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THE REGIME-DEPENDENT EVOLUTION OF CREDIBILITY: A FRESH LOOK AT HONG KONG'S LINKED EXCHANGE RATE SYSTEM

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An estimated Markov-switching DSGE modeling framework that allows for parameter shifts across regimes is employed to test the hypothesis of regime-dependent credibility of Hong Kong's linked exchange rate system. The baseline model distinguishes two regimes with respect to the time-series properties of the risk premium. Regime-dependent impulse responses to macroeconomic shocks reveal substantial differences in spreads. To test the sensitivity of the results, a number of robustness checks are performed. The findings contribute to efforts at modeling exchange rate regime credibility as a nonlinear process with two distinct regimes.

Keywords: Markov-Switching DSGE Models, Exchange Rate Regime Credibility, Interest Rate Risk Premia, Hong Kong

1. INTRODUCTION

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 was 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

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were assumed to have hollowed out to the point where the only choices left to policy makers were whether to let exchange rates float or fix them permanently via a currency board or a monetary union.

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 October 17, 1983, also known as 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 7.75–7.85.

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.[1] 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.[2] Thus, we ask how much credibility do policy makers gain by implementing a currency board and what are the effects of losing 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 regime, a spread between the rates will open as they take positions against the board. In essence, this is a change in market sentiment as in Agenor (2006).

A closer look at HKD and USD interbank interest rates motivates the UIP theory quite well. Figure 1 plots the 3-month interbank rate offered in Hong Kong [HIBOR (Hong Kong Interbank Offered Rate)] versus one of the main USD rates—the London based USD LIBOR (London Interbank Offered Rate).[3] The HK

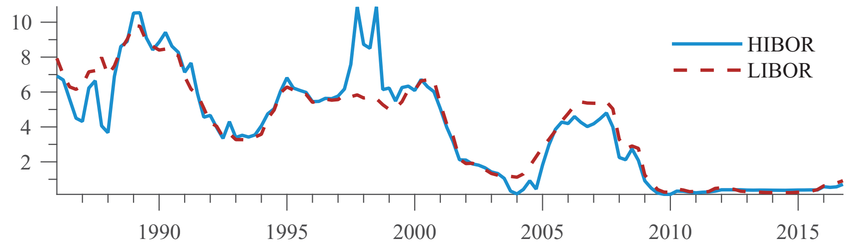

FIGURE 1. HKD, HIBOR, and USD LIBOR, annualized 3-month interbank interest rates from 1986Q1 to 2016Q4. Sources: Eurostat and Datastream.

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 United States 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 toward 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 1 suggests what it might take to call the credibility of Hong Kong's exchange rate system into question. In what follows, we develop a full-fledged DSGE model with Markov-switching (MS-DSGE) to identify and interpret time-varying credibility and utilize it to study the effects of loss and gain of trust in the exchange rate system. In contrast to reduced form models, 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, while the rich data structure controls for the complex relationships among macroeconomic variables.[4]

The remainder of this paper is organized as follows. The next section lays out the theory, followed by Section 3 that deals with the solution and estimation technicalities of MS-DSGE models. Section 4 discusses the data used at the estimation stage, which is the main topic of Section 5. Section 6 presents the economic implications of the model and Section 7 discusses the robustness of the results. Finally, Section 8 concludes.

2. MODELING THE HONG KONG ECONOMY

To analyze the perceptions toward the exchange rate regime in Hong Kong, we utilize a baseline DSGE model of a small-open economy based on the seminal works of Monacelli (2005) and Justiniano and Preston (2010) in combination with a fixed exchange rate channel. We introduce the key equations of the model and then extend it to a Markov-switching DSGE model with the aim of capturing the features of the data exhibited in Figure 1.

2.1. A Baseline DSGE Model

On the demand side, consumers choose the optimal amount of consumption c_t following the usual Euler equation with habit formation:

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

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

Consumption c_t is a bundle of domestic and foreign items, π_t stands for consumer price index (CPI) based inflation, i_t denotes the nominal interest rate, and ϑ_t is a preference shock that follows a first-order autoregression [AR(1)] with normal innovations ε_t^ϑ and standard deviation σ_ϑ. The parameters in the Euler equation are as follows: h, which represents the habit parameter; σ—the risk-aversion/inverse of the elasticity of substitution, and ρ_ϑ—the autoregressive coefficient of the preference shock. On the supply side, there are two types of producers: domestic firms that 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 á la 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 $\pi_{F,t}$:

$$(1+\beta\delta_H)\pi_{H,t} = \beta E_t\{\pi_{H,t+1}\} + \delta_H \pi_{H,t-1} + \lambda_H(\theta_H) mc_t, \quad \textbf{(3)}$$

$$(1+\beta\delta_F)\pi_{F,t} = \beta E_t\{\pi_{F,t+1}\} + \delta_F \pi_{F,t-1} + \lambda_F(\theta_F)\psi_t + \mu_{F,t}, \quad \textbf{(4)}$$

where δ_H and δ_F denote the indexation parameters for the home and foreign economy, β is 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

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their prices more frequently. The final determinant of domestic goods inflation $\pi_{H,t}$ is the marginal costs of 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 υ_t [Monacelli (2005)]:

$$\psi_t = q_t - (1-\alpha)\upsilon_t, \tag{5}$$

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 $\varepsilon_t^{\mu_F}$:

$$a_t = \rho_a a_{t-1} + \varepsilon_t^a \quad \text{with} \quad \varepsilon_t^a \sim N(0, \sigma_a^2), \tag{6}$$

$$\mu_{F,t} = \rho_\mu \mu_{F,t-1} + \varepsilon_t^{\mu_F} \quad \text{with} \quad \varepsilon_t^{\mu_F} \sim N(0, \sigma_{\mu_F}^2). \tag{7}$$

Exchange rate dynamics in small-open economy models are determined by the UIP relation. In a floating exchange rate setup, the UIP is given by

$$(i_t - E_t\{\pi_{t+1}\}) - (i_t^* - E_t\{\pi_{t+1}^*\}) = \triangle e_t - \chi d_t - \phi_t. \tag{8}$$

Following Benigno (2001), Schmitt-Grohe 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

$$d_t = y_t - (c_t + \alpha(q_t + \alpha\upsilon_t)) + \frac{1}{\beta}d_{t-1}, \tag{9}$$

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 (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:

$$\phi_t = \rho_\phi \phi_{t-1} + \varepsilon_t^\phi. \tag{10}$$

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

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

$$\triangle e_t = 0. \tag{11}$$

Substituting through the UIP (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:

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

This derivation introduces several appealing properties to the model. First, the interest rates are not modeled as an identity as in Gali and Monacelli (2005), which is not supported by the data (see Figure 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 interpretation of ϕ_t, specified by equation (10), changes, as it is no longer a UIP shock. Here, it captures exogenous events driving a wedge between domestic and foreign interest rates.

The small-open economy is represented by equations (1)–(12). 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^*:

$$y_t^* = c_{y^*} y_{t-1}^* + \varepsilon_t^{y^*} \quad \text{with} \quad \varepsilon_t^{y^*} \sim N(0, \sigma_{y^*}^2), \tag{13}$$

$$\pi_t^* = c_{\pi^*} \pi_{t-1}^* + \varepsilon_t^{\pi^*} \quad \text{with} \quad \varepsilon_t^{\pi^*} \sim N(0, \sigma_{\pi^*}^2), \tag{14}$$

$$i_t^* = c_{i^*} i_{t-1}^* + \varepsilon_t^{i^*} \quad \text{with} \quad \varepsilon_t^{i^*} \sim N(0, \sigma_{i^*}^2). \tag{15}$$

2.2. A Markov-Switching DSGE Model for Hong Kong

As evident from Figure 1, HKD interest rates have exhibited significant nonlinearities throughout the existence of the linked exchange rate system. To model this feature of the data, we allow for time variation in the risk premium through a Markov-switching component with the aim of capturing changing perceptions toward the board.

