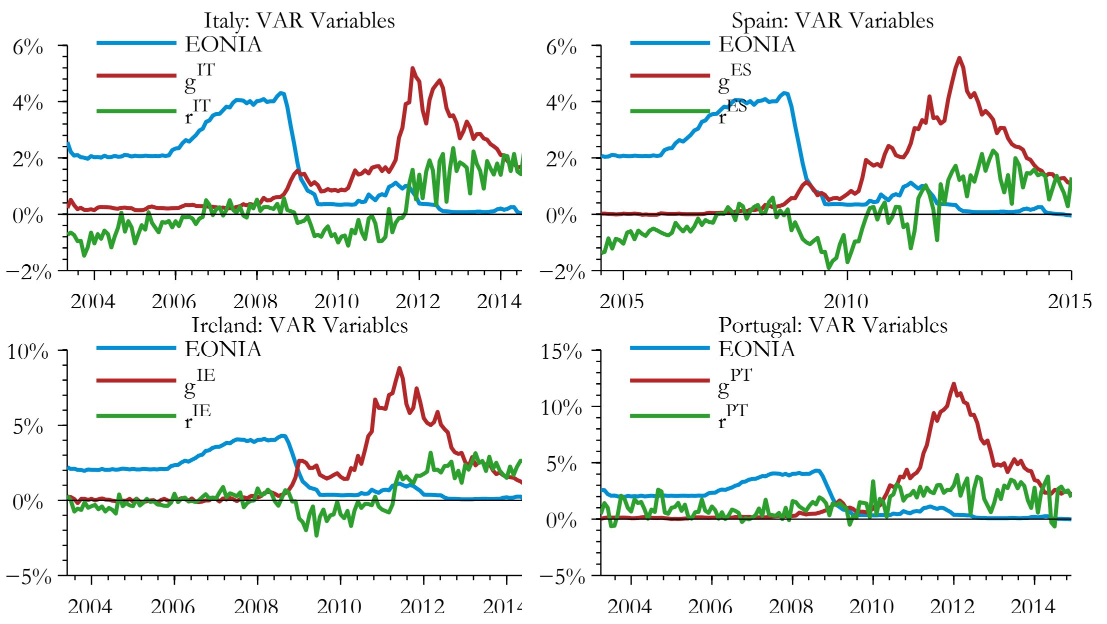

Figure 4.2: *VAR variables for Italy, Spain, Ireland, and Portugal: EONIA, the 10-year government bond spread between each country and Germany* g_t^h*, and the long-term lending rate spread between each country and Germany* r_t^h*. Source: ECB's MFI monetary statistics and the FRED database.*

4.2.3 Choosing the trigger variables

The choice of trigger variables in the probit stage is of crucial importance. Omitting relevant explanatory variables increases the variance of the error term, which potentially biases the estimates. Therefore, care should be taken when specifying equation (4.3) of the regime-switching VAR. We use a multitude of macro and financial variables as trigger variables and test each one for the informational content regarding the switching mechanism.

Macroeconomic developments are among the main determinants of interest rate spreads. To capture the impact of macroeconomic fundamentals, three main types of variables will be considered in this study. The full set of variables including data sources is listed in Appendix D.2.

The first type groups country specific variables: broad macroeconomic indicators (e.g. production growth, HICP and debt-to-GDP ratio), financial market information (e.g. bank stock indices and CDS spreads), as well as information regarding the banking sector (e.g. the volume of ECB's main refinancing operations (MROs) and long-term refinancing operations (LTROs)).

Apart from domestic macroeconomic developments, interest rate spreads are also influenced by global conditions and contagion. For example, tighter global liquidity and/or contagion might lead to fund outflows from countries, resulting in larger spreads. This is captured in the second group of trigger variables. There are several price-based or quantity-based measures of global liquidity and contagion in the literature. We take the VSTOXX and the MOVE indices to represent market sentiment about global financial conditions, as well as the European Economic Policy Uncertainty index developed by Baker et al. (2015). To assess the issue of contagion, we also incorporate lending rate spreads of different countries as potential trigger variables.

Finally, we introduce two dummy variables that aim to capture the effects of policy announcements from the ECB. The first one incorporates the LTRO announcements from July, October, and December 2009. The second variable captures several monetary policy announcements from July, August, and September of 2012. In a panel discussion in July 2012,the president of the ECB Mario Draghi communicated the ECB's support for the euro.[8] In September 2012 the ECB announced the Outright Monetary Transactions (OMT) programme. Altavilla and De Grauwe (2010) find that these measures alone have reduced sovereign bond yields in Italy and Spain by more than two percentage points.

[8]The speech has been often labelled in the media as the "Whatever-it-takes speech". De Grauwe and Ji (2013) have shown empirically that the temporary disconnect of market expectations from fundamentals and the existence of jumps between multiple equilibria was an important element of the euro area crisis.

4.2.4 Time series properties

Typically, in time series analysis the question of stationarity is meticulously discussed. Testing the VAR variables with an ADF test reveals that most variables are stationary with the exception of the government bond spreads of Spain and Ireland and the lending rate spread in Ireland. Nevertheless, in MS-VAR models, the stationarity assumption is not needed for the dependent and the independent variables. These models rely upon an assumption quite a bit stronger than stationary residuals, and namely, that the true residuals (if the regime were known) are independent and normal. Because the regime is not known, that is not really a testable hypothesis. All one can test is whether the standardised residuals are uncorrelated and have constant variance. Note that passing those tests does not make the model valid, just not rejectable. We present tests for normality of the estimated residuals in Appendix D.3.

Turning to the probit model, the stationarity issue is not as simple. We test all variables for a unit-root with the ADF and Pierre-Perron tests. Since many of the variables appear non-stationary, there might be several pitfalls. Park and Phillips (2000) have shown that while the estimator in binary dependent variable models is consistent even with integrated regressors, it has special asymptotic properties. Riddel (2003) has documented that the explanatory variables might fail to pass the t-tests for coefficient diagnostics even when they are indeed informative. Therefore we rely on our use of Bayesian techniques and the consistency of the estimator to alleviate the problem — we use credible (probability) intervals of the posterior distribution instead of asymptotic intervals. Informally, to assess significance one can also look at the estimated transition probabilities, since the model should reduce to the fixed probability case (flat probabilities) if the variables are insignificant. Furthermore, as is standard practice, we estimate the models with the variables in first differences as a separate case. This brings the total amount of trigger variables per country up to twenty five. To address potential multicollinearity issues at the estimation stage we do not choose any pair of variables with a correlation coefficient greater than 0.5 in absolute value. Correlation matrices may be found in Appendix D.5.

Another potential issue associated with probit models is the inclusion of dummy variables. This may lead to the problem of quasi-complete separation, which arises when the explanatory variable has too much predictive power over the dependent variable. In the case of binary variables, too many coinciding "ones" or "zeroes" on both sides of the regression might distort the estimator. Gelman *et al.* (2008) suggest the use of Bayesian estimation to remedy the situation over the standard maximum likelihood estimator, or, if the former is undesirable, to drop the variables in question.

Therefore, when setting the prior for the trigger variables regression, we omit the dummies at the maximum likelihood stage. For brevity, we report the results only for the regressors that are significantly different from zero for each country with the exception of the policy announcement variables, which are included in all regressions. Nevertheless, we would emphasize that the empirical model description is illustrative and does not try to incorporate all the technical elements that can be found in the literature on the subjects that are addressed.

4.2.5 Regime identification

Finally, we turn our attention to the regime identification scheme. How does one identify periods with breakdown in the pass-through? This question requires thorough deliberation. In a single equation framework, where lending rates are explained through policy rates, one may order the states by imposing that the lower regression coefficient of the policy rate is attributed to the first state. In a VAR framework, regime ordering is not as straightforward. Moreover, we model the lending rate spread across two countries instead of the lending rates per se. In this setup, if monetary policy transmission has become heterogeneous, unexpected movements of the policy rate should affect the two counties differently, whereas if both lending rates react in similar manner one should not observe any difference in the spread. Hence, we propose three different regime identification strategies: (i) impulse response identification (IR); (ii) Markov-switching constant; (iii) Markov-switching conditional mean.

The first identification scheme orders the regimes by calculating the impulse responses of the lending rate spread to a shock in the policy rate for each state and imposing the "stronger" IR as the second regime. We define "stronger" by comparing the cumulative responses across regimes for twelve months ahead.[9] The second strategy allocates the regimes according to the size of the constant in the lending rate VAR equation — the higher constant is allocated to the second regime. The economic intuition is that if the homogeneity across countries has changed, this might be reflected in a level shift of the lending rate. In the third strategy we calculate the conditional mean of the lending rate VAR equation at each iteration and allocate the higher of the two to the second regime. The rationale is similar to the second regime identification strategy — a level shift of the lending rate is an indication of heterogeneous transmission of monetary policy. The difference to the regime identification strategy above is that using the conditional mean controls for additional information through the other explanatory variables.

[9]For robustness we also consider 9 to 18 months ahead, and the findings remain unchanged.

Note that neither of these strategies imposes any regimes ex-ante. They separate the data based on parameter mean values, which does not ensure that the posterior distributions do not overlap. Simply put, ordering by the cumulative IRFs, for example, does not guarantee that the difference between the responses will be statistically significant. Therefore, we do not assume a priori that there has been any change in the pass-through. This can be examined in our model only after we plot the actual impulse responses ex-post.

4.3 Estimation results

In the following sections we present the estimation results for Italy, Spain, Ireland, and Portugal individually, as different risk assessment across countries may give rise to potentially different movements of the interest rate spreads. For example, even when the spreads of all countries respond to the same set of economic news, e.g. about macroeconomic data and/or monetary policy, the spreads in some countries may react more strongly when there are concerns over the pace and sustainability of reforms. At the same time, different countries may be more or less exposed to global factors when cross-border flows differ across countries. For each state we will look at the transmission of monetary policy to the lending rates via impulse response functions, examine the regime probabilities and inspect the trigger variables. Per country we focus on a representative set of the significant trigger variables out of the full list given in Appendix D.2.

4.3.1 Italy

The top panel of Figure 4.3 presents the estimated regimes. Following Hamilton (1989) we interpret a value below 0.5 as the economy being in the first regime, and above 0.5 as a realisation of the second regime. In the bottom panel we analyse the state-contingent impulse response of the lending rate spread.[10] We normalise the EONIA shock across the states. If the monetary policy transmission is homogeneous across countries, the lending rates in the different countries should not react differently to a monetary policy shock.

[10] The full set of impulse responses is available in the Appendix.

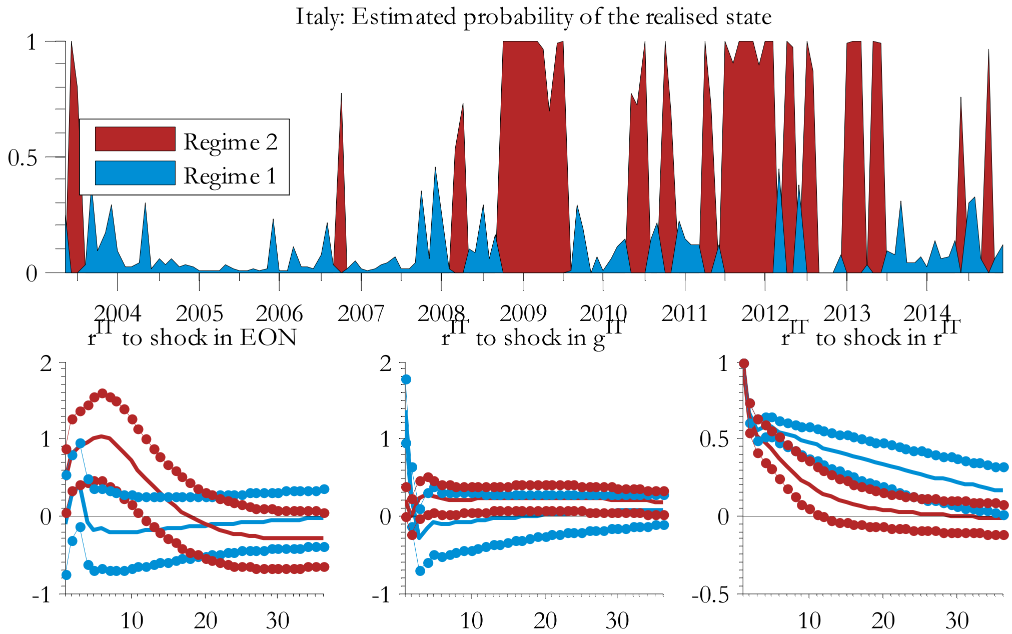

Figure 4.3: *Regime probabilities and IRFs. Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: State-contingent impulse responses of the lending rate spread to a shock in each variable.*

For Italy, however, this is not the case. A 100 basis point increase in EONIA leads to a significant opening of the lending rate spread in the second regime in contrast to the first, which indicates that the lending rates rise higher than in Germany.[11] Confusing as the estimates might appear, they have a clear economic interpretation — in regime one, market participants behave as if they are in a comfort zone and do not feel compelled or encouraged to pull the lending rates further away from the German rates. However, in the second regime, market participants anticipate a "dark corner" and act to increase the lending rate spreads vis-à-vis Germany.

The second regime was prevalent during the outbreak of the financial crisis 2008 – 2009, between the months of August 2011 and 2012, and throughout the first half of 2013 — the latter two associated with the euro area sovereign debt crisis. Rising fiscal imbalances and weak demand took a toll on Italy with the crisis escalating in the autumn of 2011, leading to political turmoil with government bond yields increasing to an all-time high. Following a political change, Italian bond yields stabilized for a short time, but in the beginning of 2013 fears grew again. The economy started to recover slightly in 2013, with a major contributor being an improvement in the current account deficit, which turned positive in 2014.

[11] These results are amplified by the presence of the zero lower bound. With EONIA being flat after the middle of 2012, the response of the spread is characterised by the persistence of the policy rate. This can be observed in the reaction of EONIA to a shock in EONIA for the second regime, and also in the residuals for the policy rate, which are plotted in Figure D.1 in the Appendix. To deal with this problem we also explore using shadow rate estimates for the euro area instead of EONIA, which are discussed in detail in the next section.

What contributed to the regime shifts? We examine the trigger variables whose coefficients in the probit regression are significantly different from zero. A positive coefficient decreases the probability of staying in the first regime and increases the switching probability to the second regime. We plot a representative set of trigger variables in Figure 4.4. The bottom panel shows the transition probability for the first state.[12] One of the main obstacles for the recovery of the Italian economy has been a fiscal burden. Lower tax income and weak demand have put a large strain on the government finances. A rising nominal debt-to-GDP ratio and worsening net foreign asset position have been important developments, and are a natural choice for trigger variables. The debt-to-GDP ratio increased steadily over the past years, reaching 160% in 2014. The net foreign asset position fell to minus five per cent of GDP in 2011. Both prove to be important indicators associated with a higher probability of switching to the regime of impaired monetary policy transmission. Among global financial variables, both the VIX and the Economic Policy Uncertainty index are significant, while the MOVE index does not contain information regarding the regime switching. Monetary policy in the form of actual borrowing in the MROs and LTROs did not alleviate the problems either, as both variables do not influence the transition probabilities.

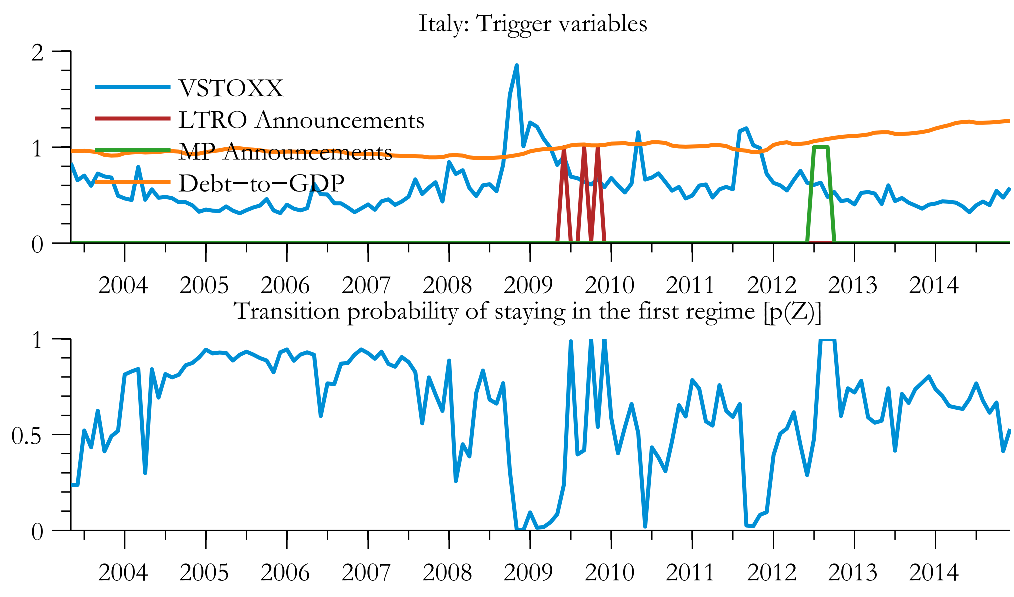

Figure 4.4: *Trigger variables and transition probabilities. Top panel: Representative trigger variables for Italy. VSTOXX and Debt-to-GDP have been rescaled for expositional clarity. Bottom panel: Transition probabilities for staying in the first regime. A falling probability indicates higher change to switch to the second state and vice versa.*

The unconventional monetary policy announcements of the ECB have had a temporary positive effect. The dummy variables for the LTRO announcements as well as the "whatever-it-takes" speech and the OMT announcements have strong negative coefficients. Their effects are evident in the

[12]Note that the transition probabilities are symmetric, as evident from eq. (4.6).

transition probabilities — they contribute to the spikes in the middle of 2009 and 2012. The model suggests that through the strong influence on the transition probabilities, the ECB announcements played a major role in the actual regime switches in August 2009 and August 2012.[13]

Another potential matter is the issue of contagion — spillover effects of the sovereign debt crisis across euro area countries were a major concern for the common monetary policy. The anecdotal evidence suggests that the increasing lending rate spreads originated in certain countries before spreading to further countries. To model this diaspora, we estimate the probit regression adding lagged lending spreads of Spain, Ireland and Portugal. In Italy, market sentiment towards the development of lending rates in other debt-ridden countries influenced the domestic lending rates adversely, with Spain being the most important contributor. An interesting point about this finding is that the inverse is not true, as there were no signs of contagion effects from Italy to Spain. Next we turn to the explanation for this phenomenon, which is related to the specifics of the Spanish economy.

4.3.2 Spain

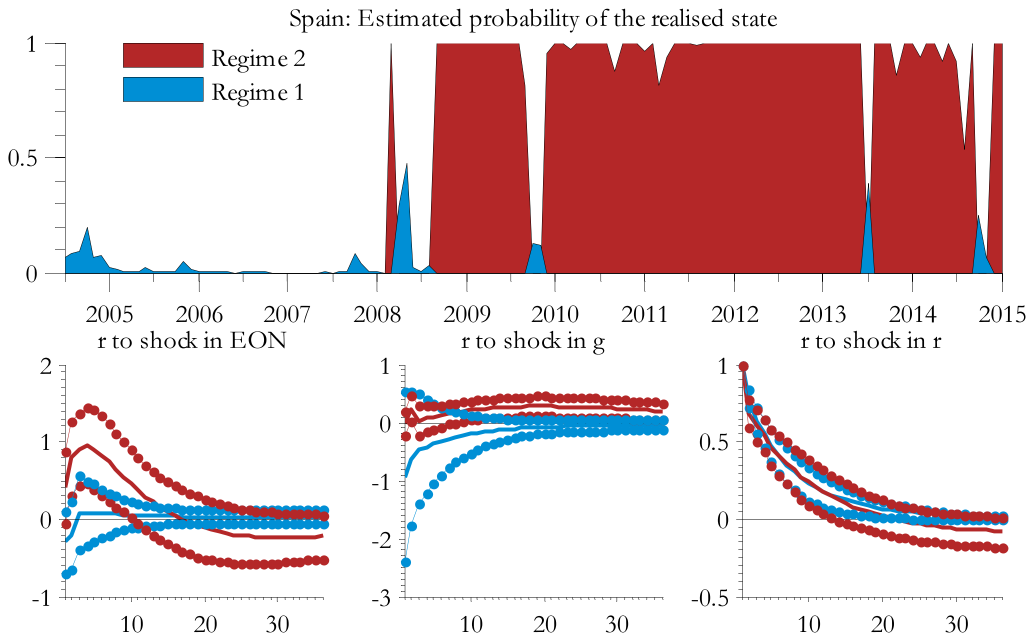

Figure 4.5: *Regime probabilities and IRFs. Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: State-contingent impulse responses of the lending rate spread to a shock in each variable.*

[13]We present the distributions of the estimated parameters from the probit model in Appendix D.6.

The model for Spain exhibits both remarkable similarities and notable differences compared to that for Italy. On the surface, the impulse response estimates seem equivalent, while the realised states have a higher persistence, with the second regime being highly dominant after September of 2008 (see Figure 4.5). This suggests a longer duration of the pass-through breakdown in Spain. The impulse response of the lending rate spread exhibits similar dynamics to the Italian one. However, the drivers of the endogenous transition probabilities uncover stark heterogeneity across both countries. The

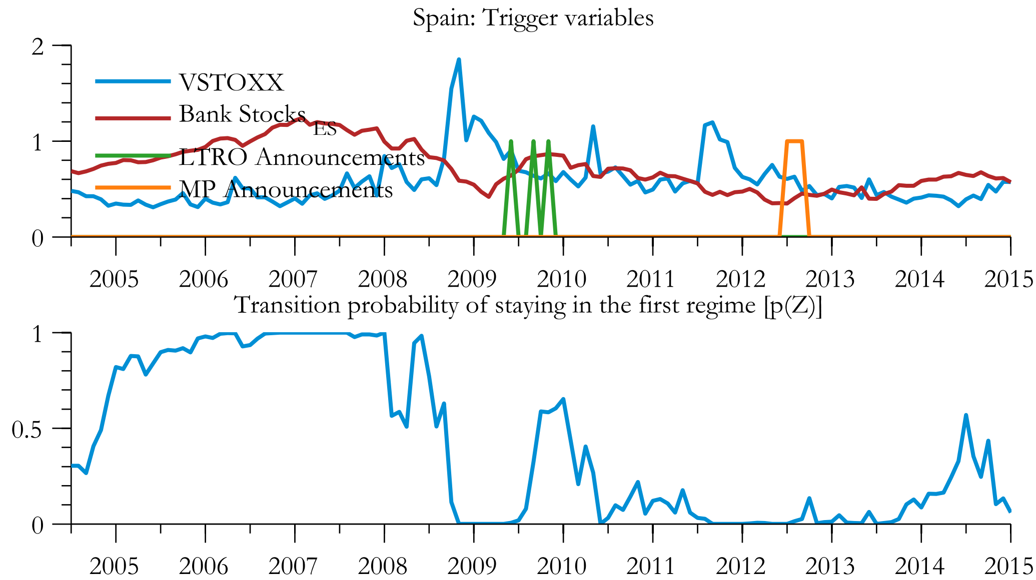

Figure 4.6: *Trigger variables and transition probabilities. Top panel: Representative trigger variables for Spain. VSTOXX and Bank Stocks have been rescaled for expositional clarity. Bottom panel: Transition probabilities for staying in the first regime. A falling probability indicates higher change to switch to the second state and vice versa.*

policy announcements by the ECB did not strengthen the monetary policy transmission or alleviate the rising spread between the Spanish and German lending rates. The main drivers behind the persistence of the second state seem to have been problems in the Spanish financial sector. After the near collapse of several banks, the Spanish central bank requested funds from the European Financial Stability Facility in June 2012.[14] This is reflected in the model by a significant negative coefficient of the Spanish bank stocks indicator (see Appendix D.6). A rising index implies higher valued banks, and a negative coefficient affects positively the probability of switching from the second to the first regime. Hence, a banking crisis reflected in falling bank stock prices would lengthen the state of impaired pass-through.

Moreover, the main refinancing operations of the ECB do not appear to have alleviated the problem either. The notion that the problems in Spain were coming from within the country are strengthened by the fact that the lending rate spreads of other countries are not statistically significant, implying

[14]For an overview of the distress in the financial sector, see International Monetary Fund (2013).

no contagion effects. In terms of estimation, including the nominal debt-to-GDP ratio turned out to be problematic, as the model did not exhibit convergence using the Gibbs sampler even with long chains of 100 000 draws. On the other hand, the issue of the zero lower bound does not seem to be of high importance — the EONIA residuals pass all normality tests (see Appendix D.3).

4.3.3 Ireland

Next we turn our attention to Ireland, where a breakdown in interest rate pass-through similar to that of Italy and Spain is also identified. Figure 4.7 shows that, on average, the reaction of the lending rate spread is similar, and there is a clear overreaction of the spreads to a tightening in the policy rate. The realisation and the persistence of the second regime are similar to those in Italy during the outbreak of the financial crisis in 2008 and in the periods associated with the euro area sovereign debt crisis in 2010, 2011, and 2012, before the monetary policy transmission returns to normal in 2013.

Notably no global variables deliver information regarding regime the switching. Neither VSTOXX, nor the MOVE index, or the European policy uncertainty index have any predictive power over the regimes. This points to somewhat different financial conditions in Ireland than in Italy or Spain.

Similar to Italy, Ireland's debt burden has played an important role in the impairment of the monetary policy transmission — the estimated coefficient in the probit model is significant and positive. In contrast to Spain, the banking indicators are not informative, from which it can be inferred that the state of the banking sector was not the source of the pass-through breakdown. The ECB's monetary policy announcements are insignificant. Thus, they did not contribute to the return to the first state in the middle of 2012.

The other significant trigger variable is the volume of ECB's main refinancing operations, which enters the model with a positive coefficient, implying that an increase in these operations leads to a rising probability of transitioning to the second regime of heterogeneous pass-through. This might seem counterintuitive, but the MROs can be seen as an indicator for the state of the economy; in a "bad state" the ECB provides greater liquidity assistance, and as the economy recovers the volumes decrease. If instead of the MROs one uses CDS spreads between Ireland and Germany, the results remain similar, since the variables exhibit high positive correlation (Appendix D.5).

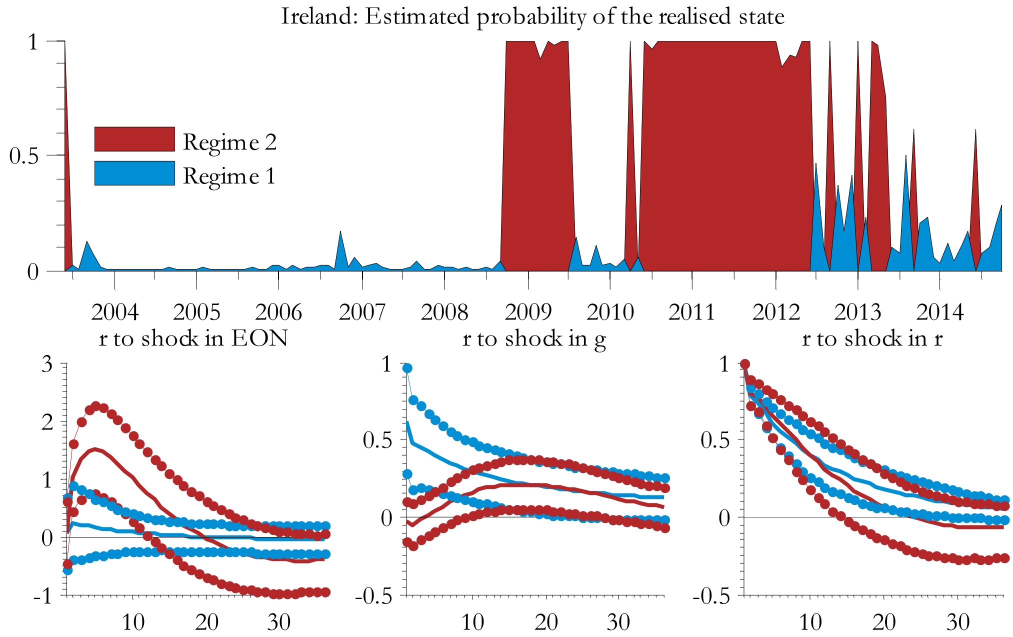

Figure 4.7: *Regime probabilities and IRFs. Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: State-contingent impulse responses of the lending rate spread to a shock in each variable.*

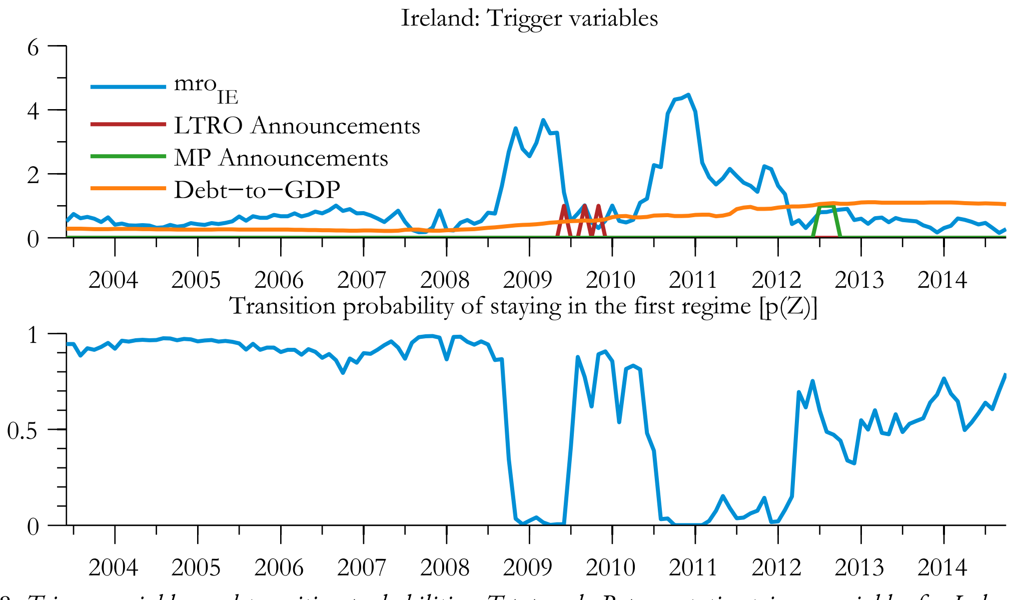

Figure 4.8: *Trigger variables and transition probabilities. Top panel: Representative trigger variables for Ireland. The MRO variable has been rescaled for expositional clarity. Bottom panel: Transition probabilities for staying in the first regime. A falling probability indicates a higher chance for a regime shift.*

4.3.4 Portugal

The last country to be examined is Portugal. We do not find a change in the interest rate pass-through. There was no setup in which the Gibbs sampler managed to identify different reactions of the lending rate spread to an unexpected shock in EONIA. Most impulse responses also show no significant interaction across the VAR variables, as is evident from Figure 4.9. Since the model does not identify two distinct regimes, the estimated states are arbitrary, as they do not carry dissimilar information. The realised states in the top panel of Figure 4.9 were not robust to the prior specification, in contrast to all the other countries. In all cases the estimated impulse responses of the lending rate spread turned out to be insignificant, irrespective of the regime estimation.

Notably the lending rates of Portugal exhibit high volatility (see Figure 4.2). Surprisingly, they fail to pass a no-seasonality test, which is not expected from long-term rates, as it clashes with standard economic intuition. Furthermore, coupled with a flat policy rate, the residuals of the model also reject the normality tests (see Appendix D.3). Due to these issues, and specifically because of the lack of regime identification, we refrain from examining any potential trigger variables.

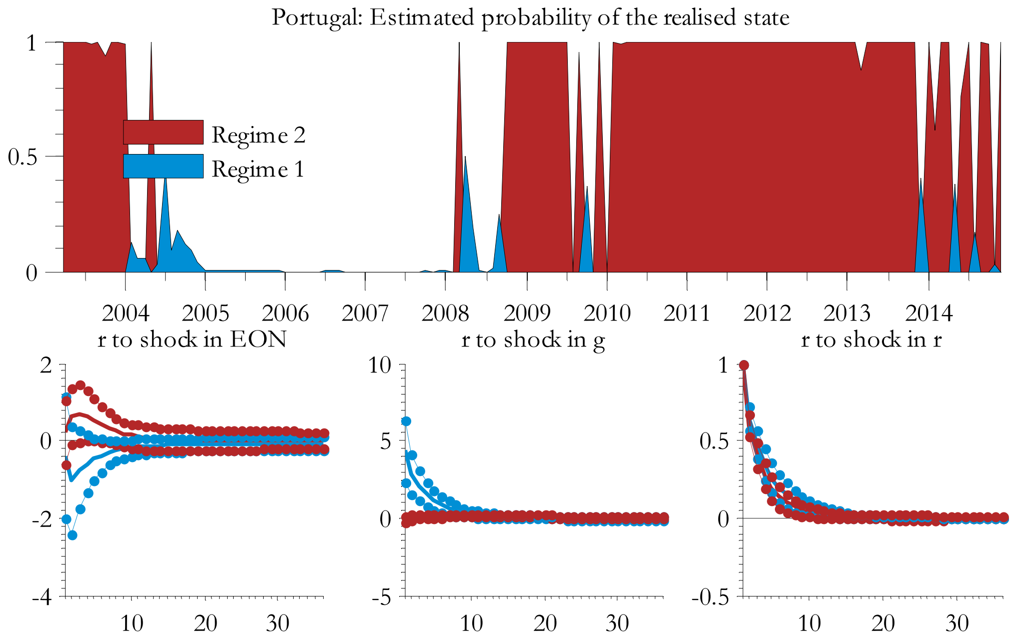

Figure 4.9: *Regime probabilities and IRFs. Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: State-contingent impulse responses of the lending rate spread to a shock in each variable.*

So far we have presented the baseline results, where EONIA is used as a proxy for the policy rate. This setup presents one potential challenge — the existence of the zero lower bound. The literature provides several other proxies for the policy rate, and we shall explore them in detail in the next section.

4.3.5 Dealing with the zero lower bound

Recently, a number of researchers have used shadow rate models to characterise the term structure of interest rates and/or to quantify the stance of monetary policy, e.g. Wu and Xia (2014), Krippner (2014), Pericoli and Taboga (2015). The fictitious shadow short rate is a measure for the stance of monetary policy in a zero lower bound environment, summarizing the joint impact of conventional and unconventional monetary policy in a parsimonious manner. Unlike the observed short-term interest rate, the shadow rate is not bounded below by zero per cent, dampening its historical correlation with macroeconomic time series.

