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The Credibility of Hong Kong's Currency Board System: Looking Through the Prism of MS-VAR Models with Time-Varying Transition Probabilities

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Abstract

This paper takes seriously the idea that the coefficients of a VAR and the variance of shocks may be time-varying and so employs a Markov regime-switching VAR model to describe and analyse the time-varying credibility of Hong Kong's currency board system. The endogenously estimated discrete regime shifts are made dependent on macroeconomic fundamentals. This enables us to determine which changes in macroeconomic variables can trigger switches between the low and high credibility regimes. We carry out extensive testing to search for the most appropriate specification of the Markov regime-switching model. We find strong evidence of regime switching behaviour that portrays the time-varying nature of credibility in the historical data. Our own conditional volatility index provides anticipatory signals and amplifies the regime-switching transition probabilities.

Keywords: Markov regime-switching VAR, exchange rate regime credibility, Hong Kong
JEL-Classification: C11, C32, F31, F41

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1 Introduction

In order to overcome financial crisis episodes, currency board exchange rate regimes have been implemented with success in countries such as Argentina, Estonia, and Hong Kong. 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. The basic concept of a currency board is simple. It requires the monetary base to be 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 (100 percent reserve backing). As a result, currency board systems have been adopted as a tool to safeguard external financial stability.

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 monetary union.[1]

The Hong Kong government adopted the currency board system on 17 October 1983 during of the "Black Saturday Crisis". Under the currency board system, 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 note-issuing 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 bit the bullet on appreciation and introduced a symmetric target zone with a narrow HKD/USD band of [7.75, 7.85].[2] While exchange rate interventions at the boundaries of the band are automatic, the HKMA also reserves the right to inject or withdraw liquidity intramarginally.

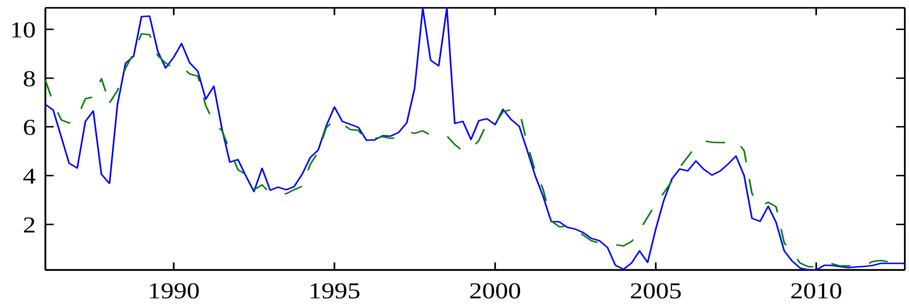
The default view of a currency board system is that it lends credibility to the exchange rate and monetary policy by relinquishing the devaluation option. However, this is not always the case. One can point to numerous historical episodes where currency boards fail to enhance

[1] 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.

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

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

Figure 1: HKD HIBOR (—) and USD LIBOR (- -), annualized 3-month interest rates.



Eyeballing the interest-rate differentials in Figure 1 shows that interest rates have been on equal levels in normal times, but that 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.[3] 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 fixed exchange rate regimes. 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 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. Furthermore, in the further course of the global financial crisis abundant liquidity provided by advanced economies' central banks and optimism about the Chinese economy led

[3] The empirical research investigating the credibility of peg exchange rate systems was initiated by the works Svensson (1991), Svensson (1993). He has developed various techniques to extract devaluation expectations from interest rate differentials. De Grauwe (1994) has also used interest rate differentials to shed light on time-varying credibility.

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 nonlinear. Recent papers have stressed the importance of nonlinear effects and amplification dynamics during financial crises. 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 nonlinear dynamics and destabilize markets. Bianchi (2011) and Jermann and Quadrini (2012) have formalized 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 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 regime dynamics. See, for example, Altavilla and De Grauwe (2010), Arestis and Mouratidis (2005), Chen (2006) and Sarantis and Piard (2004). 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 jump probabilities. In our view, such models have much to contribute and offer us a promising avenue of empirical research.[4]

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. Three approaches can be identified in the literature. Genberg and Hui (2011) have provided econometric evidence using option-based 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.

The remainder of the paper is organised as follows. In section 2 we describe how to think

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

about the time-varying changes in credibility from a conceptual standpoint. In Section 3 we discuss the model's methods of inference. Section 4 presents the data and the identification strategy while section 5 discusses the empirical results. Section 6 deals with the robustness checks, and the final section concludes.

2 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 probabilities (henceforth MS-BVAR). The advantage of this framework is that we can endogenise the probabilities associated with the regime switching. This feature might be of great importance in modelling rare events such as currency or banking crises, as self-fulfilling expectations play a major role there.

The structural MS-BVAR of order p can be written in the general form as

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

y_t is a $T \times N$ vector with N variables and T observations. a_{s_t} is the intercept of the regression, while A_i are $N \times N$ coefficient matrices. ε_t is an $N \times 1$ vector of i.i.d. structural innovations. $\varepsilon \sim N(0, \Sigma(s_t)^2)$. The model coefficients are subject to regime shifts with s_t denoting the corresponding state. Assuming that A_0 is known and invertible, the model can be rewritten in reduced form:

$$y_t = c(s_t) + B_1(s_t)y_{t-1} + ... + B_p(s_t)y_{t-p} + u_t, \tag{2}$$

where $c = A_0^{-1}c_0$ and $B_i = A_0^{-1}A_i$, $i = 1, ..., p$. The innovations of the reduced form residuals are $u_t = A_0\varepsilon_t \sim N(0, \Omega^2(s_t))$, and their variance-covariance matrix Ω^2 is given by $(A_0^{-1})\Sigma^2(s_t)(A_0^{-1})'$.

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

$$P(s_t = s_i|s_{t-1} = s_j, z_t) = \begin{bmatrix} p(z_t) & 1-p(z_t) \\ 1-q(z_t) & q(z_t) \end{bmatrix}. \tag{3}$$

The probabilities of staying in the respective state are given by the diagonal of P. In contrast to a fixed transition probabilities model, they are each function of a leading variable z_t and the outcome of a Probit model as in Filardo (1994) and Filardo and Gordon (1998).

$$P(s_t = 1) = P(S_t^* \geq 0). \tag{4}$$

$$S_t^* = \gamma_0 + \gamma_1 z_t + \gamma_2 S_{t-1} + u_t. \tag{5}$$

$u_t \sim N(0, 1)$, where identification is achieved by assuming the variance to be unity, w.l.o.g.[5] The transition probabilities across regimes $p(z_t)$ and $q(z_t)$ are then derived from the cumulative

[5] See Filardo and Gordon (1998), p. 104.

distribution function (CDF) of the normal distribution.

$$
\begin{aligned}
p(z_t) &= P(u_t \leq -\gamma_0 - \gamma_1 z_t | z_t) = \Phi(-\gamma_0 - \gamma_1 z_t), & (6) \\
q(z_t) &= P(u_t \geq -\gamma_0 - \gamma_1 z_t - \gamma_2 | z_t) = 1 - \Phi(\gamma_0 - \gamma_1 z_t - \gamma_2). & (7)
\end{aligned}
$$

The γ_1 parameter allows us to endogenize, the probabilities as the variation of the leading variable will affect the frequency of regime changes. The model setup nests the fixed probabilities case if $\gamma_1 = 0$. Thus 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 nonlinear 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 estimates of the parameters and responses to the underlying shocks - see next section for details.

3 Inference

The model is estimated using Bayesian techniques, by combining the likelihood with prior information to evaluate the posterior using a GIBBS sampler. The inference stage can be divided in two parts: (i) estimating the VAR, given the path of the states, and (ii) estimating the transition probabilities and the trajectory of the regimes, given the VAR coefficients.

The estimation of the VAR parameters in a Bayesian setting is straightforward, given a history of the regimes. We begin by expressing equation (2) as a VAR(1):

$$
Y = XB + U. \tag{8}
$$

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

$$
Y_d = \begin{bmatrix} \frac{diag(\delta_1\sigma_1,...,\delta_N\sigma_N)}{\tau} \\ \mathbf{0}_{N(p-1)\times N} \\ \ldots\ldots\ldots \\ diag(\sigma_1, \ldots\ldots, \sigma_n) \\ \ldots\ldots\ldots \\ \mathbf{0}_{1\times N} \\ \frac{diag(\delta_1\mu_1,...,\delta_N\mu_N}{\tau} \end{bmatrix}, \qquad X_d = \begin{bmatrix} \frac{J_p \otimes diag(\delta_1\sigma_1,...,\delta_n\sigma_n)}{\lambda} & \mathbf{0}_{Np\times 1} \\ \mathbf{0}_{N\times NP} & \mathbf{0}_{N\times 1} \\ \ldots\ldots\ldots\ldots & \ldots\ldots\ldots \\ \mathbf{0}_{1\times Np} & \epsilon \\ \frac{\mathbf{1}\otimes diag(\delta_1\sigma_1,...,\delta_N\sigma_N)}{\lambda} & \mathbf{0}_{N\times 1} \end{bmatrix}. \tag{9}
$$

$\delta_1 ... \delta_N$ control the tightness of the priors on the first lag, while τ controls the priors on the sum of coefficients. We follow the literature in setting the priors and choose $\lambda = 0.2$ and $\tau = 5\lambda$.

The constant has a flat prior of $\varepsilon = 0.00001$. The priors for the means of the VAR coefficients δ_i and σ_i are estimated via a three-year training sample.

Defining $Y^* = [Y', Y_d']'$, $X^* = [X', X_d']'$, $\boldsymbol{\beta} = vec(B)$ and T^* as the length of Y^*, this boils down to

$$Y^* = X^* B + U^*. \tag{10}$$

It follows that the parameters of the model are given by:

$$B = (X'^* X^*)^{-1}(X'^* Y^*) \tag{11}$$

$$V = (Y^* - X^* B)'(Y^* - X^* B) \tag{12}$$

and the posterior by

$$p(\boldsymbol{\beta}|\Omega) \sim N(\boldsymbol{\beta}, \Omega \otimes (X^* X^*)^{-1}) \tag{13}$$

$$p(\Omega|\boldsymbol{\beta}) \sim iW(S^*, T^*). \tag{14}$$

To estimate the history of the states we impose a normal prior on the parameters of the transition probabilities equation. Regarding the priors, the most important assumption is the mean of the γ_1 coefficient, for which we choose 0 to reflect the idea that the probabilities for switching the regime are influenced symmetrically by the regime of the previous period.