Analytically, we allow for time variation in the risk premium by introducing regimes into the variance of the innovation ε_t^{ϕ}:

$$\phi_t = \rho_\phi \phi_{t-1} + \varepsilon_t^{\phi} \quad \text{with} \quad \varepsilon_t^{\phi} \sim N\left(0, \sigma_\phi^2(s_t)\right). \tag{16}$$

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

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1n^s} \\ \vdots & \ddots & \vdots \\ p_{n^s1} & \cdots & p_{n^sn^s} \end{bmatrix}, \tag{17}$$

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, whereas in high credibility state the domestic rates should follow foreign interest rates [Agenor (2006), Genberg and Hui (2011)], an observation evident from Figure 1.[5]

A key point that motivates our modeling approach is the evolution of HIBOR. It replicates USD interest rate dynamics for prolonged periods of time, followed by sudden shifts with large deviations and a return to the status quo in a mean-reverting fashion. This behavior is reminiscent of a Markovian process, which allows for sudden shifts between different parameter spaces in a probabilistic fashion.[6]

An alternative framework would be to incorporate stochastic volatility as in Justiniano and Primiceri (2008). There is, however, a key notable difference between both approaches—the speed of parameter adjustment. The stochastic volatility of Justiniano and Primiceri (2008) is introduced as a random walk (RW) in the log-level and a variance parameter governs the speed at which the parameters are allowed to change, whose value has large implications for the system. Stable values of this parameter assume gradual changes. For example, a value employed in the literature of 0.01^2 would translate to a variation of about 25% over a sample of 40 years [Justiniano and Primiceri (2008), p. 613], while the HIBOR jumped from 6% to 10% over two quarters.[7] This feature makes the method unsuitable for capturing events such as the "Black Monday" and its aftermath.

Given the absence of capital in the model, a third option would be to follow Amisano and Tristani (2011) in terms of modeling choice. The authors postulate a MS-DSGE model with heteroscedasticity and derive the exact likelihood computation under the assumption of no predetermined states. By comparison, the advantage of the more general MS-DSGE framework presented here is that it allows for testing the hypothesis of risk premium heteroscedasticity versus alternative models with different jump parameters, which is important in the context of DSGE models, where all variables are intertwined. It could be that changes in the interest rate spread are not simply driven by exogenous stochastic shifts but are a product of other changing parameters and the MS framework could help against self-selection bias.[8]

However, the modeling choice does not come without a cost. The main drawback of a MS-DSGE model is the reliance on an ad-hoc assumption of a predefined number of regimes. What is the rationale for the existence of different states of the economy and if the notion is correct, then how many?

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.[9] Jeanne and Mason (2000) propose an empirical test of sunspot-driven multiple equilibria in the currency crisis 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 as a test for sunspot equilibria, as illustrated in Mouratidis (2008).

The second theory for regime switching uses the "animal spirits" concept of DeGrauwe (2010) and DeGrauwe 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, modeling the dynamics of the exchange rate through the interest rate in more detail is of particular interest.

For our main specification, we assume a binary number of regimes, $n^s = 2$, with the aim of identifying a state of low volatility versus alternative periods of high volatility. In the robustness section, we test formally for a three-regime model. Following Billio et al. (2015), we use the Bayes factor, the ratio between predictive likelihoods to test the two-state versus the three-state model and the outcome is slightly in favor of the specification with two regimes.[10] We estimate and present the three-regime model as a robustness check to highlight eventual differences that might arise under a different assumption.

Given equations (16) and (17) and a choice for n^s, we are 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

$$B_1(s_t)X_t = E_t\{A_1(s_t, s_{t+1})X_{t+1}\} + B_2(s_t)X_{t-1} + C_1(s_t)Z_t, \tag{18}$$

$$Z_t = R(s_t)Z_{t-1} + \epsilon_t \quad \text{with} \quad \epsilon_t \sim N(0, \Sigma(s_t)). \tag{19}$$

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 baseline version, the matrices in equation (18) are equivalent across the regimes, while in the robustness checks we allow for structural parameters to shift as well. In the next section, we discuss how to solve and estimate (18) and (19) with the actual data.

3. 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 (2007), Farmer et al. (2011), Foerster (2016), Miah (2014), and Cho (2016). Notably, all revolve around the idea of a minimal-state-variable solution introduced by McCallum (1983) but explore different avenues. Davig and Leeper (2007) use the notion of bounded shocks, while the latter three employ the concept of mean square stability. As MS-DSGE models may have more than one stable solution, each method needs to offer a way for choosing among stable solutions. In models where the shocks are unbounded, both Farmer et al. (2011) and Cho (2016) provide checks for uniqueness and determinacy. Farmer et al. (2011) propose a likelihood test to choose among several solutions. Cho (2016) introduces the concept of a "no-bubble condition." Intuitively, this concept is based on forward-solving the state-space system and it can be shown that in the limit, only one of the multiple solutions leads to a nonexplosive path and thus can be economically relevant. Finally, Foerster (2016) follows Farmer et al. (2011), while the method of Miah (2014) does not guarantee the finding of all the stable solutions. Due to the appealing property of Cho (2016) to isolate a unique solution among several stable options, we choose this algorithm to solve the model.

The solution takes the form

$$X_t = \Omega^*(s_t)X_{t-1} + \Gamma^*(s_t)Z_t, \tag{20}$$

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

Equation (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 the 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 the 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 realized states, and Y the data matrix, then the posterior $p(\theta, P, S|Y)$ can be evaluated using Bayes' rule:

$$p(\theta, P, S|Y) = \frac{p(Y|\theta, P, S)\, p(S|P)\, p(\theta, P)}{\int p(Y|\theta, P, S)\, p(S|P)\, p(P, \theta)\, d(\theta, P, S)}. \tag{21}$$

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 of Moeller (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 20th draw to reach a sample of 10,000 per batch. In all cases, the parameters converge to the same means.[11]

4. 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^*, and 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 USD LIBOR. Output is measured in real per-capita terms, where the trend component has been removed via the Hodrick–Prescott (HP) filter with a smoothing parameter of 1,600. 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 2016; altogether 124 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:

$$\begin{bmatrix} \triangle\, \mathrm{GDP}_t \\ \triangle \mathrm{CONS}_t \\ \mathrm{INFL}_t \\ \mathrm{HIBOR}_t \\ \mathrm{TOT}_t \\ \triangle\, \mathrm{GDP}_t^{\mathrm{US}} \\ \mathrm{LIBOR}_t \end{bmatrix} = \begin{bmatrix} y_t \\ c_t \\ \pi^{(q)} + \pi_t \\ i^{(q)} + i_t \\ v_t + R_v \\ y_t^* \\ i^{(q)*} + i_t^* \end{bmatrix}, \tag{22}$$

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, labeled 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.

5. PRIORS AND POSTERIOR ESTIMATES

Table 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 labor 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.

The persistence of the foreign variables is centered 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 United States 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.

TABLE 1. Estimated coefficients at the posterior mean

	Distribution	Prior mean	M_1	M_2: $S_t = 1$	M_2: $S_t = 2$
p_{11}	Beta	0.95	—	0.964	
				[0.929, 0.989]	—
p_{22}	Beta	0.9	—	0.934	
				[0.873, 0.979]	—
β	PM	0.983	0.983	0.983	—
φ	Gamma	2	2.077	2.127	
			[1.684, 2.503]	[1.729, 2.568]	—
θ_H	Beta	0.375	0.878	0.877	
			[0.855, 0.899]	[0.85, 0.901]	—
θ_F	Beta	0.375	0.856	0.858	
			[0.827, 0.883]	[0.829, 0.887]	—
α	PM	0.5	0.5	0.5	—
σ	Gamma	1	3.543	3.438	
			[2.351, 4.987]	[2.066, 4.976]	—
η	Gamma	2	2.242	2.342	
			[1.839, 2.665]	[1.949, 2.764]	—
h	Beta	0.2	0.556	0.567	
			[0.457, 0.652]	[0.442, 0.688]	—
δ_H	Beta	0.2	0.41	0.425	
			[0.286, 0.538]	[0.301, 0.558]	—
δ_F	Beta	0.2	0.697	0.696	
			[0.587, 0.796]	[0.588, 0.796]	—
χ	Gamma	0.01	0.009	0.01	
			[0.006, 0.013]	[0.007, 0.012]	—
ρ_a	Beta	0.7	0.938	0.924	
			[0.837, 0.984]	[0.799, 0.982]	—
ρ_{μ_F}	Beta	0.7	0.956	0.942	
			[0.909, 0.985]	[0.868, 0.983]	—
ρ_ν	Beta	0.7	0.521	0.527	
			[0.355, 0.689]	[0.359, 0.695]	—
ρ_ϕ	Beta	0.7	0.712	0.704	
			[0.533, 0.860]	[0.528, 0.854]	—
c_{y^*}	Beta	0.85	0.902	0.896	
			[0.837, 0.965]	[0.830, 0.960]	—
c_{π^*}	Beta	0.85	0.675	0.696	
			[0.565, 0.767]	[0.594, 0.782]	—
c_{i^*}	Beta	0.85	0.923	"0.921	
			[0.9, 0.944]	[0.884, 0.956]	—
σ_{μ_F}	IGamma	2	0.223	0.227	
			[0.174, 0.283]	[0.176, 0.289]	—
σ_a	IGamma	2	5.796	5.841	
			[4.544, 7.363]	[4.46, 7.589]	—
σ_ν	IGamma	2	12.996	13.327	
			[10.00, 16.672]	[10.167, 17.28]	—