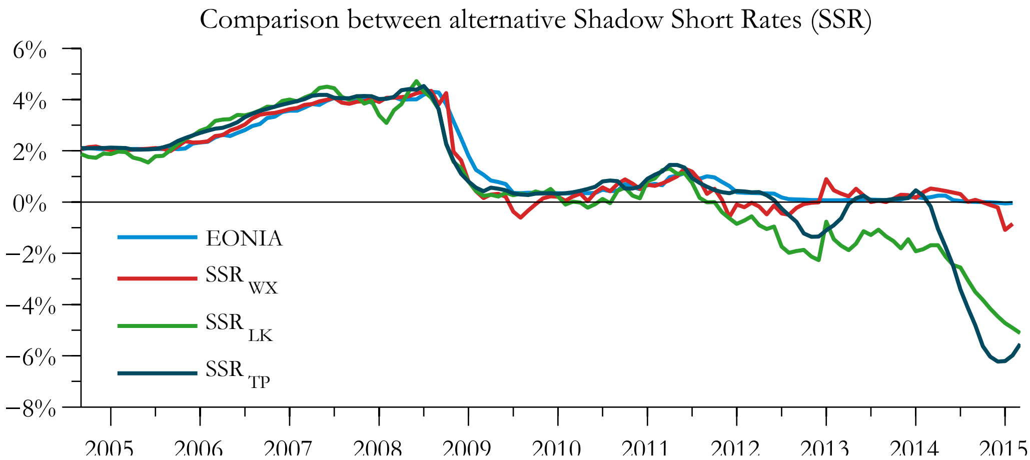

Figure 4.10: *Different shadow EONIA estimates.* SSR_{WX} *was taken from Wu and Xia (2014),* SSR_{LK} *from Krippner (2014) and* SSR_{TP} *from Pericoli and Taboga (2015). The latter was interpolated from quarterly data by a quadratic method (match average).*

There are various approaches in the literature to estimating a shadow rate. Wu and Xia (2014) construct the rate as a linear function of three latent variables (factors), which follow a VAR(1) process. The latent factors and the shadow rate are estimated with an extended Kalman filter based around forward rates for n = 0.25, 0.5, 1, 2, 5, 7, and 10 years ahead. These forward rates are constructed with end-of-month Nelson-Siegel-Svensson yield curve parameters. Whenever the Wu-Xia shadow rate is above 0.25 per cent, it is exactly equal to the model implied one-month interest rate. Krippner (2014), in turn, has suggested a modification to the Black (1995) approach to allow for closed-form solutions to the option pricing problem. This allows for considerable simplification when estimating the shadow rate. Pericoli and Taboga (2015) also use a modification of the approach of Black (1995). However, they employ an exact Bayesian method for their shadow short rate estimation. This method relies on discretizing the pricing equation, effectively discretizing the state space of the model, without introducing too high numerical errors.

Figure 4.10 reveals a large discrepancy between the different shadow rates at the end of the sample period. According to Krippner (2014), the shadow rate has been negative since 2011, falling to minus five per cent in 2014 and 2015, much further below the estimate of Wu and Xia (2014), which was around zero to minus one per cent. For the same period, Pericoli and Taboga (2015) estimate values lower than minus six per cent. Considering the disagreement between the three rates, one has to take these estimates with a grain of salt.

Another issue that has to be taken into account is the different sample sizes of the SSR estimates. For example, the shadow rate of Wu and Xia starts in June 2004, while the estimates provided by Krippner date back to 1995. We control for that by estimating both models starting in June 2004, yet this is also an imperfect solution. First of all, the results are not directly comparable to the previous section, because the sample size is significantly shorter. Second, the SSR is model dependent, and extending the dataset forward or backward would also alter the original estimates. Hence, a shadow rate that starts in 1995, and is truncated to June 2004, would not be equal to the same rate estimated by the same model with data starting in June 2004.

In the following graphs, for each country we plot the estimated realised regimes for the shadow rates, and the impulse responses of the lending rate spread to a shock to the policy rate. Note that we do not estimate the models with the rate of Pericoli and Taboga (2015) due to the drawback that it is only available at a quarterly frequency.

The main findings are that under Wu and Xia's estimates our results remain qualitatively unchanged for all countries. Quantitatively the responses of the lending rate spread to a 100 basis point increase in the policy rate are smaller, as evident from the figures below — about a quarter of the estimated responses with the EONIA rate in the second state, while in the first regime there is no significant effect suggesting that monetary policy shocks affected all countries equally. We still do not find distinct states with Portuguese data. One can conclude that using EONIA as a proxy for the policy rate amplifies the results, yet the findings are not driven by the zero lower bound.

By contrast, if one uses the shadow short rate of Krippner (2014), the estimates paint a different picture for Italy and Spain, while they produce similar responses to Wu and Xia's short rate and EONIA for Portugal and Ireland. For Italy (Figure 4.11, right panel) the model does not identify different responses of the lending rate spread initially. However, three months later, the spread reacts by becoming negative following a tightening of the short rate, which is at odds with the other two rates. This feature is also evident in Spain (Figure 4.12, right panel), where it is more pronounced — after the fourth month the second state is associated with a negative spread, while

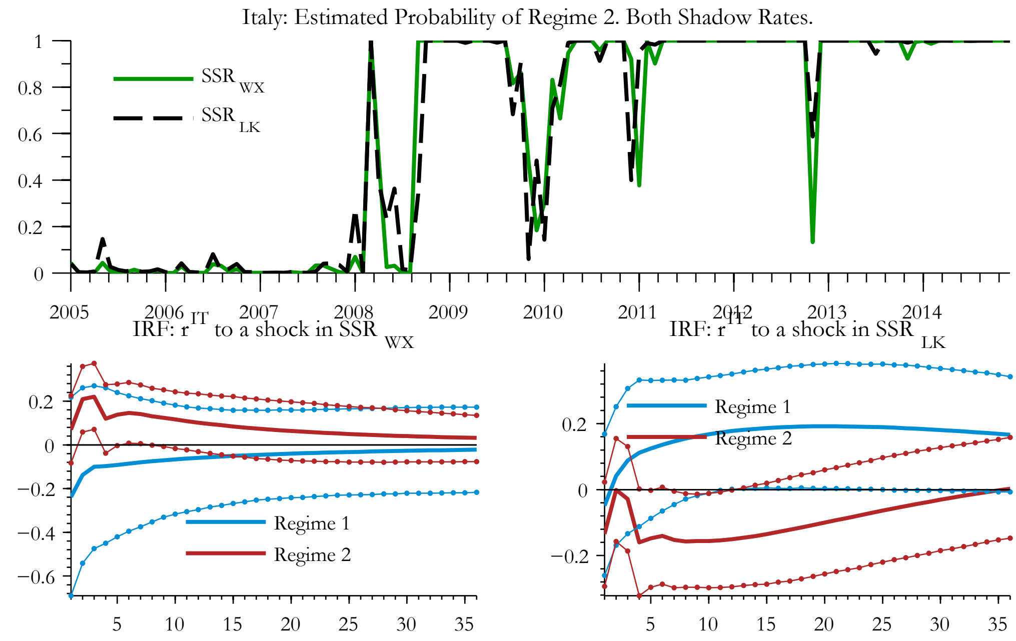

Figure 4.11: *Alternative model estimates for each shadow rate as the policy variable for Italy.* SSR_{WX} *has been taken from Wu and Xia (2014),* SSR_{LK} *from Krippner (2014). Top panel: Estimated probability for regime two under each SSR. Bottom panels: Impulse response function of the lending rate to a unit shock in the policy variable for regime one (blue) and regime two (red).* SSR_{WX} *shown left and* SSR_{LK} *right. For the models to be comparable, the estimation sample has been constrained to the shortest data series and the lag length has been kept constant across the SSR models. The model setup is identical to the EONIA scenario.*

the first state is associated with a positive spread following a policy rate shock. Comparing the results for Italy and Spain, it is fair to say that the estimation results with SSR are less robust. One reason for this could be the sharp decrease of the shadow rate of Krippner (2014), which falls below zero in 2011 and never turns positive, with values reaching minus five per cent. This coincides with the whole period of the lending rate spread being positive, hence a downward movement of the policy rate is associated with an upward movement of the lending rate, which is exactly what we find — following a positive shock, the spread closes and following a negative shock the spread opens.

The results for Ireland, and Portugal appear to be robust. They differ mostly in the size of the estimated confidence intervals of the responses, nevertheless carry the same economic interpretation. The monetary policy transmission has recovered for Ireland following the middle of 2013, and we do not identify any breakdown in pass-through during the financial crisis for Portugal. It is notable that in all models the estimated realisation of the first and second regime is highly similar, which is encouraging. One drawback of the shadow rates is that they are not existing interest rates, and banks do not have access to funds at these rates. They remain a theoretical construct. Therefore we also conduct robustness checks using the measure by Illes et al. (2015) for banks' weighted average cost of liabilities, and our findings remain largely unchanged (see Appendix D.8).

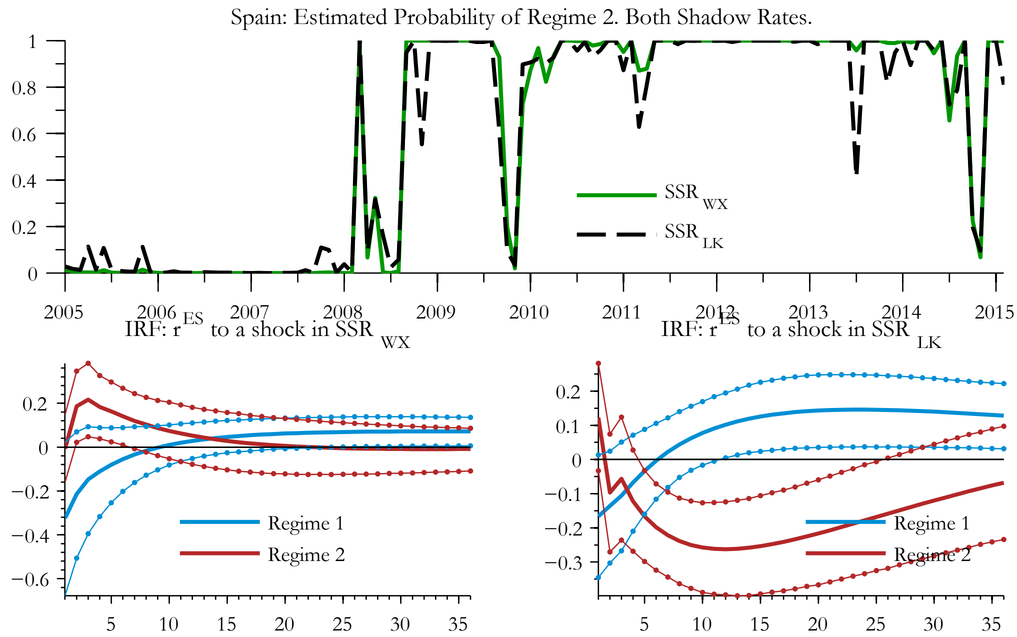

Figure 4.12: *Alternative model estimates for each shadow rate as the policy variable for Spain.* SSR_{WX} *has been taken from Wu and Xia (2014),* SSR_{LK} *from Krippner (2014). Top panel: Estimated probability for regime two under each SSR. Bottom panels: Impulse response function of the lending rate to a unity shock in the policy variable for regime one (blue) and regime two (red).* SSR_{WX} *shown left and* SSR_{LK} *right. For the models to be comparable the estimation sample has been constrained to the shortest data series and the lag length has been kept constant across the SSR models. The model setup is identical to the EONIA scenario.*

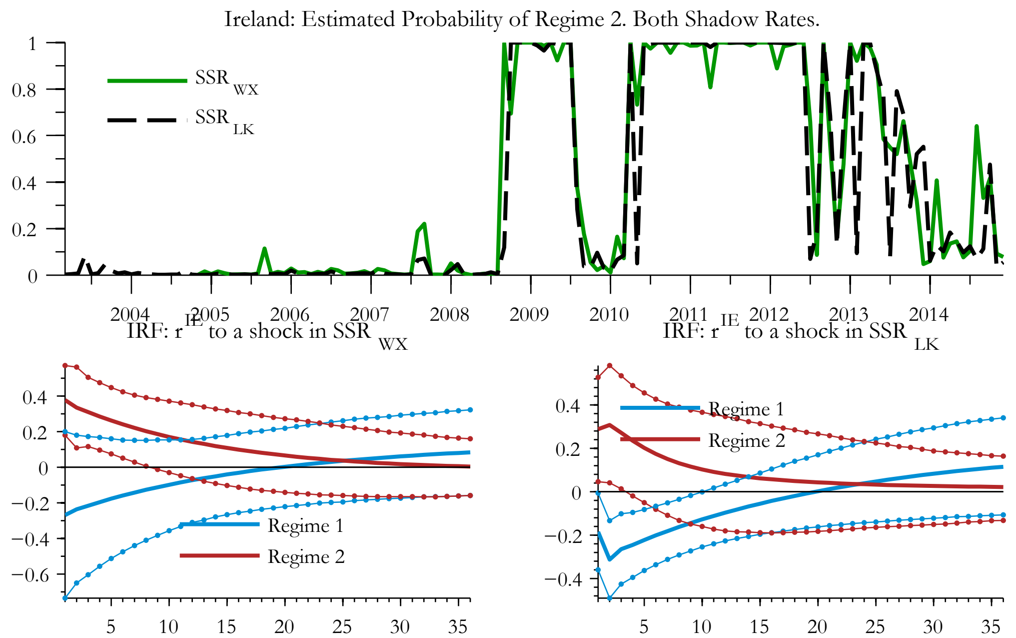

Figure 4.13: *Alternative model estimates for each shadow rate as the policy variable for Ireland.* SSR_{WX} *has been taken from Wu and Xia (2014),* SSR_{LK} *from Krippner (2014). Top panel: Estimated probability for regime two under each SSR. Bot-tom panels: Impulse response function of the lending rate to a unity shock in the policy variable for regime one (blue) and regime two (red).* SSR_{WX} *shown left and* SSR_{LK} *right. For the models to be comparable the estimation sample has been constrained to the shortest data series and the lag length has been kept constant across the SSR models. The mod-el setup is identical to the EONIA scenario.*

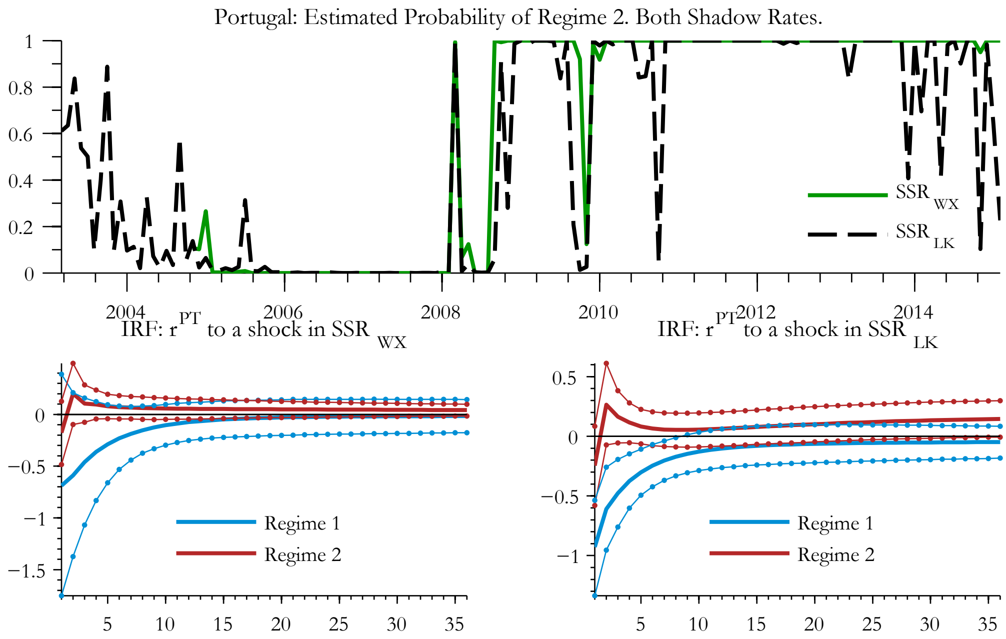

Figure 4.14: *Alternative model estimates for each shadow rate as the policy variable for Portugal. SSR_{WX} has been taken from Wu and Xia (2014), SSR_{LK} from Krippner (2014). Top panel: Estimated probability for regime two under each SSR. Bot-tom panels: Impulse response function of the lending rate to a unity shock in the policy variable for regime one (blue) and regime two (red). SSR_{WX} shown left and SSR_{LK} right. For the models to be comparable the estimation sample has been constrained to the shortest data series and the lag length has been kept constant across the SSR models. The model setup is identical to the EONIA scenario.*

4.4 Concluding remarks

The effect of monetary policy on lending rates is central in the policy debate on the design of optimal euro area monetary policy. This topic has received renewed interest among economists and policy makers in the aftermath of the global financial crisis and the euro area sovereign debt crisis. Monetary policy and lending rates are endogenous variables, determined, possibly, by various economic shocks. Can any causal link between the two be established? How do monetary policy and lending rates interact? In this chapter we strive to better understand these mechanisms by revisiting the question whether Italy, Spain, Ireland, and Portugal have experienced heterogeneity in the transmission of the common monetary policy, and investigate what the triggers of these changes were. We approach the question individually for each country through the lens of a Markov-switching VAR with endogenous transition probabilities.[15]

[15] Although the time series specifications deal with non-linearity and heterogeneity, they do not allow for cross-sectional dependence. By way of qualification, it therefore must be conceded that we need to be cautious when interpreting these results. There may be spillover effects from one country to another magnifying at times of financial crisis, due to exposures to common shocks, or simply due to the stance of the global financial cycle that could invalidate the cross-sectional independence assumption. These global factors are mostly unobserved. Furthermore, we are aware that there are limitations to the use of switching models for forecasting. Although MS models fit well in-sample they

Through endogenising the transition probabilities between different regimes, we find that the debt burden has played an important role for the impairment of the pass-through in both Italy and Ireland, with Italy also being affected by global risk factors, measured by euro area-wide implied volatility indices. Moreover, ECB monetary policy announcements, such as the OMT and LTRO announcements, have had a temporary positive effect for Italy, and also an important positive, albeit smaller effect for Spain.[16] In contrast to the other countries, we cannot identify any significant change in the interest rate pass-through for Portugal. Following the most recent debates in the literature, we address the potential pitfall of using EONIA as a proxy for the policy rate of the ECB by looking at alternative estimates such as shadow rates and proxies for bank funding conditions. Alternative shadow rate estimates derived from dynamic factor models provide a remedy for the issue of the zero lower bound, yet come at the cost that different models yield different shadow rate estimates. We conclude that the flatness of EONIA as the main policy rate amplifies the results, but does not alter the key findings.

do not necessarily generate superior out-of-sample forecasts [Ferrara *et al.* (2012)].

[16]What else can the ECB do to fix the wedge in the relationship between policy and lending rates hampering growth in the euro area periphery? Recently the ECB has unveiled a targeted offer of four-year loans designed to encourage banks to lend more to small- and medium-sized enterprises. To take advantage of the facility, which are available at a cheap fixed rate, banks must sign up commitments to business lending, similar in design to the Bank of England's Funding for Lending Scheme [ECB (2014)].

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A

Appendix to chapter 1

A.1 Log-linearized system of equations

Endogenous equations:

Euler equation:

$$c_t = E_t\{c_{t+1}\} + \frac{1}{\sigma}(E_t\{\pi_{t+1}\} - i_t) + \frac{1}{\sigma}(1 - \rho_\vartheta)\vartheta_t. \tag{A.1}$$

Domestic price inflation:

$$(1 + \beta\delta_H)\pi_{H,t} = \beta E_t\{\pi_{H,t+1}\} + \delta_H \pi_{H,t-1} + \lambda_H mc_t + \mu_{H,t}. \tag{A.2}$$

Import price inflation:

$$(1 + \beta\delta_F)\pi_{F,t} = \beta E_t\{\pi_{F,t+1}\} + \delta_F \pi_{F,t-1} + \lambda_F \psi_t + \mu_{F,t}. \tag{A.3}$$

Market clearing:

$$y_t - (1 - \alpha)c_t - \alpha\eta(s_t + q_t) = \alpha y_t^*. \tag{A.4}$$

Law of one price:

$$\psi_t = q_t - (1-\alpha)s_t. \tag{A.5}$$

Terms of trade:

$$\triangle s_t = \pi_{F,t} - \pi_{H,t}. \tag{A.6}$$

Nominal exchange rate:

$$\triangle e_t = 0. \tag{A.7}$$

Interest rate parity:

$$\pi_t^* - \pi_t = \triangle q_t. \tag{A.8}$$

Marginal cost:

$$mc_t = \sigma c_t + \varphi y_t + \alpha s_t - (1+\varphi)a_t. \tag{A.9}$$

CPI:

$$\pi = (1-\alpha)\pi_{H,t} + \alpha\pi_{F,t}. \tag{A.10}$$

Foreign asset budget constraint:

$$c_t + d_t + \alpha(q_t + \alpha s_t) - \frac{1}{\beta}d_{t-1} = y_t. \tag{A.11}$$

Interest rate reaction function:

$$i_t = i_t^* - \chi d_t - \phi_t. \tag{A.12}$$

Exogenous processes:

Domestic shocks:

$$a_t = \rho_a a_{t-1} + \varepsilon_t^a \quad \text{with} \quad \varepsilon_t^a \sim N(0, \sigma_a^2), \tag{A.13}$$

$$\vartheta_t = \rho_\vartheta \vartheta_{t-1} + \varepsilon_t^\vartheta \quad \text{with} \quad \varepsilon_t^\vartheta \sim N(0, \sigma_\vartheta^2), \tag{A.14}$$

$$\mu_{H,t} = \rho_\mu \mu_{H,t-1} + \varepsilon_t^{\mu_H} \quad \text{with} \quad \varepsilon_t^{\mu_H} \sim N(0, \sigma_{\mu_H}^2), \tag{A.15}$$

$$\mu_{F,t} = \rho_\mu \mu_{F,t-1} + \varepsilon_t^{\mu_F} \quad \text{with} \quad \varepsilon_t^{\mu_F} \sim N(0, \sigma_{\mu_F}^2), \tag{A.16}$$

$$\phi_t = \rho_\phi \phi_{t-1} + \varepsilon_t^\phi \quad \text{with} \quad \varepsilon_t^\phi \sim N(0, \sigma_\phi^2). \tag{A.17}$$

World variables:

$$y_t^* = c_{y^*} y_{t-1}^* + \varepsilon_t^{y^*} \quad \text{with} \quad \varepsilon_t^{y^*} \sim N(0, \sigma_{y^*}^2), \tag{A.18}$$

$$\pi_t^* = c_{\pi*} \pi_{t-1}^* + \varepsilon_t^{\pi^*} \quad \text{with} \quad \varepsilon_t^{\pi^*} \sim N(0, \sigma_{\pi^*}^2), \tag{A.19}$$

$$i_t^* = c_{i*} i_{t-1}^* + \varepsilon_t^{i^*} \quad \text{with} \quad \varepsilon_t^{i^*} \sim N(0, \sigma_{i^*}^2). \tag{A.20}$$

A.2 Solving a MS-DSGE Model

This section will sketch the solution method employed in the paper. For details and proofs, see Cho (2015). The model is cast in the following state-space form:

$$X_t = E_t\{A(s_t, s_{t+1}) X_{t+1}\} + B(s_t) X_{t-1} + C(s_t) Z_t, \tag{A.21}$$

with Z_t following an AR(1) process.[1] From the perspective of time point t by forward iteration the model at time $t + k$ may be represented by

$$X_t = E_t\{M_k(s_t, s_{t+1}, ..., s_{t+k}) X_{t+k}\} + \Omega_k(s_t) X_{t-1} + \Gamma_k(s_t) Z_t, \tag{A.22}$$

where $\Omega_1(s_t) = B(s_t), \Gamma_1(s_t) = C(s_t)$ and for $k = 2, 3, ...$:

$$\Omega_k(s_t) = \Xi_{k-1}^{-1}(s_t) B(s_t), \tag{A.23}$$

$$\Gamma_k(s_t) = \Xi_{k-1}^{-1}(s_t) C(s_t) + E_t\{F_{k-1}(s_t, s_{t+1}) \Gamma_{k-1}(s_{t+1})\} R, \tag{A.24}$$

$$\Xi_{k-1}(s_t) = (I_n - E_t\{A(s_t, s_{t+1}) \Omega_{k-1(s_{t+1})}\}), \tag{A.25}$$

$$F_{k-1}(s_t, s_{t+1}) = \Xi_{k-1}^{-1}(s_t)^{-1} A(s_t, s_{t+1}). \tag{A.26}$$

It may be shown that given initial values, under some regularity conditions such as invertibility of $\Xi_k \; \forall k$, the sequence $E_t\{M_k(s_t, s_{t+1}, ... s_{t+k}) X_{t+k}\}$ is well defined, unique and real-valued. In the limit as $k \to \infty$, the model (A.22) is said to be Forward Convergent if the parameter matrices are convergent, i.e. $\lim_{k\to\infty} \Omega_k(s_t) = \Omega^*(s_t)$; $\lim_{k\to\infty} \Gamma_k(s_t) = \Gamma^*(s_t)$ and $\lim_{k\to\infty} F_k(s_t, s_{t+1}) = F^*(s_t, s_{t+1})$. If

$$\lim_{k\to\infty} E_t\{M_k(s_t, s_{t+1}, ..., s_{t+k}) X_{t+k}\} = 0_{(n\times 1)}, \tag{A.27}$$

then the solution is

$$X_t = \Omega^*(s_t) X_{t-1} + \Gamma^*(s_t) Z_t. \tag{A.28}$$

---

[1]Note that $A(s_t, s_{t+1}) = B_1(s_t)^{-1} A_1(s_t, s_{t+1})$ in (A.21). $B(s_t)$ and $C(s_t)$ are similarly defined.

Equation (A.27) is called the *non-bubble condition* and, if satisfied, implies the existence of a unique solution to the model. As k tends to infinity, this condition should hold and all solutions, for which it does not should be ruled out as they are not economically relevant. Thus, if the model is forward convergent and eq. (A.27) is satisfied, then eq. (A.28) is the only relevant MSV solution to the model cast in the form of (A.21).

The existence of (A.28) alone is a necessary but not sufficient condition for determinacy, due to the volatility induced by the regime-switching feature. The MSV solution is only the *fundamental part* of the solution, but there may exist a non-fundamental part that is arbitrary, which leads to a multiplicity of equilibria. Assuming the non-fundamental component takes the form

$$W_t = E_t\{F(s_t, s_{t+1})W_{t+1}\}, \tag{A.29}$$

the concept for determinacy and indeterminacy deals with interaction of the matrices Ω_j^* and F_j^* when switching between states. Defining

$$\Psi_{\Omega^*\times\Omega^*} = [p_{ij}\Omega_j^* \otimes \Omega_j^*], \qquad \Psi_{F^*\times F^*} = [p_{ij}F_j^* \otimes F_j^*],$$

$j = \{1, 2\}$, mean-square stability is characterized by

$$r_\sigma(\Psi_{\Omega^*\times\Omega^*}) < 1, \qquad r_\sigma(\Psi_{F^*\times F^*}) \leq 1, \tag{A.30}$$

where $r_\sigma(\cdot)$ represents the maximum absolute eigenvalue of the argument matrix. The intuition behind these conditions is straightforward. The first one concerns the transition between the matrices $\Omega^*(s_t)$ of the fundamental part of the solution (A.28). As long as the biggest absolute eigenvalue is smaller than one, the system would be stable under regime-switching. The F_j^* matrix governs the non-fundamental switching part and as long the biggest eigenvalue lies on or within the unit-circle, the forward solution is the determinate equilibrium.

A.3 $\mathcal{M}_1$: Convergence diagnostics – figures and tables

	Lag 1	Lag 5	Lag 10	Lag 50		Thin	Burn	Total(N)	Nmin	I-stat
φ	0.615	0.104	0.008	0.009	φ	1.000	5	1510	937	1.612
θ_H	0.658	0.170	0.054	0.005	θ_H	1.000	5	1510	937	1.612
θ_F	0.630	0.095	0.035	0.010	θ_F	1.000	5	1510	937	1.612
σ	0.737	0.265	0.046	0.038	σ	1.000	5	1510	937	1.612
η	0.636	0.141	0.015	-0.002	η	1.000	5	1510	937	1.612
δ_H	0.655	0.160	0.056	-0.008	δ_H	1.000	5	1510	937	1.612
δ_F	0.626	0.105	0.026	0.030	δ_F	1.000	5	1510	937	1.612
χ	0.617	0.084	-0.025	0.025	χ	1.000	5	1510	937	1.612
ρ_a	0.617	0.089	0.011	-0.011	ρ_a	1.000	5	1510	937	1.612
ρ_{μ_F}	0.627	0.133	0.023	-0.005	ρ_{μ_F}	1.000	5	1510	937	1.612
ρ_{μ_H}	0.633	0.108	-0.003	-0.021	ρ_{μ_H}	1.000	5	1510	937	1.612
ρ_ν	0.632	0.131	0.034	0.010	ρ_ν	1.000	5	1510	937	1.612
ρ_ϕ	0.615	0.088	0.013	-0.012	ρ_ϕ	1.000	5	1510	937	1.612
c_{y^*}	0.631	0.126	0.013	0.002	c_{y^*}	1.000	5	1510	937	1.612
c_{π^*}	0.643	0.106	-0.008	-0.016	c_{π^*}	1.000	5	1510	937	1.612
c_{i^*}	0.636	0.114	0.007	-0.005	c_{i^*}	1.000	5	1510	937	1.612
σ_{μ_F}	0.661	0.143	0.044	0.014	σ_{μ_F}	1.000	5	1510	937	1.612
σ_{μ_H}	0.683	0.186	0.049	0.010	σ_{μ_H}	1.000	5	1510	937	1.612
σ_a	0.924	0.740	0.604	0.126	σ_a	1.000	5	1510	937	1.612
σ_ν	0.737	0.274	0.058	0.048	σ_ν	1.000	5	1510	937	1.612
σ_ϕ	0.643	0.130	0.016	-0.019	σ_ϕ	1.000	5	1510	937	1.612
σ_{y^*}	0.626	0.114	0.028	0.005	σ_{y^*}	1.000	5	1510	937	1.612
σ_{π^*}	0.653	0.126	0.007	-0.003	σ_{π^*}	1.000	5	1510	937	1.612
σ_{i^*}	0.644	0.088	0.015	-0.020	σ_{i^*}	1.000	5	1510	937	1.612

Table A.1: *Left: Autocorrelation among the draws, based on a sample of 10000. Right: Raferty-Lewis convergence diagnostics with q=0.025, r=0.1, s=0.95. An I-statistic less than 5 indicates convergence.*

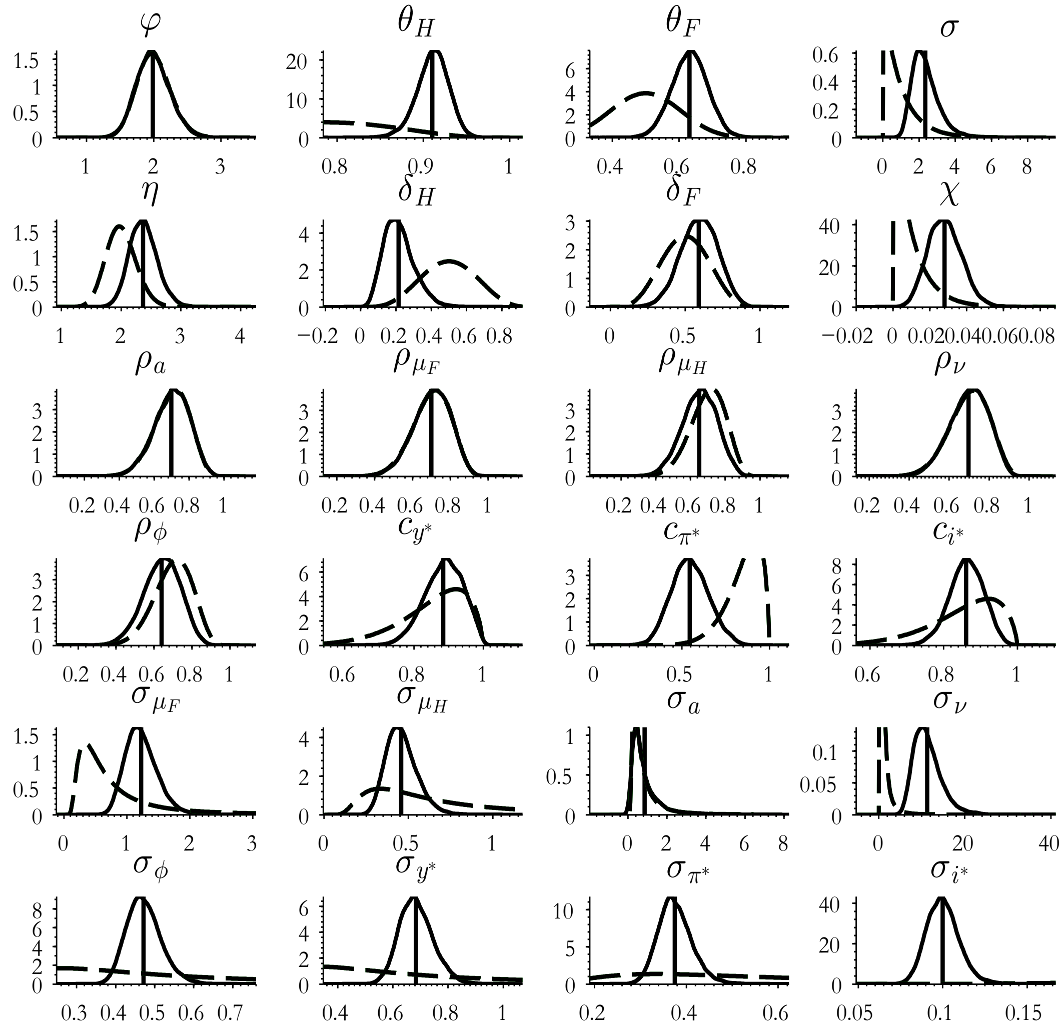


Figure A.1: $\mathcal{M}_1$*: Prior (- -) and posterior (—) distributions of the parameters.*