Next, we provide a roadmap for the estimation stage.[6] Given the initial conditions for the coefficients [$\boldsymbol{\beta}^0$, Ω^0], the transition probabilities [$q(z_t)^0$, $p(z_t)^0$], and the parameters associated with the latent variable $\Gamma^0 = [\gamma_0, \gamma_1, \gamma_2]$, denoting the iteration number by j:

1. Draw S_T^j using a Hamilton filter conditional on Γ^{j-1} and S_t^{*j-1}, .
2. Conditional on S_T^j and Ω^{j-1}, draw the VAR coefficients $\boldsymbol{\beta}^j$ (eq. 13).
3. Conditional on $\boldsymbol{\beta}^j$, draw Ω^j from the inverse Wishart (eq. 14).
4. Given S_T^j, z_t^j, draw the latent variable S_t^{*j} and evaluate the transition probabilities (equations 6 and 7).
5. Draw Γ^j (eq. 5).
6. Let $j = j + 1$ and go back to step 1 until the desired number of iterations is reached.

In the following sections we lay out the data and apply the estimation strategy to Hong Kong's currency board system.

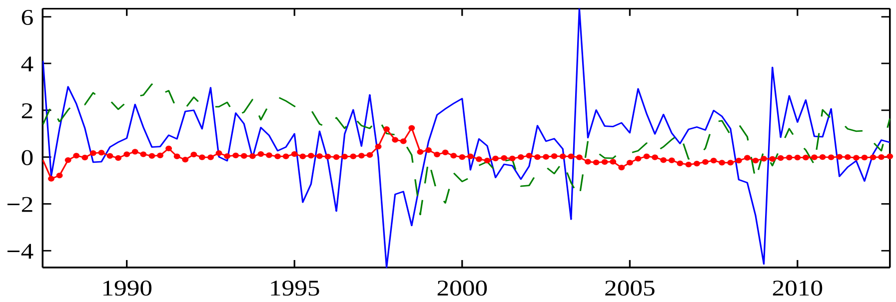
4 Data and Identification

The data for Hong Kong comprise 105 quarterly observations from the last quarter of 1986 to the last quarter of 2012. For the sake of clarity, we use a small set of variables for the main model - the per capita real GDP growth rate (expressed in log differences), the CPI inflation

[6] For a detailed derivation, see Carter and Kohn (1994), Chib (1996), Filardo and Gordon (1998), Amisano and Fagan (2010) or Banbura et al. (2010) among others.

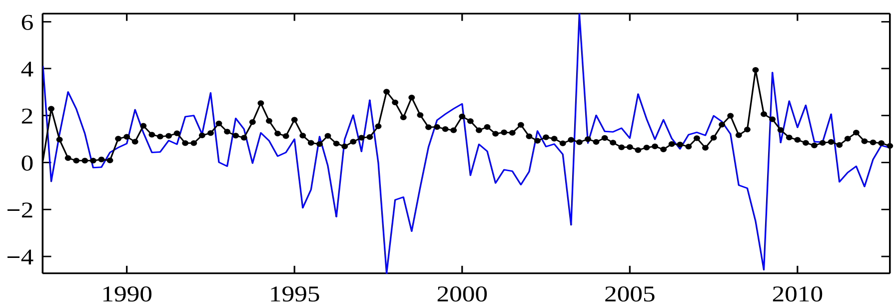
rate and the spread between the 3-month HIBOR and the 3-month LIBOR. We then embed the endogenous switching mechanism into the standard VAR.

Figure 2: GDP growth rate (—), Inflation (- -), HIBOR-LIBOR spread (-.-)



When using the method of Filardo (1994), the choice of the indicator variable is critical. The time series should have a leading property and be representative of the expectations of the economic agents and should capture the uncertainty. Equity markets provide an informative gauge of the price of uncertainty. They reveal investors' assessments of how risks impact 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 a volatility index. In order to capture the uncertainty of the Hong Kong financial markets, we turn to the Hang Seng index (HSI), which starts at 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, plotted against the rate of GDP growth. The index appears to be countercyclical: a fall in the GDP growth rate is associated with a rise in uncertainty.

Figure 3: GDP (—) and HSVI (-.-)



We achieve identification using a Cholesky ordering. In the main specification, we follow the literature of ordering the nominal variables last, assuming no contemporaneous response of the real variables to changes in nominal variables in the current period. For robustness we also explore other orderings, which do not lead to a qualitative change in the results. To address

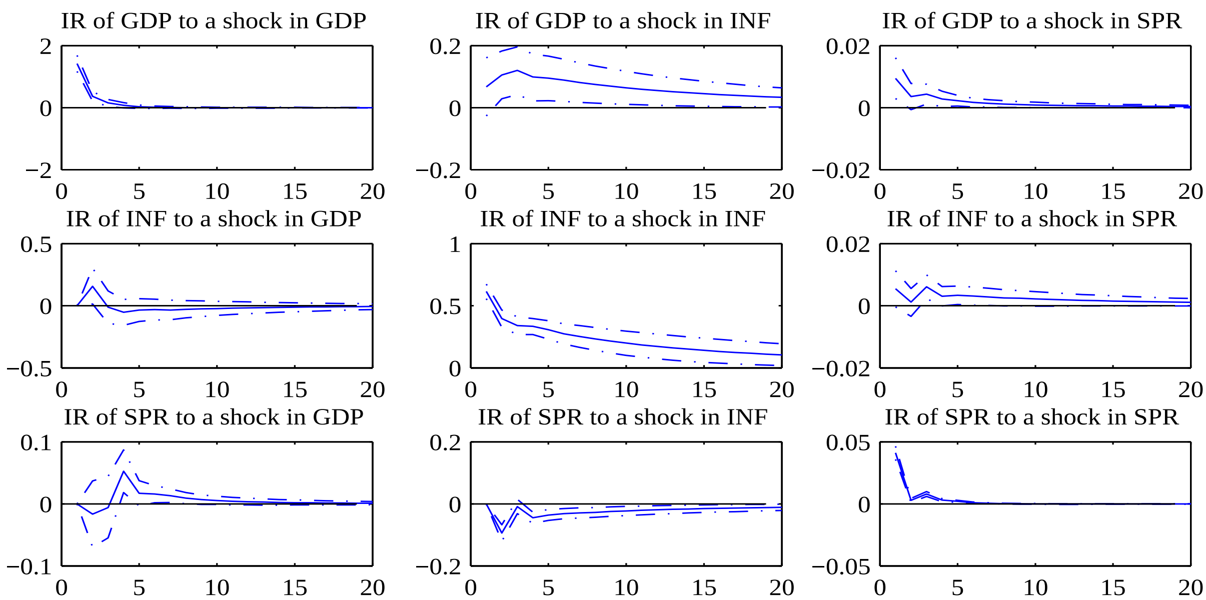
[7] However, an obvious concern is over causality. Since stock markets are forward looking and respond to economic forecasts, the MS VAR-based results might simply reflect a tendency for financial markets to become more volatile and unpredictable when an economic downturn looms on the horizon.

the issue of state labelling, we use the simple condition that the higher variance of the interest rate reduced form shock is attributable to the second regime, i.e. $\sigma_i^2(1) < \sigma_i^2(2)$. The lag order is 3 using the Akaike criterion, which results in an estimation window spanning from 1987Q3 to 2012Q4. Following the roadmap specified above, we run the GIBBS sampler 30000 times. We discard the first 25000 as a burn-in period, leaving us with 5000 draws in total.[8]

5 Baseline Estimation Results

Figures 4 and 5 display the key results. Figure 4 shows the conditional impulse responses for the first regime. Each column shows the dynamics of the system following a shock to the variables in the Cholesky ordering. We assume that that the system cannot switch between regimes after an innovation is realized. The impulse responses are plotted with the 68% probability intervals from the posterior distribution.

Figure 4: State Conditional Impulse Response Functions for the First Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

In the first regime, after a one standard deviation increase in output, inflation reacts procyclically while the spread does not react significantly (Figure 4, first column). The rise in prices is positive, albeit short, as inflation returns to its original level after a few quarters. A shock to inflation in the first regime has no effect on output initially but over time reacts marginally positively (Figure 4, second column). The interest rate differential reacts negatively to rising prices, meaning that interest rates fall initially. This behaviour can be explained by the absence of autonomous monetary policy, which does not allow the monetary authority to

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

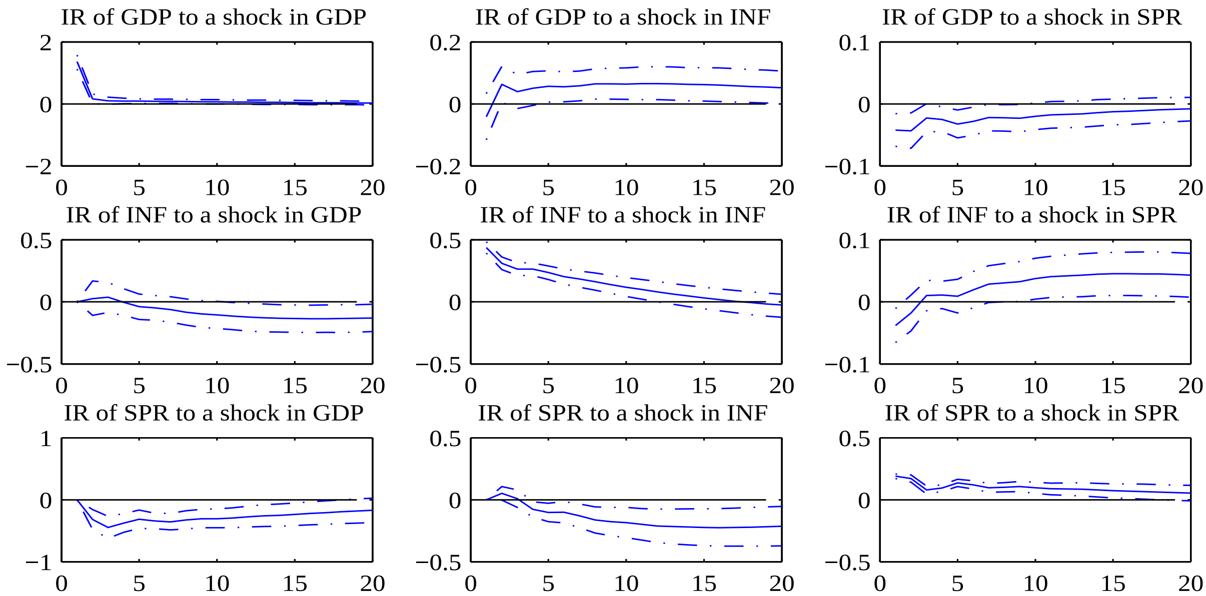
raise the interest rates. In this regime, an opening of the spread does not seem to have a significant effect on the other macroeconomic variables (Figure 4, third column). Output rises marginally, while inflation does not react at all.

In contrast, the system behaves differently in the second regime, as illustrated in Figure 5. First, output does not seem to have a significant effect on inflation. A rise in GDP in the second state does not seem to have any effect on prices while the spread responds strongly and counter-cyclically, in contrast to the first regime. This suggests, that a rise in demand during the second regime would help to reduce any existing spread. In contrast, a contraction in output would increase the HIBOR relative to the LIBOR. In general, such dynamics are usually observed during a recession or economic crisis. In summary it can be said that the economy exhibits strong non-linearities in its response to shocks.