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Table 1. Continued

	Distribution	Prior mean	M_1	M_2: $S_t = 1$	M_2: $S_t = 2$
σ_ϕ	IGamma	2	0.269 [0.242, 0.301]	0.089 [0.077, 0.135]	0.552 [0.448, 0.682]
σ_{y^*}	IGamma	1	0.505 [0.454, 0.559]	0.505 [0.456, 0.561]	—
σ_{π^*}	IGamma	1	1.534 [1.329, 1.778]	1.506 [1.304, 1.741]	—
σ_{i^*}	IGamma	1	0.126 [0.112, 0.141]	0.127 [0.113, 0.144]	—
R_v	Normal	0	0.001 [−0.282, 0.279]	0.001 [−0.107, 0.105]	—
$\mathbb{M}$:			−727.732	−662.727	

Note: $\mathcal{M}_1$: 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 last row presents the marginal data density based on the harmonic mean estimator, showing a preference for the MS-DSGE model.

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 labor supply φ is not identified due to the absence of labor series and is therefore centered 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 $\theta = 0.89$. This is also evident in the backward-looking component $\delta_H = 0.41$, 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 gross domestic product (GDP) deflator instead of the CPI. We now turn to the time-varying coefficients.

6. 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 nonoverlapping posterior distributions (plotted on Figure 2), suggesting heteroscedasticity of the risk premium. The means of $\sigma_\phi(1)$ and $\sigma_\phi(2)$ lie at 0.09 and 0.55, respectively.

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 3. The bottom plot depicts the US and Hong Kong interest rates. The figure clearly

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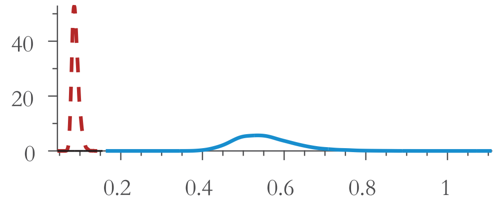

FIGURE 2. Posterior densities of the switching parameter $\sigma_\phi(s_t)$ under the first (—) and second regime (- -).

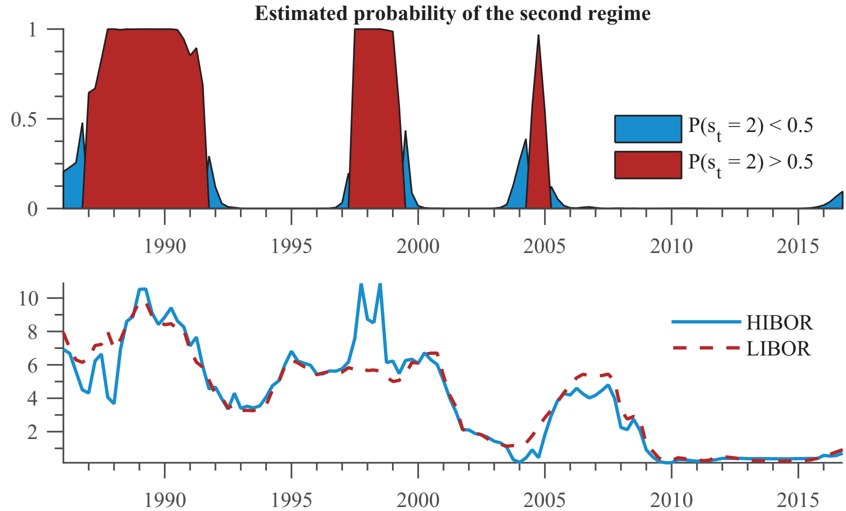

FIGURE 3. Regime probabilities and interest rates. Top panel: Estimated probability of the second state. Values below 0.5 indicate a realization of the first regime and values above 0.5—a realization of the second regime. Bottom panel: Annualized 3-month interbank interest rates.

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.

The Hong Kong stock market crashed on October 19, 1987 with shares losing almost half of their value.[12] The crisis spread quickly to other Asian markets, Europe, and the United States. 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

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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 7 years, the HIBOR was almost identical to the LIBOR, with the exceptions of two minor discrepancies in 1991 and the Mexican crisis in 1995.

Hong Kong's linked exchange rate system was put to a test during the Asian crisis in 1997–1998. With Asian currencies tumbling, speculative attacks on the HKD intensified in October 1997. As commercial banks collectively sold to the HKMA more HKD's than the balances in their clearing accounts, they faced a liquidity shortage when the foreign exchange transactions had to be settled. Uncertain of the supply of liquidity, commercial banks bid funds aggressively in the interbank market, driving the HIBOR overnight interest rate to 280% at one time. Subsequently, the impact on Hong Kong deepened. In 1998, Hong Kong's stock market dropped significantly as speculators started several attacks. Faced with the worsening economy, the Hong Kong government changed from being a passive regulator to an active market participant by accumulating large positions in local blue-chip stocks. Ultimately, the HKD was not spared of speculative pressure but the HKD's peg on USD was one of the very few instances of tight foreign exchange anchors that escaped the wave of huge devaluations hitting the Asian currencies.

The HKMA followed through the stock market operation with a package of technical reforms in September 1998 to strengthen the resilience of the currency board arrangements. These reforms can be broadly categorized into the three areas: (a) making the commitment to the link even more explicit, (b) revamping the mechanism for providing liquidity assistance, and (c) further improving the transparency of the currency board arrangements. 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 toward 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 US dollar [Chen et al. (2013) and Genberg and Hui (2010), 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.

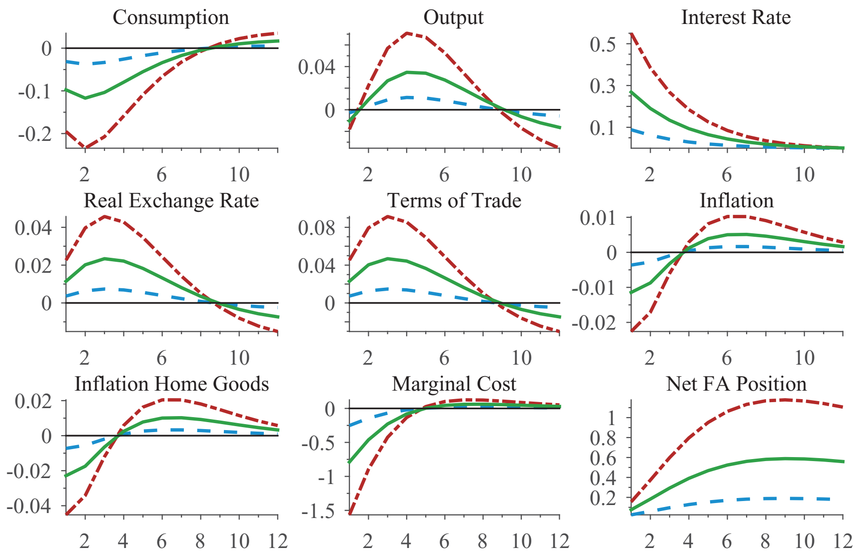

FIGURE 4. Impulse responses following a risk premium shock for state one: "high credibility" $\sigma_\phi(1)$ (- -), state two: "low credibility" $\sigma_\phi(2)$ (-.-), and the no-switching version $\mathcal{M}_1$ (—).