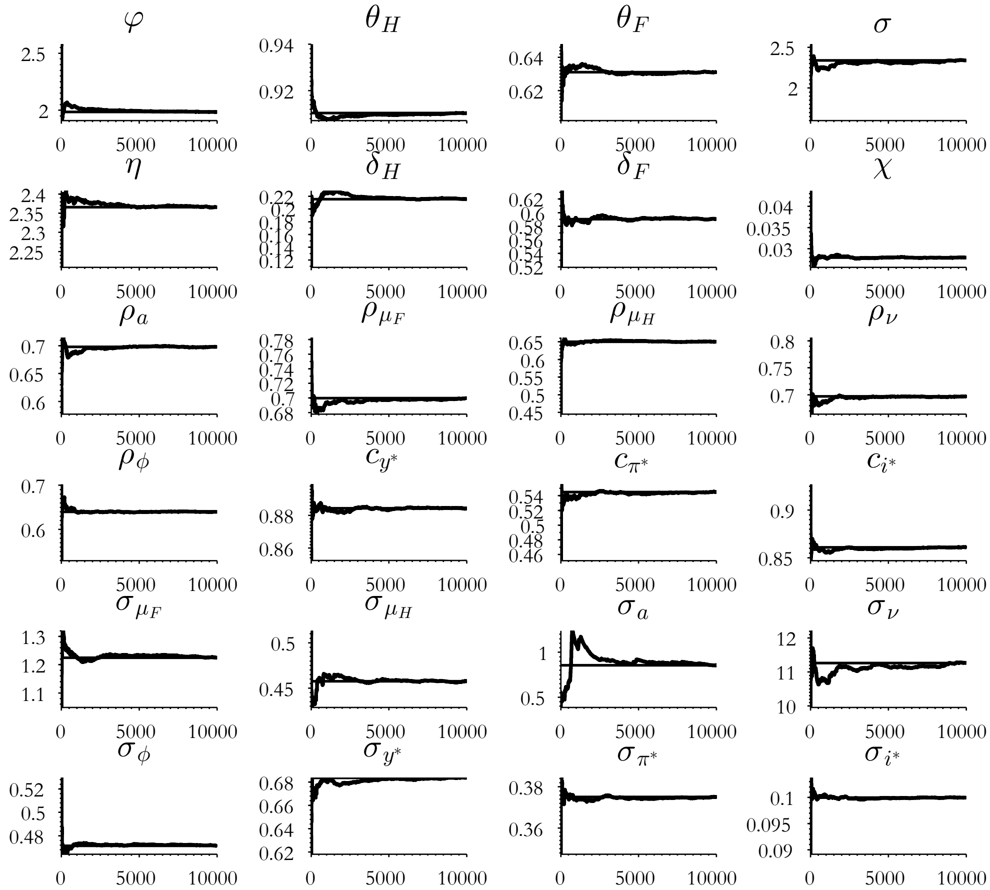


Figure A.2: $\mathcal{M}_1$*: Recursive means of the parameters calculated over the draws from the posterior distribution.*

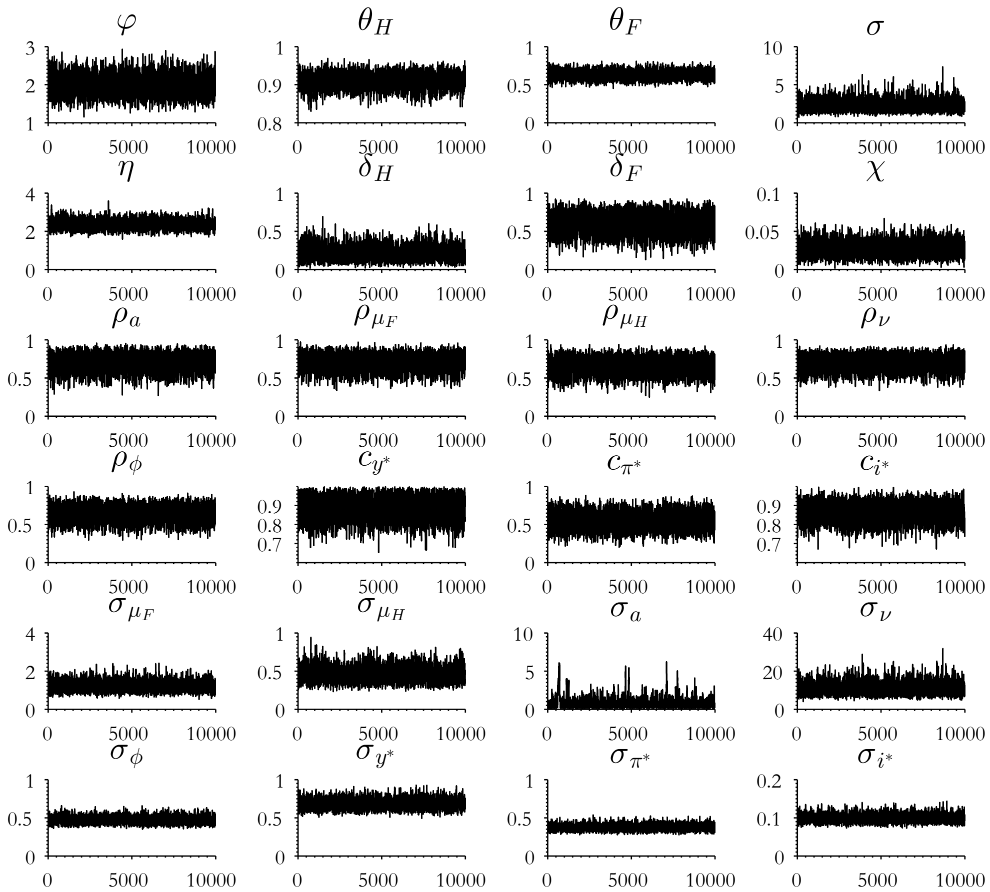


Figure A.3: $\mathcal{M}_1$*: Trace plots of the parameters.*

A.4 $\mathcal{M}_2$: Convergence diagnostics – figures and tables

	Lag 1.	Lag 5	Lag 10	Lag 50
p_{11}	0.616	0.131	0.014	0.001
p_{22}	0.548	0.072	-0.002	-0.008
φ	0.593	0.071	-0.018	0.001
θ_H	0.640	0.139	0.024	0.011
θ_F	0.612	0.135	0.063	-0.002
σ	0.650	0.175	0.064	0.031
η	0.583	0.067	-0.004	-0.021
δ_H	0.602	0.111	0.033	-0.006
δ_F	0.597	0.120	0.022	0.016
χ	0.632	0.144	0.024	-0.008
ρ_a	0.568	0.036	-0.016	0.018
ρ_{μ_F}	0.582	0.085	-0.011	-0.018
ρ_{μ_H}	0.580	0.086	-0.006	0.005
ρ_ν	0.607	0.116	0.026	0.027
ρ_ϕ	0.556	0.047	-0.004	-0.013
c_{y^*}	0.581	0.075	-0.002	0.030
c_{π^*}	0.577	0.074	0.031	-0.018
c_{i^*}	0.600	0.086	0.034	0.009
σ_{μ_F}	0.667	0.187	0.055	-0.012
σ_{μ_H}	0.668	0.195	0.086	0.051
σ_a	0.976	0.920	0.874	0.584
σ_ν	0.675	0.214	0.087	0.036
σ_ϕ	0.636	0.152	0.042	-0.013
σ_{y^*}	0.602	0.098	0.020	-0.019
σ_{π^*}	0.619	0.100	0.035	-0.004
σ_{i^*}	0.613	0.089	-0.013	-0.010
σ_ϕ	0.508	0.058	-0.004	0.002

	Thin	Burn	Total(N)	Nmin	I-stat
p_{11}	2.000	14	3642	937	3.887
p_{22}	2.000	14	3642	937	3.887
φ	2.000	14	3642	937	3.887
θ_H	2.000	14	3642	937	3.887
θ_F	2.000	14	3642	937	3.887
σ	2.000	14	3642	937	3.887
η	2.000	14	3642	937	3.887
δ_H	2.000	14	3642	937	3.887
δ_F	2.000	14	3642	937	3.887
χ	2.000	14	3642	937	3.887
ρ_a	2.000	14	3642	937	3.887
ρ_{μ_F}	2.000	14	3642	937	3.887
ρ_{μ_H}	2.000	14	3642	937	3.887
ρ_ν	2.000	14	3642	937	3.887
ρ_ϕ	2.000	14	3642	937	3.887
c_{y^*}	2.000	14	3642	937	3.887
c_{π^*}	2.000	14	3642	937	3.887
c_{i^*}	2.000	14	3642	937	3.887
σ_{μ_F}	2.000	14	3642	937	3.887
σ_{μ_H}	2.000	14	3642	937	3.887
σ_a	2.000	14	3642	937	3.887
σ_ν	2.000	14	3642	937	3.887
σ_ϕ	2.000	14	3642	937	3.887
σ_{y^*}	2.000	14	3642	937	3.887
σ_{π^*}	2.000	14	3642	937	3.887
σ_{i^*}	2.000	14	3642	937	3.887
σ_ϕ	2.000	14	3642	937	3.887

Table A.2: *Left: Autocorrelation among the draws, based on a sample of 10000. Right: Raferty-Lewis convergence diagnostics with q=0.025, r=0.1, s=0.95. An I-statistic less than 5 indicates convergence.*

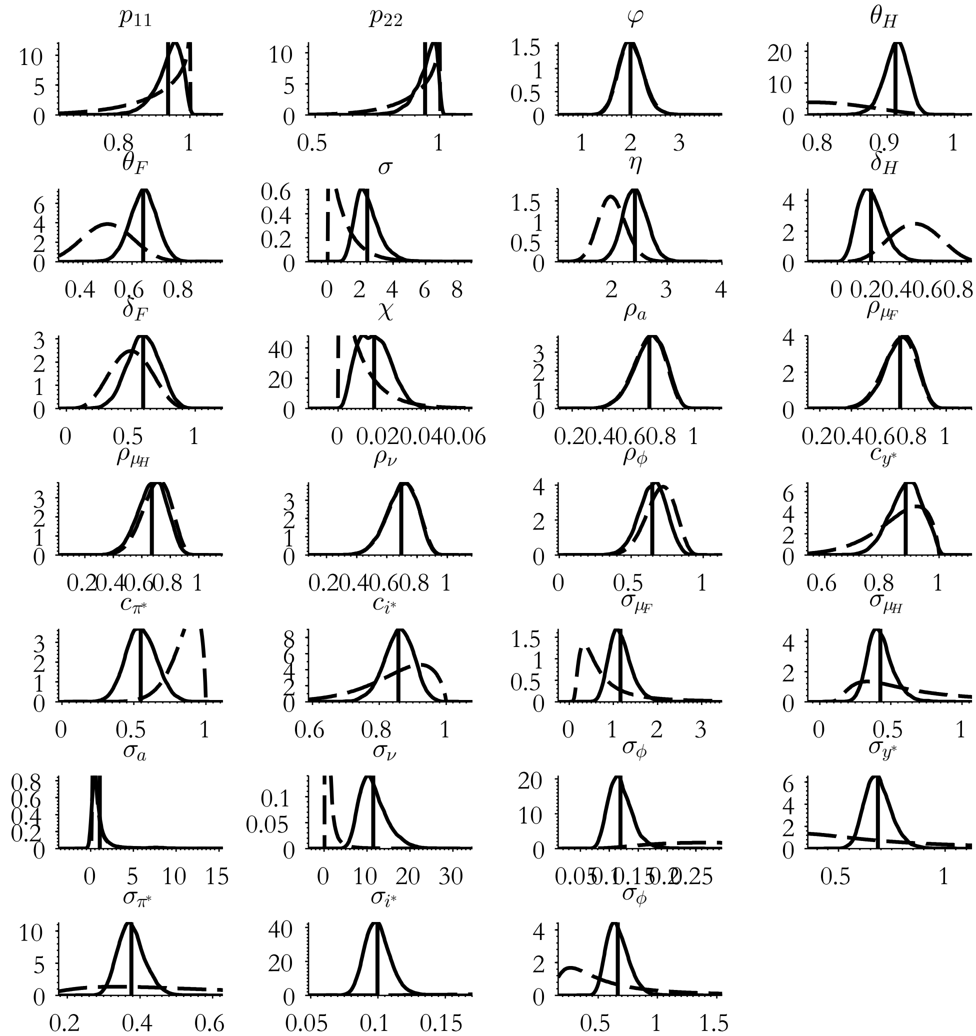


Figure A.4: $\mathcal{M}_2$: *Prior (- -) and posterior (—) distributions of the parameters.*

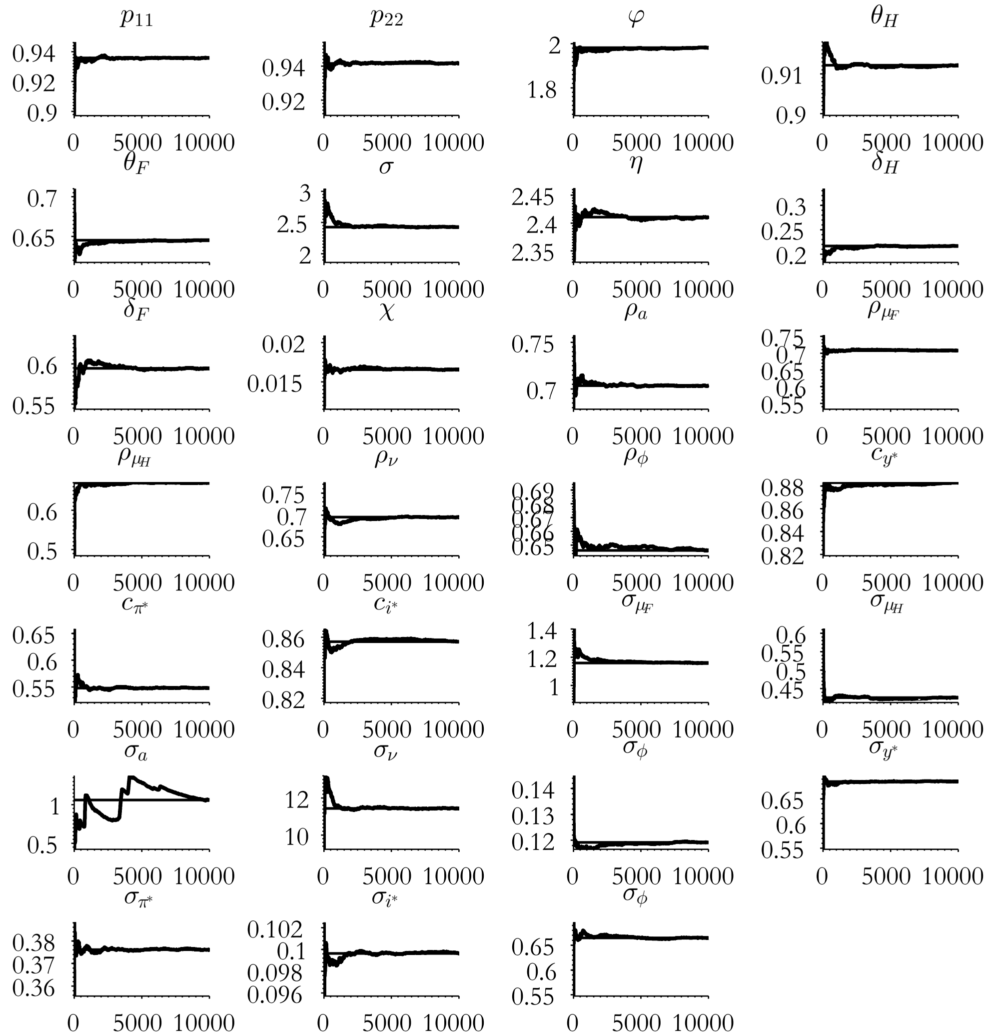


Figure A.5: $\mathcal{M}_2$: *Recursive means of the parameters calculated over the draws from the posterior distribution.*

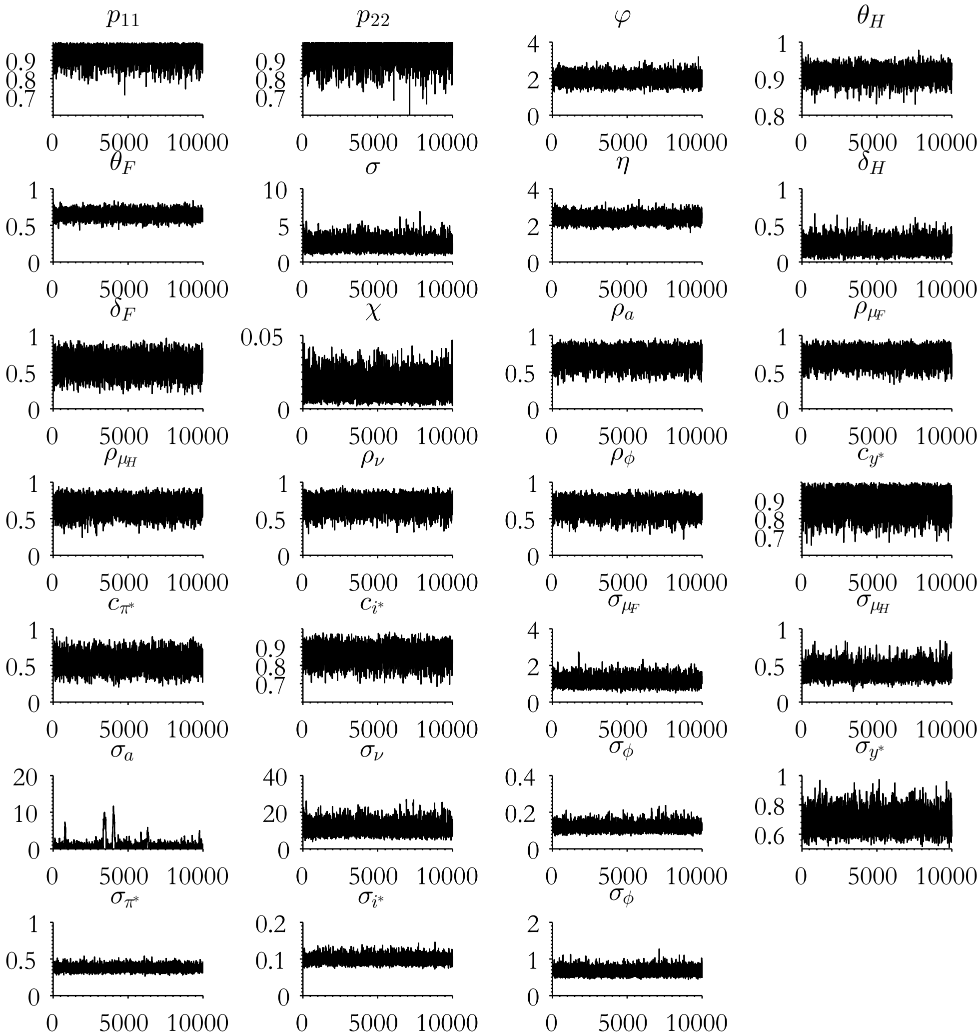


Figure A.6: $\mathcal{M}_2$: *Trace plots of the parameters.*

A.5 $\mathcal{M}_2$: Variance decomposition tables

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	0.06	0.72	0.13	0.40	5.70	0.03	92.87	0.09
4	0.11	1.00	0.16	0.25	14.96	0.09	83.36	0.07
8	0.15	1.12	0.15	0.34	23.40	0.14	74.64	0.06
12	0.16	1.14	0.14	0.69	26.59	0.16	71.06	0.06
20	0.17	1.13	0.14	1.04	28.21	0.17	69.08	0.06
40	0.18	1.13	0.15	1.13	28.55	0.17	68.64	0.06
∞	0.18	1.13	0.15	1.13	28.55	0.17	68.63	0.06

Table A.3: *Forecast error variance decomposition of consumption for horizon $h = \{1, ..., \infty\}$. State 1: $\sigma_\phi(low)$, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	0.06	0.71	0.13	0.39	5.56	0.03	90.54	2.59
4	0.10	0.98	0.15	0.25	14.65	0.08	81.61	2.16
8	0.14	1.10	0.14	0.34	22.96	0.13	73.24	1.94
12	0.16	1.12	0.14	0.68	26.11	0.15	69.79	1.85
20	0.17	1.11	0.14	1.02	27.72	0.16	67.88	1.79
40	0.18	1.11	0.14	1.11	28.06	0.17	67.46	1.77
∞	0.18	1.11	0.15	1.11	28.06	0.17	67.46	1.77

Table A.4: *Forecast error variance decomposition of consumption for horizon $h = \{1, ..., \infty\}$. State 2: $\sigma_\phi(high)$, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	0.03	5.31	0.00	73.85	19.33	0.09	1.38	0.00
4	0.03	7.85	0.00	74.69	16.24	0.08	1.10	0.00
8	0.03	7.10	0.00	75.69	15.85	0.08	1.26	0.00
12	0.03	6.83	0.00	75.38	16.35	0.08	1.32	0.00
20	0.03	6.80	0.00	75.28	16.47	0.08	1.32	0.00
40	0.03	6.80	0.00	75.27	16.47	0.08	1.34	0.00
∞	0.03	6.80	0.00	75.26	16.47	0.08	1.34	0.00

Table A.5: *Forecast error variance decomposition of inflation for horizon $h = \{1, ..., \infty\}$. State 1: $\sigma_\phi(low)$, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	0.03	5.30	0.00	73.83	19.32	0.09	1.38	0.03
4	0.03	7.85	0.00	74.68	16.23	0.08	1.10	0.03
8	0.03	7.10	0.00	75.66	15.84	0.08	1.26	0.03
12	0.03	6.83	0.00	75.35	16.35	0.08	1.32	0.03
20	0.03	6.80	0.00	75.26	16.46	0.08	1.32	0.03
40	0.03	6.80	0.00	75.24	16.47	0.08	1.34	0.03
∞	0.03	6.80	0.00	75.24	16.47	0.08	1.34	0.03

Table A.6: *Forecast error variance decomposition of inflation for horizon $h = \{1, ..., \infty\}$. State 2: $\sigma_\phi(high)$, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	1.07	5.88	0.02	6.51	43.62	0.22	42.64	0.04
4	0.41	4.07	0.01	8.34	76.00	0.40	10.75	0.01
8	0.28	3.39	0.01	6.17	82.23	0.46	7.45	0.01
12	0.27	3.26	0.01	6.37	82.53	0.47	7.09	0.01
20	0.29	3.22	0.01	6.96	81.67	0.46	7.37	0.01
40	0.30	3.20	0.01	7.07	81.27	0.46	7.68	0.01
∞	0.30	3.20	0.01	7.07	81.26	0.46	7.69	0.01

Table A.7: *Forecast error variance decomposition of output for horizon $h = \{1, ..., \infty\}$. State 1: $\sigma_\phi(low)$, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	1.06	5.81	0.02	6.43	43.09	0.22	42.13	1.24
4	0.41	4.06	0.01	8.32	75.77	0.40	10.72	0.31
8	0.28	3.38	0.01	6.16	82.06	0.46	7.44	0.21
12	0.27	3.25	0.01	6.36	82.37	0.47	7.07	0.20
20	0.29	3.22	0.01	6.95	81.51	0.46	7.36	0.21
40	0.30	3.19	0.01	7.06	81.11	0.46	7.67	0.21
∞	0.30	3.19	0.01	7.06	81.10	0.46	7.68	0.21

Table A.8: *Forecast error variance decomposition of output for horizon $h = \{1, ..., \infty\}$. State 2: $\sigma_\phi(high)$, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	0.24	0.01	30.44	0.23	0.16	0.00	5.73	63.19
4	0.58	0.23	23.93	7.70	6.70	0.03	28.36	32.47
8	0.62	0.55	12.15	16.06	19.16	0.10	37.36	14.00
12	0.59	0.69	8.07	16.96	26.38	0.14	38.09	9.08
20	0.58	0.76	5.97	16.07	31.98	0.18	37.76	6.70
40	0.58	0.78	5.51	15.60	33.66	0.19	37.53	6.16
∞	0.58	0.78	5.50	15.58	33.69	0.19	37.53	6.15

Table A.9: *Forecast error variance decomposition of the interest rate for horizon* $h = \{1, ..., \infty\}$*. State 1:* $\sigma_\phi(low)$*, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_{μ_H}	ε_a	ε_ν	ε_ϕ
1	0.01	0.00	1.52	0.01	0.01	0.00	0.29	98.16
4	0.05	0.02	2.22	0.71	0.62	0.00	2.63	93.74
8	0.12	0.11	2.33	3.08	3.67	0.02	7.16	83.52
12	0.16	0.18	2.16	4.54	7.06	0.04	10.20	75.66
20	0.19	0.25	1.98	5.32	10.59	0.06	12.51	69.09
40	0.20	0.27	1.93	5.46	11.78	0.07	13.14	67.15
∞	0.20	0.27	1.93	5.46	11.81	0.07	13.15	67.11

Table A.10: *Forecast error variance decomposition of the interest rate for horizon* $h = \{1, ..., \infty\}$*. State 2:* $\sigma_\phi(high)$*, in per cent.*

B

Appendix to chapter 2

B.1 $\mathcal{M}_2$: State-contingent variance decomposition tables

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.02	7.97	0.42	3.41	10.77	77.35	0.06
4	0.04	10.31	0.60	3.35	29.74	55.91	0.05
8	0.05	8.47	0.53	2.57	46.47	41.87	0.04
12	0.05	7.05	0.45	2.19	55.08	35.15	0.03
20	0.06	5.78	0.38	2.06	62.51	29.17	0.03
40	0.06	5.05	0.41	2.86	65.94	25.65	0.03
∞	0.06	4.97	0.43	3.05	66.21	25.25	0.03

Table B.1: *Forecast error variance decomposition of consumption for horizon* $h = \{1, ..., \infty\}$. *State 1: "high credibility"* $\sigma_\phi(1)$*, in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.02	7.85	0.42	3.36	10.61	76.20	1.55
4	0.04	10.17	0.59	3.30	29.34	55.17	1.38
8	0.05	8.38	0.53	2.55	46.00	41.45	1.04
12	0.05	6.99	0.45	2.17	54.61	34.85	0.88
20	0.06	5.74	0.38	2.05	62.07	28.96	0.74
40	0.06	5.02	0.41	2.85	65.52	25.49	0.66
∞	0.06	4.94	0.43	3.03	65.80	25.09	0.65

Table B.2: *Forecast error variance decomposition of consumption for horizon* $h = \{1, ..., \infty\}$. *State 2: "low credibility"* $\sigma_\phi(2)$, *in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.04	57.80	0.05	31.08	8.01	3.01	0.00
4	0.02	52.01	0.02	42.50	4.37	1.08	0.00
8	0.01	54.49	0.02	40.24	4.03	1.21	0.00
12	0.01	53.28	0.02	41.20	4.31	1.17	0.00
20	0.01	50.40	0.02	44.18	4.27	1.11	0.00
40	0.02	49.79	0.02	44.85	4.23	1.10	0.00
∞	0.02	49.77	0.02	44.86	4.23	1.10	0.00

Table B.3: *Forecast error variance decomposition of inflation for horizon* $h = \{1, ..., \infty\}$. *State 1: "high credibility"* $\sigma_\phi(1)$, *in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.04	57.75	0.05	31.06	8.01	3.01	0.08
4	0.02	52.00	0.02	42.48	4.37	1.08	0.03
8	0.01	54.47	0.02	40.22	4.03	1.21	0.04
12	0.01	53.26	0.02	41.19	4.30	1.17	0.04
20	0.01	50.38	0.02	44.17	4.27	1.11	0.04
40	0.02	49.77	0.02	44.83	4.23	1.10	0.04
∞	0.02	49.75	0.02	44.84	4.23	1.10	0.04

Table B.4: *Forecast error variance decomposition of inflation for horizon* $h = \{1, ..., \infty\}$. *State 2: "low credibility"* $\sigma_\phi(2)$, *in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.66	45.73	0.26	0.32	50.67	2.36	0.00
4	0.10	12.54	0.33	0.05	82.94	4.03	0.01
8	0.07	7.13	0.29	0.20	89.86	2.45	0.00
12	0.07	6.19	0.27	1.20	89.83	2.43	0.00
20	0.08	5.81	0.27	4.61	86.41	2.81	0.00
40	0.09	5.45	0.37	7.87	83.29	2.92	0.01
∞	0.09	5.36	0.41	8.21	83.04	2.89	0.01

Table B.5: *Forecast error variance decomposition of output for horizon* $h = \{1, ..., \infty\}$. *State 1: "high credibility"* $\sigma_\phi(1)$, *in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.66	45.72	0.26	0.32	50.66	2.36	0.02
4	0.10	12.52	0.33	0.05	82.82	4.03	0.16
8	0.07	7.12	0.29	0.20	89.76	2.45	0.11
12	0.07	6.19	0.27	1.20	89.74	2.43	0.10
20	0.08	5.81	0.27	4.61	86.30	2.81	0.13
40	0.09	5.45	0.37	7.86	83.18	2.91	0.14
∞	0.09	5.35	0.41	8.20	82.93	2.88	0.14

Table B.6: *Forecast error variance decomposition of output for horizon* $h = \{1, ..., \infty\}$. *State 2: "low credibility"* $\sigma_\phi(2)$, *in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.14	0.03	57.44	0.01	0.13	1.53	40.73
4	0.33	0.03	57.40	0.23	7.94	9.58	24.50
8	0.36	0.02	36.19	3.99	34.11	13.78	11.55
12	0.30	0.02	21.41	9.35	51.26	11.43	6.24
20	0.22	0.01	10.95	14.82	63.20	7.69	3.10
40	0.17	0.01	6.96	16.91	68.47	5.52	1.96
∞	0.16	0.01	6.63	17.02	69.07	5.26	1.85

Table B.7: *Forecast error variance decomposition of the interest rate for horizon* $h = \{1, ..., \infty\}$. *State 1: "high credibility"* $\sigma_\phi(1)$, *in per cent.*

$t+h$	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.01	0.00	5.22	0.00	0.01	0.14	94.61
4	0.05	0.00	8.18	0.03	1.13	1.37	89.23
8	0.09	0.01	9.43	1.04	8.89	3.59	76.94
12	0.12	0.01	8.46	3.69	20.25	4.52	62.96
20	0.12	0.00	6.22	8.41	35.87	4.37	45.01
40	0.11	0.00	4.70	11.42	46.24	3.73	33.79
∞	0.11	0.00	4.56	11.71	47.53	3.62	32.46

Table B.8: *Forecast error variance decomposition of the interest rate for horizon* $h = \{1, ..., \infty\}$. *State 2: "low credibility"* $\sigma_\phi(2)$*, in per cent.*

B.2 $\mathcal{M}_2$: Convergence diagnostics – figures and tables

This section contains additional material for the main MS specification $\mathcal{M}_2$.