Similarly, inflation shocks also follow a scenario which occurs in economic recessions. An increase in inflation leads to a rise in output and a narrowing of the spread. Since in recessions demand and inflation fall, news of rising inflation is often seen as a sign of recovery and is followed by analogous behaviour of the macroeconomic variables.

Most importantly, a positive HIBOR-LIBOR spread leads to a fall in output. While unresponsive in the first regime, the difference between the interest rates is negatively affected by both inflation and output shocks in the second state.[9]

Figure 5: State Conditional Impulse Response Functions for the Second Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

While the empirical nature of the method does not allow us to attach a structural interpretation to the regimes, the dynamics of the system mirror the analysis of an earlier work by Blagov and Funke (2013) who isolate the effects of credibility loss in a structural Markov-Switching

[9] The reduced form variance-covariance matrices are presented in the Appendix.

DSGE model. The macroeconomic variables do not react to widening of the spread during the first regime, which replicates the responses in the high credibility regime. On the other hand, in the low-credibility regime, the spread has a detrimental effect on the economy, which is replicated with the MS-BVAR. Naturally, the switching in all variables captures more than just the perceptions as to the currency board.[10] Nevertheless the model is able to replicate the loss and gain of credibility of LERS in terms of impulse responses following a positive interest rate differential.[11]

Figure 6 depicts the transition probabilities for both states (top and middle) plus the probability of the realization of the second state (bottom). The model locates the system was in the second regime after the stock-market crash of 1987 an all the way up to the end of 1991, as in Blagov and Funke (2013). Then, the probability peaks at one again during the Asian and Russian crises and there is a lone spike 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 on the service sector, increasing costs and sharply curbing demand, especially in tourism-related businesses.[12] Moreover the second state is prevalent during the appreciation pressures on the Remninbi prior 2005 and all the way up to the global financial crisis at the end of 2008.

The time-varying transition probabilities provide us with additional insight into the nature of regime switching. The HSVI index is highly informative for the Hong Kong economy and the non-linearities in the data. It is evident that the probability of staying in the first regime - 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 transition probability of the first regime is at its lowest following the 1987 stock market crash and picks up only after 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, suggesting the recovery and the end of the contagion effects from the Asian and Russian crises.

The appreciation pressure of 2004 was accompanied by the steady decline in the probability for the first state which implies that there was information contained in the HSVI. Similar to Blagov and Funke (2013), we note that the financial crisis was not particularly burdensome for the currency board, as evidenced by the strong rise in the transition probability for the first state after 2006.[13] The model estimates that the system was back in the state of low-

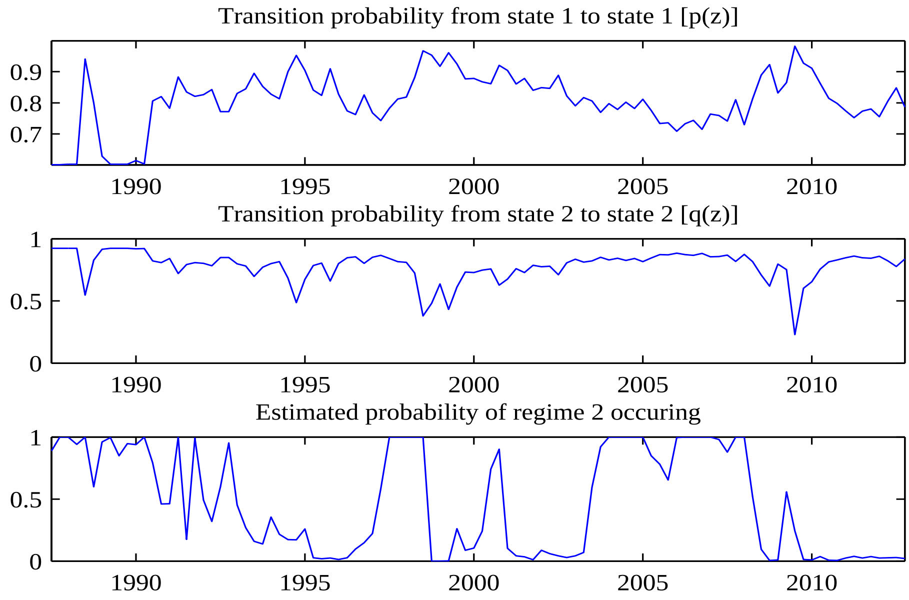
[10] It should be stressed that reverse causation may lead to an attenuation bias in the present context, since a reduced perceived sustainability of the currency board system may shape the Markov-switching trigger variable. Therefore any significant coefficient should provide a lower bound for the absolute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

[11] 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.

[12] For detailed surveys on the economic impacts of the SARS epidemic in Hong Kong, see "The World Health Report, 2003" (WHO, 2003) and Knobler et al. (2004).

[13] Hong Kong's financial institutions have coped relatively well with the global financial crisis due to their

Figure 6: Transition and Regime Switching Probabilities



Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

interest rate spread already in 2009. Overall the results highlight that short-lived volatility shocks may lead to a significant propagation and amplification mechanism 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.

6 Robustness of the Results

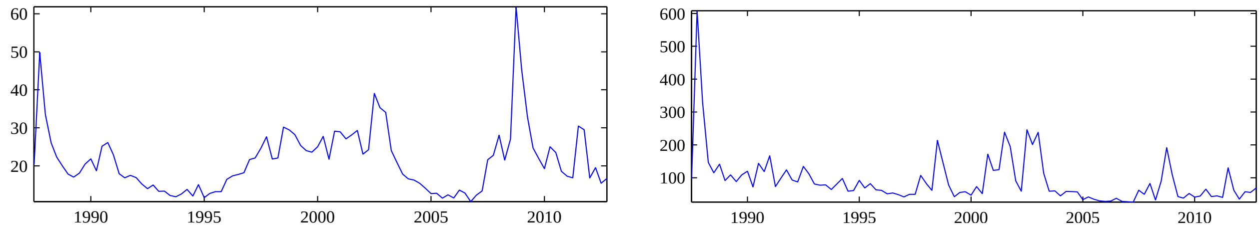
We now turn to the robustness analysis. To that end, we estimate the model with different indices and perform a handful of tests to asses the robustness of our results. In the MS-BVAR framework, the choice of the leading variable is of high importance for estimation. Therefore, we look at several different indicators and check whether we can gain additional information from financial data regarding the Hong Kong economy. The variables are: VIX© (the Chicago Board Options Exchange Market Volatility Index) and the Equity Market Uncertainty Index (EMUI) developed by Scott Baker, Nicholas Bloom and Steven Davis (http://www.policyuncertainty.com), the St. Louis Financial Stress Index © (STLOU) and the spread between the 1 year HKD forward rate and the spot rate (FDmS).[14]

The VIX is a broad index derived from S&P 500 options. It has the appealing property for a leading variable of incorporating the one month ahead expectations of agents regarding

high capital adequacy ratios and their minimal exposure to securitised products.

[14] One rationale for choosing the EMUI 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 needed to capture the full amount of uncertainty in the economy.

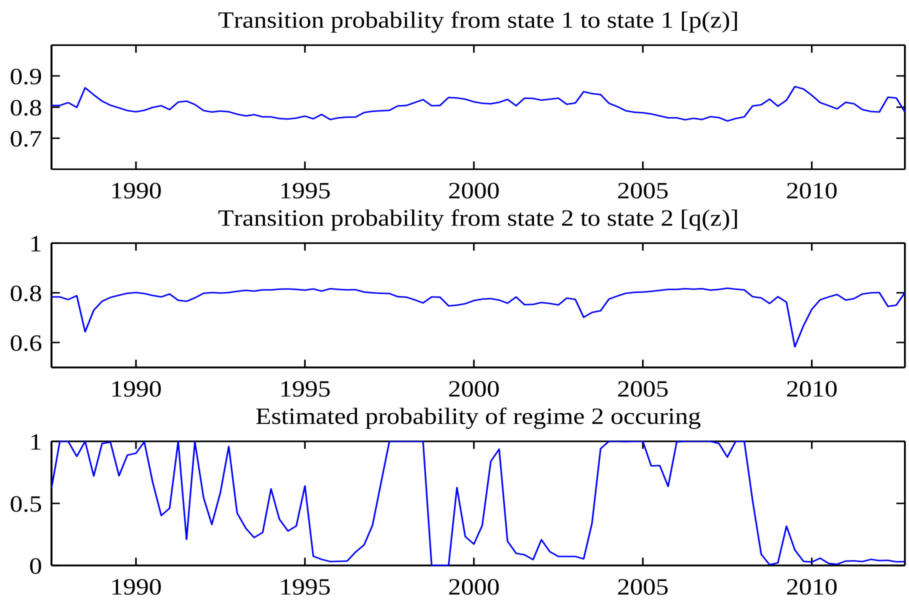
Figure 7: Market Volatility Indices



(a) VIX Index (b) Equity Market Uncertainty Index

stock market volatility. Hence it is a natural starting point for our robustness analysis. Figure 8 displays the VIX index for the period from 1987 to the end of 2012. We plot the transition probabilities of the model with the index being the leading variable in the left panel of Figure 7. As evident, they are almost flat, with minor exceptions. This implies that in this setup VIX is not informative for the Hong Kong economy. Econometrically this can be tested by a simple hypothesis test on the coefficient γ_1 in equation 5. Indeed, the probability interval contains the zero.[15] This means that the model reduces to a fixed probabilities case. In terms of the prevalent second regime, Figure 8 does not offer additional insight compared to the HSVI index with some minor exceptions around the dot-com bubble and the boom in the middle of the nineties. 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 as well as the 2004-2009 period in contrast to Blagov and Funke (2013).

Figure 8: Transition and Regime Switching Probabilities (VIX)



Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

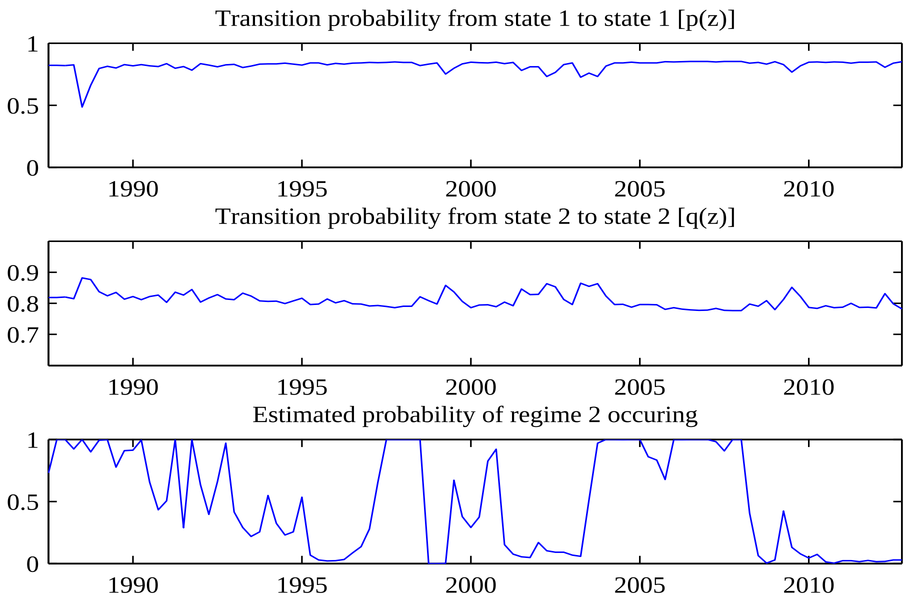
While the stock market volatility of the S&P 500 options might not be directly informative

[15] See Table A1 in the appendix for additional details.

for the currency board of Hong Kong, other types of uncertainty may play an important role. One such factor might be economic news. 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 gauge the uncertainty of stock markets.