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 analyze responses of the macroeconomic variables in each regime separately. Figure 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 nonexistent. 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 improving terms of trade.

As evident from Figure 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 "noncredible" regime. In the second regime, all variables exhibit strong cyclical behavior. Larger risk premium shocks

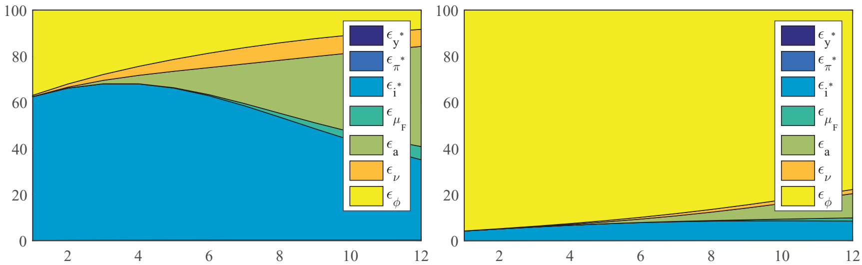

FIGURE 5. Variance decomposition of the interest rate for state one: "high credibility" $\sigma_\phi(1)$ and state two: "low credibility" $\sigma_\phi(2)$. The X-axis shows the variance decomposition horizon in quarters, the Y-axis is in percent.

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 nonlinear 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 5, while the full tables with all variables may be found in the appendix.

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 65%, 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 the 3 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.

The Markov-switching extension opens the possibility of counter-factual analysis, i.e., what would have happened if the second regime has not been in

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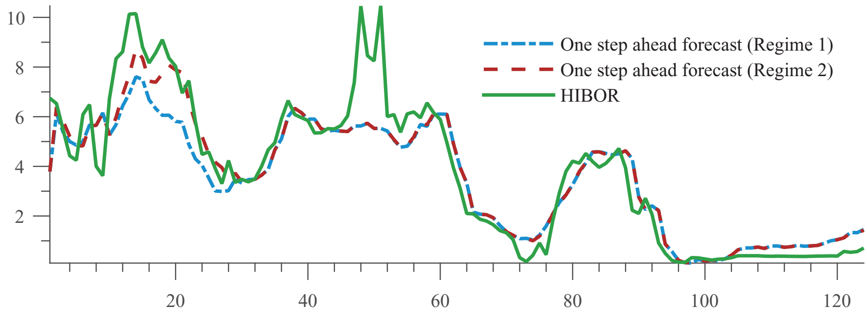

FIGURE 6. Counterfactual simulation of the HIBOR from a one-step ahead Kim's filter projection.

place throughout the identified periods. To investigate the question, we turn to the one-step ahead in-sample projection from Kim's filter plotted on Figure 6 along with the actual HIBOR dynamics.[13]

Two important conclusions are to be drawn from the figure. First, the recovery in the aftermath of the "Black Monday" would have been swifter, as the interest rates would have been around 2% lower, ceteris paribus (comparing the path under regime two with the path under regime one). While the existence of certainty equivalence and the lack of explicit financial sector modeling prevent a proper quantification of these results, it is straightforward to expect that lower interest rates after a crisis should boost investments and foreign direct investment inflow. Second, it is evident that the model cannot predict the spillover effects from the Asian and Russian crisis. Both the regimes do not associate the 1998–2000 period with higher interest rates. This also holds for the appreciation pressures coming from the Chinese currency adjustment in 2004. These findings are in line with the variance decomposition analysis.

7. ROBUSTNESS CHECKS

In the baseline Markov-switching model ($\mathcal{M}_2$), we allow for time-variation of the risk premium in order to capture the effects of changing perceptions toward Hong Kong's linked exchange rate system. While the model might be more flexible than its linear counterpart, it could very well be that other parameters are also time-varying. Therefore, we test the robustness of our findings by estimating several additional specifications. In particular, we estimate a model with heteroscedasticity in all exogenous variables ($\mathcal{M}_3$), we allow for shifts in the Philips curve through the Calvo parameter θ_H ($\mathcal{M}_4$), and we present the results from a three-regime MS model ($\mathcal{M}_5$).[14] The coefficients for each specification are reported in Table A.9 in the appendix. The remaining estimation output and the diagnostics are available in Tables A.1–A.8, A.10 and A.11, and Figures A.1–A.3, respectively. The last row presents the marginal data density based on the harmonic mean estimator, which we use for model comparison. We find that the data is mostly in favor of the

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models with volatility in the exogenous variables, such as $\mathcal{M}_2$ and $\mathcal{M}_3$, with the latter having a slightly higher estimate than the former. All nonlinear specifications outperform the linear model by far.

7.1. $\mathcal{M}_3$: Heteroscedastic Innovations

In this specification, we allow for heteroscedasticity in the exogenous variables, by letting the variances σ_ϕ (the risk premium), σ_a (technology), σ_{μ_F} (inflation of imports), and σ_ν (preferences) be time-varying. The risk premium volatility coefficient is estimated 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 (see Table A.9 in the appendix). This supports our modeling strategy in two ways. First, it serves as evidence that the captured heteroscedasticity 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 $\mathcal{M}_2$ and may be found in Table A.9 in the appendix. In terms of the marginal data density, we find a value of -661, slightly higher than -662, which would suggest a slight preference for $\mathcal{M}_3$. However, since the model does not provide value added to the baseline specification.

7.2. $\mathcal{M}_4$: Switching in the Calvo Parameter

We investigate next whether there have been shifts to the Philips curve by allowing for changes in one of the structural parameters of the model—the Calvo parameter, θ_H. The rationale is that different price dynamics would put pressure on domestic interest rates through the UIP relation [equation (8)]. We estimate a two-state MS-DSGE model and we do not find support for this hypothesis. The estimates for all parameters are similar to the linear model. With regard to the price-indexation parameter, θ_H, the model estimates a value of 0.9 and a second value of 0.38, which is completely overlapping the prior. The regime with $\theta_H = 0.9$ is prevalent throughout the whole sample without ever switching to the regime with $\theta_H = 0.38$, which we take as clear evidence, that there is no information in the data for a second regime with regard to the Calvo parameter.[15]

7.3. $\mathcal{M}_5$: A Three-State Markov-Switching Model

Finally, we turn our attention to a three-regime MS-DSGE model. In Section 2.2, we tested formally for the number of regimes and we found a borderline statistical argument for a two-state version. A binary choice is in line with the emphasis on a credible versus a noncredible regime, as represented by a low and a high volatility of the interest rates. Nevertheless, a three-state model could be beneficial for several reasons. First, it may sharpen identification, for example by allowing for a medium-volatility scenario. Second, it may highlight the sensitivity of these types of models toward a change in one of the main assumptions, namely the existence of several representations of the world.

To reduce the complexity at the estimation stage, we impose a restriction on the transition matrix that regime changes across the three states is possible only in consecutive order, thus excluding transitions from regime one to regime three and vice versa. Thus, the transition matrix P is given by

$$P = \begin{bmatrix} p_{11} & p_{12} & 0 \\ p_{21} & p_{22} & p_{23} \\ 0 & p_{32} & p_{33} \end{bmatrix}, \quad (\mathbf{23})$$

where p_{21}, p_{23}, and p_{32} are linear combinations of the rest of the parameters in each row, respectively. Regarding the priors, we order the risk premium volatility in ascending order, supporting the notion of a low-volatility regime, a medium risk premium volatility, and a high volatility state. We set the prior for p_{33} at 0.95 and the prior for switching from state two either to state one or three at 0.025.