	Lag 1	Lag 5	Lag 10	Lag 50		Thin	Burn	Total(N)	(Nmin)	I-stat
p_{11}	0.537	0.134	0.059	0.007	p_{11}	2	12	3124	937	3.334
p_{22}	0.661	0.192	0.058	-0.001	p_{22}	2	12	3124	937	3.334
φ	0.738	0.236	0.054	-0.017	φ	2	12	3124	937	3.334
θ_H	0.753	0.298	0.107	-0.023	θ_H	2	12	3124	937	3.334
θ_F	0.739	0.252	0.054	-0.005	θ_F	2	12	3124	937	3.334
σ	0.784	0.387	0.183	-0.053	σ	2	12	3124	937	3.334
η	0.724	0.236	0.055	0.008	η	2	12	3124	937	3.334
h	0.751	0.272	0.098	0.008	h	2	12	3124	937	3.334
δ_H	0.749	0.253	0.067	-0.016	δ_H	2	12	3124	937	3.334
δ_F	0.717	0.220	0.049	0.008	δ_F	2	12	3124	937	3.334
χ	0.723	0.260	0.086	-0.014	χ	2	12	3124	937	3.334
ρ_a	0.881	0.630	0.460	-0.023	ρ_a	2	12	3124	937	3.334
ρ_{μ_F}	0.815	0.441	0.242	-0.009	ρ_{μ_F}	2	12	3124	937	3.334
ρ_ν	0.721	0.241	0.076	0.006	ρ_ν	2	12	3124	937	3.334
ρ_ϕ	0.727	0.223	0.044	-0.009	ρ_ϕ	2	12	3124	937	3.334
c_{y^*}	0.730	0.233	0.075	0.011	c_{y^*}	2	12	3124	937	3.334
c_{π^*}	0.759	0.302	0.091	-0.009	c_{π^*}	2	12	3124	937	3.334
c_{i^*}	0.733	0.258	0.074	0.013	c_{i^*}	2	12	3124	937	3.334
σ_{μ_F}	0.788	0.362	0.169	-0.020	σ_{μ_F}	2	12	3124	937	3.334
σ_a	0.815	0.417	0.217	-0.024	σ_a	2	12	3124	937	3.334
σ_ν	0.801	0.397	0.197	-0.040	σ_ν	2	12	3124	937	3.334
σ_ϕ	0.780	0.372	0.176	0.022	σ_ϕ	2	12	3124	937	3.334
σ_{y^*}	0.733	0.221	0.077	0.022	σ_{y^*}	2	12	3124	937	3.334
σ_{π^*}	0.751	0.261	0.064	0.057	σ_{π^*}	2	12	3124	937	3.334
σ_{i^*}	0.729	0.203	0.044	-0.005	σ_{i^*}	2	12	3124	937	3.334
R_v	0.709	0.206	0.071	0.008	R_v	2	12	3124	937	3.334
σ_ϕ	0.739	0.398	0.247	0.002	σ_ϕ	2	12	3124	937	3.334

Table B.9: *Left: Autocorrelation among the draws, based on a sample of 10,000. Right: Raferty-Lewis convergence diagnostics with q=0.025, r=0.1, s=0.95. An I-statistic less than 5 indicates convergence.*

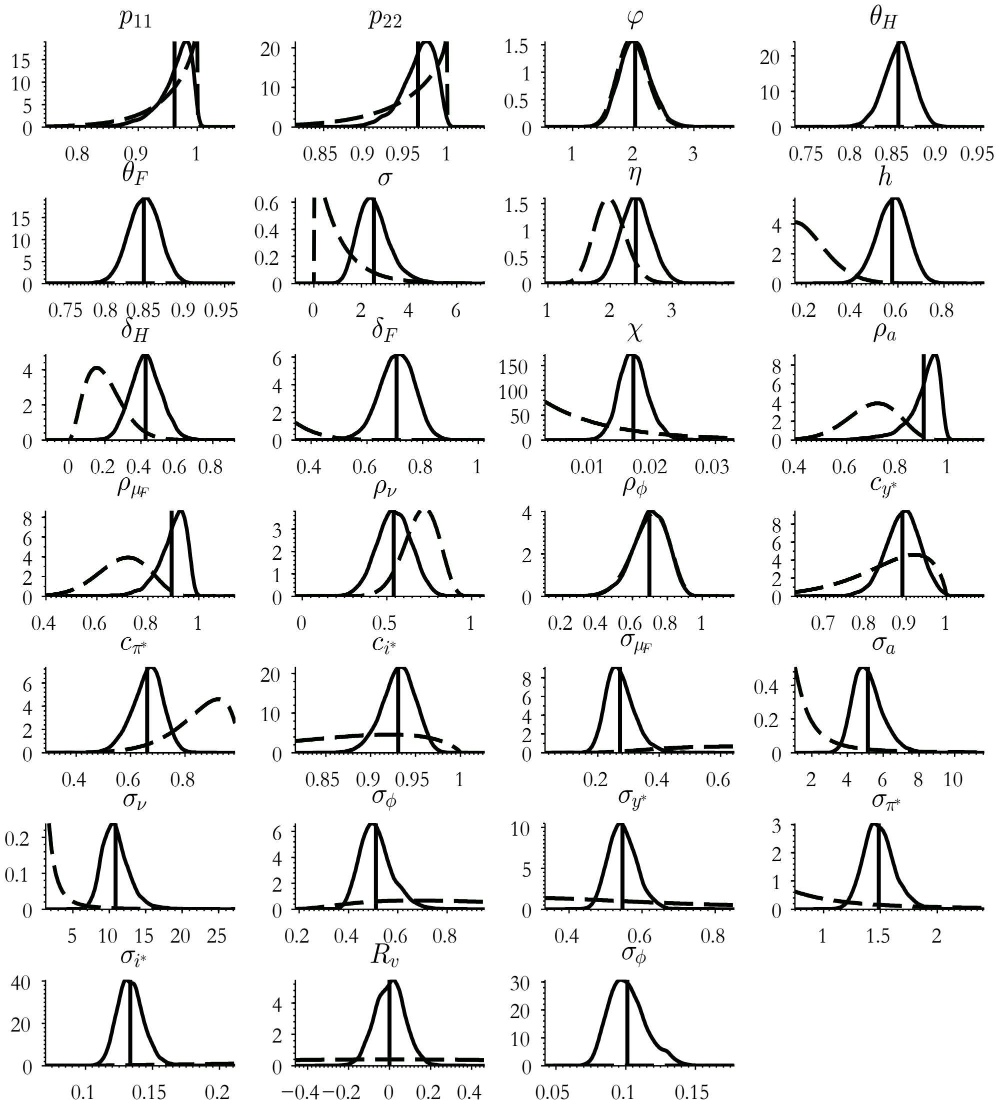


Figure B.1: $\mathcal{M}_2$*: Prior (- -) and posterior (—) parameter distributions.*

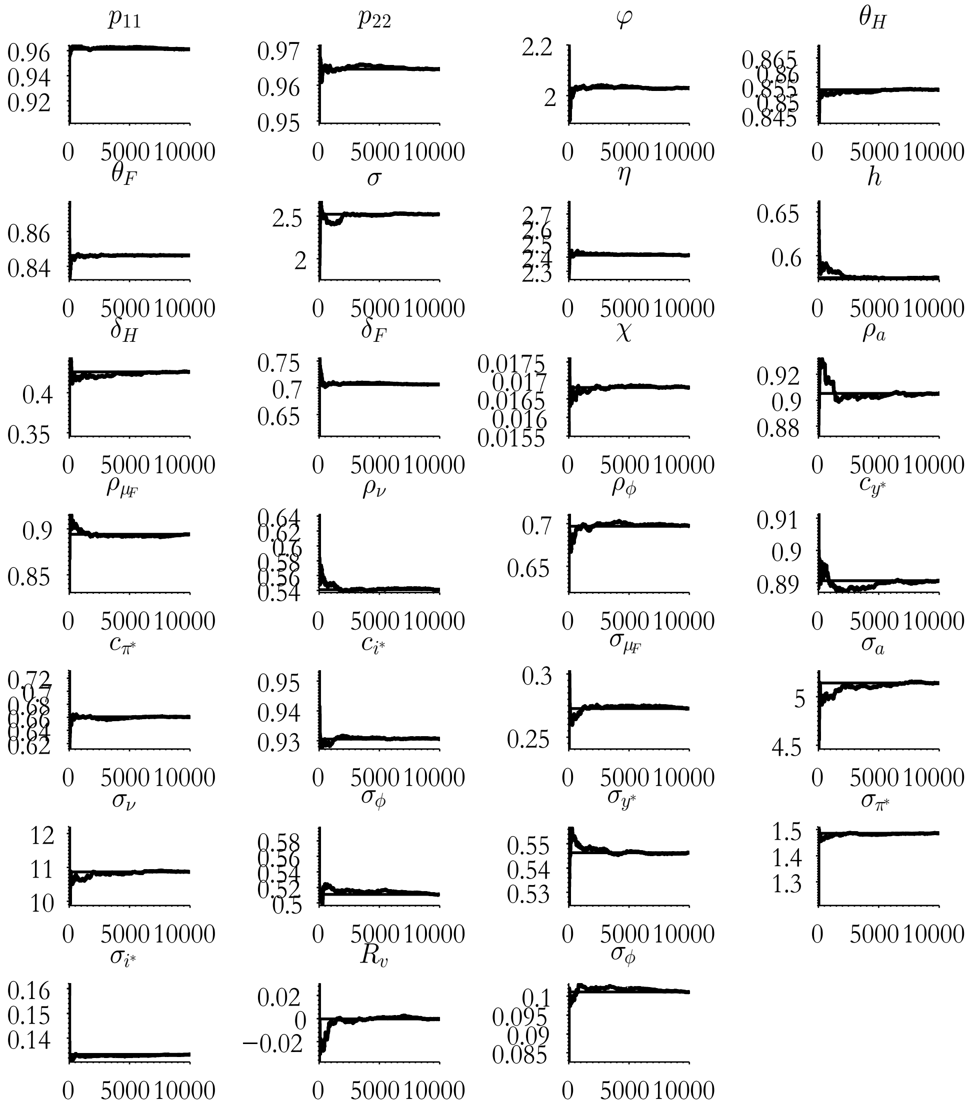


Figure B.2: $\mathcal{M}_2$*: Recursive means of the parameters calculated over the draws from the posterior distribution.*

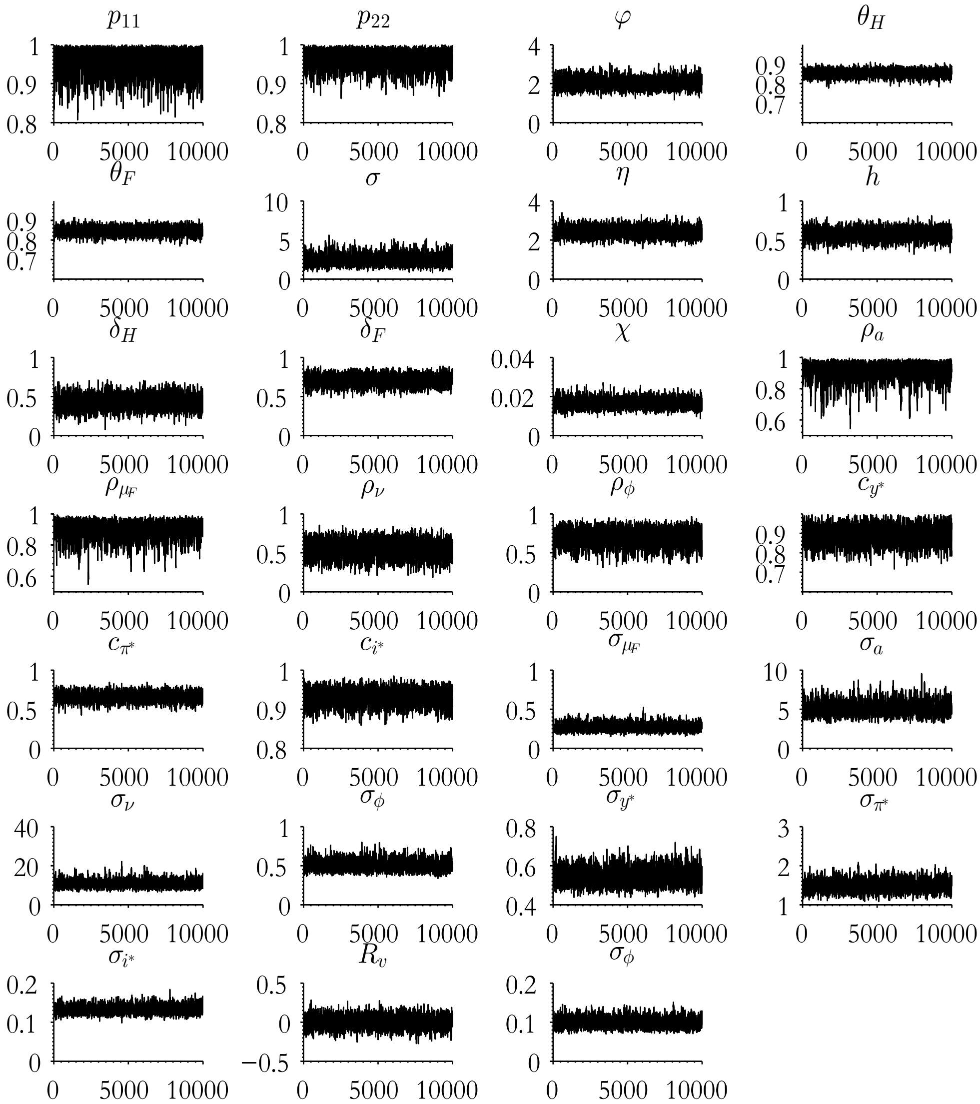


Figure B.3: $\mathcal{M}_2$*: Trace plots of the parameters.*

B.3 $\mathcal{M}_3$: Convergence diagnostics — figures and tables

This section contains additional material for the main robustness specification $\mathcal{M}_3$.

	Dist.	Prior Mean	$\mathcal{M}_1$	$\mathcal{M}_2 : s_t = 1$	$\mathcal{M}_2 : s_t = 2$	$\mathcal{M}_3 : s_t = 1$	$\mathcal{M}_3 : s_t = 2$
p_{11}	$Beta$	0.950	—	0.961 [0.904, 0.993]	—	0.952 [0.889, 0.990]	—
p_{22}	$Beta$	0.950	—	0.964 [0.925, 0.991]	—	0.968 [0.932, 0.992]	—
β	PM	0.983	0.983	0.983	—	0.983	—
φ	Gam	2.000	2.010 [1.625, 2.431]	2.029 [1.639, 2.458]	—	2.036 [1.652, 2.455]	—
θ_H	$Beta$	0.375	0.861 [0.834, 0.887]	0.854 [0.825, 0.881]	—	0.844 [0.814, 0.871]	—
θ_F	$Beta$	0.375	0.843 [0.812, 0.874]	0.846 [0.814, 0.878]	—	0.838 [0.803, 0.871]	—
α	PM	0.500	0.500	0.500	—	0.500	—
σ	Gam	1.000	2.684 [1.752, 3.809]	2.524 [1.564, 3.752]	—	2.304 [1.450, 3.397]	—
η	Gam	2.000	2.282 [1.895, 2.701]	2.412 [2.026, 2.815]	—	2.426 [2.044, 2.839]	—
h	$Beta$	0.200	0.565 [0.459, 0.666]	0.575 [0.461, 0.682]	—	0.569 [0.455, 0.679]	—
δ_H	$Beta$	0.200	0.422 [0.281, 0.564]	0.426 [0.291, 0.567]	—	0.437 [0.305, 0.573]	—
δ_F	$Beta$	0.200	0.712 [0.602, 0.811]	0.706 [0.603, 0.802]	—	0.723 [0.615, 0.819]	—
χ	Gam	0.010	0.014 [0.009, 0.019]	0.017 [0.013, 0.021]	—	0.017 [0.013, 0.021]	—
ρ_a	$Beta$	0.700	0.908 [0.777, 0.975]	0.905 [0.777, 0.973]	—	0.901 [0.763, 0.974]	—
ρ_{μ_F}	$Beta$	0.700	0.918 [0.830, 0.972]	0.894 [0.790, 0.962]	—	0.886 [0.769, 0.961]	—
ρ_ν	$Beta$	0.700	0.546 [0.381, 0.713]	0.541 [0.374, 0.703]	—	0.520 [0.359, 0.693]	—
ρ_ϕ	$Beta$	0.700	0.705 [0.531, 0.857]	0.697 [0.524, 0.844]	—	0.685 [0.515, 0.834]	—
c_{y^*}	$Beta$	0.850	0.900 [0.825, 0.968]	0.891 [0.820, 0.957]	—	0.889 [0.817, 0.957]	—
c_{π^*}	$Beta$	0.850	0.649 [0.543, 0.743]	0.661 [0.562, 0.745]	—	0.645 [0.547, 0.731]	—
c_{i^*}	$Beta$	0.850	0.923 [0.894, 0.951]	0.931 [0.898, 0.959]	—	0.926 [0.896, 0.954]	—
σ_{μ_F}	$IGam$	2.000	0.264 [0.202, 0.342]	0.273 [0.208, 0.354]	—	0.298 [0.228, 0.384]	0.318 [0.227, 0.433]
σ_a	$IGam$	2.000	5.459 [4.216, 7.002]	5.142 [3.984, 6.628]	—	4.469 [3.467, 5.779]	5.614 [4.122, 7.577]
σ_ν	$IGam$	2.000	11.001 [8.370, 14.300]	10.869 [8.290, 14.233]	—	9.782 [7.511, 12.636]	10.113 [7.246, 13.855]
σ_ϕ	$IGam$	2.000	0.292 [0.260, 0.329]	0.101 [0.082, 0.126]	0.511 [0.418, 0.629]	0.109 [0.088, 0.135]	0.527 [0.415, 0.682]
σ_{y^*}	$IGam$	1.000	0.550 [0.492, 0.615]	0.546 [0.488, 0.614]	—	0.546 [0.489, 0.612]	—
σ_{π^*}	$IGam$	1.000	1.540 [1.322, 1.797]	1.486 [1.282, 1.725]	—	1.474 [1.270, 1.696]	—
σ_{i^*}	$IGam$	1.000	0.134 [0.119, 0.150]	0.133 [0.119, 0.150]	—	0.134 [0.119, 0.151]	—
R_v	$Norm$	0.000	-0.001 [-0.298, 0.296]	-0.000 [-0.117, 0.116]	—	-0.002 [-0.118, 0.117]	—

Table B.10: *Parameter estimates for model $\mathcal{M}_3$ compared to $\mathcal{M}_1$ and $\mathcal{M}_2$. PM indicates point mass, Gam denotes the Gamma distribution, $IGam$ denotes the inverse Gamma distribution, and $Norm$ stands for the Normal distribution.*

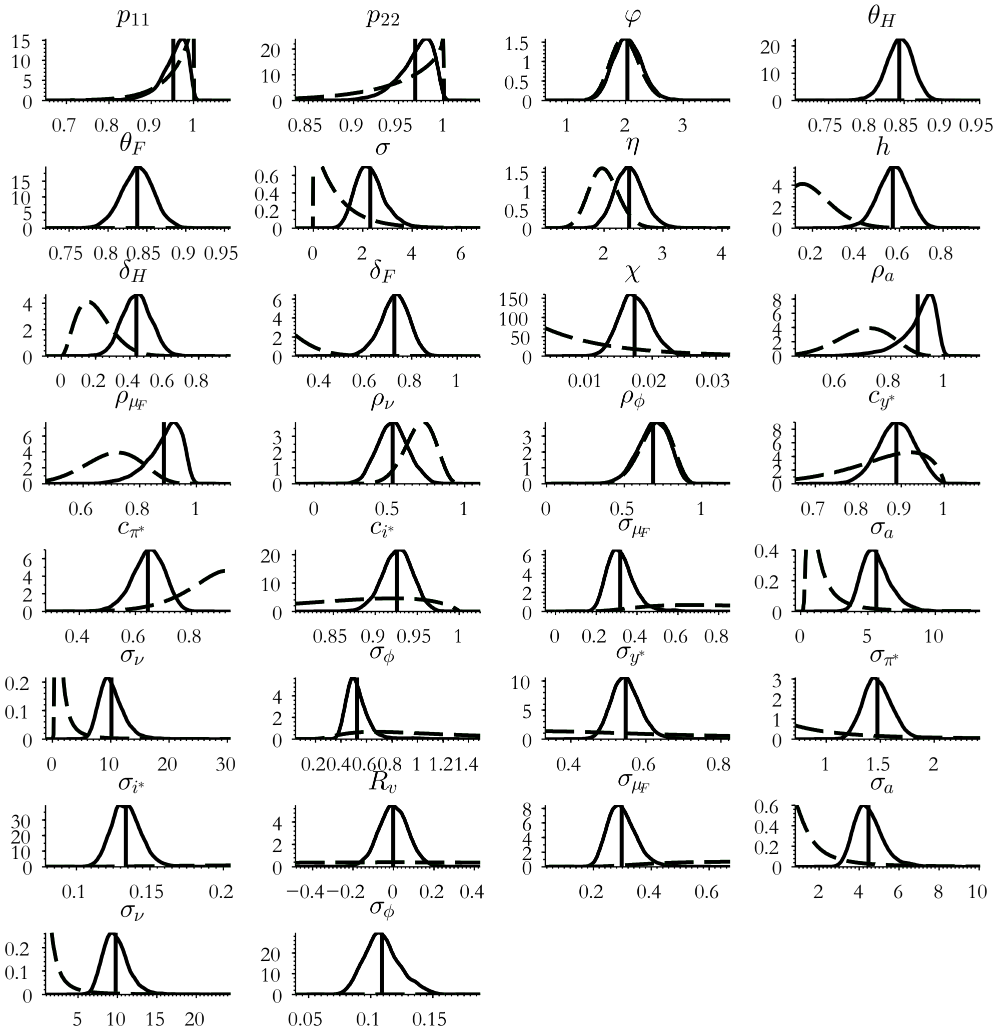


Figure B.4: $\mathcal{M}_3$*: Prior (- -) and posterior (—) parameter distributions.*

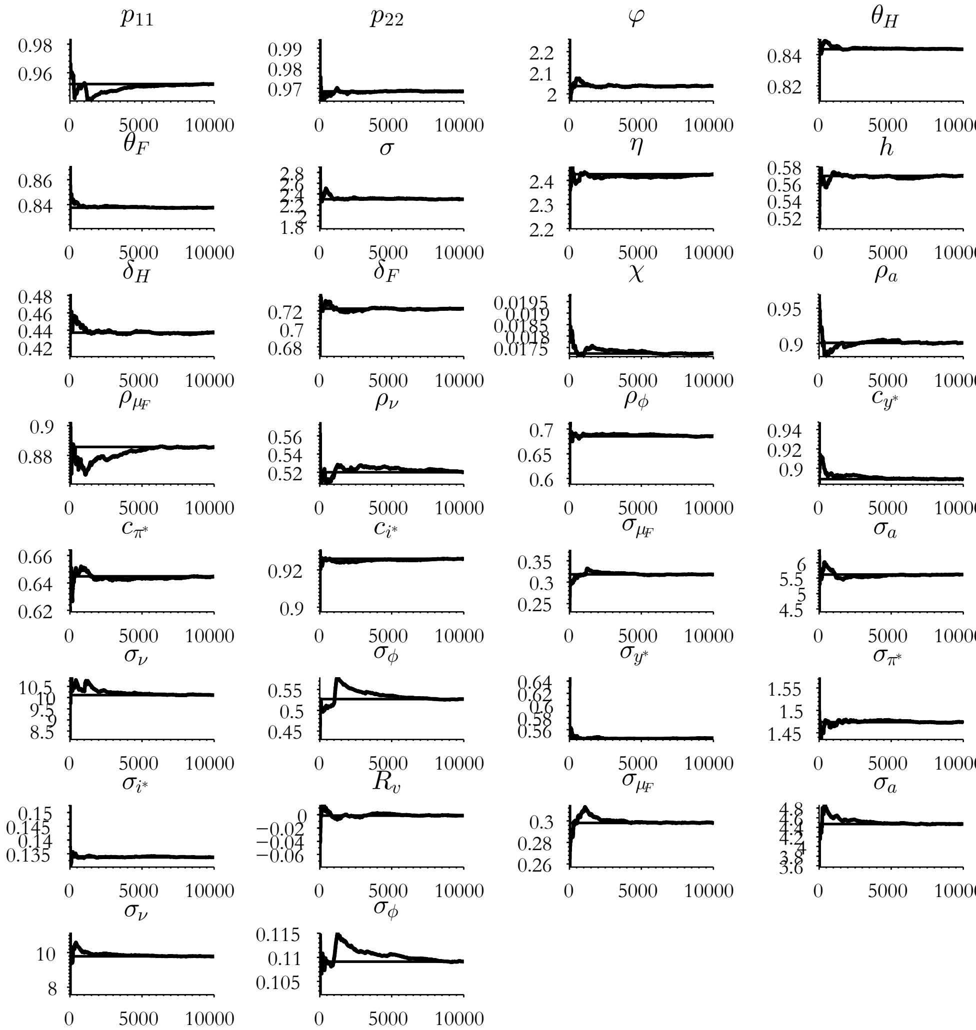


Figure B.5: $\mathcal{M}_3$*: Recursive means of the parameters calculated over the draws from the posterior distribution.*

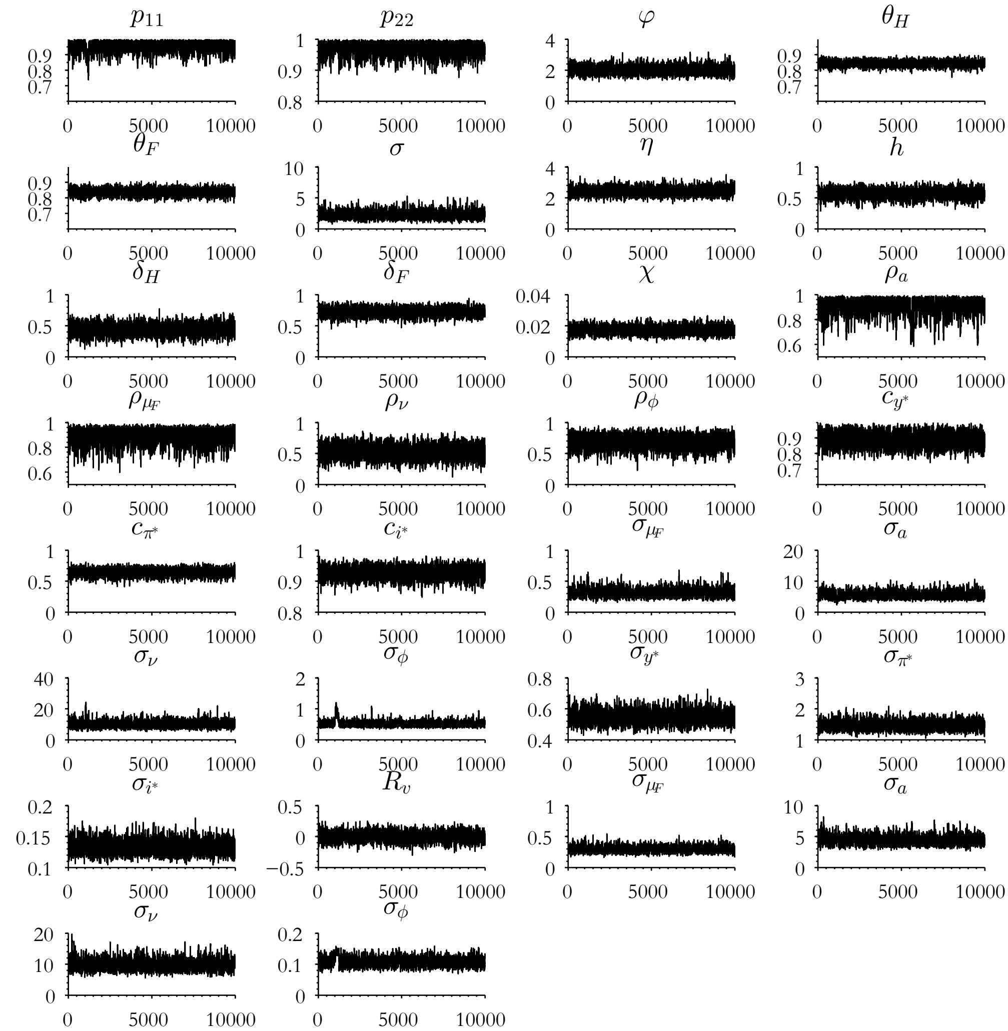


Figure B.6: $\mathcal{M}_3$*: Trace plots of the parameters.*

C

Appendix to chapter 3

C.1 Supplementary tables and figures

z Variable	Coefficient	Std. deviation	95% Probability Interval
HSVI	-0.7030	0.2973	[-1.2132; -0.2401]
VIX	-0.0117	0.0197	[-0.0449; 0.0203]
EMUI	0.0021	0.0026	[-0.0017; 0.0068]
STLOU	-0.5859	0.3189	[-1.1532; -0.1544]
FDmS	1.7024	1.7089	[-1.0911; 4.5511]

Table C.1: *Estimates for* $\hat{\gamma}_1$ *under the different specifications.*

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$		σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	2.066 [1.260, 3.115]	0.085 [-0.088, 0.256]	0.013 [0.001, 0.025]	σ_y^2	1.903 [1.147, 2.711]	-0.065 [-0.213, 0.071]	-0.057 [-0.109, -0.008]
$\sigma_{y,\pi}$	0.085 [-0.088, 0.256]	0.397 [0.303, 0.504]	0.004 [-0.001, 0.009]	$\sigma_{y,\pi}$	-0.065 [-0.213, 0.071]	0.202 [0.147, 0.263]	-0.016 [-0.033, 0.001]
$\sigma_{y,spr}$	0.013 [0.001, 0.025]	0.004 [-0.001, 0.009]	0.002 [0.001, 0.003]	$\sigma_{y,spr}$	-0.057 [-0.109, -0.008]	-0.016 [-0.033, 0.001]	0.041 [0.031, 0.053]

Table C.2: *Reduced form variance-covariance matrices for the heteroskedastic VAR model with HSVI as trigger variable. First regime (left) and second regime (right). 95% credible intervals in brackets.*

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$		σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	2.464 [1.341, 3.571]	0.063 [-0.134, 0.249]	0.010 [-0.002, 0.023]	σ_y^2	1.685 [1.067, 2.543]	-0.036 [-0.179, 0.088]	-0.054 [-0.103, -0.008]
$\sigma_{y,\pi}$	0.063 [-0.134, 0.249]	0.397 [0.301, 0.508]	0.005 [0.000, 0.011]	$\sigma_{y,\pi}$	-0.036 [-0.179, 0.088]	0.203 [0.148, 0.266]	-0.017 [-0.035, -0.001]
$\sigma_{y,spr}$	0.010 [-0.002, 0.023]	0.005 [0.000, 0.011]	0.002 [0.001, 0.002]	$\sigma_{y,spr}$	-0.054 [-0.103, -0.008]	-0.017 [-0.035, -0.001]	0.041 [0.030, 0.052]

Table C.3: *Reduced form variance-covariance matrices for the VAR model with VIX as trigger variable. First regime (left) and second regime (right). 95% credible intervals in brackets.*

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$		σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	2.135 [1.259, 3.264]	0.091 [-0.088, 0.268]	0.012 [0.000, 0.023]	σ_y^2	1.883 [1.132, 2.688]	-0.065 [-0.211, 0.068]	-0.055 [-0.106, -0.007]
$\sigma_{y,\pi}$	0.091 [-0.088, 0.268]	0.394 [0.301, 0.502]	0.005 [0.000, 0.011]	$\sigma_{y,\pi}$	-0.065 [-0.211, 0.068]	0.207 [0.154, 0.266]	-0.016 [-0.033, -0.000]
$\sigma_{y,spr}$	0.012 [0.000, 0.023]	0.005 [0.000, 0.011]	0.002 [0.001, 0.002]	$\sigma_{y,spr}$	-0.055 [-0.106, -0.007]	-0.016 [-0.033, -0.000]	0.041 [0.030, 0.052]

Table C.4: *Reduced form variance-covariance matrices for the VAR model with EMUI as trigger variable. First regime (left) and second regime (right). 95% credible intervals in brackets.*

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$		σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	3.384 [2.436, 4.469]	-0.236 [-0.478, -0.012]	-0.012 [-0.021, -0.002]	σ_y^2	1.772 [1.274, 2.358]	-0.045 [-0.269, 0.169]	-0.147 [-0.224, -0.079]
$\sigma_{y,\pi}$	-0.236 [-0.478, -0.012]	0.351 [0.219, 0.492]	0.000 [-0.003, 0.004]	$\sigma_{y,\pi}$	-0.045 [-0.269, 0.169]	0.588 [0.414, 0.793]	0.047 [0.010, 0.088]
$\sigma_{y,spr}$	-0.012 [-0.021, -0.002]	0.000 [-0.003, 0.004]	0.001 [0.000, 0.001]	$\sigma_{y,spr}$	-0.147 [-0.224, -0.079]	0.047 [0.010, 0.088]	0.058 [0.041, 0.078]

Table C.5: *Reduced form variance-covariance matrices for the VAR model with STLOU as trigger variable. First regime (left) and second regime (right). 95% credible intervals in brackets.*

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$		σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	2.252 [1.764, 2.783]	-0.013 [-0.152, 0.128]	0.002 [-0.012, 0.016]	σ_y^2	2.511 [1.468, 3.878]	-0.153 [-0.332, -0.001]	-0.406 [-0.630, -0.222]
$\sigma_{y,\pi}$	-0.013 [-0.152, 0.128]	0.369 [0.298, 0.448]	-0.002 [-0.007, 0.003]	$\sigma_{y,\pi}$	-0.153 [-0.332, -0.001]	0.086 [0.049, 0.132]	0.056 [0.025, 0.093]
$\sigma_{y,spr}$	0.002 [-0.012, 0.016]	-0.002 [-0.007, 0.003]	0.004 [0.003, 0.005]	$\sigma_{y,spr}$	-0.406 [-0.630, -0.222]	0.056 [0.025, 0.093]	0.112 [0.069, 0.167]

Table C.6: *Reduced form variance-covariance matrices for the VAR model with FDmS as trigger variable. First regime (left) and second regime (right). 95% credible intervals in brackets.*

C.2 VIX as trigger variable

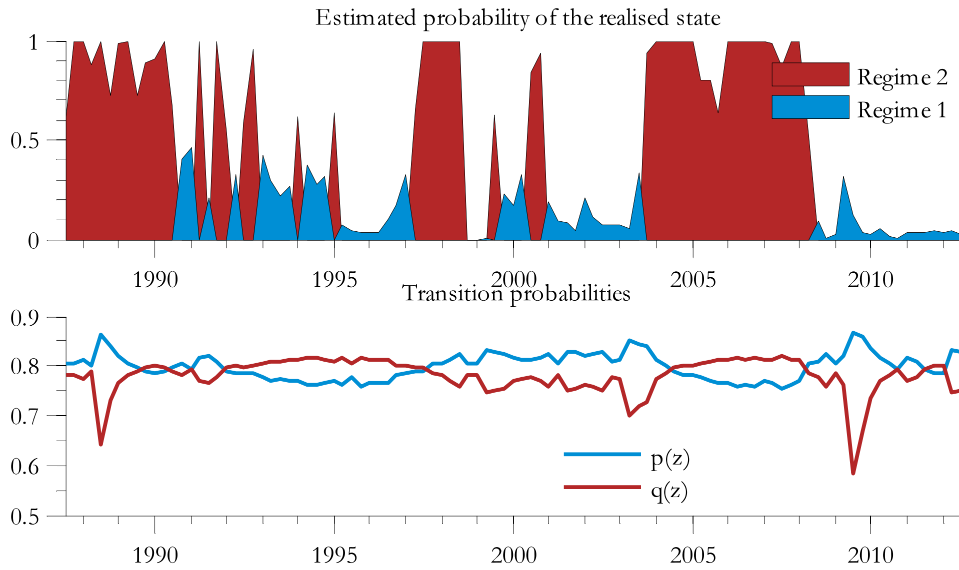


Figure C.1: *Regime switching and transition probabilities (VIX). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities* $p(z)$ *and* $q(z)$*.*

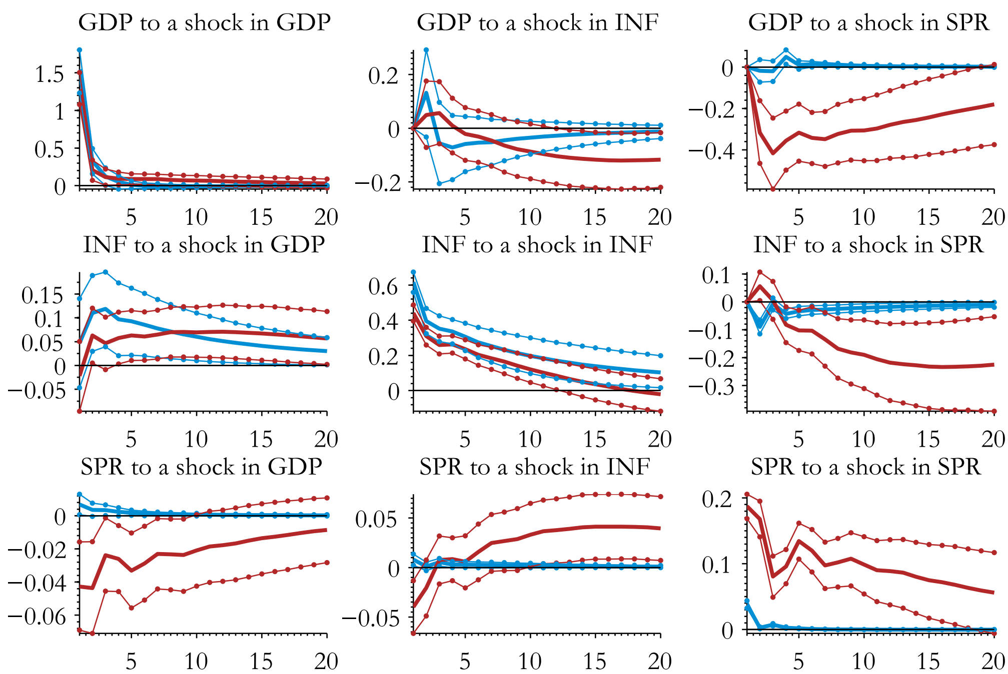
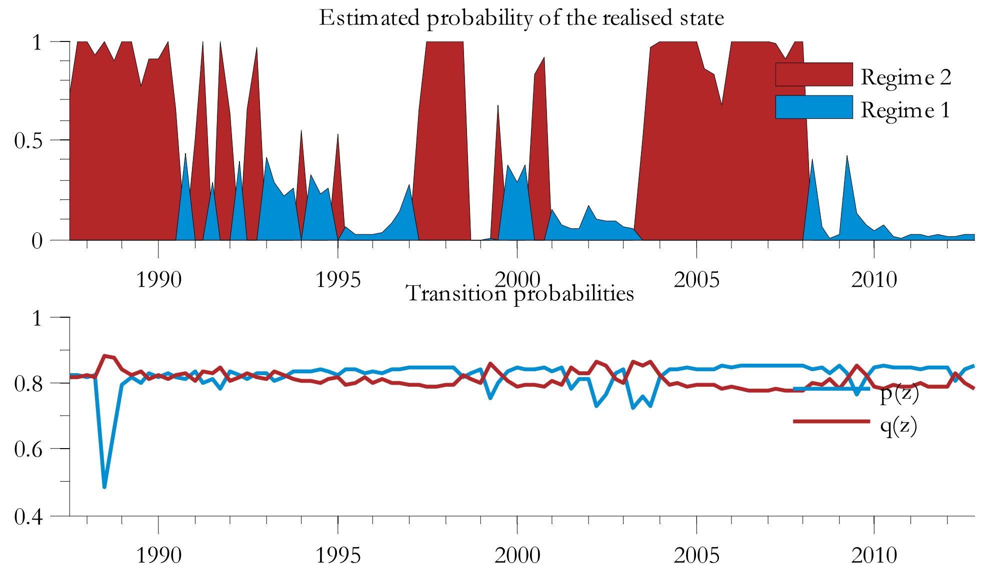


Figure C.2: *State-contingent impulse responses (VIX). Regime one (blue) and regime two (red) with standard 68% probability intervals.*

C.3 Equity Market Uncertainty Index as trigger variable



Regime switching and transition probabilities (EMUI). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities $p(z)$ and $q(z)$.