The index is depicted on the right panel of Figure 7 and Figure 9 shows the transition probabilities implied by the model with the EMUI as the leading variable. Equity market uncertainty has a small effect on the variation of the transition probability of the second regime. However, again the credible interval for γ_1 contains zero. Similar to the VIX index, uncertainty reflected by the news articles does not bring additional insight on the Hong Kong economy compared to the HSVI. The probabilities are flat around 0.8, which implies on average longer and even durations of both regimes.

Figure 9: Transition and Regime Switching Probabilities (EMUI)

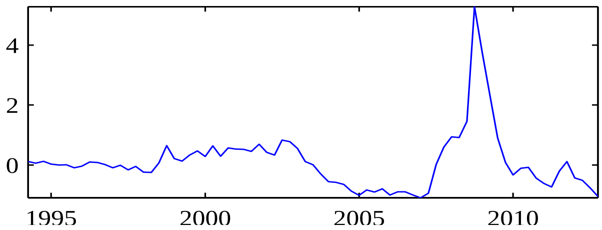


Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

Both robustness check specifications confirm the estimated regime switches in the main model, and the macroeconomic system behaves as depicted by the impulse response functions.[16] The crises periods are associated with higher volatility of the spread rates and lower volatility of output and inflation. Shocks to the interest rate spread in the first regime do not have a significant effect on output or inflation, while the system reacts negatively under the second regime, where both output and inflation contract for prolonged periods after an increase in the spread.

[16] See Figures A3 and A4 for the impulse responses under VIX and Figures A7 and A8 for EMUI in the Appendix.

Figure 10: St. Louis Stress Index

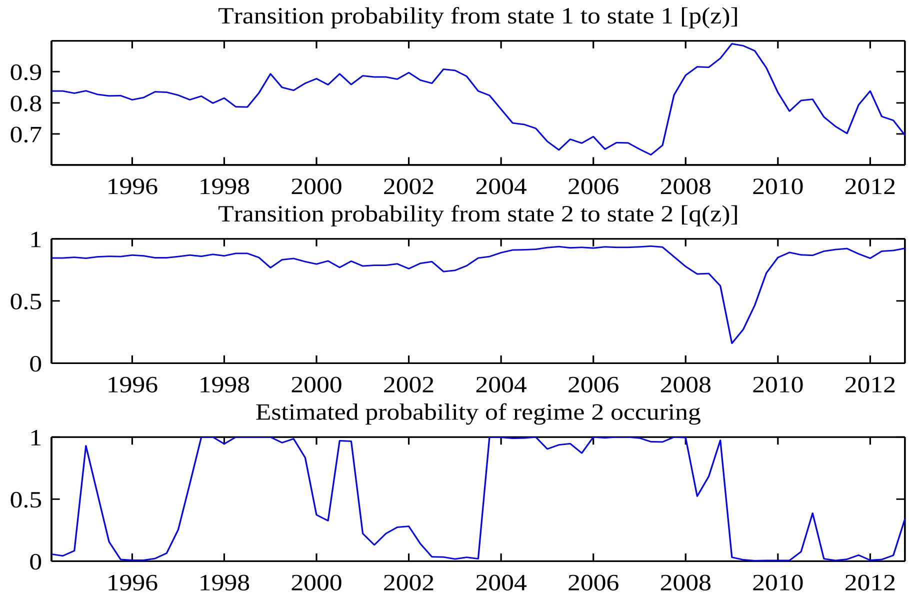


Next we turn our attention to the St. Louis Financial Stress Index, composed by the Federal Reserve Bank of St. Louis. The index is a composite index comprised of a multitude of financial time series such as six yield spreads, eighteen weekly series and other macroeconomic indicators. Hence, it is different from the EMUI, being on raw data, and it provides different information than does the VIX, which is based solely on S&P 500 options. The index, presented in Figure 10, is centred around zero, which represents the average financial stress on the markets. Positive and negative values represent above average and below average financial stress, respectively. STLOU is available from 1993 onwards, which reduces our sample by 24 observations. Therefore we reduce the lag length to 1, based on the BIC criterion.

The financial stress indicator presents interesting and different results compared to the other estimations. It is informative for the Hong Kong economy, as evident from Figure 11. Due to data availability, there is nothing we can say regarding the stock market crash in 1987 and its aftermath. The probability of the first state 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 $(1 - P(S_t = 0|S_{t-1} = 0))$ is increasing. The index shows a steady decline of the state associated with low interest rate volatility beginning in 2004 and leading all the way up to the financial crisis, reaching its lowest levels during the appreciation pressure in 2005 and once more in the middle of 2007. It also estimates a high transition probability, of around 0.9, for the second regime, implying a long average duration of the second regime. Consequently, the system estimates that the economy was much longer in the state of high interest rate volatility. After a brief stint during 1995, the probability of the second regime hits 1 at the onset of the Asian crisis and remains high throughout the turbulent period all the way up to 2001, except a minor fall below 0.5 in the beginning of the new century.

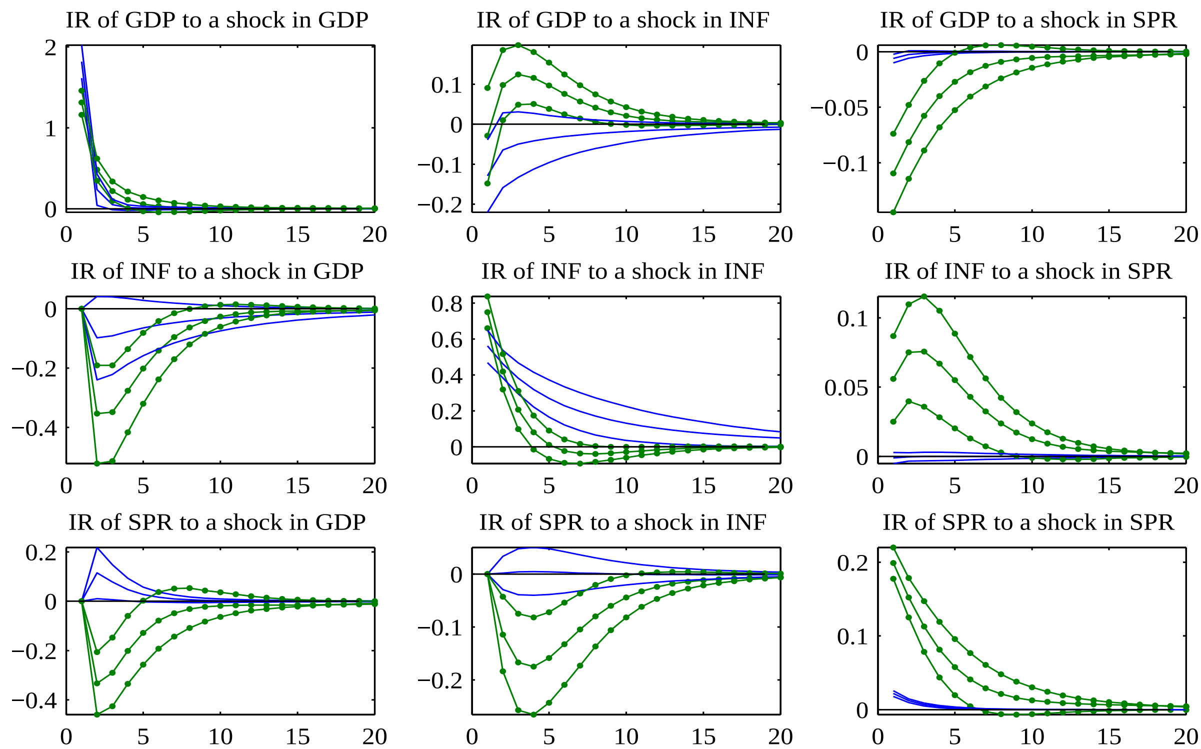
The next switch to the second regime is in the middle of 2003, similar to our main indicators. The economy does not return to the first state until 2009. This model also associates higher volatility of output with the first regime, which explains the sharp rise in the transition probability of the first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

Figure 11: Transition and Regime Switching Probabilities (STLOU Index)



Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

Figure 12: State Conditional Impulse Responses (STLOU)

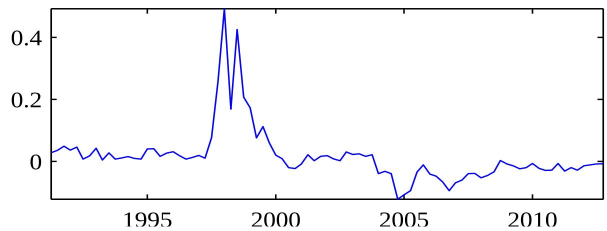


Blue: impulse responses in the first state (middle line). Green: impulse responses in the second state (middle line). One standard deviation shocks along the main diagonal. 68% probability intervals. Separate graphs are available in the Appendix.

In contrast to the other indicator variables, the model suggests slightly different macroeconomic dynamics. Figure 12 combines the impulse responses from both states. Based on the HSVI index, a widening of the spread in the low-volatility regime was associated with no response to output or inflation. In the second state, however, a positive difference between HIBOR and LIBOR leads to deflation, and after about eight quarters inflation picks up again, all while output remains negative. There is a difference compared to the St. Louis index, according to which, even though output does fall, the response is smaller. A notable point is that this model specification exhibits a “price puzzle” following a positive interest rate differential. Another difference is in the responses to output shocks in the first regime. Inflation does not react to output, while interest rates rise as a consequence of positive demand shocks above the LIBOR rates.