The estimated parameters are presented on Table A.9 in the appendix. For the non-switching parameters, we find close resemblance to the baseline version. The model identifies three-different risk premium volatility regimes with $\sigma_\phi^{\mathcal{M}_5}(1) = 0.04$, $\sigma_\phi^{\mathcal{M}_5}(2) = 0.18$, and $\sigma_\phi^{\mathcal{M}_5}(3) = 0.79$. Compared to the baseline DSGE model, where $\sigma_\phi^{\mathcal{M}_1} = 0.26$, both the first and the second regime exhibit a lower volatility, closer to the MS-DSGE model with two states estimate $\sigma_\phi^{\mathcal{M}_2}(1) = 0.10$. The third regime estimate stands even higher risk premium volatility than the two-state model, $\sigma_\phi^{\mathcal{M}_5}(3) = 0.79$ versus $\sigma_\phi^{\mathcal{M}_2}(3) = 0.52$, suggesting that the financial shocks during a period with loss of credibility have an even more pronounced effect.

The top panel of Figure 7 plots the estimated regimes from the three-state model, while the bottom panel shows the probability for the high volatility regime, analogous to main MS-DSGE specification. Qualitatively, the figure carries similar economic interpretation to the two-state version (Figure 3). The notable difference is that the appreciation pressures toward 2005, identified as a lone spike in $\mathcal{M}_2$, are attributed to the second regime. Moreover, the economy remained in that state until the middle of 2009, instead of returning to the low volatility regime in 2006, i.e., the uncertainty regarding the linked exchange rate system remained elevated. Other than that, the high volatility regime has come in place during the last quarter of 1987—when the probability in both models $\mathcal{M}_5$ and $\mathcal{M}_2$ peak to 1—which captures the stock market crash.

Given the higher estimate of the risk premium volatility in the third regime, the response of the variables following a risk premium shock is even more pronounced than the two state version and the economy is hardly reacting to interest rate shocks in the other two regimes due to their smaller magnitude. Figure 8 plots the impulse response functions of the three-state model versus the linear DSGE

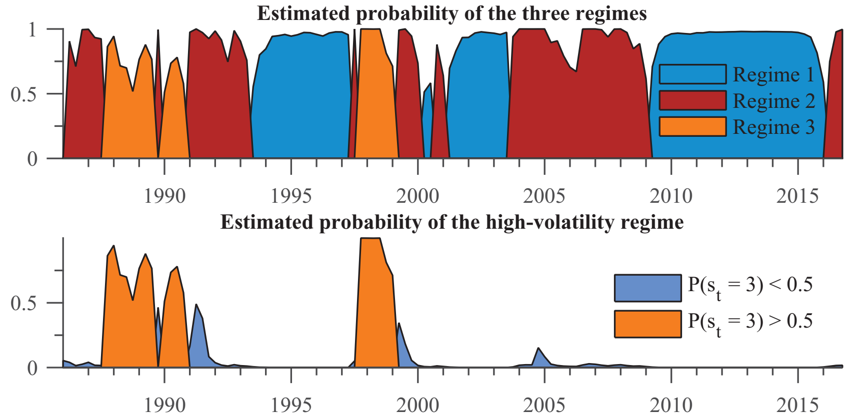

FIGURE 7. A three-state Markov-switching model for Hong Kong. Top panel: Estimated probabilities for the three states. $\hat{\sigma}_\phi(1) = 0.05$, $\hat{\sigma}_\phi(2) = 0.15$, and $\hat{\sigma}_\phi(3) = 0.80$. Bottom panel: Estimated probability of the high volatility regime.

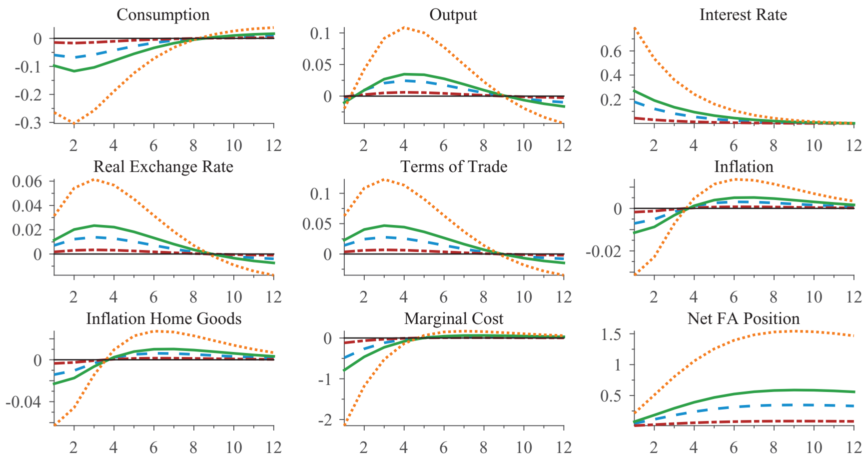

FIGURE 8. Impulse responses following a risk premium shock for state one (- -), state two (-.-), state three (...), and the no-switching version $\mathcal{M}_1$ (—).

version. Similarly to the main MS-DSGE comparison to the baseline model, the linear version is overestimating the impact of the shocks in the first and second regime and underestimating them throughout the loss of credibility periods.

The marginal data density is estimated at -681 for the three-state model. Comparing the value to the two-regime model estimate of -662, the data seem in favor of the baseline specification $\mathcal{M}_2$, which is in line with the test based on predictive likelihoods in Section 2.2.

8. CONCLUDING REMARKS

This paper 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.[16]

We are essentially modeling the exchange rate regime credibility as a nonlinear 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 endogenization of the switching parameters in the tradition in Filardo (1994).

NOTES

1. 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, pp. 329–339.

2. Oliva et al. (2001) present a signaling 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.

3. LIBOR follows the dynamics of the Federal funds rate (FFR) closely and has a directly comparable definition with HIBOR.

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 prerecession 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. See Caballero (2010) and Gertler and Kiyotaki (2010) for an assessment of this research. As noted by Blanchard (2016), DSGE model architecture allows for relevant empirical findings and facilitates coherent discussion of results.

5. An alternative modeling strategy would be to assume an abandoning of the peg and by introducing exit expectations. In the framework, this can be achieved by adding a switching parameter on the exchange rate in equation (11), introducing a Taylor rule and analysing the responses of the system in the regime with a peg, in which now the agents would know that relinquishing the fixed exchange rate system is possible. This approach has been pursued in Kriwoluzky (2015).

6. Regime-switching models are well-established models in the exchange rate literature. Engel and Hamilton (1990), Engel (1994), and Cheung and Erlandsson (2005) have popularized the

Markov-switching toolkit in exchange rate economics by showing that the Markovian process is a relevant statistical alternative to the classical martingale model for exchange rates. For some recent MS-DSGE and MS-VAR modeling approaches, see Blagov and Funke (2016) and Blagov (2017).

7. The values and the modeling choice of the variance parameter in the RW process in Justiniano and Primiceri (2008) are based upon the earlier work of Primiceri (2005) in a VAR context. The author shows that values largely different from the one employed in the study break the estimation [Primiceri (2005), p. 842]

8. An example of such bias is the earlier literature on the Great Moderation, where models that allow only for heteroscedasticity find changing volatilities hence falling in the "good luck" camp, versus models that impose homoscedasticity and allow for shifts in the Taylor rule, and find evidence for the "good policy" argument. For a survey and a reconciliation of both modeling approaches see Primiceri (2005). For more recent advances see Bianchi (2011) or Murray et al. (2015).

9. See Cho and Kasa (2008) for a modeling of an endogenous currency crisis that exhibits Markov-switching exchange rate behavior.

10. The Bayes factor of the three-state versus the two-state model is 0.97, where a value below 1 is considered "anecdotal evidence" for the two regimes, and value above 1 and below 3 is "anecdotal evidence" for three regimes. Values above 3 and 10 are typically accepted as moderate, and strong evidence, respectively, for the alternative Hypothesis H_1, in this case, the three regime model Jeffreys (1998). A conversion between these values and p-values from a frequentist perspective is not possible.

11. An alternative approach to the MCMC method is to use a Gibbs sampler, or more precisely "Metropolis within Gibbs" as in Bianchi (2011). This method, however, is computationally more intensive.

12. 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).

13. Since the model is linearized, the policy functions for each state are identical. Nevertheless, even under certainty equivalence, the uncertainty plays a role for the path of the interest rate in the updating step of the Kalman filter. However, this does not translate to the rest of the variables due to the absence of capital and a banking sector, which would feature the path of the interest rate more prominently for the real variables. This reasoning is also valid for the variance decomposition.