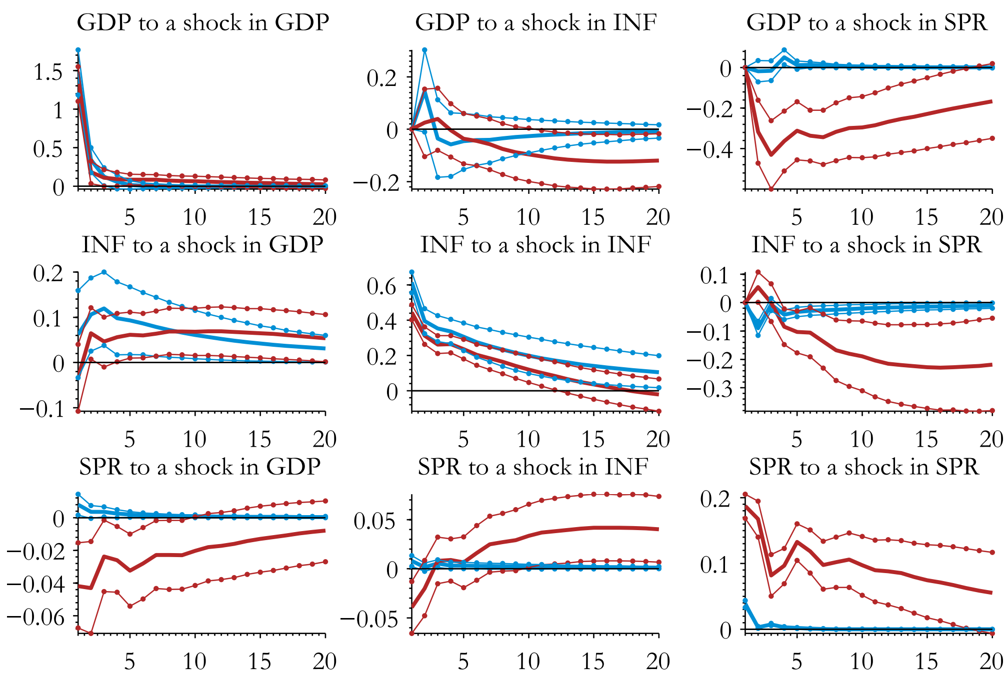


Figure C.3: *State-contingent impulse responses (EMUI). Regime one (blue) and regime two (red) with standard 68% probability intervals.*

C.4 St. Louis Stress Index as trigger variable

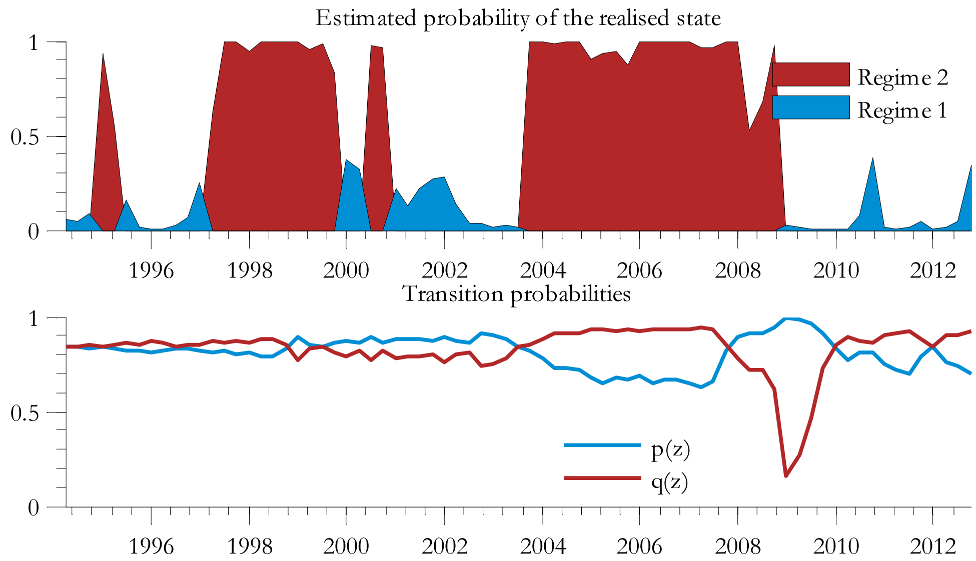


Figure C.4: *Regime switching and transition probabilities (STLOU). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities* $p(z)$ *and* $q(z)$.

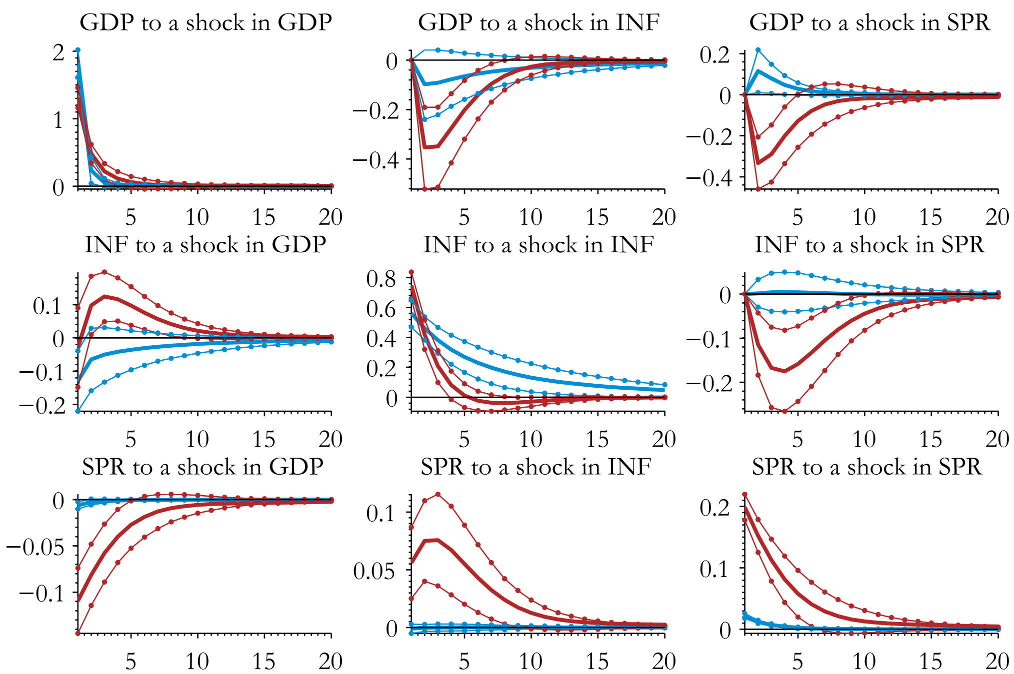


Figure C.5: *State-contingent impulse responses (STLOU). Regime one (blue) and regime two (red) with standard 68% probability intervals.*

C.5 FDmS as trigger variable

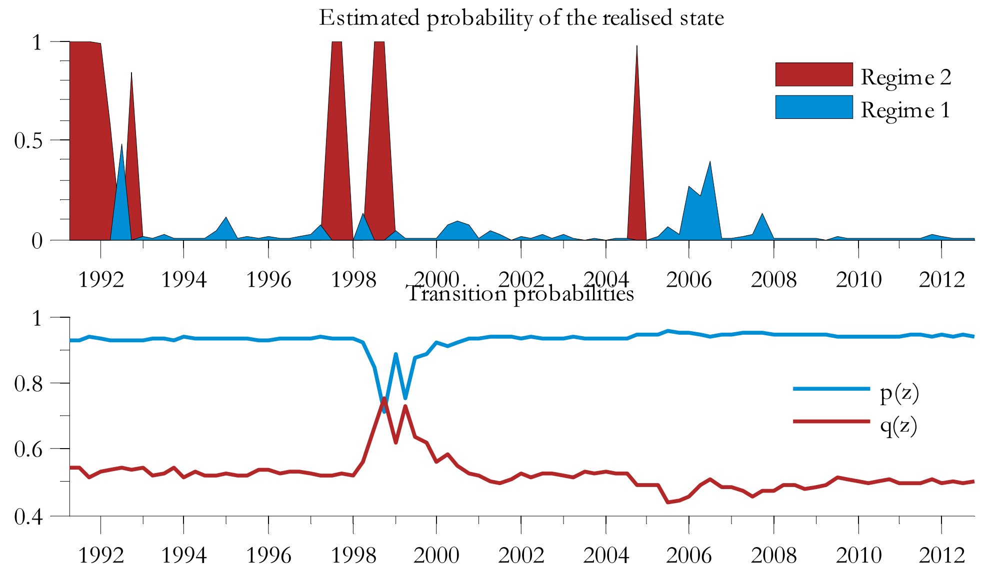


Figure C.6: *Regime switching and transition probabilities (FDmS). Top panel: Estimated probability of the second state. Values below 0.5 indicate a realisation of the first regime and values above 0.5 — a realisation of the second regime. Bottom panel: Time-varying transition probabilities* $p(z)$ *and* $q(z)$*.*

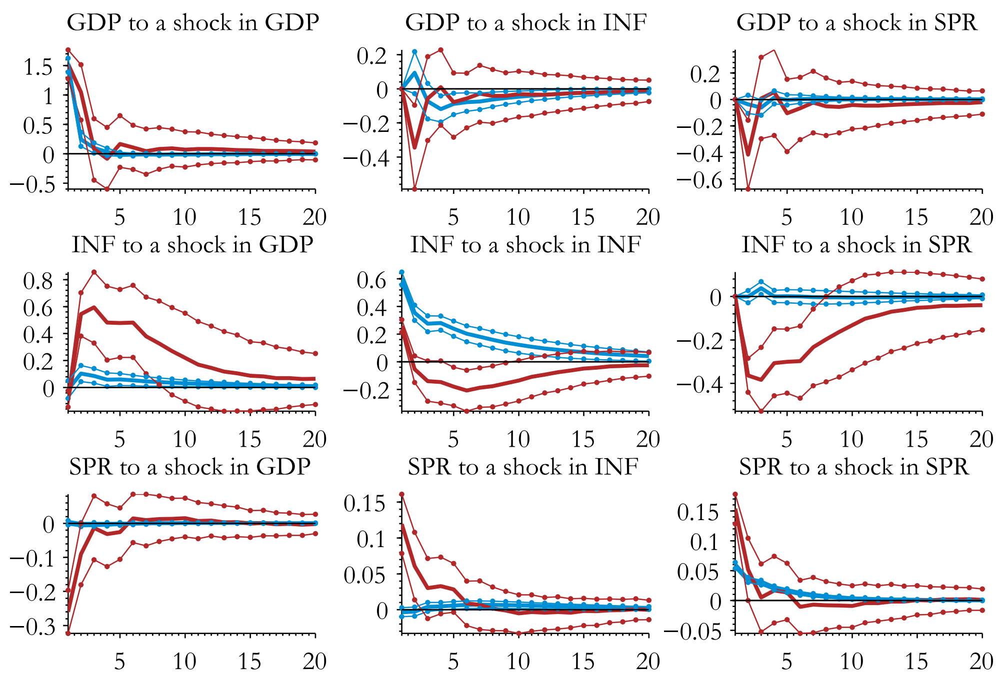


Figure C.7: *State-contingent impulse responses (FDmS). Regime one (blue) and regime two (red) with standard 68% probability intervals.*

C.6 Convergence diagnostics

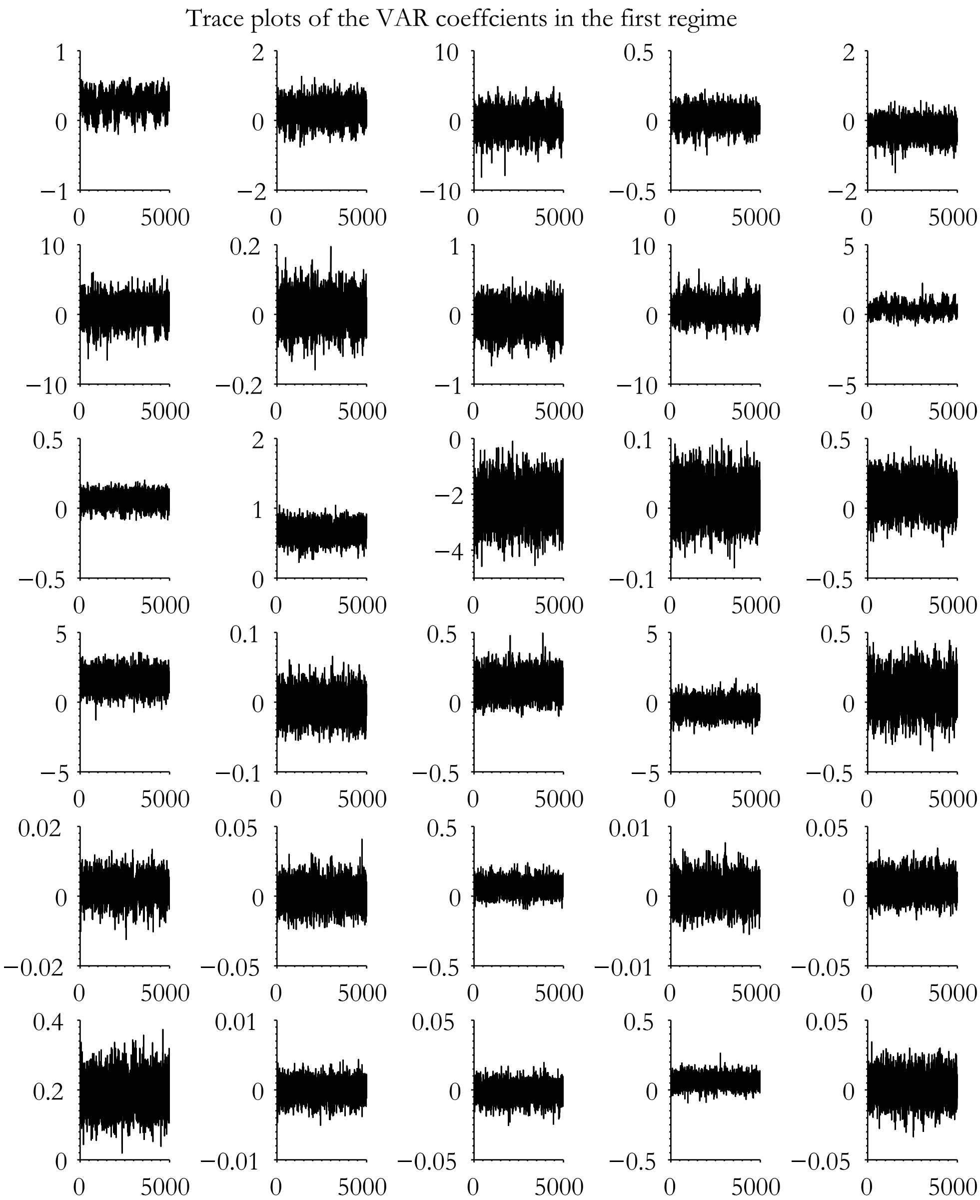


Figure C.8: *Trace plots of the VAR coefficients in the first regime with HSVI as trigger variable.*

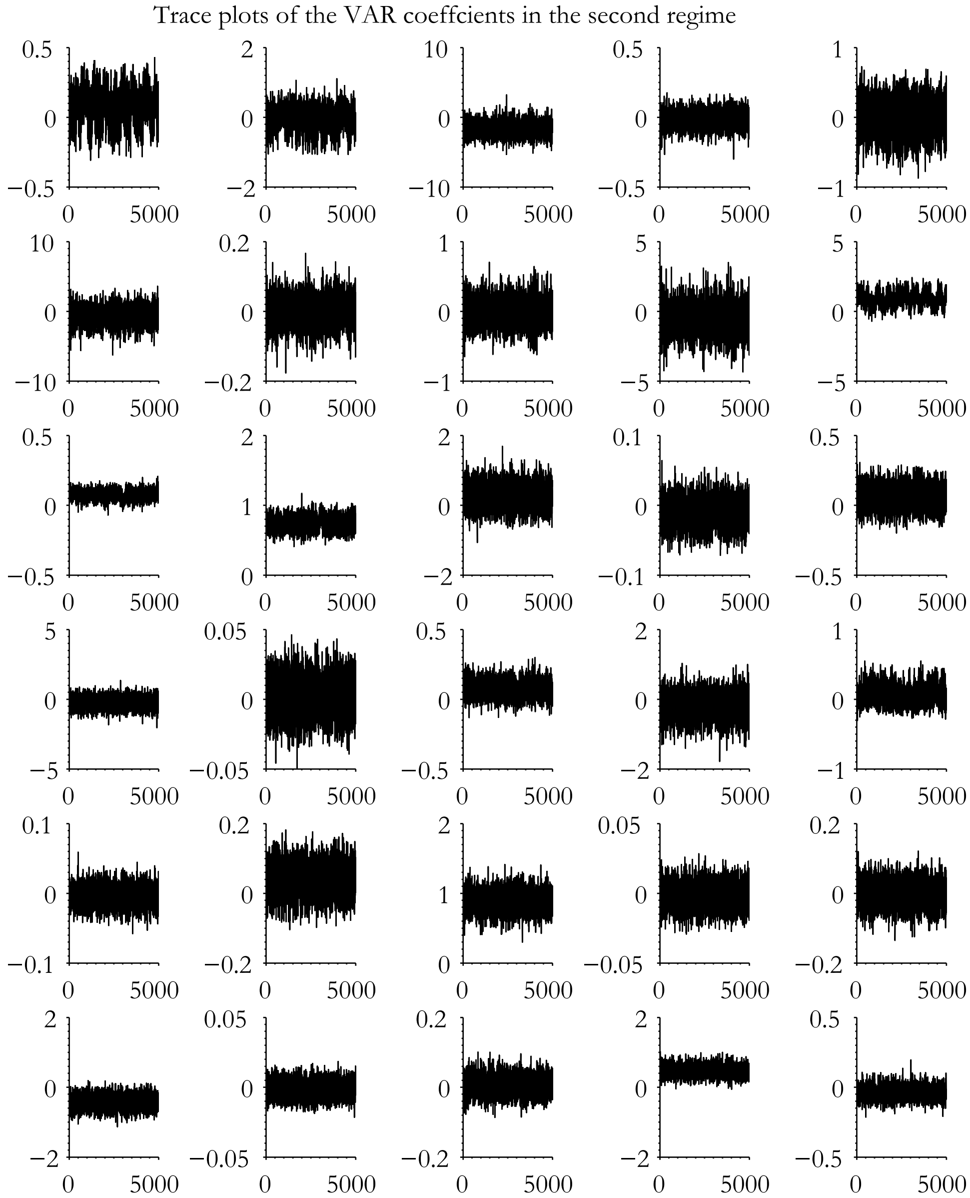


Figure C.9: *Trace plots of the VAR coefficients in the second regime with HSVI as trigger variable.*

Recursive means of the VAR coefficients in the first regime

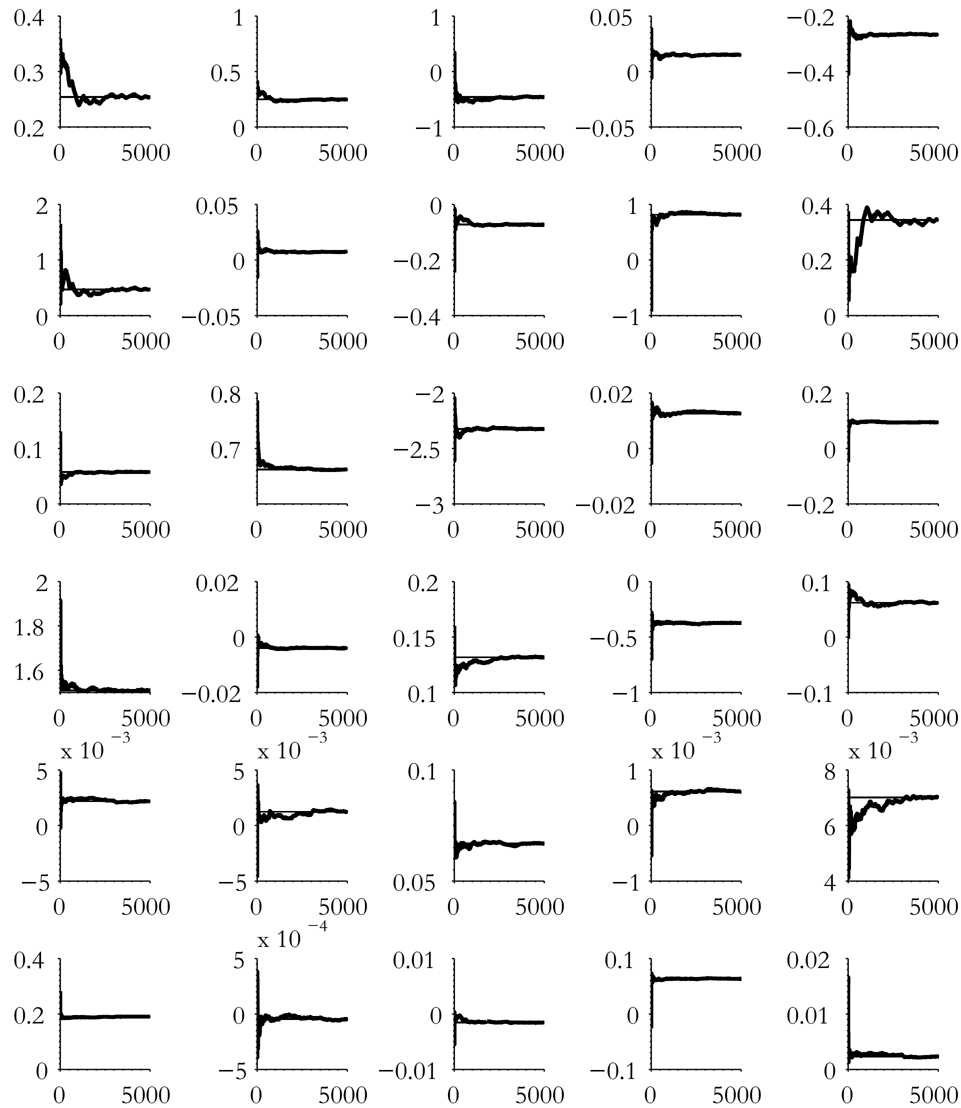


Figure C.10: *Recursive means and parameter mean values of the VAR coefficients in the first regime with HSVI as trigger variable.*

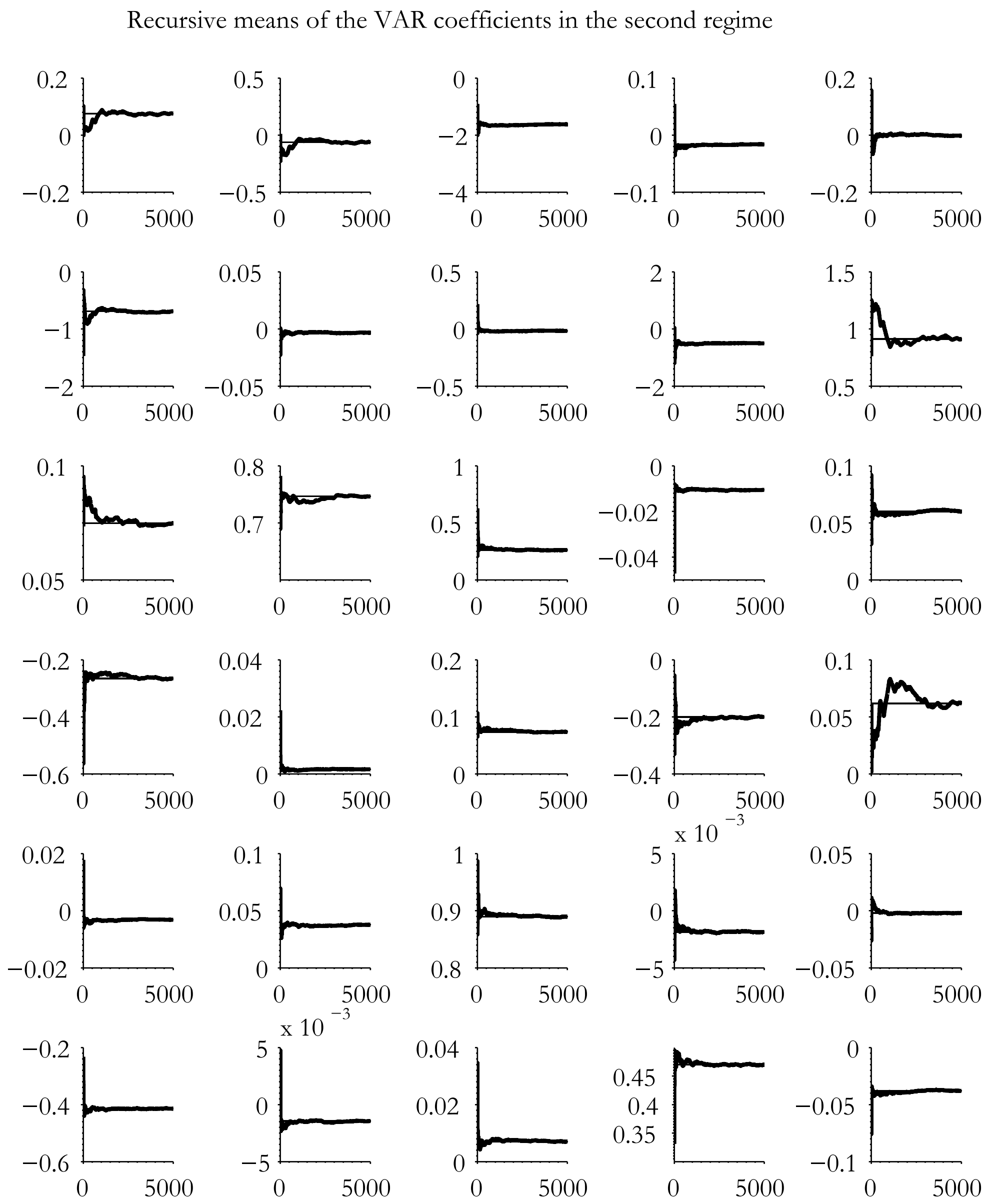


Figure C.11: *Recursive means and parameter mean values of the VAR coefficients in the second regime with HSVI as trigger variable.*

D

Appendix to chapter 4

D.1 Data sources

Data for EONIA, as well as data on long-term lending spreads have been obtained through the ECB statistical warehouse. Data for the shadow short rate (SSR) has been kindly provided by Marcello Pericoli and Marco Taboga from their paper Pericoli and Taboga (2015), and obtained through Prof. Jing Cynthia Wus website and from the website of the Reserve Bank of New Zealand. The data on government bond yields has been obtained from the FRED database.

Data on the weighted average cost of liabilities was kindly provided by Anamaria Illes, Marco Lombardi and Paul Mizen from their paper Illes et al. (2015). Data on the CDS was obtained from Makrit. The VIX, MOVE and EUROSTOXX indices were obtained from Bloomberg.

Data on the variables for the probit model have been kindly provided by Anamaria Illes and Diego Urbina at the Bank for International Settlements. All series are at a monthly frequency, with the longest data spanning the period from January 2003 to March 2015.

D.2 List of the trigger variables

Country specific variables:

- European policy uncertainty index [Baker et al. (2015)]
- Bank stocks index
- CDS spreads
- Main Refinancing Operations (MROs)
- Long-Term Refinancing Operations (LTROs)
- Industrial production growth
- HICP
- Net-foreign asset position expressed as a percentage of nominal gross domestic product.
- Debt-to-GDP ratio measured as general government gross debt as a percentage of nominal gross domestic product
- Non-Performing loans

Contagion variables:

- VSTOXX financial volatility indicator
- VIX financial volatility indicator
- MOVE financial volatility index

Policy announcement variables

- Dummy variable for the announcements of the LTROs. June, September, November 2009 - Fixed Rate Full Allotment programme.
- Dummy variable for ECB announcements: June, July and August 2012 - "Whatever it takes speeches" and OMT announcements.