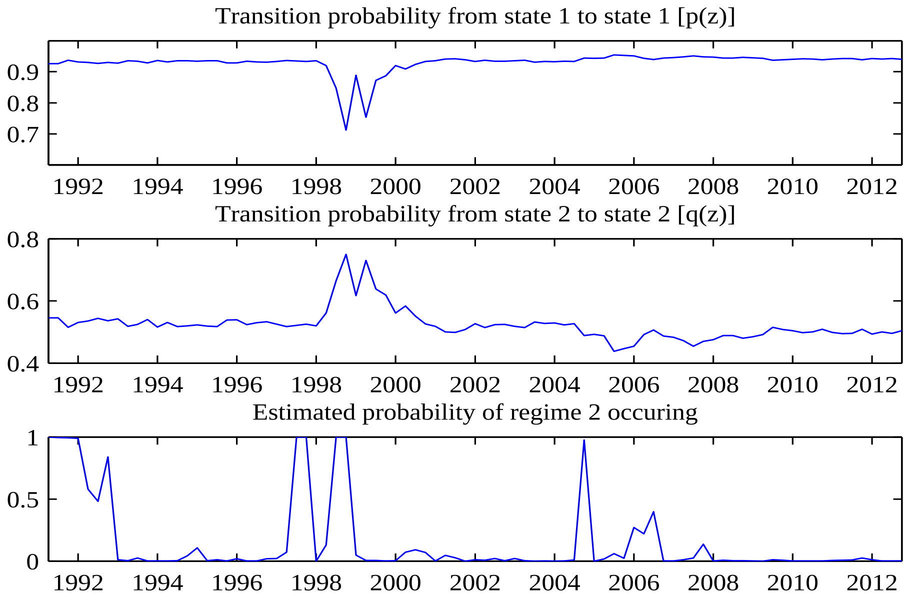
As we are interested in the credibility of the exchange rate system, it is natural to look at the dynamics of the Hong Kong dollar. We estimate the forward premium on the one year HKD forward exchange rate and use it as a leading variable in the model. The series captures the depreciation pressures of the Asian and the Russian crisis and the appreciation pressures in 2005 and thus would be highly relevant for our analysis. The data are presented in Figure 13.

Figure 13: HKD 1Y Forward Market Rate minus the Spot Rate



Estimating the model with the forward premium yields similar quantitative results, with two states characterized by a varying degree of interest rate differential volatility and dissimilar covariances between the variables. Figure 14 presents the transition probabilities and the estimated regimes. While rather flat outside of the crisis periods, they do influence the switch to the second state, especially around the onset of the Russian crisis - there is a sharp rise in the transition probability from the first to the second regime $(1 - P(S_t = 0|S_{t-1} = 0))$ beginning from 1998 and similarly an increase in the transition probability of the other regime. On the other hand, the appreciation pressures in 2005 do not seem to be captured by the probabilities from the forward premium, which is evident by the fact that around 2005 the second transition probability even falls slightly below 0.5. We can conclude that positive a forward premium is more informative 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 14: Transition and Regime Switching Probabilities (FDmS)

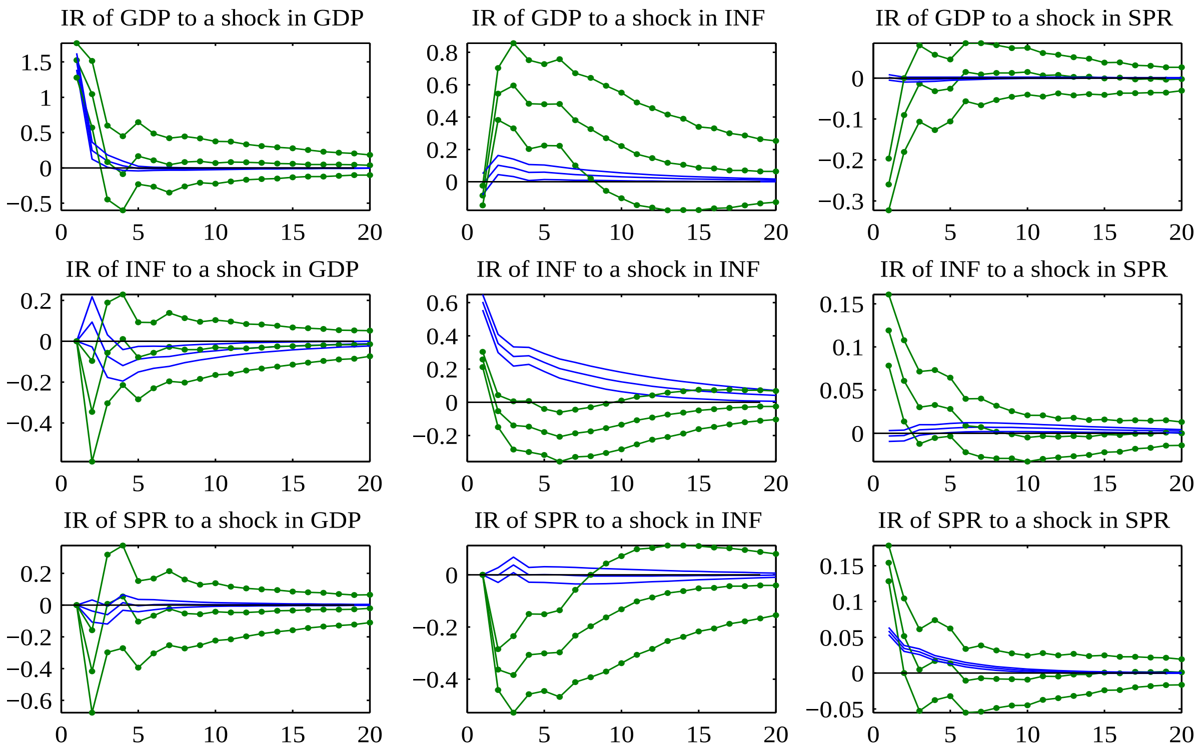


Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

The result in the last panel of Figure 14 echoes the empirical DSGE model findings of Blagov and Funke (2013), where the regime of low-credibility of the currency board is prevalent at the end of the 1987 up to 1992 and from the second quarter of 1997 to the end of 1999 and there is a lone spike in the beginning of 2005. The forward premium on the HKD leaves us with almost the same picture, with the minor exception of a drop in the first quarter of 1998. We would however that the probabilities presented here are not smoothed and are not directly comparable to the smoothed probabilities of a fixed transition probability model. In other words, they do not incorporate the full information contained in the vector S_T but are rather a good approximation.

Similar to the St. Louis index, this model exhibits slightly different behaviour in terms of impulse responses compared to the model under the HSVI. Most notably, in the second regime we again observe a "price puzzle" (third column of Figure 15). Moreover, the fall of output following a positive spread in the second state is much larger: an interest rate differential of 0.15 points leads to more than one-to-one fall in output, with demand falling by almost 0.25. This can be explained by the fact that the second regime prevails mainly during the most turbulent times in the Hong Kong economy.

Figure 15: State Conditional Impulse Responses (FDmS)



Blue: impulse responses in the first state (middle line). Green: impulse responses in the second state (middle line). One standard deviation shocks along the main diagonal. 68% probability intervals. Separate graphs are available in the Appendix.

7 Conclusions

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

This non-linear feature of currency boards is precisely the motivation for this paper to employ a Markov-Switching VAR framework with time-varying transition probabilities to study the effects of credibility in the Hong Kong 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 to debate. Furthermore, the global financial crisis, which has pushed financial markets into turmoil, highlighted the crucial role and non-linear nature of economic and financial shocks. We believe that our MS-VAR framework may be a useful step towards a more complete understanding of the role of uncertainty and/or volatility shocks on time-varying exchange rate regime credibility.

We turn to the framework by 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 the coefficients and estimate two regimes which are quite distinct from each other. The first is associated with a low interest rate spread volatility, higher inflation volatility, and largely positive covariances between output, inflation and the spread. The second state is characterized by negative covariances between the variables as well as an interest rate spread volatility of a magnitude of the order of 20 times that of the first regime. In other words, using the reduced form approach, we are able to capture the dynamics of the Hong Kong economy, which exhibit properties 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 no effect or a very small pro-cyclical effect on output and inflation, while in the latter a positive differential is detrimental to the economy.

We employ an array of other indicators to test these results and learn more about the non-linear behaviour of the Hong Kong economy. We find that famous indicators such as VIX or the Equity Market Uncertainty index do not seem to provide additional information regarding the transition between regimes. On the other hand, broader financial indicators, such as the St. Louis Stress index or the forward premium on the Hong Kong dollar, present interesting insights into the nature of switching, as well as introducing the "price puzzle" into the model.

We conclude that the conditional volatility implied by the Hang Seng index, the St. Louis financial stress index and the forward premium are valid indicators and are informative of the regime switches providing anticipatory effects.

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Appendix:

Table A1: Estimates for γ_1 under the different specifications

	coeff.	std.dev	95% Prob. 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]

Reduced Form Variance-Covariance Matrices

Table A2: Reduced Form Variance-Covariance Matrices for the HSVI

	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]
$\sigma_{y,\pi}$	0.085 [-0.088, 0.256]	0.397 [0.303, 0.504]	0.004 [-0.001, 0.009]
$\sigma_{y,spr}$	0.013 [0.001, 0.025]	0.004 [-0.001, 0.009]	0.002 [0.001, 0.003]

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	1.903 [1.147, 2.711]	-0.065 [-0.213, 0.071]	-0.057 [-0.109, -0.008]
$\sigma_{y,\pi}$	-0.065 [-0.213, 0.071]	0.202 [0.147, 0.263]	-0.016 [-0.033, 0.001]
$\sigma_{y,spr}$	-0.057 [-0.109, -0.008]	-0.016 [-0.033, 0.001]	0.041 [0.031, 0.053]

First regime (left) and second regime (right). 95% credible intervals in brackets.

Table A3: Reduced Form Variance-Covariance Matrices for the VIX index.

	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]
$\sigma_{y,\pi}$	0.063 [-0.134, 0.249]	0.397 [0.301, 0.508]	0.005 [0.000, 0.011]
$\sigma_{y,spr}$	0.010 [-0.002, 0.023]	0.005 [0.000, 0.011]	0.002 [0.001, 0.002]

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	1.685 [1.067, 2.543]	-0.036 [-0.179, 0.088]	-0.054 [-0.103, -0.008]
$\sigma_{y,\pi}$	-0.036 [-0.179, 0.088]	0.203 [0.148, 0.266]	-0.017 [-0.035, -0.001]
$\sigma_{y,spr}$	-0.054 [-0.103, -0.008]	-0.017 [-0.035, -0.001]	0.041 [0.030, 0.052]

First regime (left) and second regime (right). 95% credible intervals in brackets.

Table A4: Reduced Form Variance-Covariance Matrices for the EMUI

	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]
$\sigma_{y,\pi}$	0.091 [-0.088, 0.268]	0.394 [0.301, 0.502]	0.005 [0.000, 0.011]
$\sigma_{y,spr}$	0.012 [0.000, 0.023]	0.005 [0.000, 0.011]	0.002 [0.001, 0.002]

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	1.883 [1.132, 2.688]	-0.065 [-0.211, 0.068]	-0.055 [-0.106, -0.007]
$\sigma_{y,\pi}$	-0.065 [-0.211, 0.068]	0.207 [0.154, 0.266]	-0.016 [-0.033, -0.000]
$\sigma_{y,spr}$	-0.055 [-0.106, -0.007]	-0.016 [-0.033, -0.000]	0.041 [0.030, 0.052]

First regime (left) and second regime (right). 95% credible intervals in brackets.