14. Furthermore, we test whether sudden changes to the debt-sensitivity parameter have had an implication to the spread and thus reduced the volatility of the exogenous risk premium. We estimate the same low and high volatility states and our findings remain unchanged. The results are available upon request.

15. Results are available upon request.

16. The ability of Markov-switching frameworks to generate nontrivial 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).

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APPENDIX: $\mathcal{M}_2$: STATE-CONTINGENT VARIANCE DECOMPOSITION TABLES

TABLE A.1. Forecast error variance decomposition of consumption for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.01	7.35	0.30	4.25	10.09	76.71	1.30
4	0.02	10.26	0.44	4.98	27.06	56.02	1.22
8	0.03	8.95	0.41	3.84	43.49	42.35	0.93
12	0.03	7.50	0.34	3.20	52.91	35.23	0.78
20	0.03	5.98	0.28	2.65	62.18	28.25	0.63
40	0.04	4.84	0.27	3.44	67.87	23.03	0.52
∞	0.04	4.56	0.28	4.46	68.47	21.71	0.49

Note: State 2: "low credibility," in percent.

TABLE A.2. Forecast error variance decomposition of consumption for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.01	7.44	0.30	4.30	10.22	77.69	0.03
4	0.02	10.38	0.44	5.04	27.39	56.70	0.03
8	0.03	9.04	0.41	3.88	43.89	42.74	0.02
12	0.03	7.56	0.35	3.22	53.32	35.50	0.02
20	0.03	6.02	0.28	2.66	62.56	28.43	0.02
40	0.04	4.87	0.27	3.46	68.21	23.14	0.01
∞	0.04	4.58	0.28	4.48	68.80	21.81	0.01

Note: State 1: "high credibility," in percent.

TABLE A.3. Forecast error variance decomposition of inflation for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.03	56.96	0.04	32.62	7.53	2.75	0.07
4	0.01	49.01	0.01	45.75	4.30	0.89	0.03
8	0.01	50.46	0.01	45.06	3.51	0.92	0.03
12	0.01	50.81	0.01	44.39	3.82	0.92	0.03
20	0.01	48.85	0.02	46.24	3.98	0.88	0.03
40	0.01	47.52	0.02	47.65	3.92	0.86	0.03
∞	0.01	47.36	0.02	47.82	3.91	0.86	0.03

Note: State 2: "low credibility," in percent.

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TABLE A.4. Forecast error variance decomposition of inflation for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.03	57.00	0.04	32.64	7.54	2.76	0.00
4	0.01	49.02	0.01	45.77	4.30	0.89	0.00
8	0.01	50.47	0.01	45.07	3.52	0.92	0.00
12	0.01	50.83	0.01	44.41	3.83	0.92	0.00
20	0.01	48.86	0.02	46.25	3.98	0.88	0.00
40	0.01	47.53	0.02	47.66	3.92	0.86	0.00
∞	0.01	47.38	0.02	47.83	3.91	0.86	0.00

Note: State 1: "high credibility," in percent.

TABLE A.5. Forecast error variance decomposition of output for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.70	51.93	0.20	0.15	44.66	2.36	0.01
4	0.11	15.55	0.26	0.12	79.75	4.06	0.15
8	0.06	8.16	0.23	0.38	88.72	2.34	0.11
12	0.05	6.61	0.21	1.41	89.61	2.01	0.09
20	0.06	5.92	0.19	5.71	85.81	2.20	0.10
40	0.07	5.26	0.25	13.31	78.73	2.27	0.11
∞	0.07	4.85	0.28	15.87	76.68	2.15	0.10

Note: State 2: "low credibility," in percent.

TABLE A.6. Forecast error variance decomposition of output for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.70	51.93	0.20	0.15	44.66	2.36	0.00
4	0.11	15.57	0.26	0.12	79.86	4.06	0.00
8	0.06	8.16	0.23	0.38	88.82	2.34	0.00
12	0.06	6.62	0.21	1.41	89.69	2.02	0.00
20	0.06	5.93	0.19	5.71	85.90	2.20	0.00
40	0.07	5.27	0.25	13.33	78.81	2.27	0.00
∞	0.07	4.85	0.28	15.89	76.76	2.15	0.00

Note: State 1: "high credibility," in percent.

TABLE A.7. Forecast error variance decomposition of the interest rate for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.00	0.00	4.19	0.00	0.00	0.04	95.77
4	0.02	0.01	6.66	0.00	0.36	0.38	92.57
8	0.04	0.02	8.42	0.27	3.63	1.20	86.43
12	0.05	0.02	8.43	1.39	10.52	1.80	77.79
20	0.07	0.03	6.85	5.06	25.32	2.12	60.56
40	0.06	0.03	4.74	10.78	40.81	1.86	41.71
∞	0.06	0.03	4.20	13.22	44.21	1.71	36.57

Note: State 2: "low credibility," in percent.

TABLE A.8. Forecast error variance decomposition of the interest rate for horizon $h = \{1, \ldots, \infty\}$

	ε_{y^*}	ε_{π^*}	ε_{i^*}	ε_{μ_F}	ε_a	ε_ν	ε_ϕ
1	0.06	0.03	62.35	0.01	0.05	0.55	36.95
4	0.15	0.09	67.77	0.04	3.66	3.90	24.39
8	0.23	0.10	53.26	1.68	23.00	7.57	14.17
12	0.22	0.09	34.80	5.72	43.44	7.42	8.32
20	0.16	0.08	16.71	12.33	61.73	5.16	3.82
40	0.11	0.06	7.98	18.16	68.73	3.14	1.82
∞	0.09	0.05	6.52	20.53	68.68	2.66	1.47

Note: State 1: "high credibility," in percent.

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TABLE A.9. Parameter estimates for all models

	Distribution	Prior Mean	M_1	M_2	M_3	M_4	M_5
p_{11}	Beta	0.95	—	0.96 [0.93, 0.99]	0.97 [0.93, 0.99]	0.91 [0.78, 0.99]	0.95 [0.86, 1]
p_{22}	Beta	0.90	—	0.93 [0.87, 0.98]	0.92 [0.85, 0.97]	0.97 [0.93, 0.99]	0.95 [0.85, 1]
β	PM	0.98	0.98	0.98	0.98	0.98	0.98
φ	Gamma	2.00	2.08 [1.68, 2.5]	2.13 [1.73, 2.57]	2.13 [1.73, 2.56]	2.2 [1.79, 2.65]	2.12 [1.71, 2.57]
θ_H	Beta	0.38	0.88 [0.85, 0.9]	0.88 [0.85, 0.9]	0.87 [0.84, 0.89]	0.37 [0.25, 0.5] 0.93 [0.9, 0.96]	0.87 [0.85, 0.9]
θ_F	Beta	0.38	0.86 [0.83, 0.88]	0.86 [0.83, 0.89]	0.85 [0.82, 0.88]	0.87 [0.84, 0.89]	0.85 [0.82, 0.88]
α	PM	0.50	0.5	0.5	0.5	0.5	0.5
σ	Gamma	1.00	3.54 [2.35, 4.99]	3.44 [2.07, 4.98]	3.23 [2.1, 4.56]	4.69 [3.15, 6.55]	3.81 [2.58, 5.26]
η	Gamma	2.00	2.24 [1.84, 2.66]	2.34 [1.95, 2.76]	2.34 [1.93, 2.76]	2.28 [1.85, 2.73]	2.38 [1.99, 2.8]
h	Beta	0.20	0.56 [0.46, 0.65]	0.57 [0.44, 0.69]	0.54 [0.43, 0.65]	0.56 [0.46, 0.66]	0.53 [0.43, 0.63]
δ_H	Beta	0.20	0.41 [0.29, 0.54]	0.43 [0.30, 0.56]	0.45 [0.33, 0.57]	0.38 [0.28, 0.49]	0.42 [0.3, 0.54]
δ_F	Beta	0.20	0.70 [0.59, 0.80]	0.70 [0.59, 0.80]	0.73 [0.63, 0.82]	0.71 [0.61, 0.81]	0.71 [0.61, 0.81]
χ	Gamma	0.01	0.01 [0.01, 0.01]	0.01 [0.01, 0.01]	0.01 [0.01, 0.01]	0.01 [0.00, 0.01]	0.01 [0.00, 0.01]
ρ_a	Beta	0.70	0.94 [0.84, 0.98]	0.92 [0.80, 0.98]	0.94 [0.83, 0.98]	0.88 [0.73, 0.97]	0.96 [0.88, 0.99]
ρ_{μ_F}	Beta	0.70	0.96 [0.91, 0.99]	0.94 [0.87, 0.98]	0.94 [0.87, 0.98]	0.95 [0.89, 0.98]	0.96 [0.91, 0.99]
ρ_ν	Beta	0.70	0.52 [0.35, 0.69]	0.53 [0.36, 0.7]	0.5 [0.34, 0.67]	0.5 [0.34, 0.67]	0.51 [0.35, 0.68]