Country Regime	Italy (1)	Italy (2)	Spain (1)	Spain (2)	Ireland (1)	Ireland (2)	Portugal (1)	Portugal (2)
	0.03*	0.50	0.30	0.10	0.02*	0.50	0.04*	0.00*
p-value	0.00*	0.08	0.05	0.02*	0.18	0.50	0.00*	0.50
	0.20	0.50	0.50	0.42	0.50	0.17	0.00*	0.03*

Table D.1: *Jarque-Bera Test. Null Hypothesis: "The residuals are normally distributed with unspecified mean and standard deviation".*

Country Regime	Italy (1)	Italy (2)	Spain (1)	Spain (2)	Ireland (1)	Ireland (2)	Portugal (1)	Portugal (2)
	0.92	0.72	0.76	0.89	0.99	0.79	0.96	0.79
p-value	0.93	0.78	0.55	0.71	0.89	0.91	0.81	0.96
	0.89	0.90	0.48	0.66	0.81	0.88	0.96	0.99

Table D.2: *T-test for zero means. Null Hypothesis: "The residuals have a mean different from zero".*

D.3 State-contingent residual diagnostics

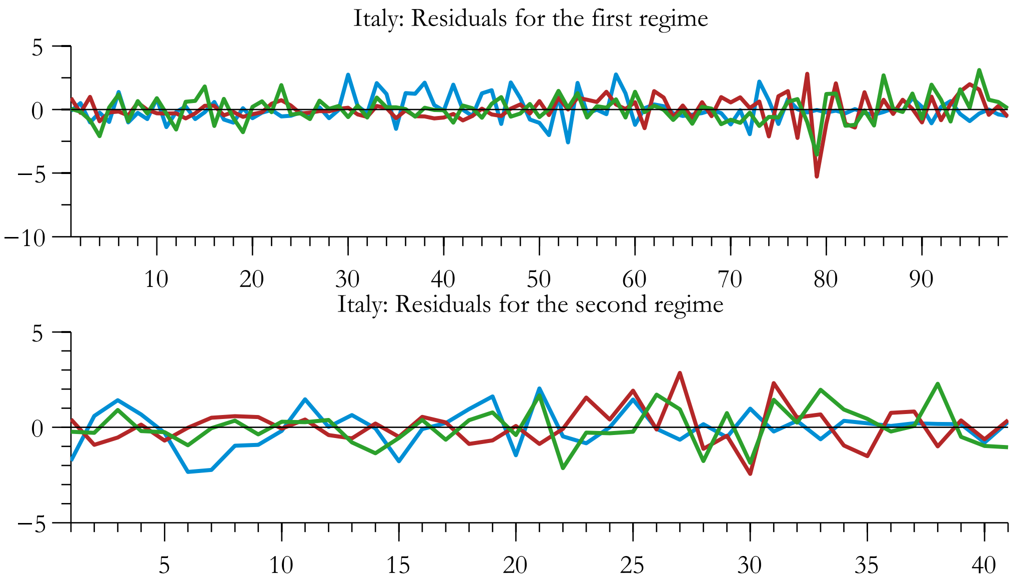


Figure D.1: *Italy: Residuals for regime one (top) and regime two (bottom).*

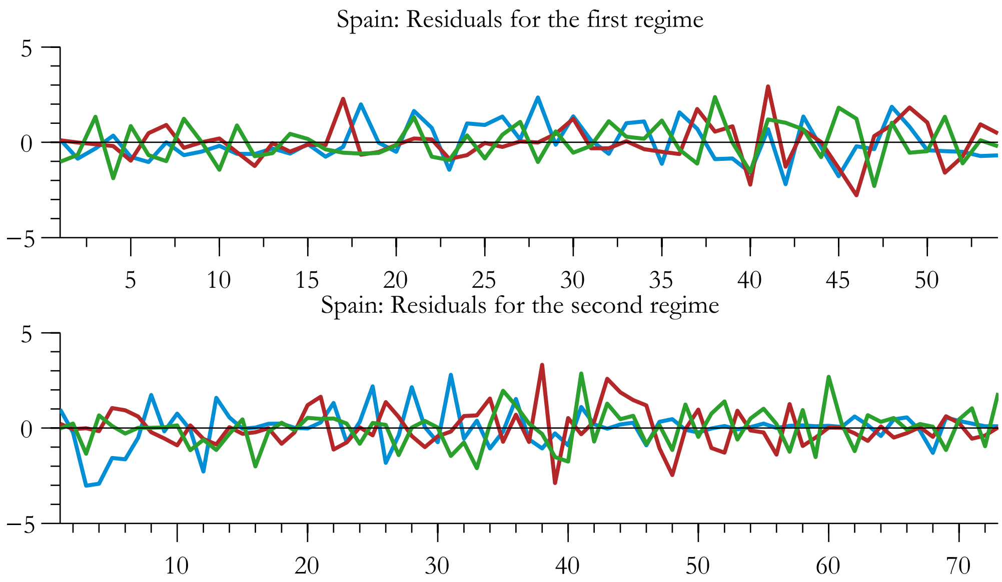


Figure D.2: *Spain: Residuals for regime one (top) and regime two (bottom).*

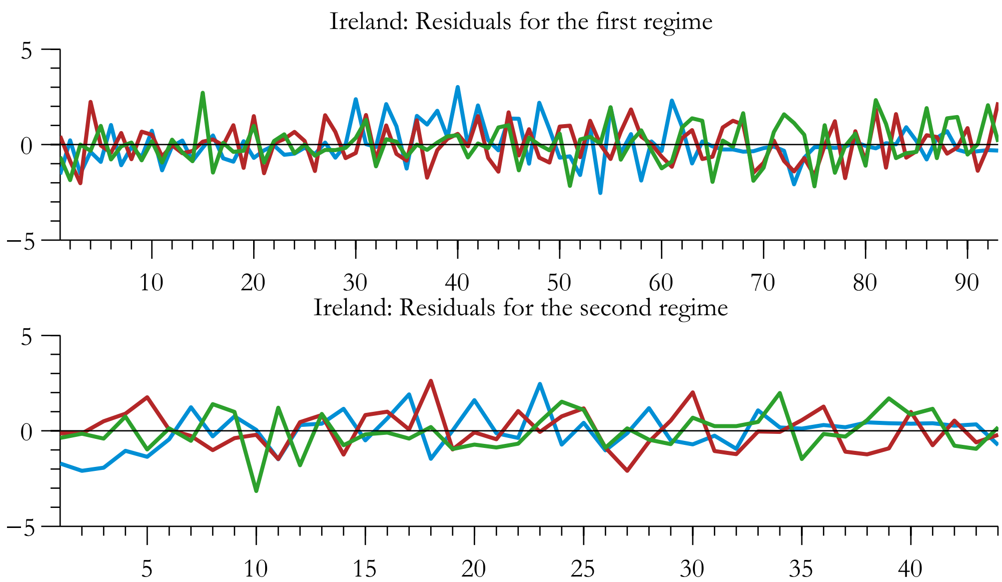


Figure D.3: *Ireland: Residuals for regime one (top) and regime two (bottom).*

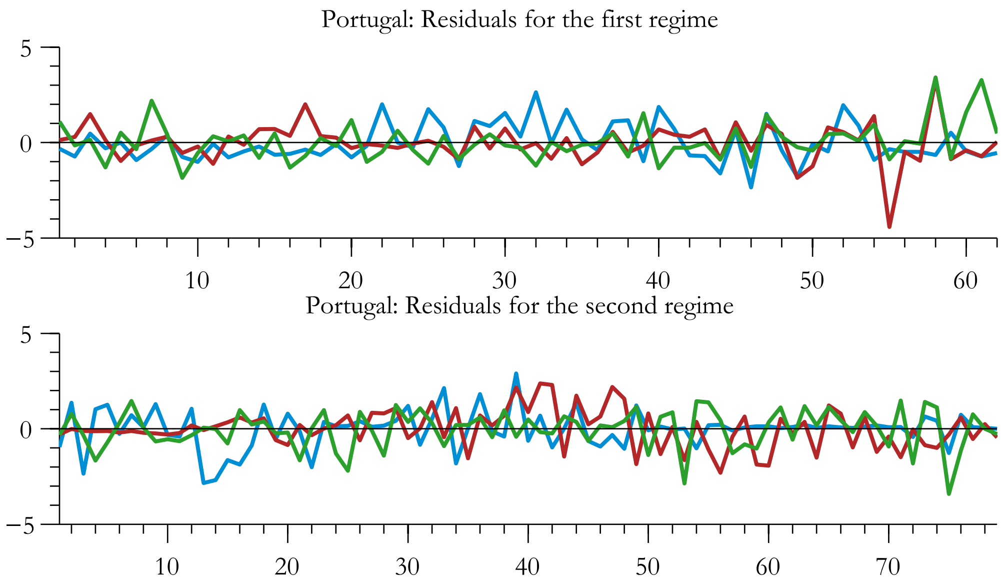


Figure D.4: *Portugal: Residuals for regime one (top) and regime two (bottom).*

D.4 Impulse responses for the EONIA specification

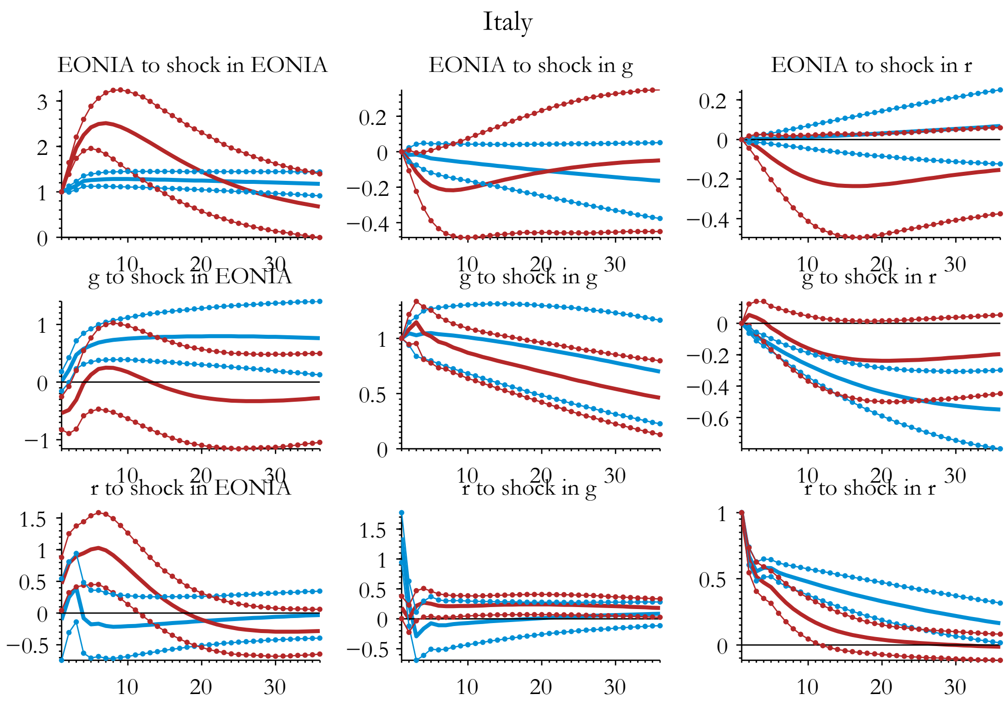


Figure D.5: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime. The interest rate pass-through may be inferred from the lower left corner, which plots the response of the lending spread to a shock in EONIA. Italy exhibits a change in the monetary policy transmission to lending rates, since the spread reacts differently across regimes. These findings are amplified due to the zero lower bound, which is evident from the response of EONIA to a shock in itself in the second regime.*

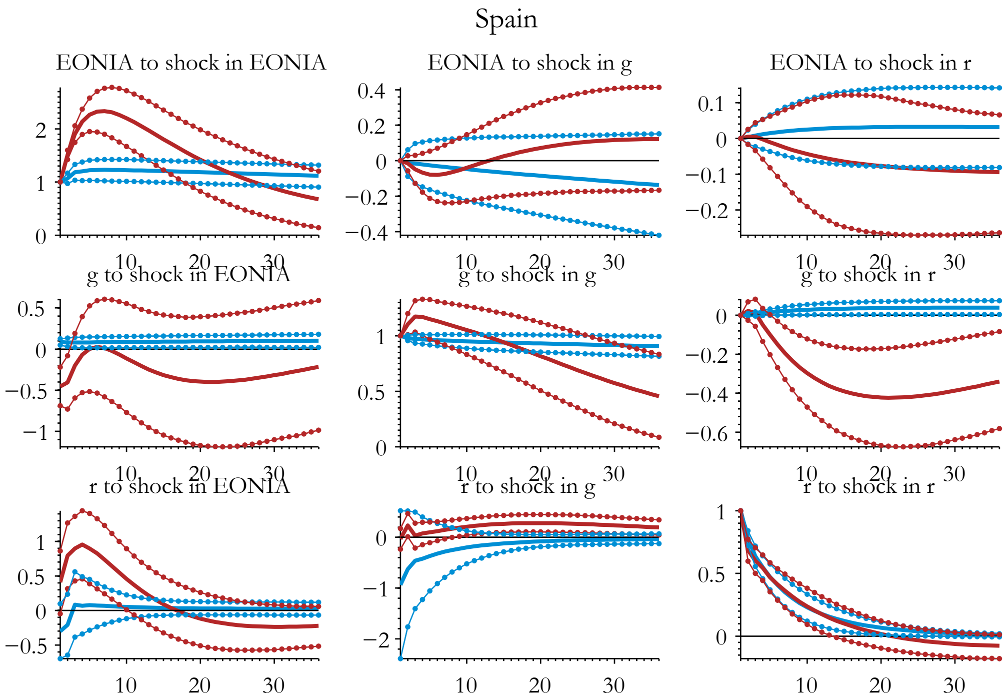


Figure D.6: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime. The interest rate pass-through may be inferred from the lower left corner, which plots the response of the lending spread to a shock in EONIA. Italy exhibits a change in the monetary policy transmission to lending rates, since the spread reacts differently across regimes.*

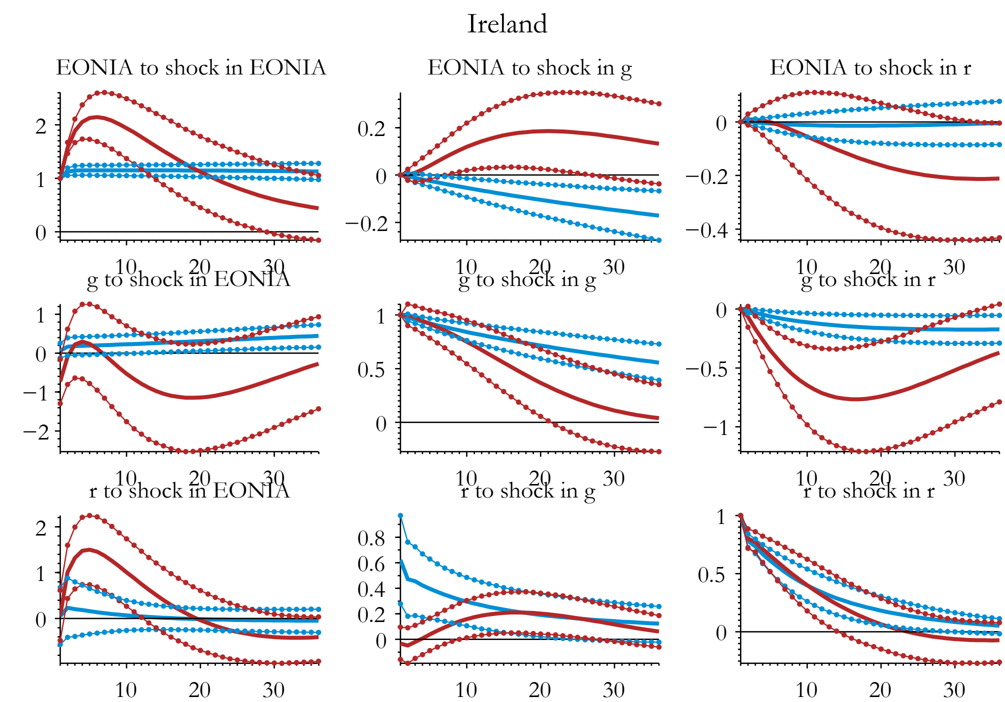


Figure D.7: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime. The interest rate pass-through may be inferred from the lower left corner, which plots the response of the lending spread to a shock in EONIA. Ireland exhibits a change in the monetary policy transmission to lending rates, since the spread reacts differently across regimes.*

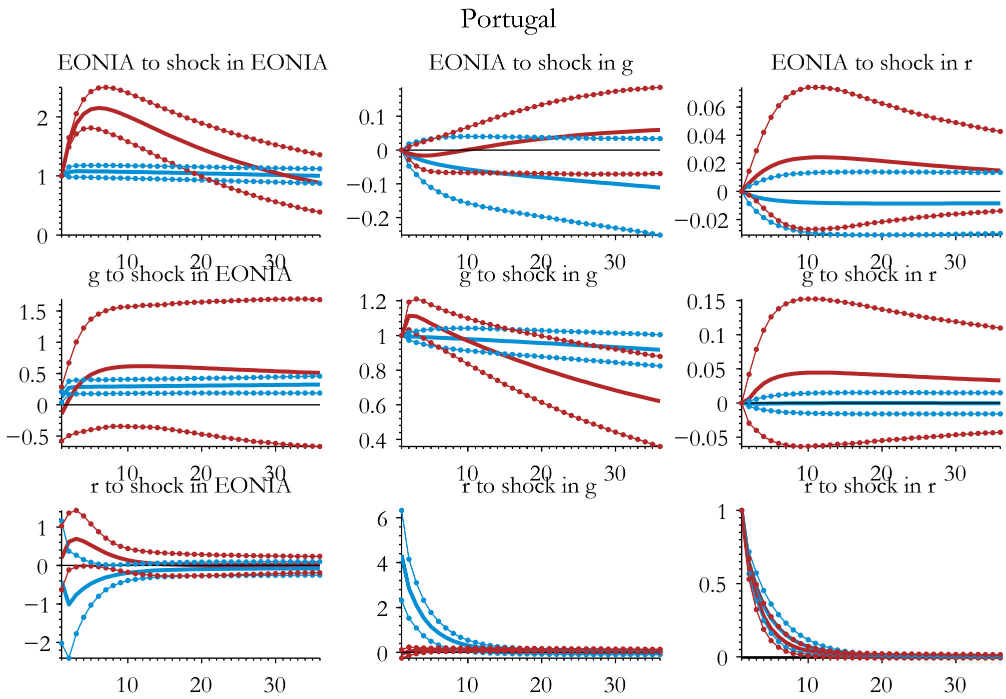


Figure D.8: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime for Portugal. The model does not identify distinctive responses of the lending rate spread to a shock in the policy rate.*

D.5 Correlation tables for the Z variables

	VSTOXX	Pol. Unc.	MOVE	Bank Stocks	CDS Spreads	Ind.Prod.	MRO	LTRO	NFA-to-GDP	Debt-to-GDP	r^{PT}	r^{ES}	r_{IE}	r^{IT}
VSTOXX	1													
Pol. Unc.	0,45	1												
MOVE	0,69	0,04	1											
Bank Stocks	-0,35	-0,71	-0,07	1										
CDS Spreads	0,2	0,79	-0,18	-0,69	1									
Ind.Prod.	-0,27	-0,13	-0,25	0,17	-0,12	1								
MRO	0,03	-0,05	-0,04	0,14	0,16	-0,06	1							
LTRO	0,12	0,1	0,01	0,08	0,19	-0,16	0,71	1						
NFA-to-GDP	-0,43	-0,07	-0,45	-0,2	0,1	0,08	-0,11	-0,1	1					
Debt-to-GDP	-0,2	0,42	-0,44	-0,57	0,51	0,07	-0,32	-0,24	0,5	1				
r^{PT}	0,1	0,53	-0,17	-0,56	0,63	0,04	0	0,05	0,07	0,52	1			
r^{ES}	-0,14	0,5	-0,4	-0,31	0,63	-0,03	-0,05	0,01	0,38	0,59	0,47	1		
r_{IE}	-0,16	0,49	-0,44	-0,41	0,65	-0,02	0,08	0,1	0,5	0,58	0,54	0,81	1	
r^{IT}	-0,14	0,45	-0,35	-0,33	0,63	-0,08	0,03	0,11	0,5	0,61	0,43	0,84	0,82	1

Table D.3: *Correlation among the trigger variables for Italy.*

	VSTOXX	Pol. Unc.	MOVE	Bank Stocks	CDS Spreads	Ind.Prod.	MRO	LTRO	NFA-to-GDP	Debt-to-GDP	r^{PT}	r^{ES}	r_{IE}	r^{IT}
VSTOXX	1													
Pol. Unc.	0,44	1												
MOVE	0,71	0,06	1											
Bank Stocks	-0,32	-0,75	-0,04	1										
CDS Spreads	0,23	0,84	-0,17	-0,78	1									
Ind.Prod.	-0,37	-0,16	-0,33	0,1	-0,06	1								
MRO	0,07	0,32	-0,07	-0,31	0,37	-0,06	1							
LTRO	0,01	0,65	-0,28	-0,7	0,77	-0,02	0,31	1						
NFA-to-GDP	-0,04	0,63	-0,32	-0,84	0,71	0,09	0,22	0,83	1					
Debt-to-GDP	-0,1	0,61	-0,4	-0,75	0,67	0,08	0,18	0,8	0,94	1				
r^{PT}	0,14	0,58	-0,13	-0,64	0,65	-0,08	0,15	0,53	0,62	0,64	1			
r^{ES}	-0,09	0,54	-0,37	-0,39	0,58	0,03	0,34	0,7	0,55	0,68	0,46	1		
r_{IE}	-0,16	0,5	-0,43	-0,44	0,6	0,01	0,34	0,7	0,58	0,72	0,54	0,82	1	
r^{IT}	-0,08	0,47	-0,31	-0,42	0,51	0	0,33	0,73	0,57	0,69	0,42	0,82	0,83	1

Table D.4: *Correlation among the trigger variables for Spain.*

	VSTOXX	Pol. Unc.	MOVE	Bank Stocks	CDS Spreads	Ind.Prod.	MRO	LTRO	NFA-to-GDP	Debt-to-GDP	r^{PT}	r^{ES}	r_{IE}	r^{IT}
VSTOXX	1													
Pol. Unc.	0,43	1												
MOVE	0,7	0,02	1											
Bank Stocks	-0,33	-0,7	-0,06	1										
CDS Spreads	0,32	0,67	-0,01	-0,55	1									
Ind.Prod.	0,02	-0,03	-0,1	0	-0,02	1								
MRO	0,48	0,31	0,34	-0,25	0,53	-0,01	1							
LTRO	0,41	0,64	0,15	-0,49	0,73	-0,04	0,46	1						
NFA-to-GDP	NA	NA	NA	NA	NA	NA	NA	NA	NA					
Debt-to-GDP	0,05	0,76	-0,31	-0,74	0,58	0,04	0,13	0,61	NA	1				
r^{PT}	0,12	0,57	-0,16	-0,58	0,53	0,04	0,21	0,4	NA	0,68	1			
r^{ES}	-0,1	0,55	-0,39	-0,34	0,25	0,06	-0,07	0,18	NA	0,71	0,46	1		
r^{IE}	-0,16	0,51	-0,44	-0,41	0,3	0,02	-0,2	0,09	NA	0,71	0,54	0,81	1	
r^{IT}	-0,11	0,49	-0,35	-0,35	0,18	0,04	-0,15	0,16	NA	0,69	0,43	0,83	0,83	1

Table D.5: *Correlation among the trigger variables for Spain.*

D.6 Empirical distributions of representative Z variables

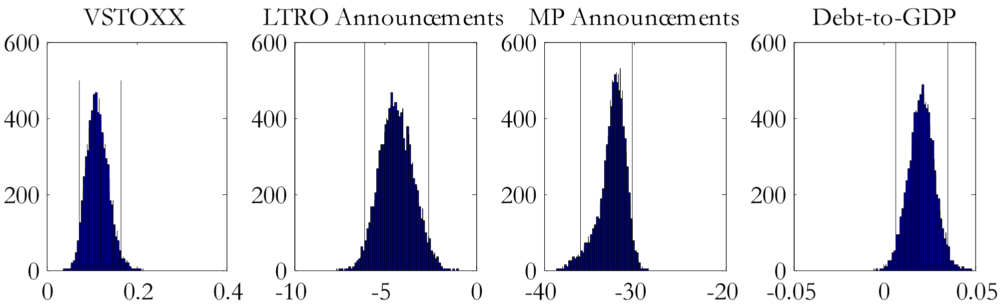


Figure D.9: *Histogram of the $\hat{\gamma}$ coefficients in the probit equation for Italy. The vertical lines indicate the 95% probability intervals. Positive coefficient increases the probability to switch from the first to the second regime. Negative coefficient increases the transition probability to switch from the second to the first regime.*

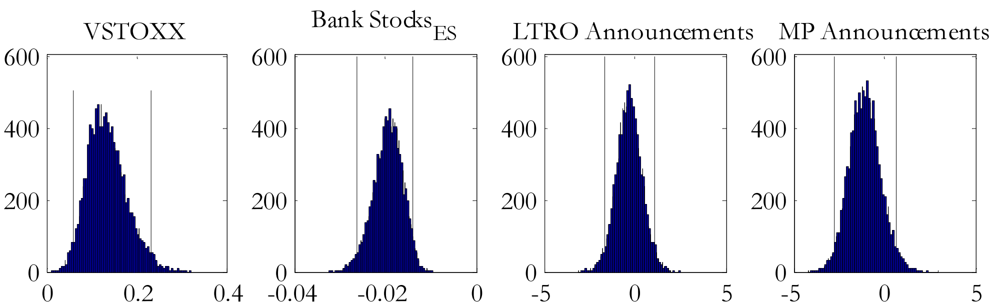


Figure D.10: *Histogram of the $\hat{\gamma}$ coefficients in the probit equation for Spain. The vertical lines indicate the 95% probability intervals. Positive coefficient increases the probability to switch from the first to the second regime. Negative coefficient increases the transition probability to switch from the second to the first regime.*

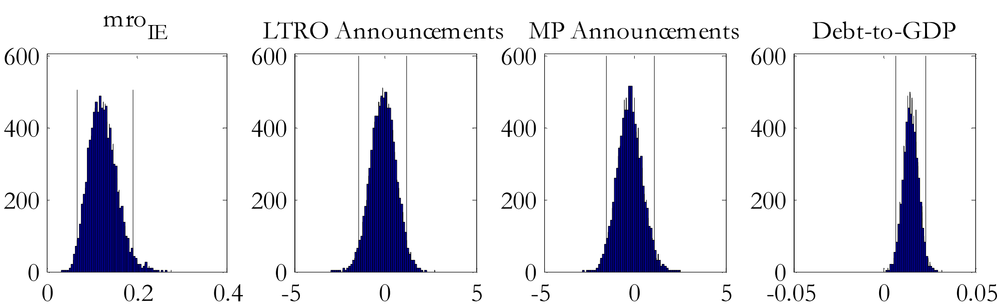


Figure D.11: *Histogram of the $\hat{\gamma}$ coefficients in the probit equation for Ireland. The vertical lines indicate the 95% probability intervals. Positive coefficient increases the probability to switch from the first to the second regime. Negative coefficient increases the transition probability to switch from the second to the first regime.*