Table A5: Reduced Form Variance-Covariance Matrices for the STLOU Index

	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]
$\sigma_{y,\pi}$	-0.236 [-0.478, -0.012]	0.351 [0.219, 0.492]	0.000 [-0.003, 0.004]
$\sigma_{y,spr}$	-0.012 [-0.021, -0.002]	0.000 [-0.003, 0.004]	0.001 [0.000, 0.001]

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	1.772 [1.274, 2.358]	-0.045 [-0.269, 0.169]	-0.147 [-0.224, -0.079]
$\sigma_{y,\pi}$	-0.045 [-0.269, 0.169]	0.588 [0.414, 0.793]	0.047 [0.010, 0.088]
$\sigma_{y,spr}$	-0.147 [-0.224, -0.079]	0.047 [0.010, 0.088]	0.058 [0.041, 0.078]

.

First regime (left) and second regime (right). 95% credible intervals in brackets.

Table A6: Reduced Form Variance-Covariance Matrices for the FDmS Index

	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]
$\sigma_{y,\pi}$	-0.013 [-0.152, 0.128]	0.369 [0.298, 0.448]	-0.002 [-0.007, 0.003]
$\sigma_{y,spr}$	0.002 [-0.012, 0.016]	-0.002 [-0.007, 0.003]	0.004 [0.003, 0.005]

	σ_y^2	$\sigma_{y,\pi}$	$\sigma_{y,spr}$
σ_y^2	2.511 [1.468, 3.878]	-0.153 [-0.332, -0.001]	-0.406 [-0.630, -0.222]
$\sigma_{y,\pi}$	-0.153 [-0.332, -0.001]	0.086 [0.049, 0.132]	0.056 [0.025, 0.093]
$\sigma_{y,spr}$	-0.406 [-0.630, -0.222]	0.056 [0.025, 0.093]	0.112 [0.069, 0.167]

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First regime (left) and second regime (right). 95% credible intervals in brackets.

VIX Index

Figure A1: VIX Index

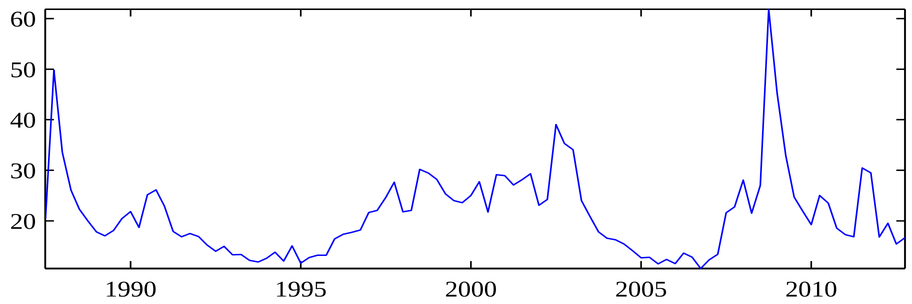
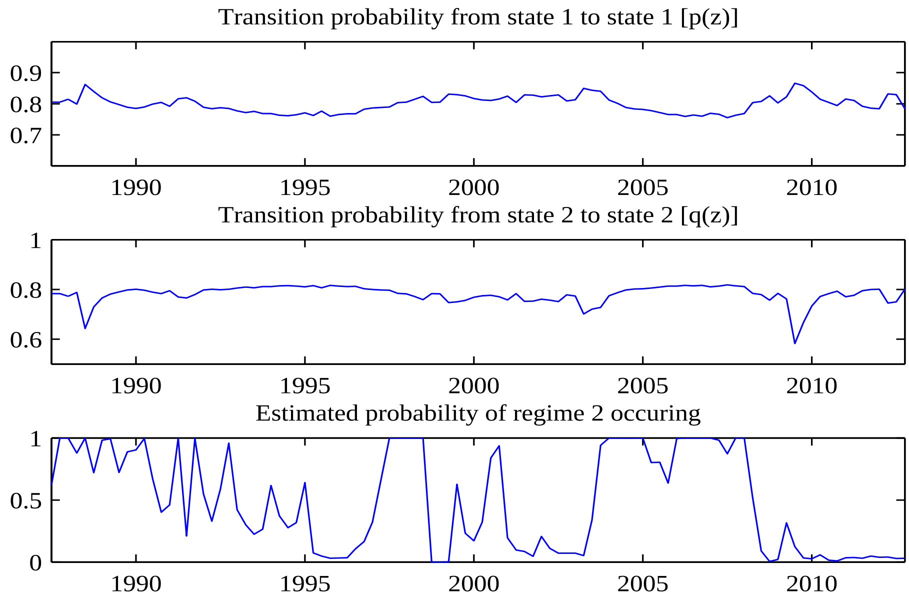
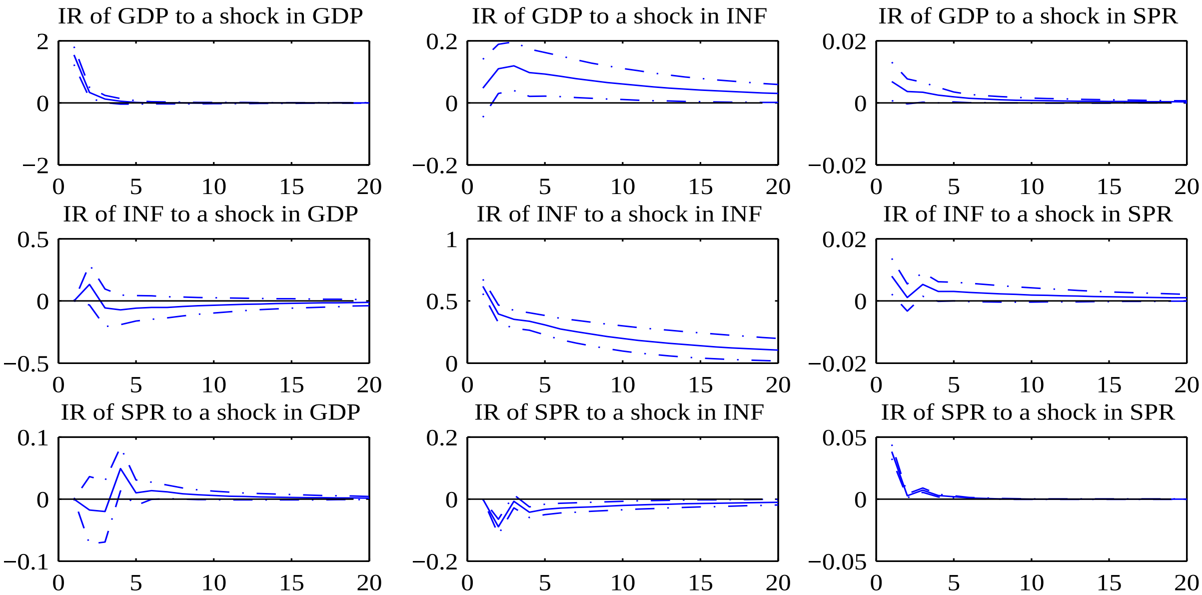


Figure A2: Transition and Regime Switching Probabilities (VIX)



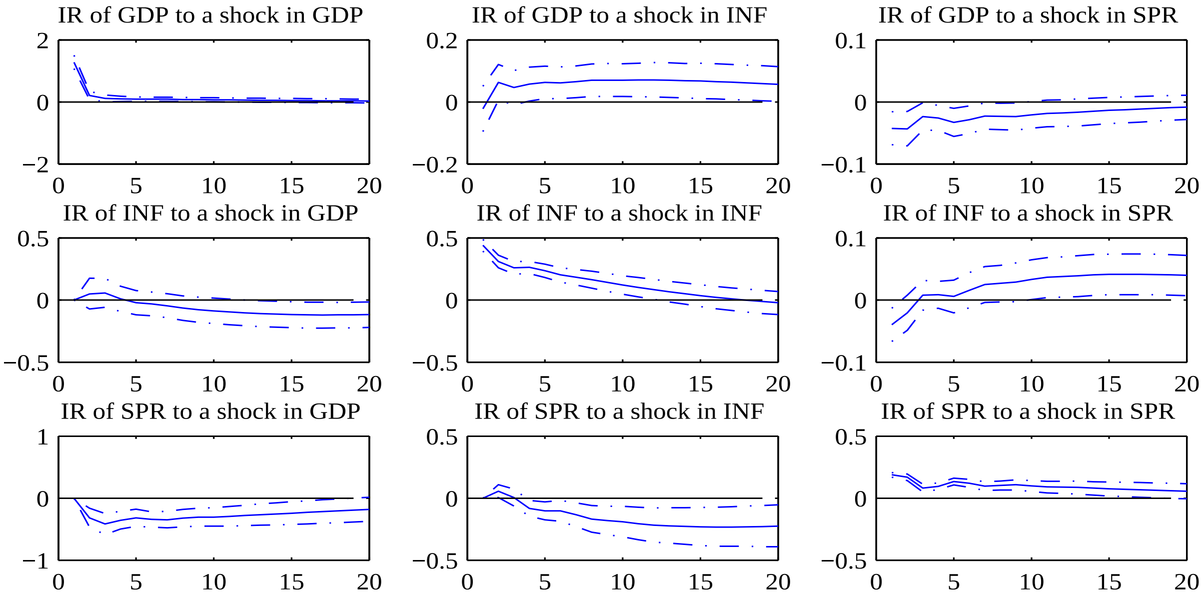
Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

Figure A3: State Conditional Impulse Response Functions for the First Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

Figure A4: State Conditional Impulse Response Functions for the Second Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