TABLE A.9. Continued

	Distribution	Prior Mean	M_1	M_2		M_3		M_4	M_5		
ρ_ϕ	Beta	0.70	0.71	0.7		0.69		0.7		0.68	
			[0.53, 0.86]	[0.53, 0.85]		[0.52, 0.84]		[0.53, 0.85]		[0.51, 0.82]	
c_{y^*}	Beta	0.85	0.90	0.9		0.89		0.9		0.9	
			[0.84, 0.97]	[0.83, 0.96]		[0.83, 0.96]		[0.83, 0.96]		[0.83, 0.96]	
c_{π^*}	Beta	0.85	0.66	0.7		0.68		0.74		0.67	
			[0.57, 0.77]	[0.59, 0.78]		[0.59, 0.76]		[0.64, 0.82]		[0.57, 0.76]	
c_{i^*}	Beta	0.85	0.92	0.92		0.92		0.92		0.92	
			[0.90, 0.94]	[0.88, 0.96]		[0.89, 0.94]		[0.90, 0.94]		[0.89, 0.94]	
σ_{μ_F}	IGamma	2.00	0.22	0.23		0.31	0.23	0.21		0.23	
			[0.17, 0.28]	[0.18, 0.29]		[0.22, 0.42]	[0.18, 0.3]	[0.16, 0.27]		[0.18, 0.28]	
σ_a	IGamma	2.00	5.80	5.84		6.62	4.79	8.144		5.55	
			[4.54, 7.36]	[4.46, 7.59]		[4.95, 8.79]	[3.71, 6.09]	[5.66, 11.5]		[4.36, 7.02]	
σ_ν	IGamma	2.00	13.00	13.33		12.94	11.53	18.291		12.76	
			[10, 16.67]	[10.17, 17.28]		[9.24, 17.68]	[8.88, 14.79]	[13.31, 24.68]		[9.82, 16.3]	
σ_ϕ	IGamma	2.00	0.27	0.09	0.55	0.10	0.52	0.267	0.04	0.18	0.79
			[0.24, 0.3]	[0.08, 0.10]	[0.45, 0.69]	[0.08, 0.11]	[0.41, 0.64]	[0.24, 0.3]	[0.03, 0.06]	[0.16, 0.21]	[0.58, 1.07]
σ_{y^*}	IGamma	1.00	0.51	0.51		0.51		0.5		0.51	
			[0.45, 0.56]	[0.46, 0.56]		[0.45, 0.56]		[0.45, 0.56]		[0.46, 0.57]	
σ_{π^*}	IGamma	1.00	1.53	1.51		1.5		1.55		1.47	
			[1.33, 1.78]	[1.3, 1.74]		[1.3, 1.74]		[1.33, 1.81]		[1.28, 1.69]	
σ_{i^*}	IGamma	1.00	0.13	0.13		0.13		0.13		0.13	
			[0.11, 0.14]	[0.11, 0.14]		[0.11, 0.14]		[0.11, 0.14]		[0.11, 0.14]	
R_s	Normal	0.00	0.00	0.00		0.00		0.00		0.00	
			[−0.28, 0.28]	[−0.11, 0.11]		[−0.09, 0.09]		[−0.10, 0.11]		[−0.09, 0.09]	
$\mathbb{M}$:			−727.73	−662.73		−661.09		−690.33		−681.93	

Note: $\mathbb{M}$ denotes the marginal data density. $\mathcal{M}_1$: linear DSGE model; $\mathcal{M}_2$: Time-varying exogenous risk premium; $\mathcal{M}_3$: Heteroscedasticity of all innovations; $\mathcal{M}_4$: Switching θ_H; $\mathcal{M}_5$: Three-state MS-DSGE model with switching in the exogenous risk premium.

$\mathcal{M}_2$: Convergence Diagnostics—Figures and Tables

TABLE A.10. Autocorrelation among the draws, based on a sample of 10,000

	Lag 1	Lag 5	Lag 10	Lag 50
p_{11}	0.529221	0.082381	0.012803	−0.016646
p_{22}	0.572313	0.123566	0.010785	0.007499
φ	0.508419	0.046369	−0.001289	0.014775
θ_H	0.589469	0.117795	0.036097	0.018483
θ_F	0.525508	0.115185	0.033848	−0.0069
σ	0.671117	0.30275	0.168298	0.00274
η	0.509816	0.076138	0.00876	−0.000017
h	0.669191	0.306358	0.199489	0.012403
δ_H	0.56644	0.100846	0.02003	0.016609
δ_F	0.522552	0.036793	0.00299	−0.008536
χ	0.706378	0.325799	0.240632	0.010896
ρ_a	0.816107	0.557673	0.383221	−0.024516
ρ_{μ_F}	0.729952	0.361844	0.205737	0.02159
ρ_v	0.512325	0.07992	0.038915	−0.033345
ρ_ϕ	0.484013	0.029833	−0.010592	−0.011194
c_{y*}	0.529194	0.046689	0.007402	0.017651
$c_{\pi*}$	0.660131	0.22902	0.115935	0.01266
c_{i*}	0.785432	0.510449	0.381826	0.007787
σ_{μ_F}	0.610871	0.16356	0.037794	0.015759
σ_a	0.681062	0.260356	0.108964	0.018144
σ_v	0.618299	0.16567	0.044789	0.001804
σ_ϕ	0.751326	0.316072	0.139028	0.008177
σ_{y*}	0.510243	0.04173	−0.015397	−0.004531
$\sigma_{\pi*}$	0.553386	0.079715	0.000306	0.012493
σ_{i*}	0.602484	0.166716	0.099756	−0.015662
R_v	0.497566	0.021021	0.002723	0.010592
$\sigma_\phi(2)$	0.623664	0.190402	0.109043	0.009007

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TABLE A.11. Raferty–Lewis convergence diagnostics with $q = 0.025$, $r = 0.1$, $s = 0.95$

	Thin	Burn	Total (N)	(Nmin)	I-stat
p_{11}	1	8	2,157	937	2.302028
p_{22}	1	8	2,157	937	2.302028
φ	1	8	2,157	937	2.302028
θ_H	1	8	2,157	937	2.302028
θ_F	1	8	2,157	937	2.302028
σ	1	8	2,157	937	2.302028
η	1	8	2,157	937	2.302028
h	1	8	2,157	937	2.302028
δ_H	1	8	2,157	937	2.302028
δ_F	1	8	2,157	937	2.302028
χ	1	8	2,157	937	2.302028
ρ_a	1	8	2,157	937	2.302028
ρ_{μ_F}	1	8	2,157	937	2.302028
ρ_v	1	8	2,157	937	2.302028
ρ_ϕ	1	8	2,157	937	2.302028
c_{y*}	1	8	2,157	937	2.302028
$c_{\pi*}$	1	8	2,157	937	2.302028
c_{i*}	1	8	2,157	937	2.302028
σ_{μ_F}	1	8	2,157	937	2.302028
σ_a	1	8	2,157	937	2.302028
σ_v	1	8	2,157	937	2.302028
σ_ϕ	1	8	2,157	937	2.302028
σ_{y*}	1	8	2,157	937	2.302028
$\sigma_{\pi*}$	1	8	2,157	937	2.302028
σ_{i*}	1	8	2,157	937	2.302028
R_v	1	8	2,157	937	2.302028
$\sigma_\phi(2)$	1	8	2,157	937	2.302028

Note: An I-statistic less than 5 indicates convergence.