D.7 Convergence diagnostics for the EONIA specification

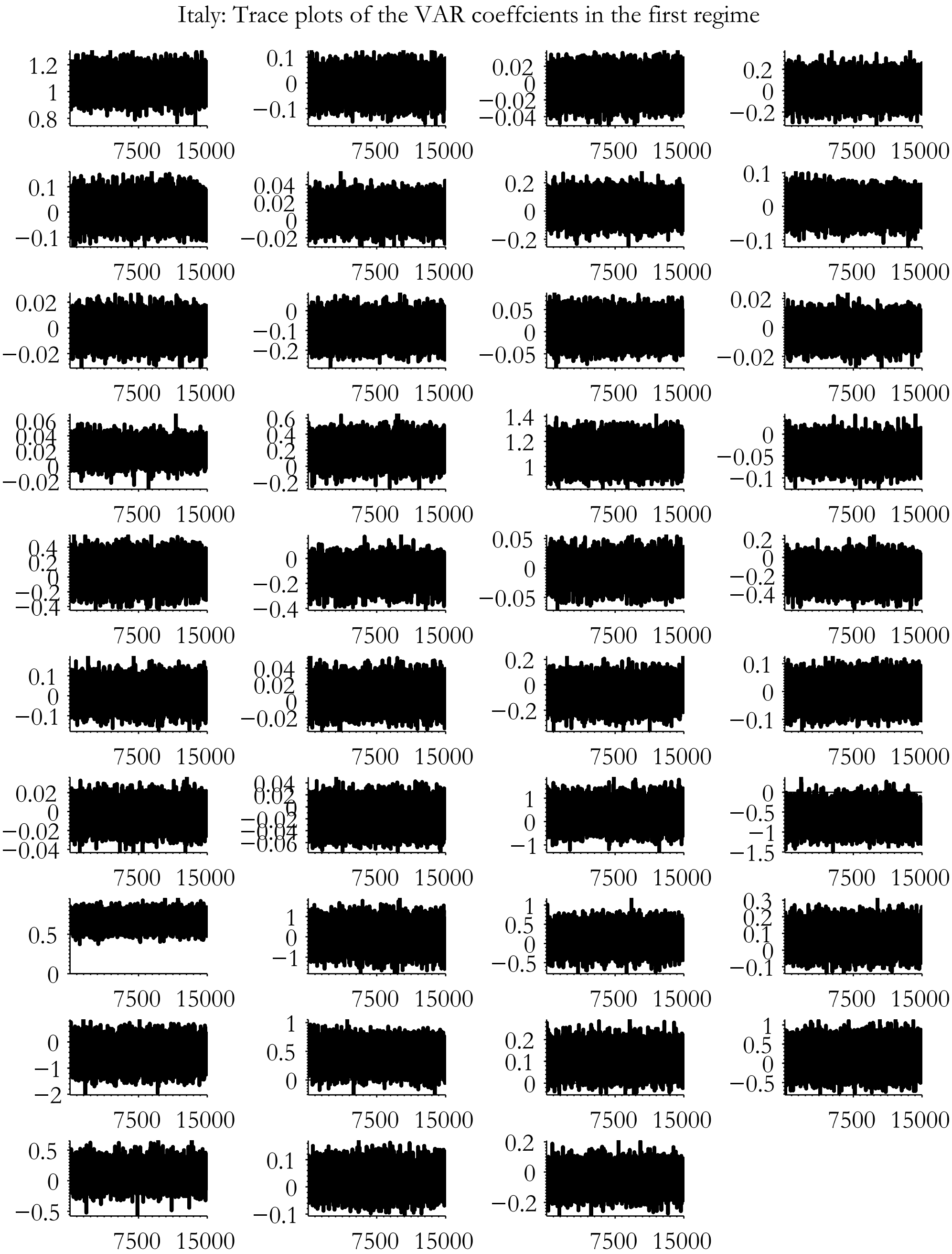


Figure D.12: *Trace plots for the VAR coefficients in the first regime.*

Italy: Trace plots of the VAR coeffcients in the second regime

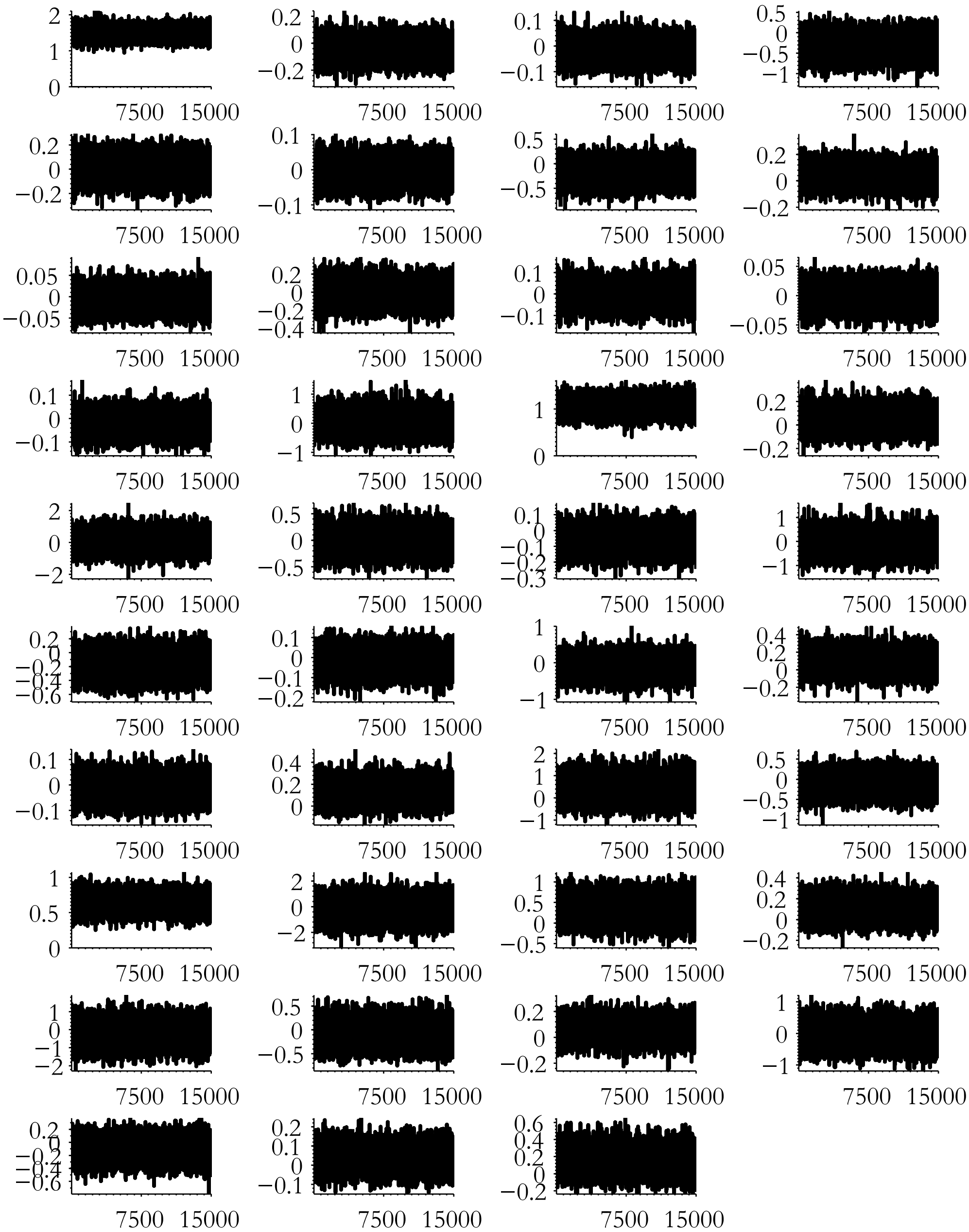


Figure D.13: *Trace plots for the VAR coefficients in the second regime.*

Spain: Trace plots of the VAR coeffcients in the first regime

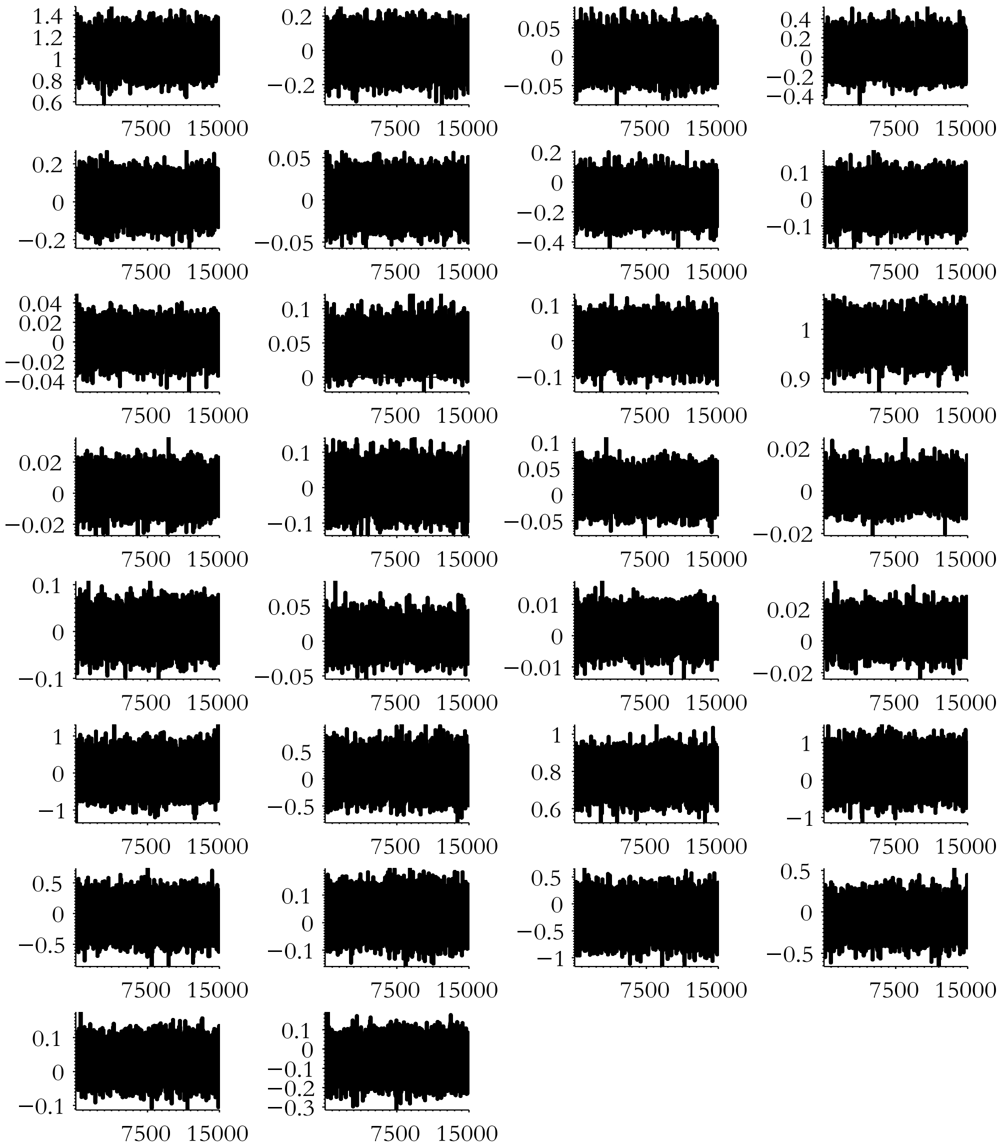


Figure D.14: *Trace plots for the VAR coefficients.*

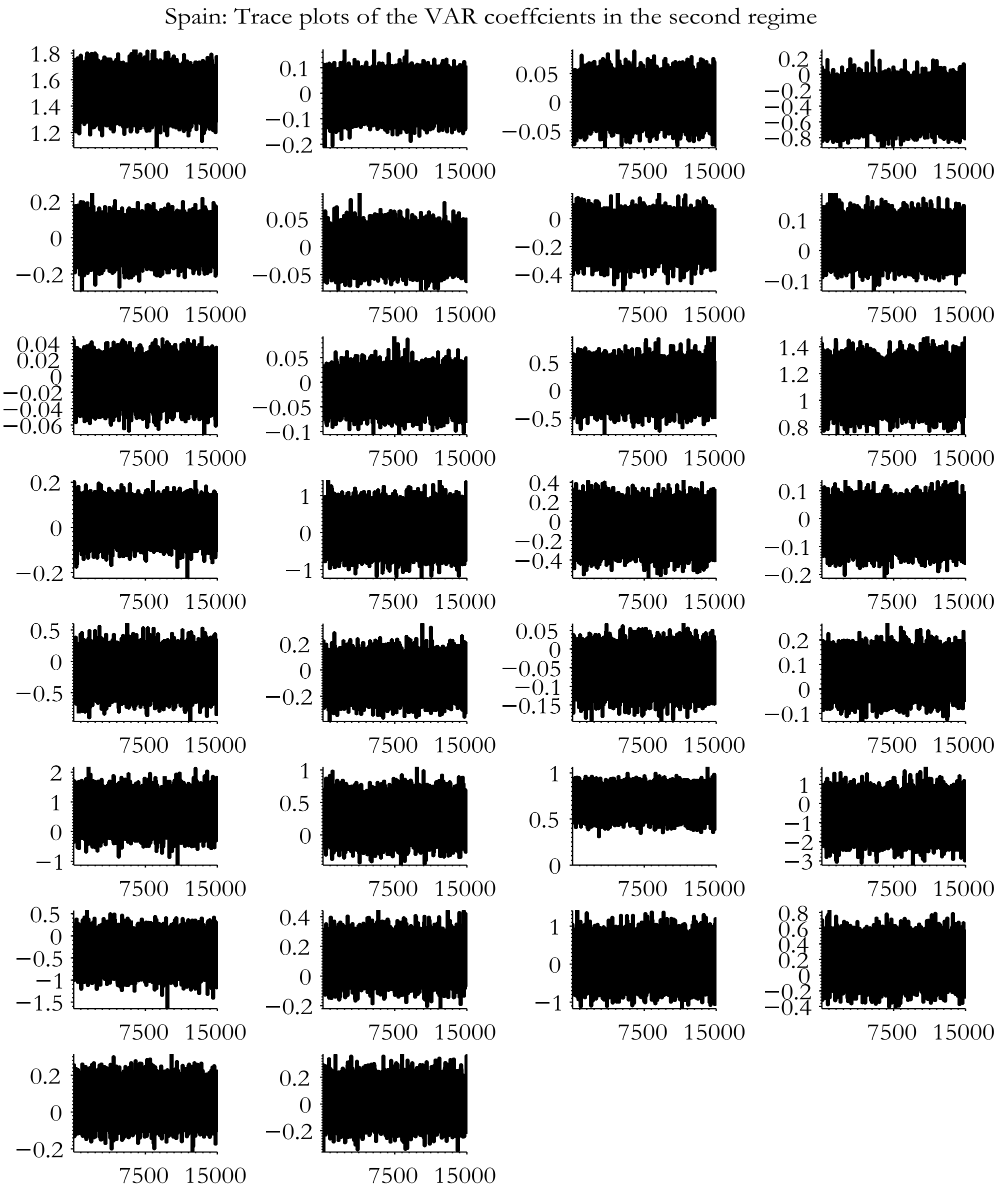


Figure D.15: *Trace plots for the VAR coefficients.*

Ireland: Trace plots of the VAR coeffcients in the first regime

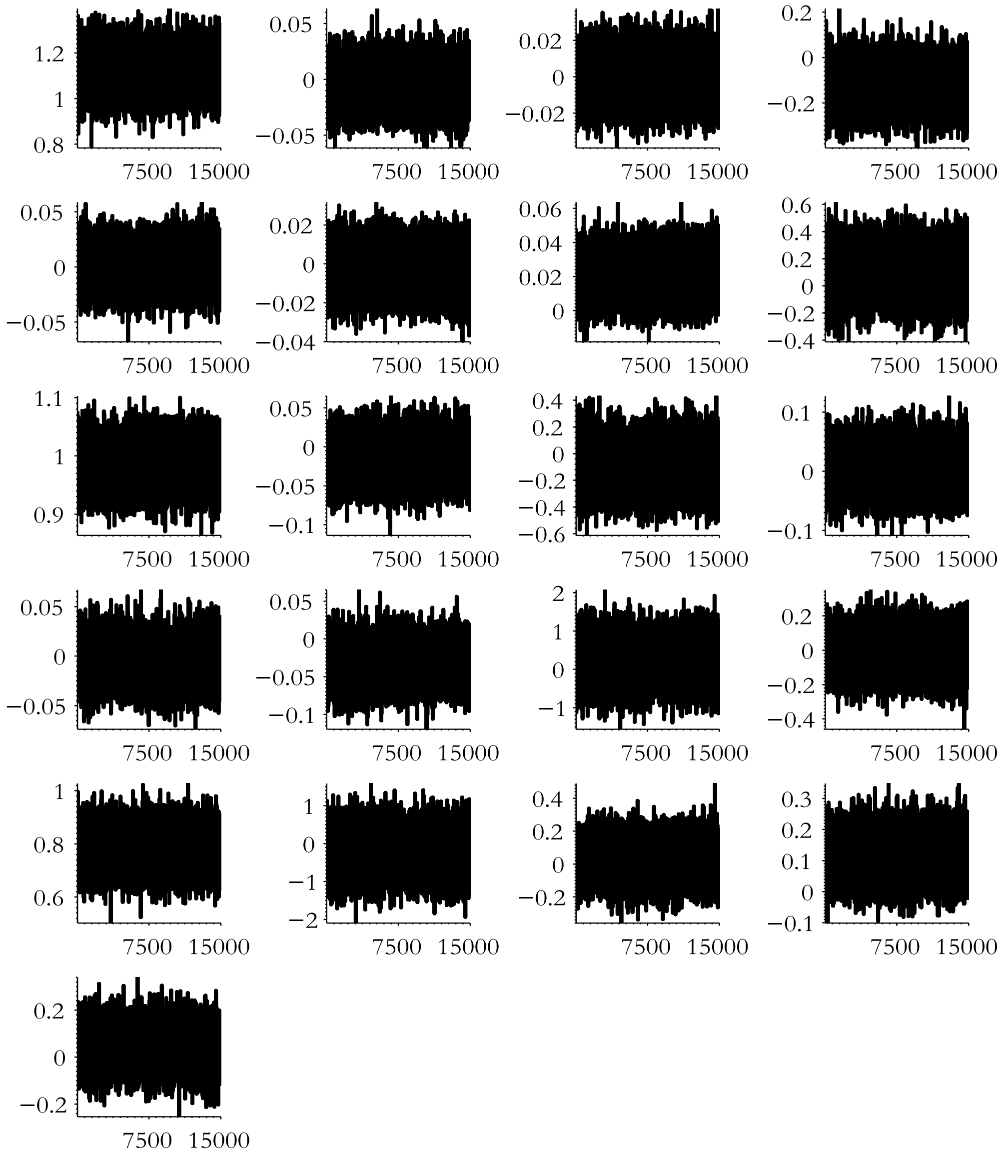


Figure D.16: *Trace plots for the VAR coefficients.*

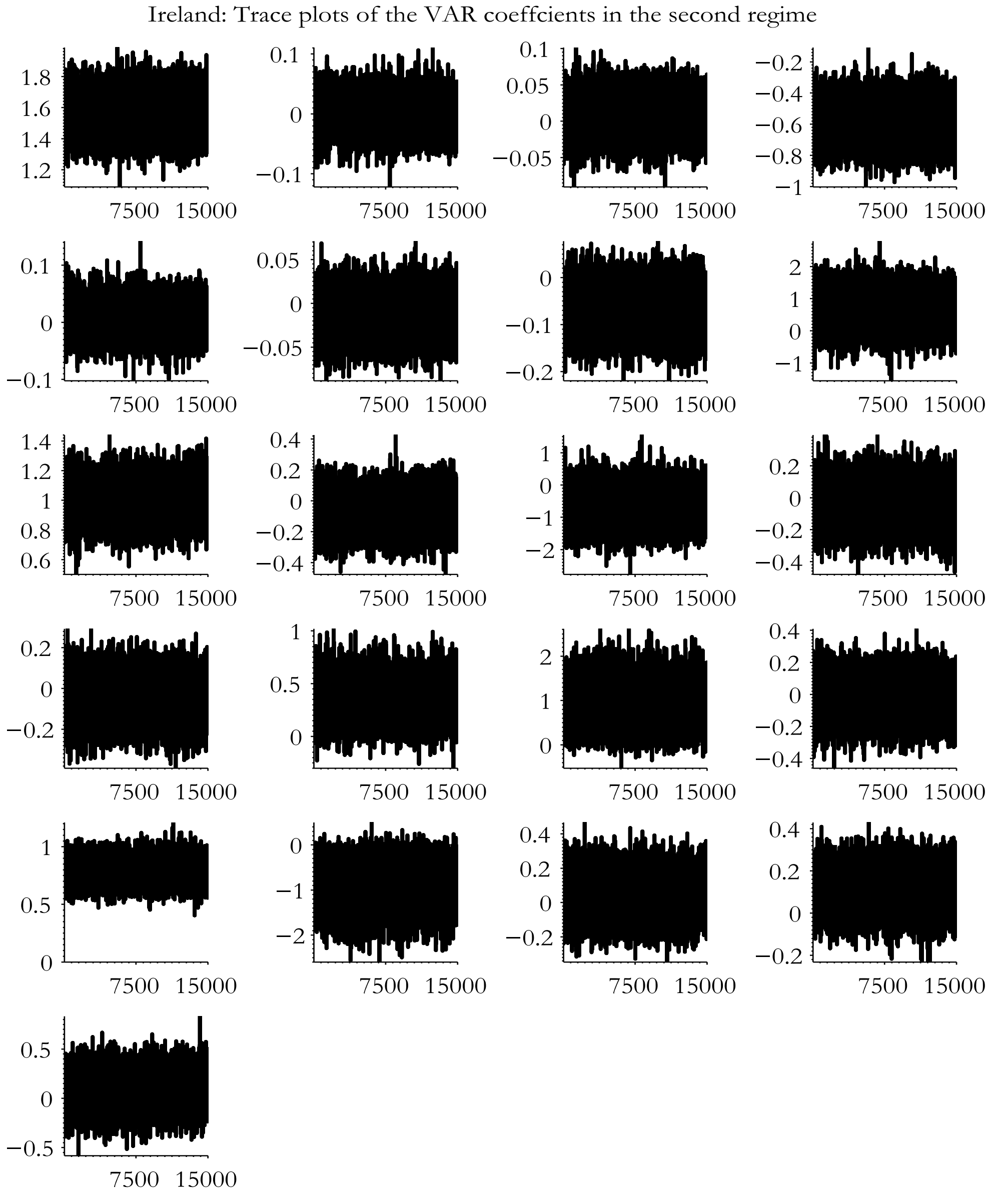


Figure D.17: *Trace plots for the VAR coefficients.*

Portugal: Trace plots of the VAR coeffcients in the first regime

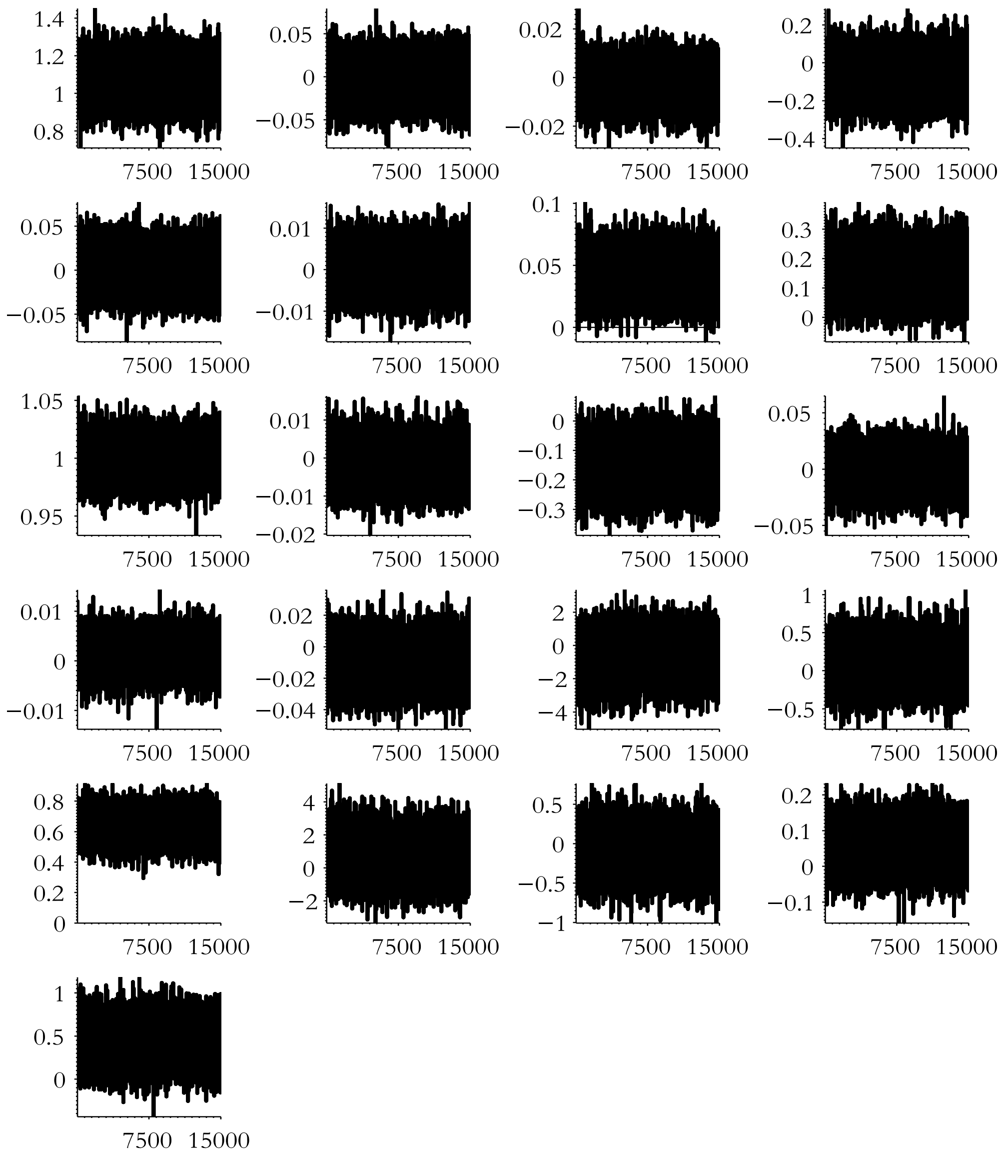


Figure D.18: *Trace plots for the VAR coefficients.*

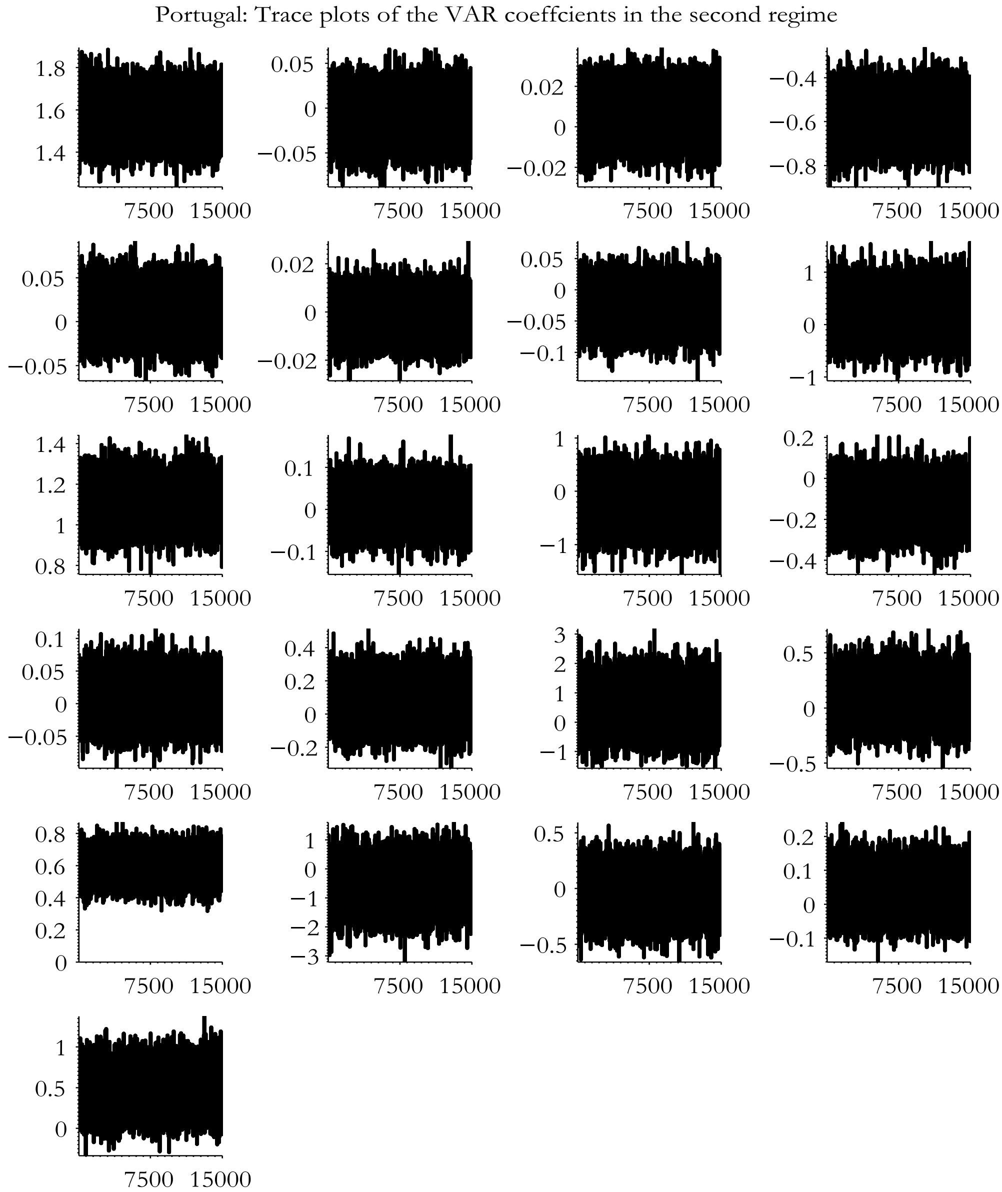


Figure D.19: *Trace plots for the VAR coefficients.*

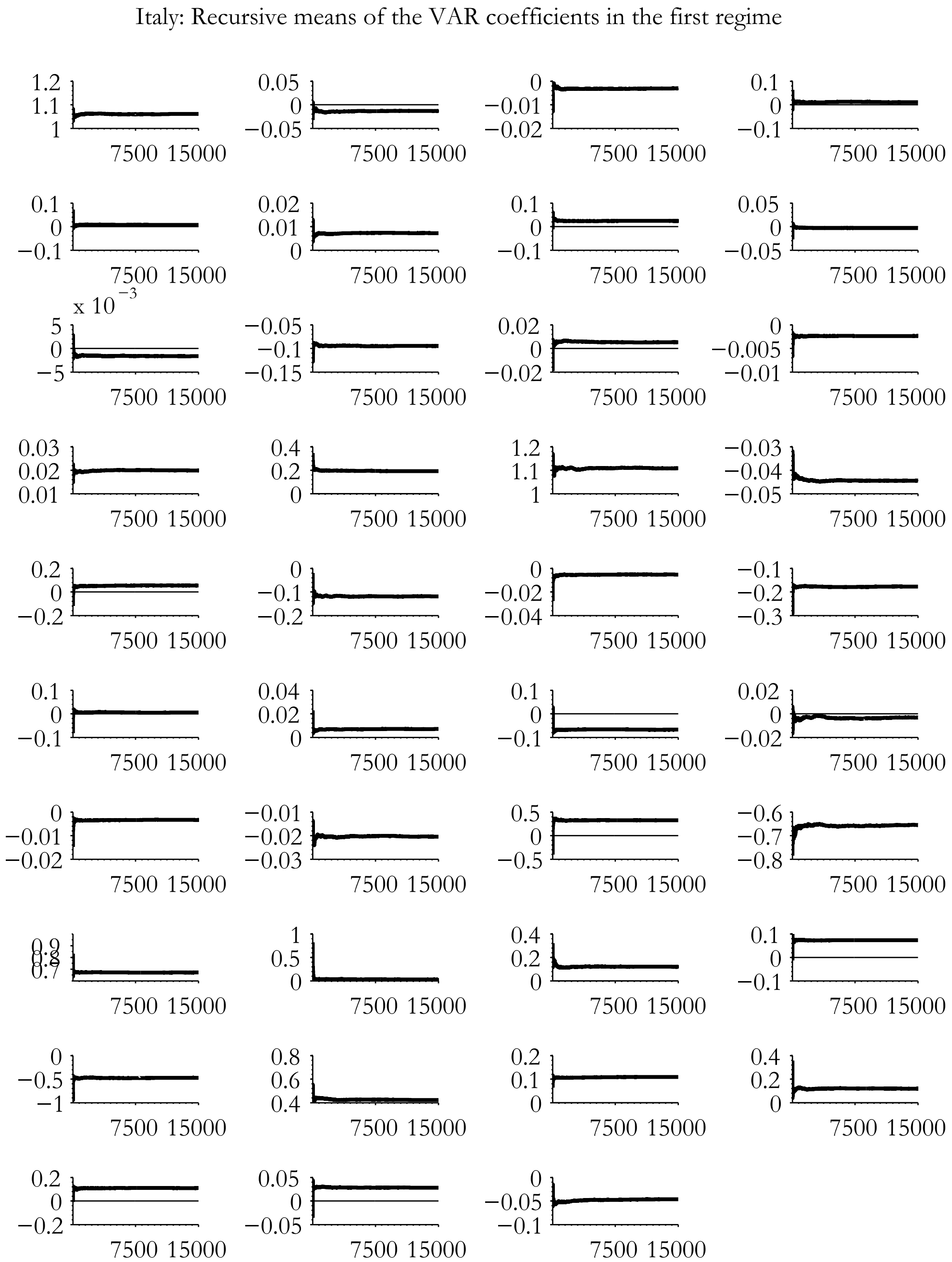


Figure D.20: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

Italy: Recursive means of the VAR coefficients in the second regime

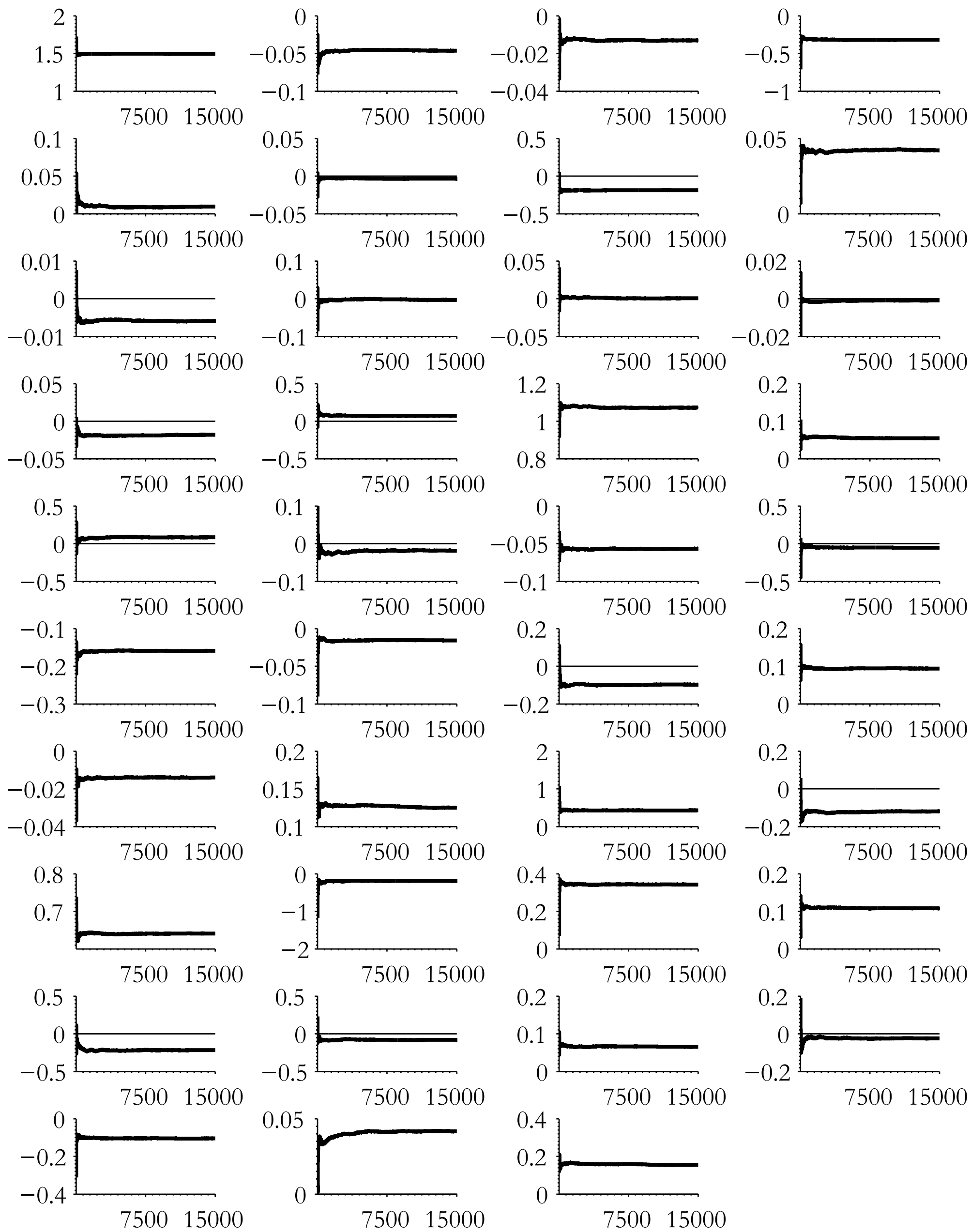


Figure D.21: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

Spain: Recursive means of the VAR coefficients in the first regime

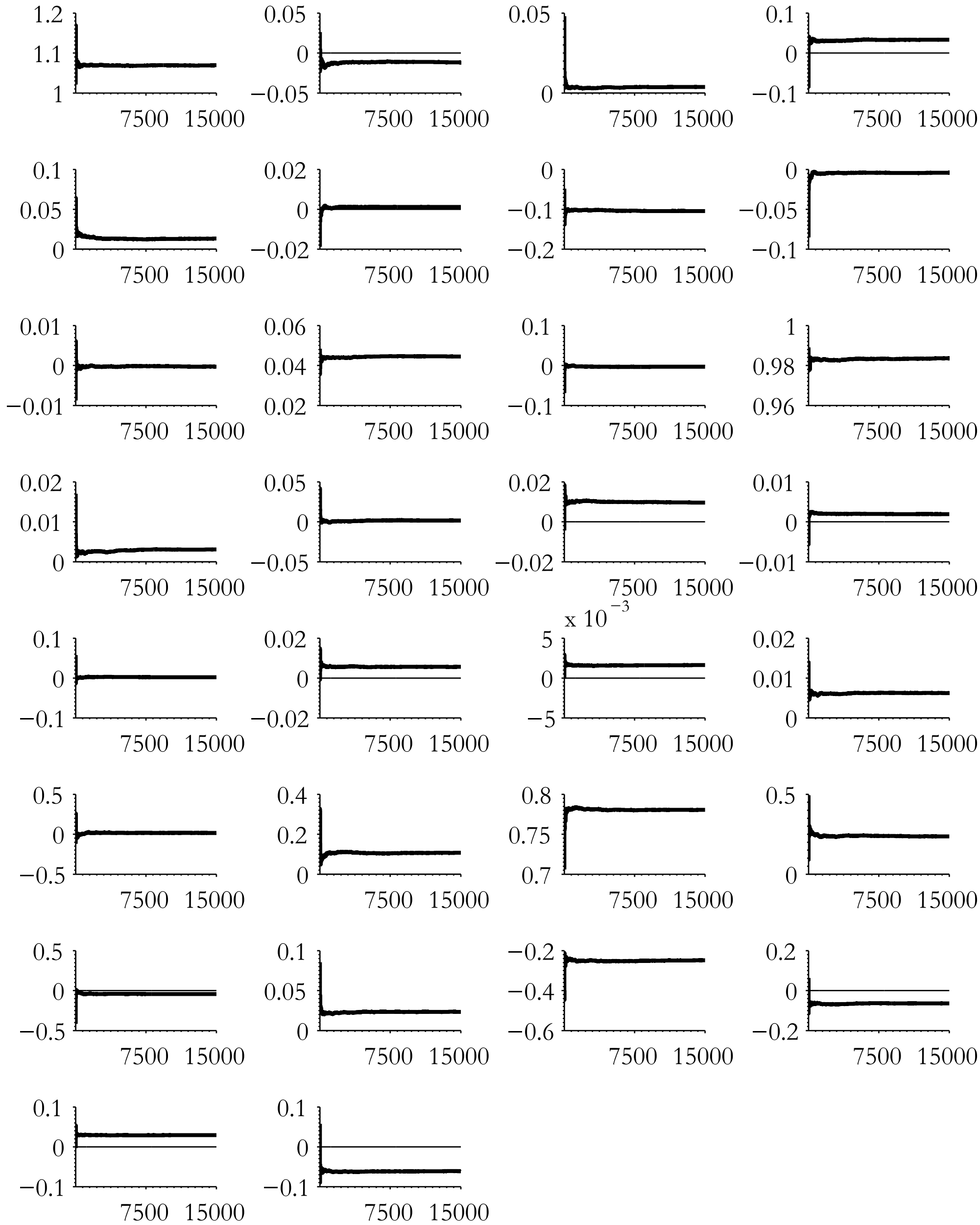


Figure D.22: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

Spain: Recursive means of the VAR coefficients in the second regime

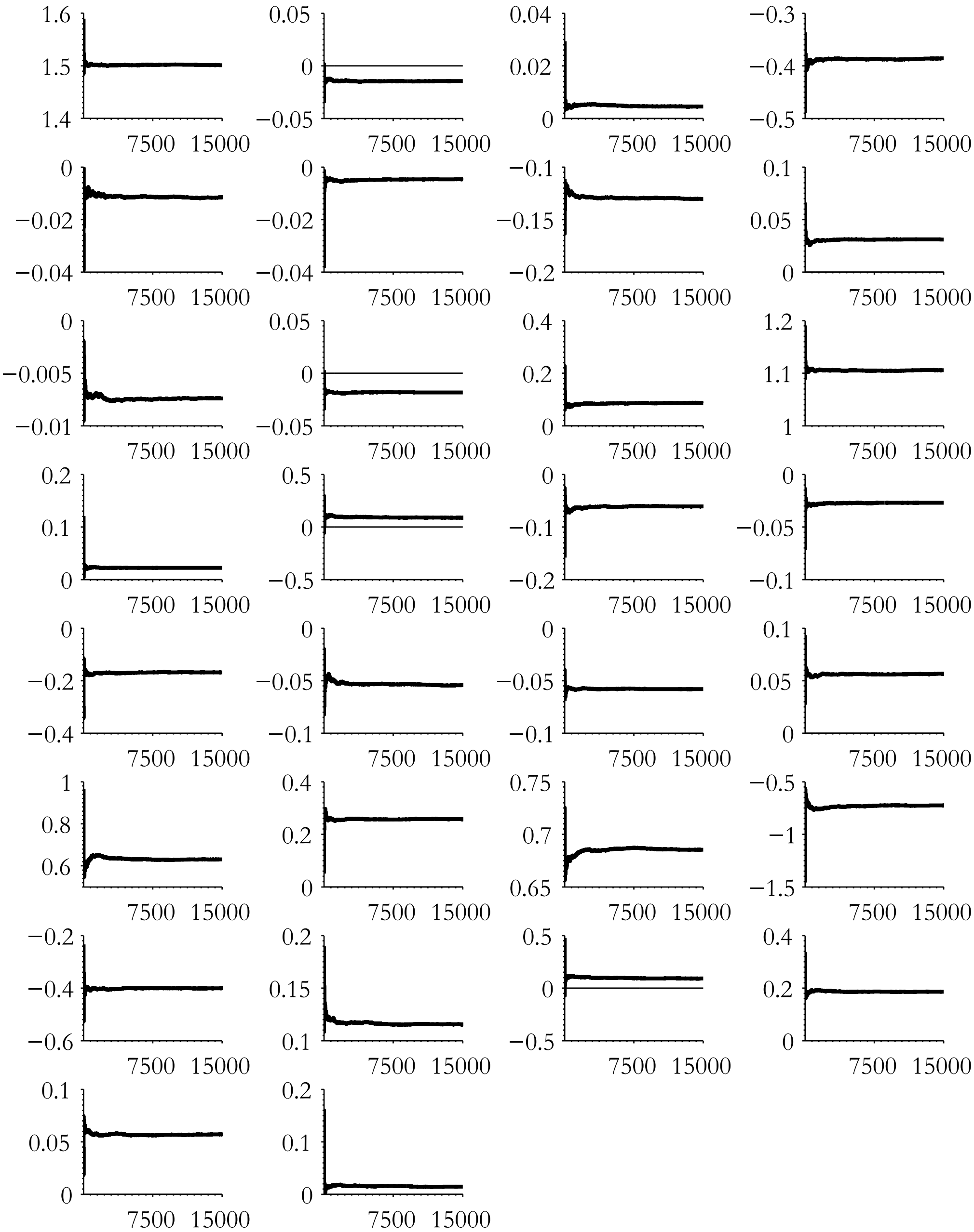


Figure D.23: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

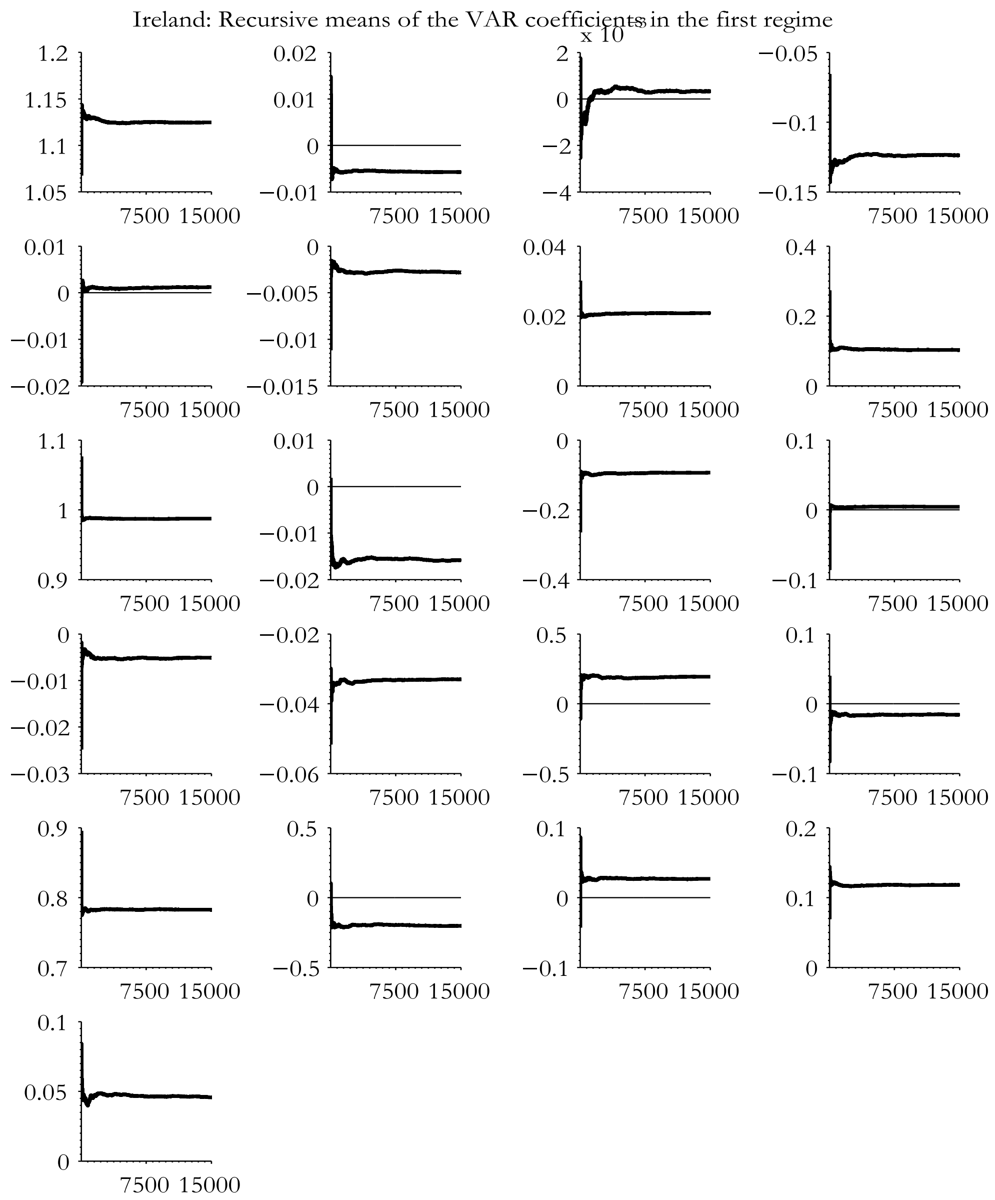


Figure D.24: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

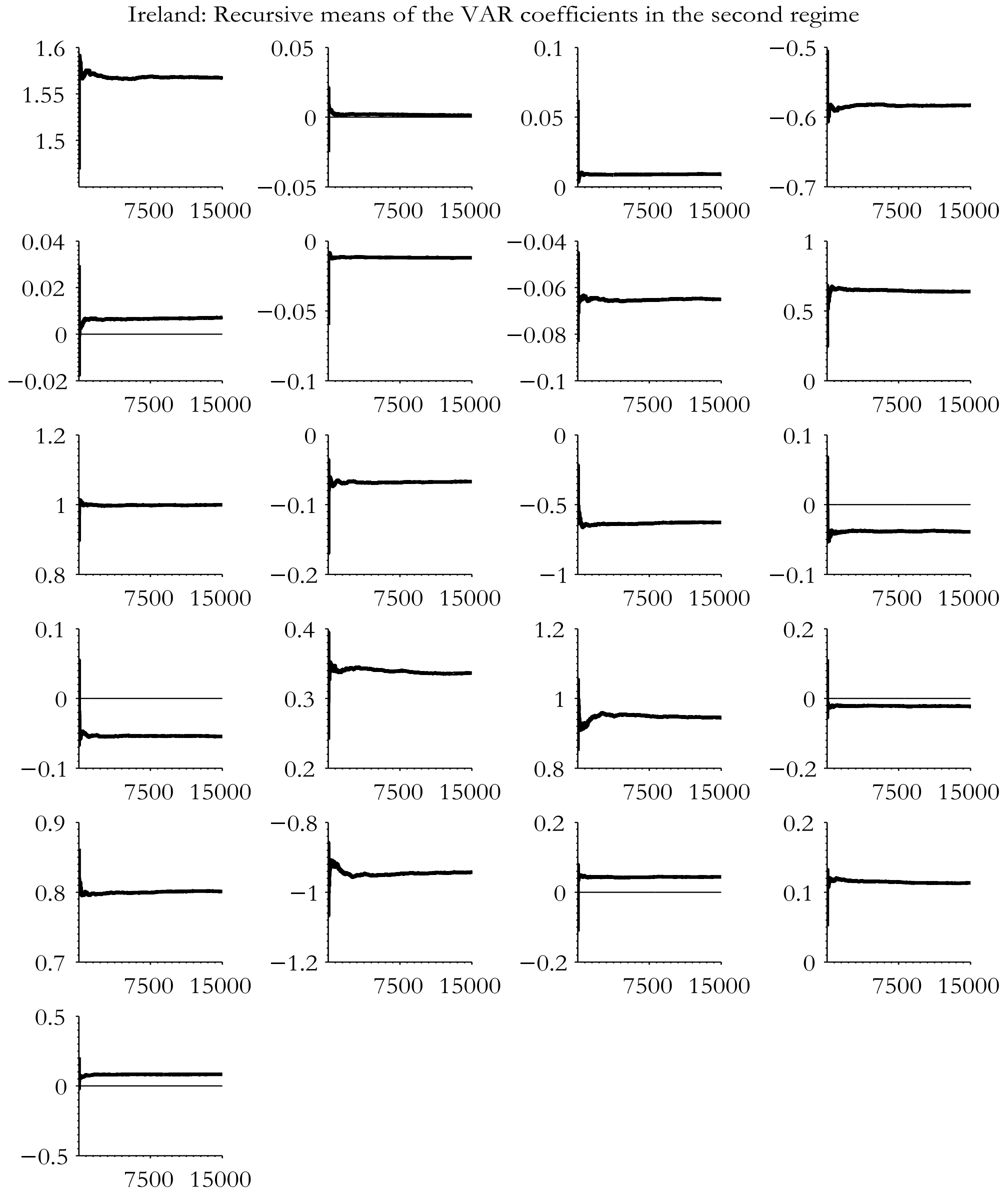


Figure D.25: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

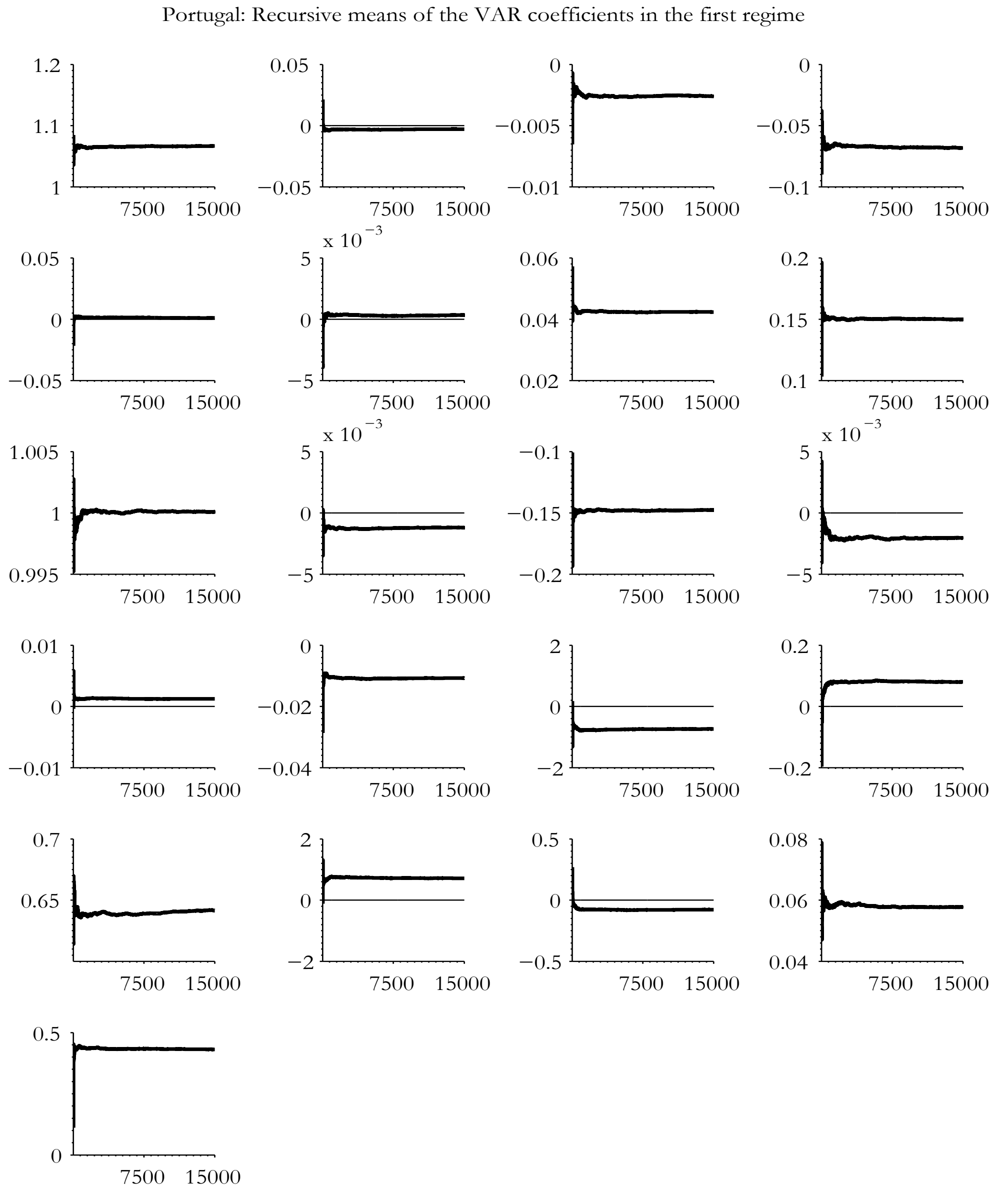


Figure D.26: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

Portugal: Recursive means of the VAR coefficients in the second regime

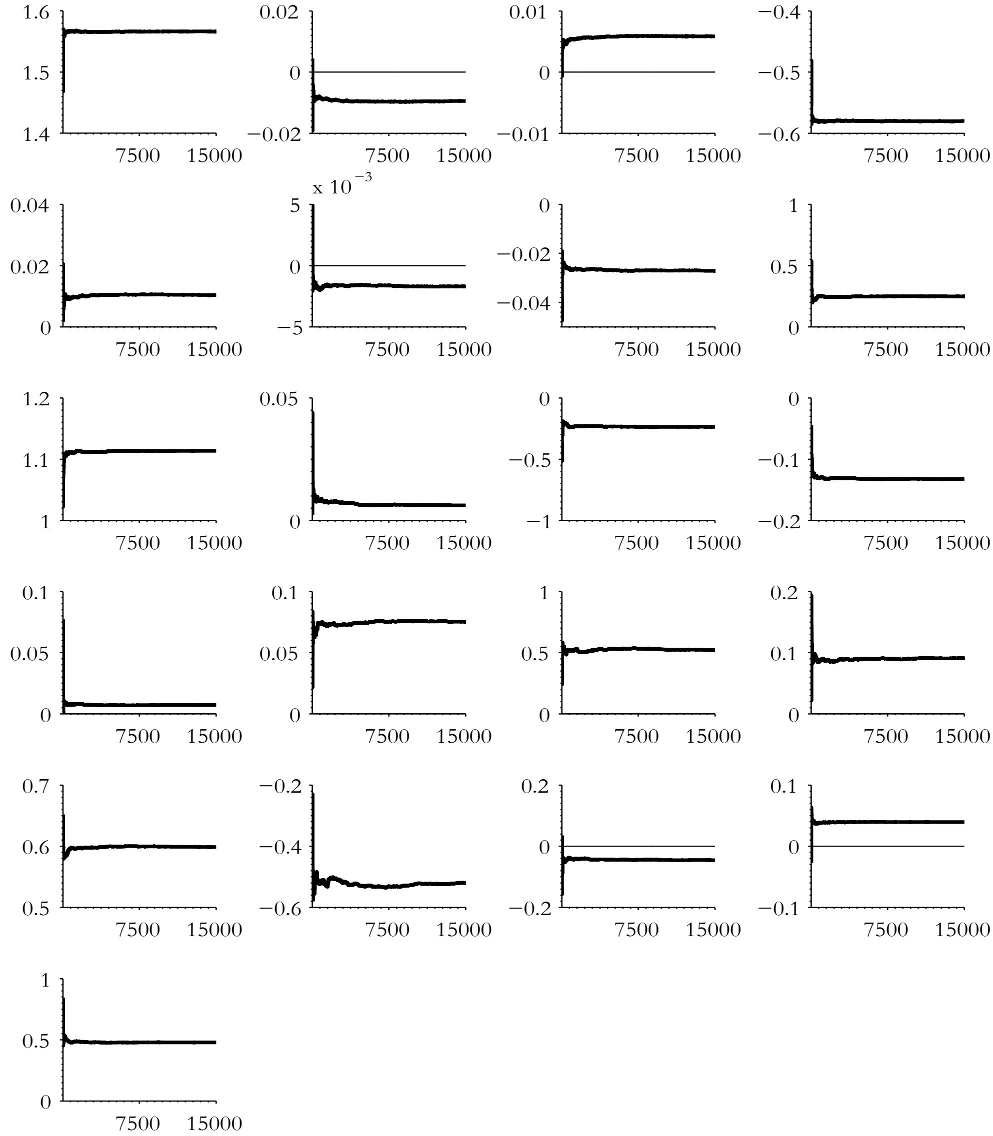


Figure D.27: *Recursive mean plots of the VAR coefficients over draws from the posterior distribution.*

D.8 Robustness check using the WACL measure

Illes et. al. (2015) suggest that since the outbreak of the crisis the interbank market rates might not be a good approximation for bank funding costs. Therefore they create a benchmark for the bank funding costs for each country, both in the short and the long term, and show that when this is taken into account there is no breakdown in the interest rate pass-through. They construct a weighted average cost of liabilities (WACL), which consists of several components of bank funding including covered bonds, five-year credit default swaps, deposit liabilities and open market operations. Therefore, this variable can be used to address two issues at hand, since it incorporates changes in bank funding costs and market expectations indirectly through its building blocks. In the following robustness exercise we introduce WACL as a VAR variable in place of sovereign bond yields, to act both as a connection between short-term and long-term rates, and to approximate bank funding conditions. Since the variable is available by country, we calculate the long-term funding costs relative to Germany: $rWACL_t^h = WACL_t^h - WACL_t^{DE}$.

Largely our findings remain unchanged. For Italy and Ireland we again identify a change in interest rate pass-through. The identified second regime has a lower persistence than in the EONIA case for Italy, and a longer persistence for Ireland. For Spain we also identify the same impulse responses of lending rate spreads as in the baseline scenario. A difference to the government bond yield scenario is that the realisation of the second regime also appears before 2008. We also find a breakdown of the pass-through in Portugal, although the results are not robust.

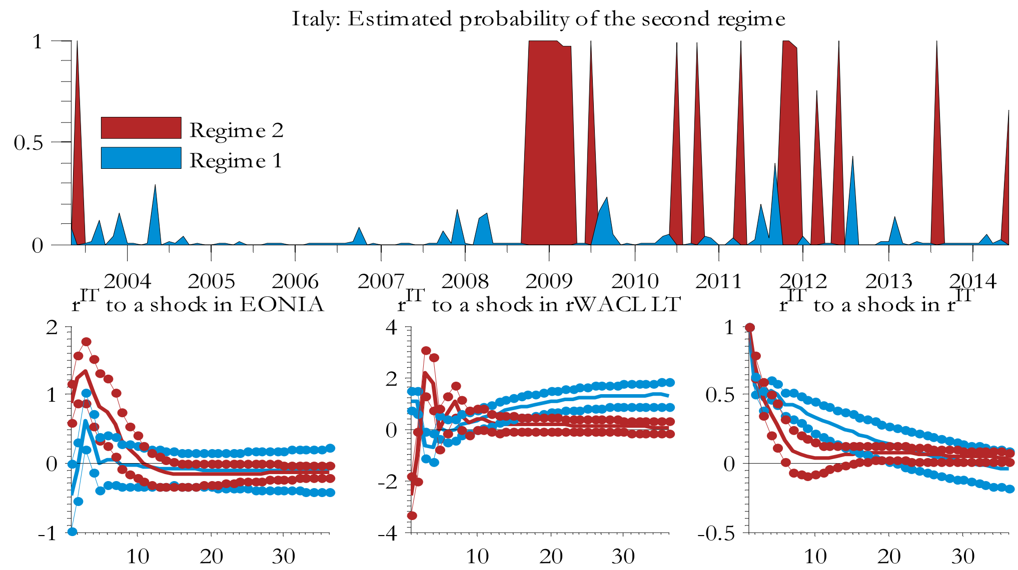


Figure D.28: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime using the weighted average cost of liabilities as an explanatory variable in place of the sovereign bond yields. After controlling for the banks' funding conditions the model identifies different responses of the lending rate to a shock in the policy rate (lower left corner).*

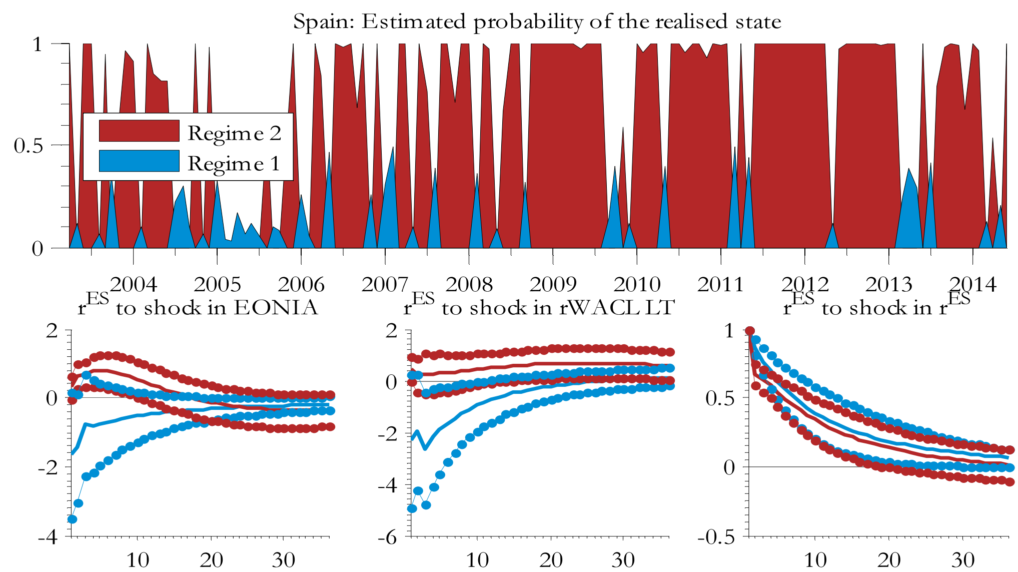


Figure D.29: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime using the weighted average cost of liabilities as an explanatory variable in place of the sovereign bond yields. After controlling for the banks' funding conditions the model identifies different responses of the lending rate to a shock in the policy rate (lower left corner).*

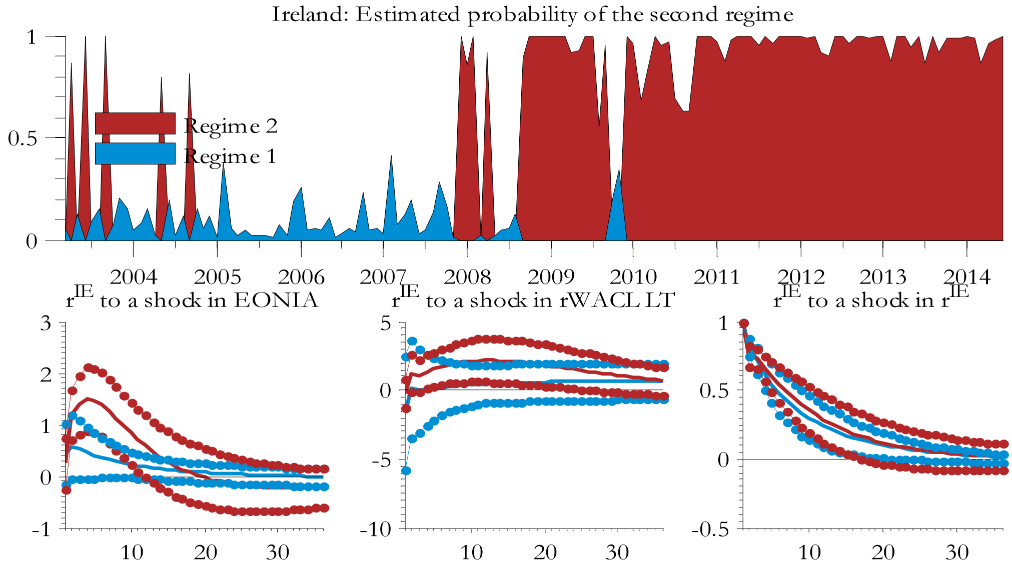


Figure D.30: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime using the weighted average cost of liabilities as an explanatory variable in place of the sovereign bond yields. After controlling for the banks' funding conditions the model identifies different responses of the lending rate to a shock in the policy rate (lower left corner).*

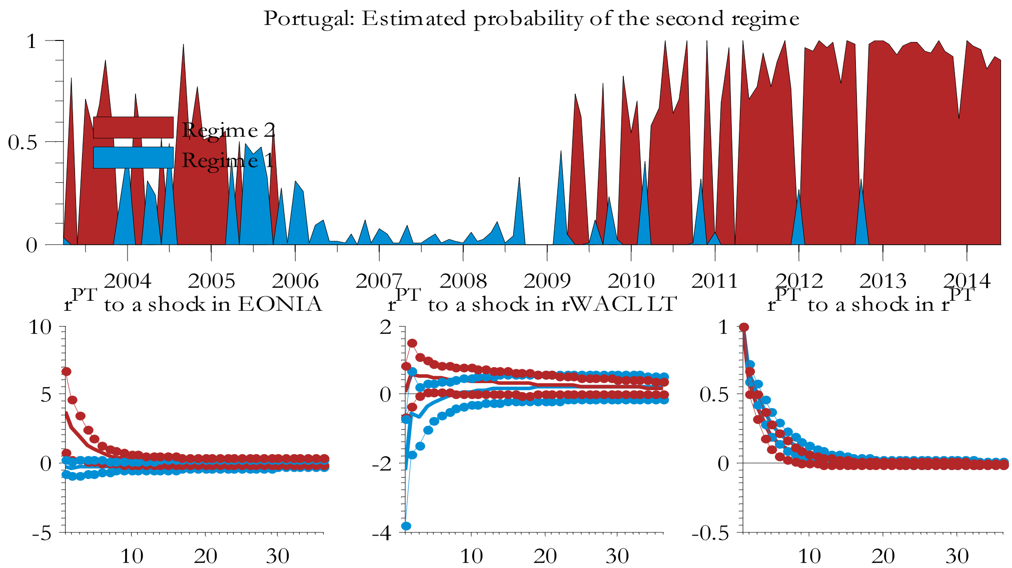


Figure D.31: *Normalized state-contingent impulse responses for the first (blue) and second (red) regime using the weighted average cost of liabilities as an explanatory variable in place of the sovereign bond yields. After controlling for the banks' funding conditions the model identifies different responses of the lending rate to a shock in the policy rate (lower left corner).*

In memory of Krum Blagov

Erklaerung

Hiermit erkläre ich, Boris Blagov, dass ich mich noch keiner Doktorprüfung unterzogen oder um Zulassung zu einer solchen beworben habe.

Die Dissertation mit dem Titel

"Four Essays on Markov-Switching DSGE and Markov-Switching VAR Models"

hat noch keiner Fachvertreterin, keinem Fachvertreter und keinem Prüfungsausschuss einer anderen Hochschule vorgelegen.

Ort, Datum　　　　　　　　　　　　　　　　　　　　　　　　　　Unterschrift

Eidesstattliche Versicherung

Ich, Boris Blagov, versichere an Eides statt, dass ich die Dissertation mit dem Titel "Four Essays on Markov-Switching DSGE and Markov-Switching VAR Models" selbst und bei einer Zusammenarbeit mit anderen Wissenschaftlerinnen oder Wissenschaftlern gemäß den beigefügten Darlegungen nach §6 Abs. 3 der Promotionsordnung der Fakultät Wirtschafts- und Sozialwissenschaften vom 24. August 2010 verfasst habe. Andere als die angegebenen Hilfsmittel habe ich nicht benutzt.