Equity Market Uncertainty Index

Figure A5: Equity Market Uncertainty Index

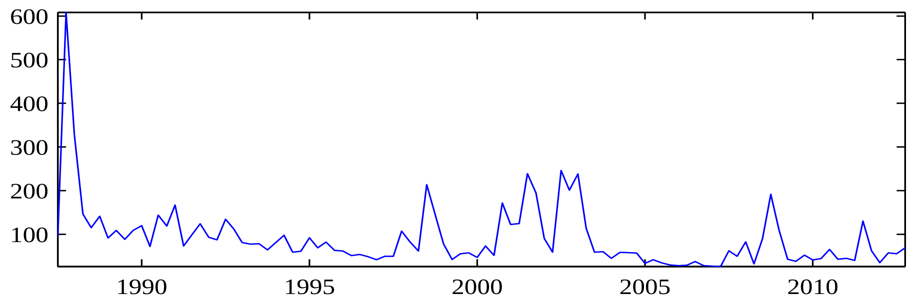
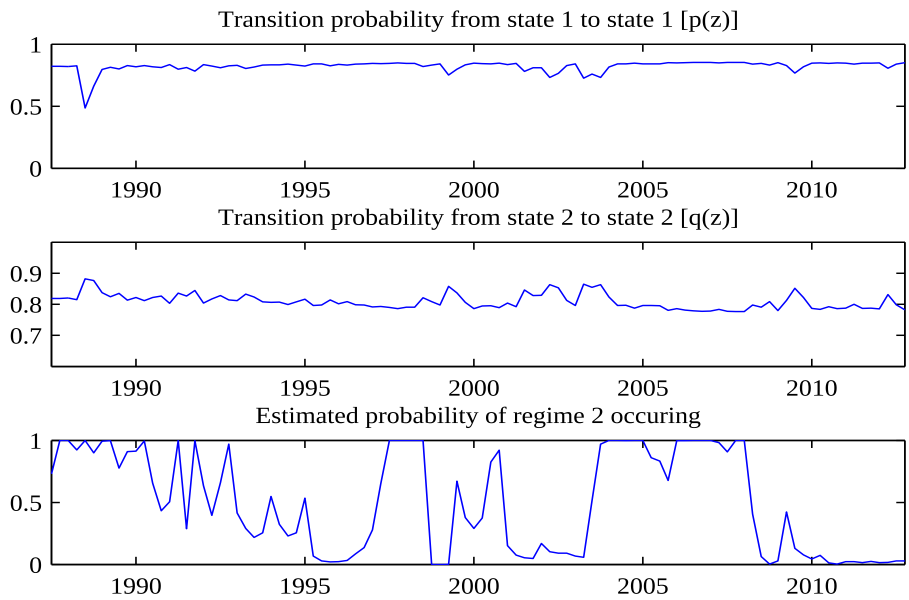
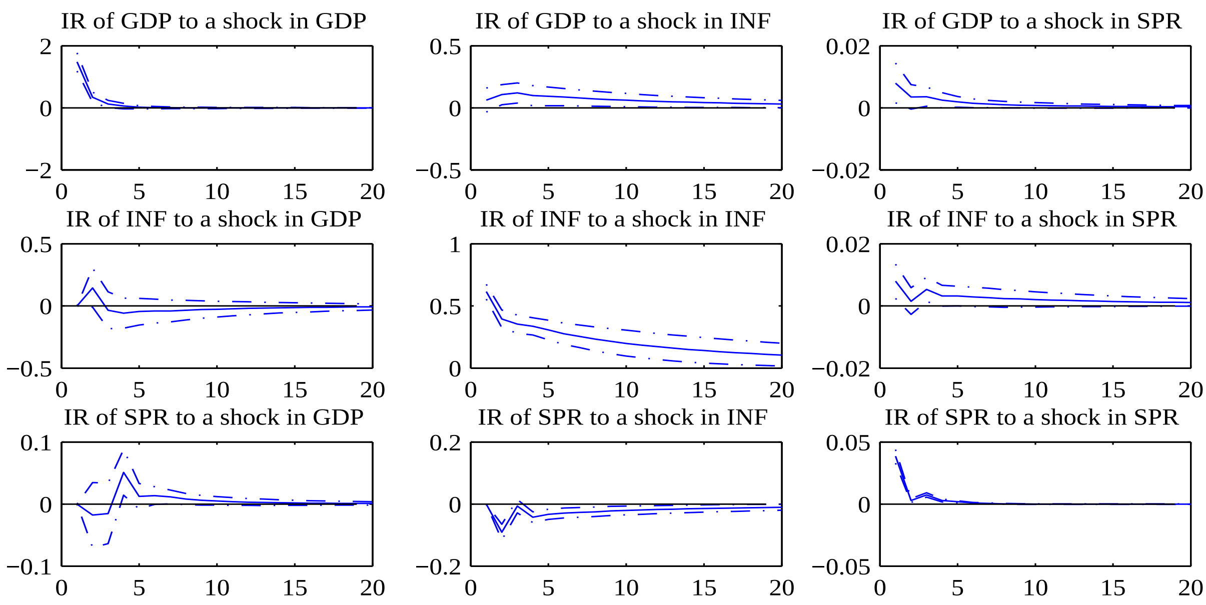


Figure A6: Transition and Regime Switching Probabilities (EMIU)



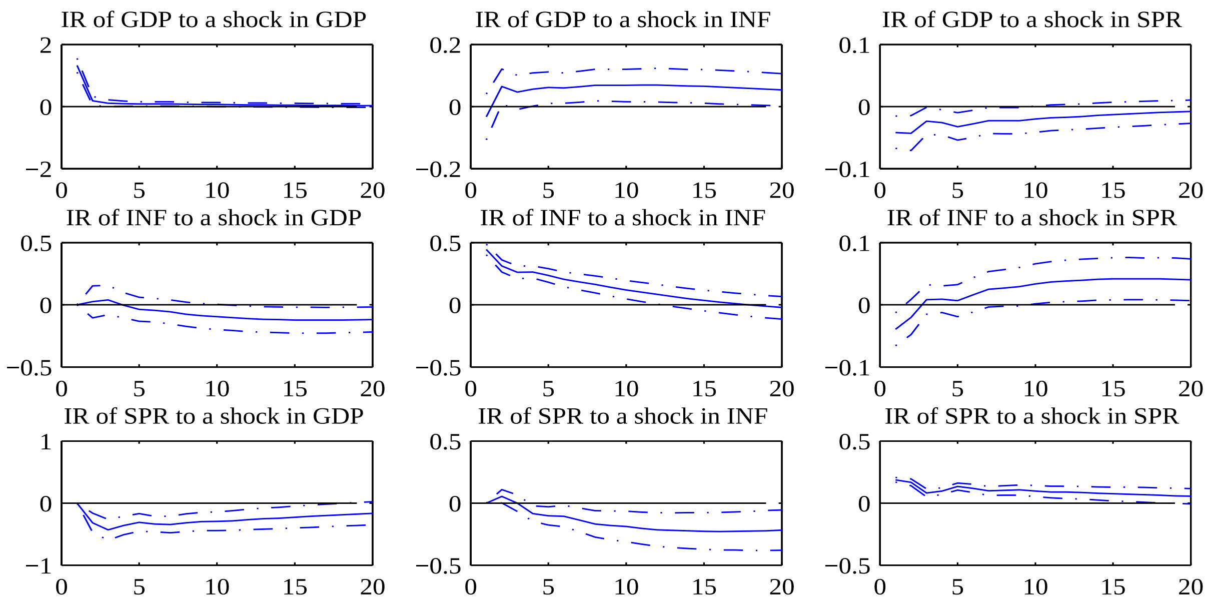
Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

Figure A7: State Conditional Impulse Response Functions for the First Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

Figure A8: State Conditional Impulse Response Functions for the Second Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

St. Louis Stress Index

Figure A9: St. Louis Stress Index

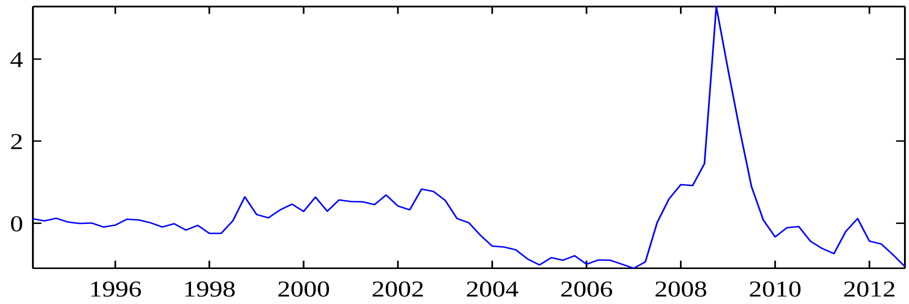
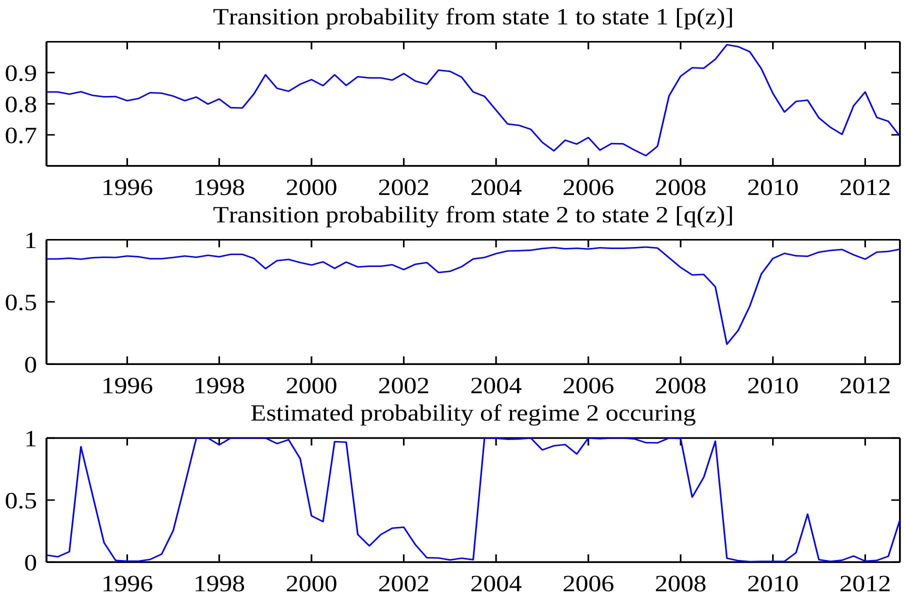
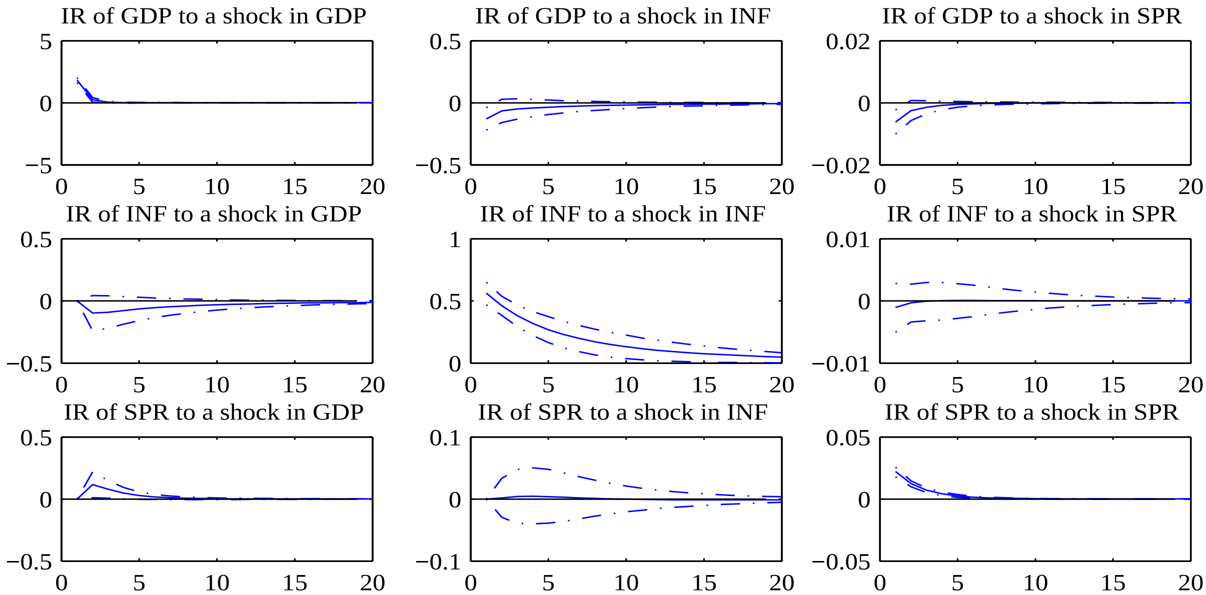