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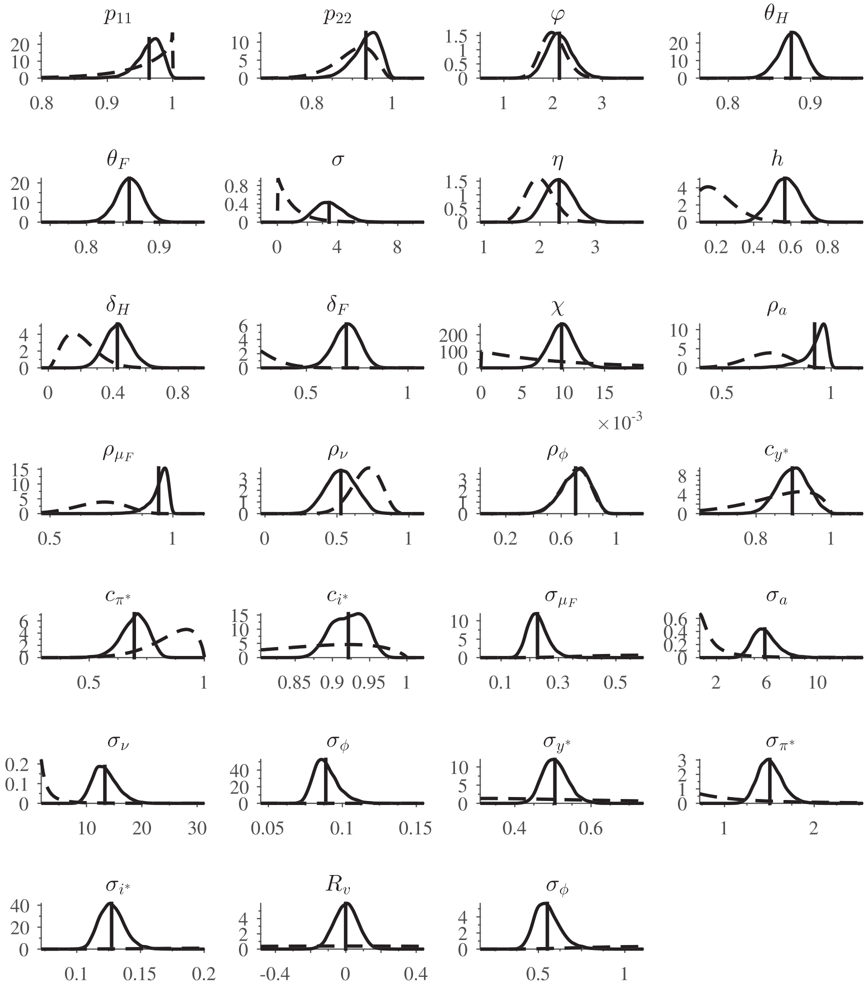

FIGURE A.1. $\mathcal{M}_2$: Prior (- -) and posterior (—) parameter distributions.

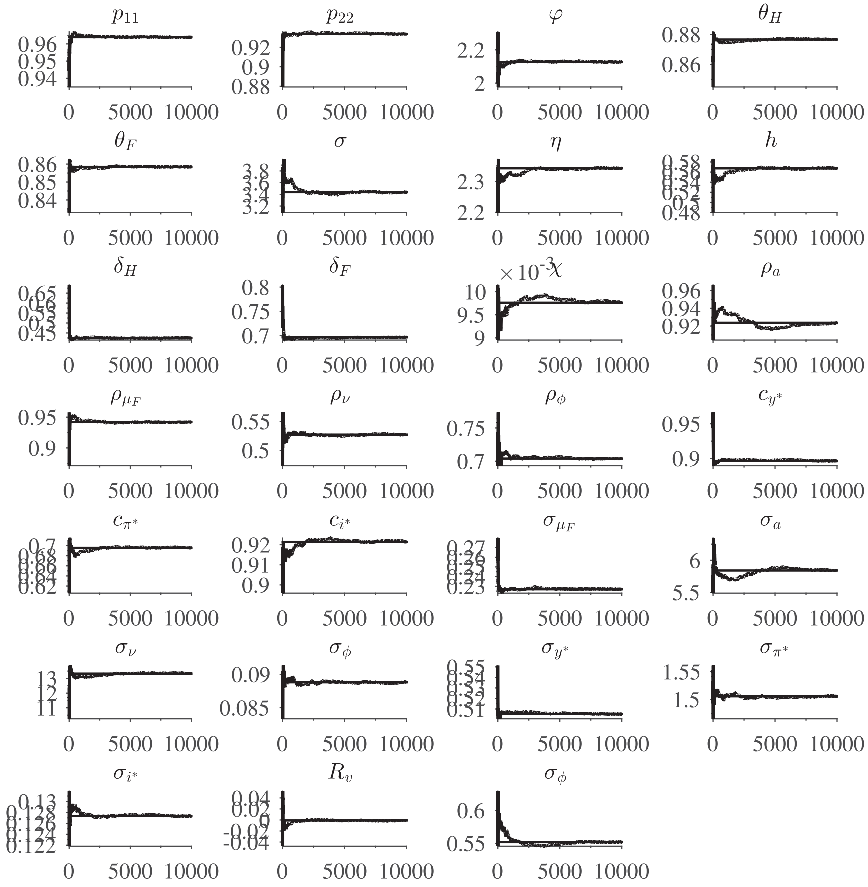

FIGURE A.2. $\mathcal{M}_2$: Recursive means of the parameters calculated over the draws from the posterior distribution.

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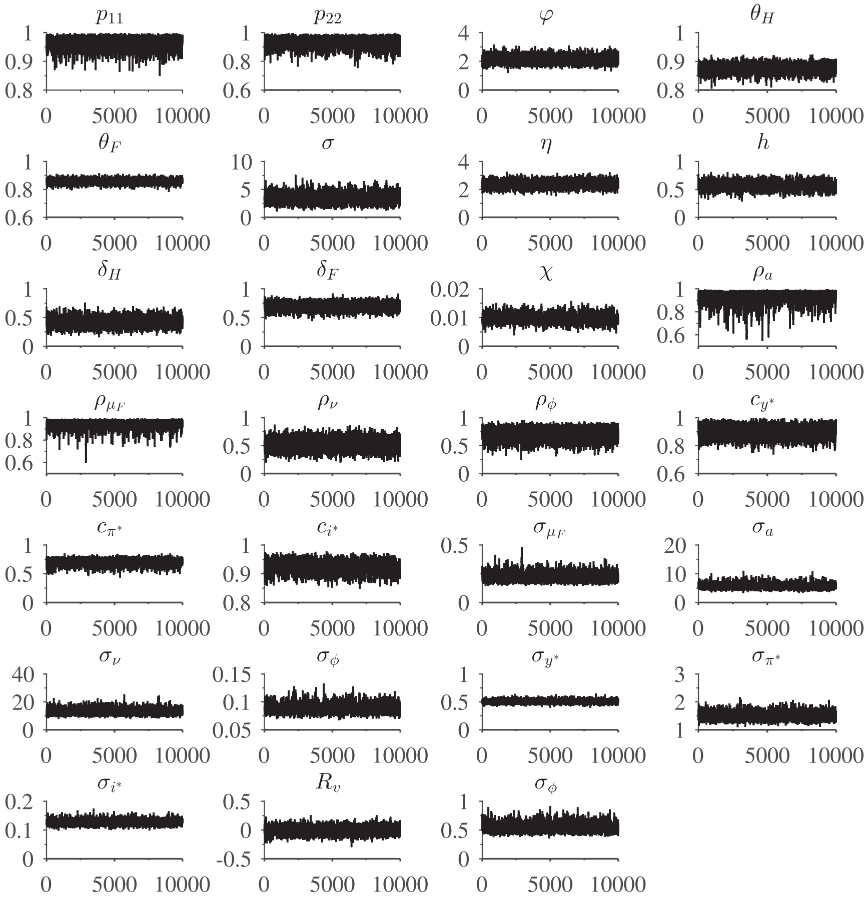

FIGURE A.3. $\mathcal{M}_2$: Trace plots of the parameters.

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