Ort, Datum

Unterschrift

Zusammenfassung

Die globale Finanzkrise war von einer großen Bedeutung für die Wirtschaft und somit für die Volkswirtschaftslehre. Sie hat zur Folge erhebliche Struktur- und Durchbrüche der gewöhnlichen Übertragungsmechanismen. Die Unfähigkeit der linearen Modelle den Umfang der Krise zu prognostizieren hat die Bedeutung der Nichtlinearitäten in der Forschung stark betont. Eine bestimmte Klasse von Modellen – die Markov-switching DSGE Modelle (MS-DSGE) - abzielt die oben genannten Nichtlinearitäten zu erfassen. Bei diesen Modellen wird es davon ausgegangen, dass die Wirtschaft eine Reihe verschiedener Zustände annehmen kann, die jeweils mit einem Satz von Parametern charakterisiert werden. In jeder Darstellung werden die Beziehungen zwischen makroökonomischen Variablen gegeben, jedoch wechselt die Wirtschaft zwischen den Regimen nach einem stochastischen Markov-prozess. Deshalb können die gleichen Schocks unterschiedliche Auswirkungen auf der Wirtschaft haben. Darüber hinaus sind die wirtschaftlichen Akteure bewusst, dass solche Übergänge auftreten können und dies berücksichtigen. Die Akteure bilden deren Erwartungen mit der Sicht, dass ein Regimeweschel möglich wäre, was zu weitere Nichtlinearitäten führt und dadurch werden der vorbeugende Effekt einer drohenden Krise modelliert.

Das einleitende Kapitel präsentiert eine kleine offene Volkswirtschaft, die nach der Eigenschaften der estnischen Wirtschaft modelliert wird. Estland hatte mehr als zwei Jahrzehnten einen festen Wechselkurssystem (FWK). Das System ist ein Währungsamt (Currency Board) - eine spezielle Form eines FWK, beidem das Basisgeld zu 100% durch Währungsreserven gedeckt ist und die Möglichkeit der Zentralbank als "lender of last resort" zu dienen abschafft. Mit einem FWK ist es zu erwarten, dass die inländischen Zinsen sich an den ausländischen Zinsen durch eine Arbitrageopportunität anpassen und dadurch konvergieren die beiden Zeitreihen. Empirisch jedoch sind die Zinsen nie identisch, wie es oft in der DSGE Literatur angenommen wird. Aus den Daten ist es offensichtlich, dass eine erhebliche Risikoprämie aufbauen kann die auch eine negative Auswirkung

auf die Wirtschaft hat. Diese Zinspanne kann aus verschiedenen Gründe, wie z.B. eine Banken- oder Finanzkrise, erscheinen und dadurch verschlechtert sich die wirtschaftliche Lage weiter.
Daher wird in diesem Modell diese Nichtlinearität der Risikoprämie explizit mit einer Markovprozess modelliert und mit Bayesianische Methoden geschätzt. Die Hauptergebnisse zeigen, dass finanzielle Schocks eine untergeordnete Rolle spielen im Fall der Bankensektor stabil ist und eine große Auswirkung haben können im Fall die Wirtschaft sich in einer Krise befindet, eine Eigenschaft die in der linearen Modellen nicht erfassen wird.
Das zweite Kapitel dieser Arbeit, mit dem Titel "The Regime-Dependent Evolution of Credibility: A Fresh Look at Hong Kong's Linked Exchange Rate System" baut auf diesem Modell auf und untersucht wie wichtig die Glaubwürdigkeit des Wechselkurssystems für eine kleine offene Wirtschaft ist. Das Modell wird für Hong Kong geschätzt, ein Land das ein Currency Board seit fast drei Jahrzehnten besitzt. Dies ist eine der am längsten laufenden FWK-Systeme und es hat eine gewisse Anzahl von spekulativen Attacken überstanden. Gehen die Händler davon aus, dass das feste Wechselkurssystem aufgehoben wird, werden sie eine Position gegen das System halten, wo sie die Währung verkaufen und Nachfrage nach ausländische Währung generieren. Um die Regierung den Wechselkurs behalten zu können, muss sie (i) genug Reserven ausländischer Währung halten und (ii) die Kapitalabwanderung vermeiden. Dies führt zu erhöhende Zinsen (um die Währung attraktiver zu halten) und wieder zu einer Leitzinsspanne. Diese Zinspanne wird mit dem MS-DSGE Modell aus dem ersten Kapitelgeschätzt und durch Varianzzerlegung und Impuls-Antwort Funktionen wird die Transmission der Zinsschocks bei "normalen" Zeiten und in Perioden der Glaubwürdigkeitsverlusts.
Die zweite Hälfte der Dissertation versucht die Themen des ersten Teils durch empirische Modelle zu vertiefen. Das dritte Kapitel " The Credibility of Hong Kong's Currency Board System: Looking Through the Prism of MS-VAR Models with Time-Varying Transition Probabilities " ist eine natürliche Fortsetzung der Frage der Glaubwürdigkeit des Wechselkurssystems. Mit Hilfe eine Markov-switching Vektorautoregression (MS-VAR) wird einen gewissen Nachteil des MS-DSGE Modelle überwunden – die Annahme, dass die Wahrscheinlichkeiten für den Regimewechsel konstant und exogen sind. Diese Annahme wird bei den DSGE Modellen getroffen nur wegen der Komplexität der Modelle. Dennoch, ist die Annahme Kritsch bei der Modellierung von Krisen, wo selbsterfüllende Erwartungen eine wichtige Rolle spielen können. Durch die Endogenisierung von der Regimewahrscheinligkeiten wird es in diesem Kapitel untersucht was den Verlust der Glaubwürdigkeit des Wechselkurssystems beeinflussen kann. Welche Variablen können ihn „triggern"?

Wir entwickeln einen eigenen Index für die Hong Kong Finanzmärkte und zeigen, dass Turbulenz auf die Heimfinanzmärkte einen Einfluss auf die Glaubwürdigkeit haben, wobei die Volatilität bei den globalen Finanzmärkten keine „spillover“ Effekts haben.
Das letzte Kapitel “Modelling the Time Variation in Euro Area Lending Spreads” untersucht die Divergenz zwischen den Kreditzinsen im Euroraum, besonders Irland, Italien, Spanien und Portugal. In den letzten Jahren hat die EZB der Leitzins niedrig gehalten, indessen die Darlehenszinsen in den o.g. Ländern gestiegen sind was auf eine Veränderung bei der Transmission der Geldpolitik hindeutet. Im vierten Kapitel wird es wieder mit Hilfe eines MS-VAR Modelles untersucht was dazu eingelegt hat. Wir finden heraus, dass globale Risikofaktoren und Volatilität auf den Finanzmärkten zu höheren Kreditzinsen in Italien und Spanien beigetragen haben und dass die Probleme im Bankensektor der Erhöhung der Darlehenszinsen in Spanien beeinflusst haben. Die Fiskalkrise hatte einen Einfluss auf der Dynamik der Kreditzinsen in Irland, wobei in Portugal wir keine Veränderung der Transmission der Geldpolitik identifizieren können. Die unkonventionelle Geldpolitik der ECB hatte kurzfristige positive Effekte in Italien bezüglich der Transmission der Geldpolitik.