Figure A10: Transition and Regime Switching Probabilities (STLOU



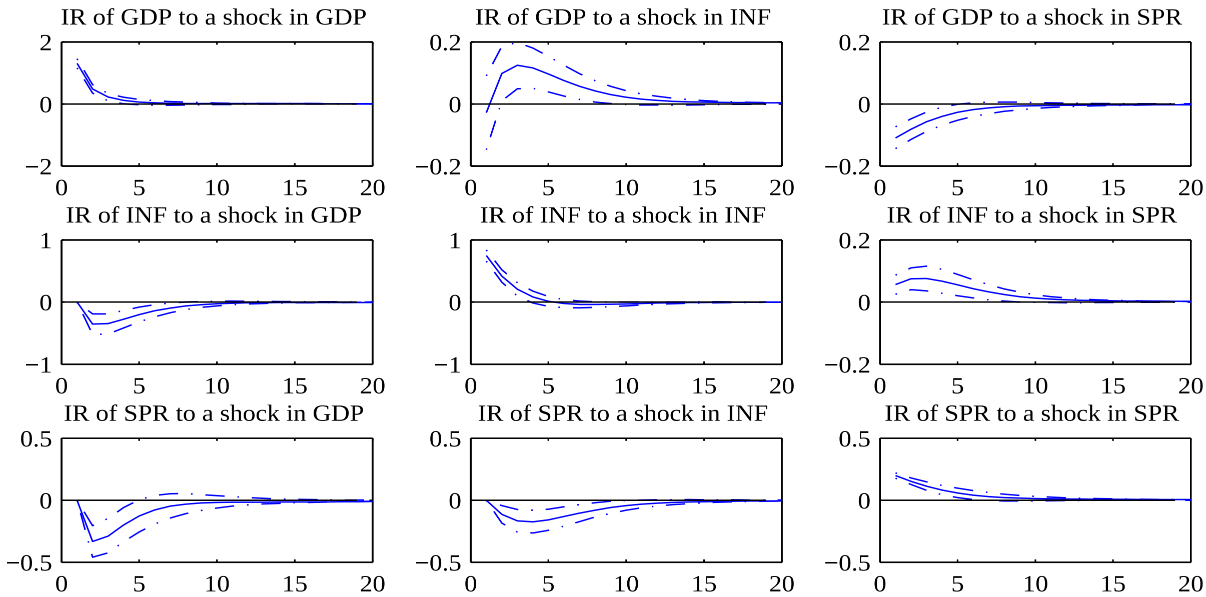
Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

Figure A11: State Conditional Impulse Response Functions for the First Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

Figure A12: State Conditional Impulse Response Functions for the Second Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

HKD 1Y Forward Market Rate over the Spot Rate

Figure A13: HKD 1Y Forward Market Rate Over the Spot Rate

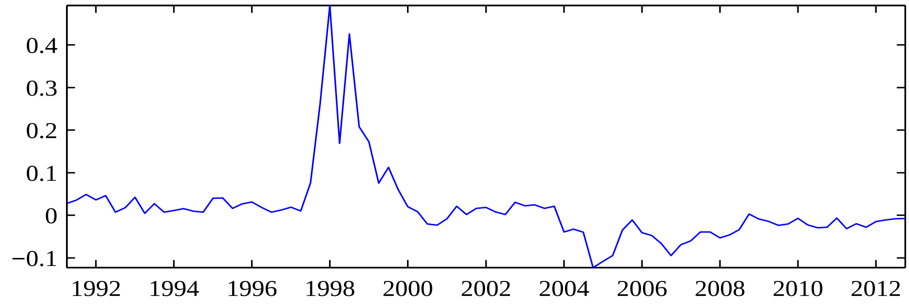
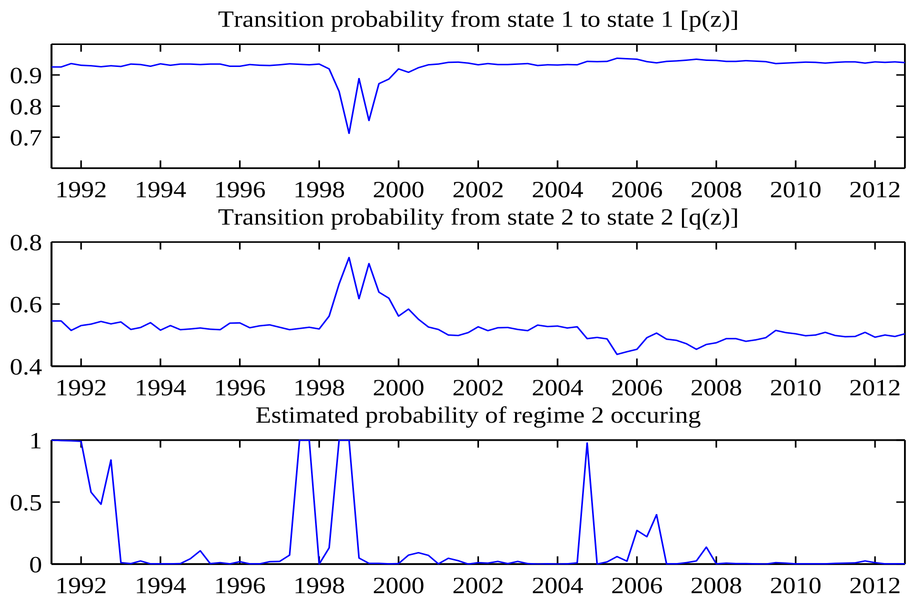
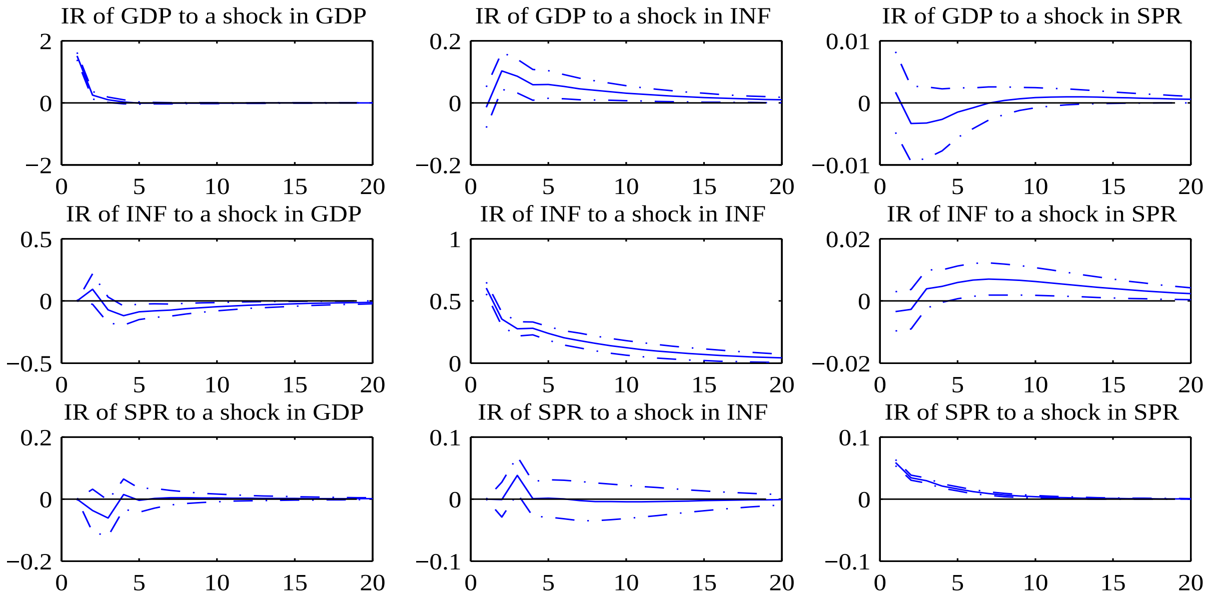


Figure A14: Transition and Regime Switching Probabilities (FDmS)



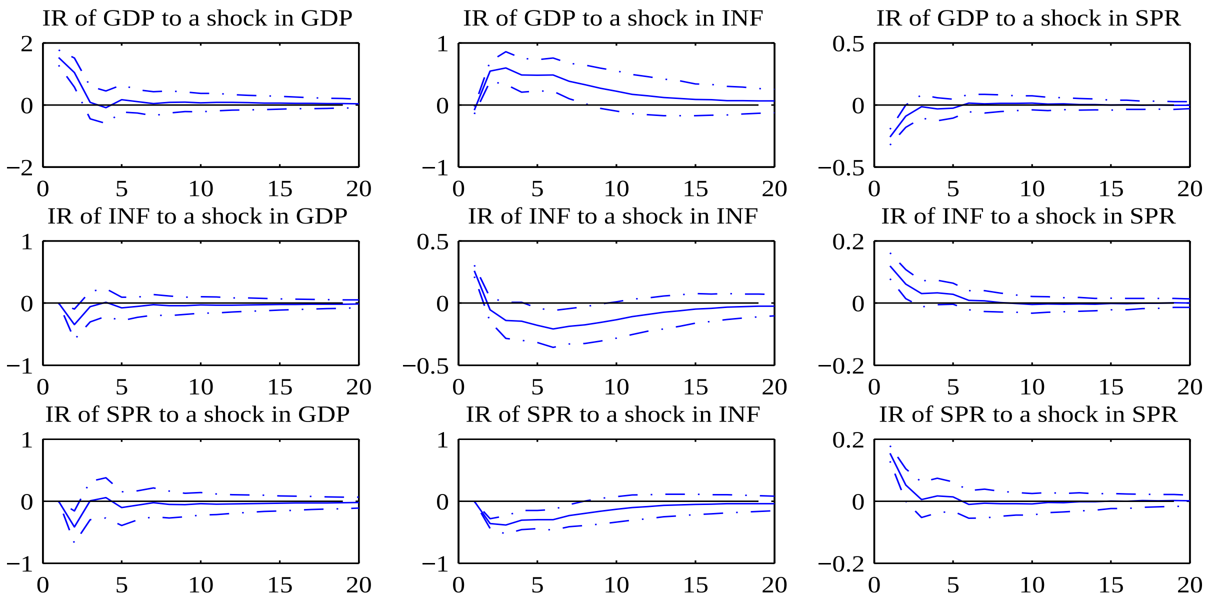
Probability of staying in the first regime (top). Transition probability for the second regime (middle). Probability of the second regime prevailing (bottom).

Figure A15: State Conditional Impulse Response Functions for the First Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

Figure A16: State Conditional Impulse Response Functions for the Second Regime



Each column contains the impulse responses to a one standard deviation shock with the shocks along the main diagonal. 68% probability intervals.

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